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An Integrated Collection-Disassembly-Distribution Model with Fuzzy Demand: Toward Sustainable Reverse Logistics

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Abstract This study addresses the integrated collection–disassembly–distribution problem under fuzzy demand. The problem provides a roadmap for effectively managing reverse supply chains under uncertain conditions. It involves collecting end-of-life products, disassembling them, and distributing the components obtained from the disassembly process to demand centers under fuzzy demand. The reuse of valuable components not only provides cost savings but also supports sustainable supply chain practices. A nonlinear mathematical model is developed to represent the problem and is tested through various scenario analyses. The results show that the proposed model provides a realistic decision-support framework that accounts for the vagueness faced by decision-makers and manufacturers. Moreover, the findings indicate that it is possible to achieve cost-effectiveness and efficient resource utilization even in the presence of demand ambiguity, highlighting the model's applicability to industries operating in volatile and unpredictable market environments.

Keywords Disassembly line balancing · environmental sustainability · fuzzy demand · reverse logistics · vehicle routing problem

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An Integrated Collection-Disassembly-Distribution Model with Fuzzy Demand: Toward Sustainable Reverse Logistics

Introduction

Rapid urbanization, industrialization, and changing consumption habits have significantly shortened the lifespan of technological products and led to a rapid increase in electronic waste. The Global E-waste Monitor 2024 (GEM2024) reports that 62 Mt of e-waste was generated worldwide in 2022, with an average annual increase of 2.3 Mt since 2010, and projections indicate that WEEE could reach 82 Mt by 2030 (e-wastemonitor, 2024; Serpe et al., 2025). This situation has increased environmental awareness, led to stricter recycling regulations, and created new challenges for businesses. As a result, companies have changed their strategies by enhancing sustainability goals and adopting green supply chain management practices, such as recycling and remanufacturing (Al-Sheyadi et al., 2019).

End-of-life products, particularly electronics, must be collected and systematically disassembled to recover useful components that can be reused in production, thereby reducing the demand for natural resources and lowering costs. At the same time, increasing environmental concerns and legislative pressure are compelling manufacturers to adopt environmentally responsible practices and integrate reverse logistics into their operations (Ilgin & Gupta, 2010; Kannan et al., 2017). Disassembly line balancing (DLB), as the reverse of assembly, plays a critical role in reverse logistics and e-waste management. To manage the collection of EOL products and distribution efficiently, the Vehicle Routing Problem (VRP) has been widely applied, enabling cost reduction, the efficient use of vehicle capacities, and improved competitiveness in the recycling market (Dantzig & Ramser, 1959; Diri Kenger et al. 2021a).

Diri Kenger et al. (2020a) proposed the integrated disassembly line balancing and routing problem (I-DLB-RP). This problem simultaneously optimizes two classical problems. The first involves balancing disassembly lines at disassembly centers, while the second focuses on designing routing plans to deliver usable components, recovered from disassembly, to remanufacturing centers. Then, the Integrated Collection-Disassembly-Distribution Problem (I-CDDP) was introduced by Diri Kenger et al., 2021a). Whereas the I-DLB-RP does not account for collecting EOL products, the I-CDDP incorporates the collection of EOL products. Most studies addressing the integration of DLB and VRP do not consider uncertainty (Habibi, et al., 2014; Diri Kenger et al., 2020a; Diri Kenger et al., 2021a; Diri Kenger et al., 2021b; Çil et al., 2023; Durmaz & Budak, 2025). In particular, the demand for usable components recovered from EOL products can be uncertain because of changing market conditions and environmental regulations (Teodorović & Pavković, 1996; Werners & Drawe, 2003; Cao & Lai, 2010; Özceylan & Paksoy, 2014; Tuncel, Zeid, & Kamarthi, 2014). In the literature, uncertainty in supply chain problems is often handled using stochastic programming and robust optimization (Birge & Louveaux, 2011; Ben-Tal et al., 2009). However, these approaches may not be suitable for reverse logistics systems. Stochastic programming requires well-defined probability distributions, but such information is usually unavailable in EOL product recovery due to limited historical data (Klibi et al., 2010; Werners & Drawe, 2003). Robust optimization, on the other hand, focuses on worst-case scenarios, which can result in overly conservative solutions (Bertsimas & Sim, 2004; Ben-Tal et al., 2009). In contrast, fuzzy set theory allows modeling uncertainty without requiring exact probabilistic information (Zadeh, 1965; Zimmermann, 2001). It also enables the use of expert knowledge and linguistic evaluations, which is particularly useful in disassembly systems, where the demand for recovered components is highly uncertain and depends on market conditions (Teodorović & Pavković, 1996; Özceylan & Paksoy, 2014). Therefore, fuzzy logic is employed to handle uncertainty and provide more reliable solutions in such environments.

In this context, this study introduces the integrated collection-disassembly-distribution under fuzzy demand (I-CDDP-FD) and proposes a mathematical model for the problem. The I-CDDP-FD extends the I-CDDP by incorporating

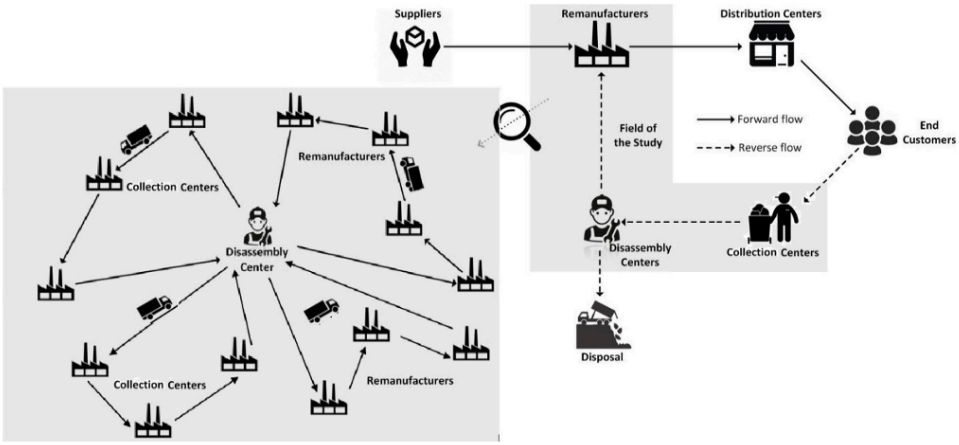
demand uncertainty. This approach ensures the simultaneous optimization of collection, disassembly, and distribution processes while considering demand uncertainty and promotes sustainable reverse logistics operations.

Problem Statement

This study addresses a two-stage RSC network. In the first stage, a vehicle with fixed capacity transfers EOL products from collection sites to the disassembly site. In the second stage, usable components are recovered through DLB and then transported to remanufacturing centers. The problem presents a two-echelon vehicle routing problem. The first echelon considers the pickup of EOL products, whereas the second echelon deals with the distribution of recovered components from the disassembly process. In real-life supply chain scenarios, much of the information is uncertain. To address this uncertainty, we adopt a fuzzy programming method that provides clearer and more precise outcomes in such situations. This technique is well suited for situations with limited historical data. Therefore, we consider the fuzziness of demand values. We also assume that inventory is held at the disassembly center, and the objective function accounts for inventory costs as well. The study demonstrated the applicability of fuzzy logic in integrating DLB and routing problems. The I-CDDP-FD is shown in Figure 1.

Figure 1

A schematic representation of the I-CDDP-FD



Literature Review

Along with the adoption of new technologies in disassembly processes, the quality of components recovered from disassembly lines is steadily increasing. Companies evaluate these components as raw materials due to their economic benefits and environmental importance. Despite being a crucial step in RSC, DLB has rarely been explored in the literature in the context of VRP integration. This section reviews previous research on integrated DLB and distribution problems. It is structured into two parts: the first part covers studies that integrate the disassembly problem with supply chain operations but exclude VRP, and the second part presents papers that address both DLB and VRP together.

A pioneering analysis of disassembly line balancing combined with distribution planning was carried out by Özceylan & Paksoy (2013). They developed a nonlinear mathematical formulation aimed at minimizing total transportation costs along with the fixed costs of workstations. Özceylan et al. (2014) focused on the integrated management of closed-loop supply chains (CLSCs) and DLB. A nonlinear programming formulation was proposed to minimize total costs, including transportation, refurbishment, purchasing, and operating costs for disassembly workstations. Özceylan and Paksoy (2014) considered the integration of RSC and DLB under uncertainty. Two distinct fuzzy mathematical programming models were proposed, and their applicability was demonstrated on benchmark datasets. Kannan et al. (2017) investigated how the multi-product DLB problem can be incorporated into recovery network planning. To address this

challenge, they developed a mixed-integer nonlinear programming (MINLP) model. Yolmeh and Saif (2021) considered both ALB and DLB problems within the context of CLSC network design under uncertainty. A MINLP model and enhanced decomposition approach were developed to solve the problem. The proposed model accounts for uncertainties in both demand and the number of returned products. Hu et al. (2024) addressed a novel integrated reverse supply chain design and DLB problem for multiple EOL products under stochastic conditions, aiming to maximize expected profit and minimize carbon emissions. A bi-objective two-stage stochastic programming model was developed and solved using an ε-constrained method and improved Benders decomposition, and its performance was demonstrated through numerical experiments and managerial insights. Sensitivity analyses were conducted, and the efficiency of the proposed approaches was tested on numerical examples. Tasoglu and Ilgin (2024) considered disassembly sequencing in the DLB problem within the RSC context. The transportation and disassembly times were characterized by uncertainty. A simulation-based genetic algorithm was proposed, and its applicability was tested on a numerical example.

Diri Kenger et al. (2020a) integrated the DLB and routing problem (I-DLB-RP) for the first time, demonstrating the advantages of combining the two problems. Five linear and nonlinear models were proposed for the novel problem, and several analyses were conducted on benchmark test problems. Diri Kenger et al. (2020b) incorporated additive manufacturing technology into the I-DLB-RP. A MINLP formulation was proposed and tested on numerical examples. Diri Kenger et al. (2021a) also considered the collection of EOL products, their disassembly, and distribution of the obtained components. The problem was defined as the integrated collection–disassembly–distribution problem (I-CDDP), and two mathematical formulations were proposed. Extensive scenario analyses were conducted on benchmark datasets. Diri Kenger et al. (2021b) integrated additive manufacturing into I-DLB-RP from a different perspective (I-DLB-RP-MAM). Within the I-DLB-RP-MAM framework, a facility carries out the disassembly of EOL products, after which a 3D-printer-equipped vehicle transports the recovered parts along with additively manufactured components to customers. A MINLP formulation was proposed, and various analyses were performed using numerical test instances. The findings show that incorporating additive manufacturing technology into the supply chain is practical and beneficial. Çil et al. (2023) considered multiple disassembly centers for the I-DLB-RP. Various solution approaches, such as LP, MINLP, and constraint programming models, were proposed for the novel problem. In addition to these mathematical models, a multi-start simulated annealing algorithm was developed for large-sized test problems. Durmaz and Budak (2025) addressed the partial DLB problem and the multi-objective green VRP for the first time. A multi-objective mixed-integer linear programming model was formulated, and an integrated multi-criteria decision-making method was used to solve the problem.

As seen in Table 1, uncertainty has not been considered in the integrated DLB and VRP literature. Increasing attention to uncertainty in RSC has complicated production and distribution planning (Özceylan & Paksoy, 2014). While parameter values are often assumed to be certain, real-world supply chains frequently face uncertainty. To address this issue, a fuzzy programming approach, which is effective for uncertain situations with limited historical data, is adopted. This study specifically focuses on the fuzziness in demand values.

Table 1

A summary of the existing literature on disassembly–distribution integration

Study	ALB	DLB	VRP	CLSC	RSC	AM	LP	NLP	CP	Heuristic Algorithm	Uncertainity
(Özceylan and Paksoy, 2013)		✓			✓			✓			
(Özceylan et al., 2014)		✓		✓				✓			
(Özceylan and Paksoy, 2014)		✓			✓			✓			Fuzzy
(Kannan et al., 2017)		✓			✓			✓			
(Diri Kenger et al., 2020a)		✓	✓				✓	✓			
(Diri Kenger et al., 2020b)		✓	✓			✓		✓			

Study	ALB	DLB	VRP	CLSC	RSC	AM	LP	NLP	CP	Heuristic Algorithm	Uncertainity
(Diri Kenger et al., 2021a)		✓	✓		✓		✓				
(Diri Kenger et al., 2021b)		✓	✓			✓		✓			
(Yolmeh and Saif, 2021)	✓	✓		✓				✓			Stochastic
(Çil et al., 2023)		✓	✓				✓	✓	✓	✓	
(Durmaz and Budak, 2024)		✓	✓		✓		✓				
(Hu et al., 2024)		✓			✓		✓				Stochastic
(Tasoglu and Ilgin, 2024)		✓			✓					✓	Stochastic
The current study		✓	✓		✓		✓	✓			Fuzzy

ALB: assembly line balancing, DLB: disassembly line balancing, VRP: vehicle routing problem, RSC: reverse supply chain, CLSC: closed loop supply chain, LP: linear programming; NLP: nonlinear programming, AM: additive manufacturing, CP: constraint programming, C-TSSP: chance-constrained two-stage stochastic programming.

Mathematical formulation and defuzzification of the model

The study proposes an MINLP model for the problem. Remanufacturing centers require several types of components. The model assumes a single disassembly center, focuses on a single product type, and accounts for multiple components obtained from the disassembly process. The assumptions for the proposed problem are explained as follows. In the proposed model, complete disassembly is performed on one type of product, and in each disassembly step, the product or subassembly is divided into at least two new subassemblies. Tasks cannot be distributed across multiple workstations. Tasks can be performed at any workstation, and the cost remains the same for all. Vehicle capacities are known, and vehicles are available to serve the remanufacturing centers. Each remanufacturing center requires multiple types of components, and the demands, although uncertain, must be fully satisfied without exceeding the vehicle capacity. The disassembly center receives a single type of EOL product from the collection centers.

Indices

c, g	Remanufacturing center, *c, g*={1,2,...,*N*}
m, t	Collection center, *m, t*={1,2,...,*E*}
i	task
k	component
j, h	workstation
A	artificial task

Sets and parameters

A_a	artificial nodes of *a*
B_i	normal nodes of *i*
$P(A_a)$	set of immediate predecessor of A_a
$P(B_i)$	set of the immediate predecessor of B_i
$S(A_a)$	set of the immediate successor of the artificial node A_a
$S(B_i)$	set of the immediate successor of the artificial node B_i
d_{B_i}	Task processing time (normal node) of B_i (s)
J	Workstations number (upper bound)
W_{time}	Working time (s)

A_a	artificial nodes of *a*
De_{gk}	demand for component *k* at remanufacturing center *g*
$\widetilde{De}_{gk}$	fuzzy demand for component *k* at remanufacturing center *g*
Ct	Fixed transportation cost from the disassembly center to the remanufacturing center *g* or collection center *t* (cents)
Sc	Fixed disassembly cost per product (cents)
CI	fixed inventory cost per component
μ	Big number (maximum number of tasks that can be assigned to station +1)
D_{cg}	Distance from the disassembly center to a remanufacturing center or between remanufacturing centers (km)
O	Fixed workstation cost in the disassembly line ($/workstation)
Q_1	Capacity of the vehicle collecting EOL products (unit)
Q_2	Capacity of the vehicle distributing components (unit)
Pr	demand satisfying profit
S_t	Supply at collection center *t* (unit)
DC_{mt}	Distance from the disassembly center to a collection center or between collection centers (km)

Integer Variables

U_g	load on the vehicle after servicing remanufacturing center *c*
UU_t	load on the vehicle after servicing collection center *m*
I_k	inventory level of component k
P	quantity of products disassembled on the disassembly line
Cyc	Cycle time (s)

Binary Variables

x_{ij}	1, if task B_i is assigned to workstation *j*; 0 otherwise
y_{cg}	1, if vehicle travels from disassembly center to remanufacturing center or between remanufacturing centers; 0 otherwise
yy_{mt}	1, if vehicle travels from disassembly center to collection center or between collection centers; 0 otherwise
z_i	1, if task B_i is performed; 0 otherwise
F_j	1, if workstation *j* is opened; 0 otherwise

$$Minimize\ O^{*}\sum_{j}^{J}F_j + Ct^{*}\sum_{c}^{N}\sum_{g,g\neq c}^{N}D_{cg}{}^{*}y_{cg} + Ct^{*}\sum_{m}^{E}\sum_{t,m\neq t}^{E}DC_{mt}{}^{*}yy_{mt} + Sc \\ {}^{*}P + CI^{*}\sum_{k}^{K}I_k - Pr^{*}\sum_{c}^{N}\sum_{g,g\neq c}^{N}\sum_{k}^{K}\widetilde{De}_{gk}{}^{*}y_{cg} \tag{1}$$

subject to

$$\sum_{i:B_i \in S(A_0)} z_i = 1 \tag{2}$$

$$\sum_{i:B_i \in S(A_a)} z_i = \sum_{i:B_i \in P(A_a)} z_i \qquad \forall a, a \neq 0 \tag{3}$$

$$\sum_{j=1}^{J} x_{ij} = z_i \qquad \forall\, i \tag{4}$$

$$\sum_{i:B_i \in S(A_a)} x_{ih} \leq \sum_{i:B_i \in P(A_a)} \sum_{j=1}^{h} x_{ij} \qquad \forall\, a, a \neq 0, h \in J \tag{5}$$

$$Cyc^{*}P = W_{time} \tag{6}$$

$$\sum_{i=1}^{I} x_{ij}{}^{*} d_{B_i} \leq Cyc \qquad \forall j \tag{7}$$

$$\sum_{i=1}^{I} x_{ij} \leq \mu^{*} F_j \qquad \forall j \tag{8}$$

$$F_{j+1} \leq F_j \qquad \forall j, j = 1, ..., J-1 \tag{9}$$

$$\sum_{g=1, g \neq c}^{N} y_{cg} = 1 \qquad \forall c, c = 2, ..., N \tag{10}$$

$$\sum_{c=1, c \neq g}^{N} y_{cg} - \sum_{c=1, c \neq g}^{N} y_{gc} = 0 \qquad \forall g, g = 1, ..., N \tag{11}$$

$$U_c - U_g + Q_2{}^{*} y_{cg} \leq Q_2 - \sum_{k=1}^{K} \widetilde{De}_{gk} \qquad \forall c, g, \;\; c, g = 2, ..., N, c \neq g \tag{12}$$

$$\sum_{t=1, t \neq m}^{E} yy_{mt} \leq 1 \qquad \forall m, m = 2, ..., E \tag{13}$$

$$\sum_{m=1, m \neq t}^{E} yy_{mt} - \sum_{m=1, m \neq t}^{E} yy_{tm} = 0 \qquad \forall t, t = 1, ..., E \tag{14}$$

$$UU_m - UU_t + Q_1{}^{*} yy_{mt} \leq Q_1 - S_t{}^{*} yy_{mt} \qquad \forall m, t, m, t = 2, ..., E, m \neq t \tag{15}$$

$$S_m{}^{*} yy_{1m} \leq UU_m \qquad \forall m, m = 2, ..., E \tag{16}$$

$$S_m{}^{*} \sum_{t=1}^{E} yy_{(mt)} \leq UU_m \qquad \forall m, m = 2, ..., E \tag{17}$$

$$\sum_{g=2}^{N}\sum_{k=1}^{K}\widetilde{De}_{gk} \leq \sum_{m=2}^{E}\sum_{t=1}^{E} S_t{*}yy_{mt} \tag{18}$$

$$I_k = P - \sum_{c=1}^{N}\sum_{g=2,\, c\neq g}^{N}\widetilde{De}_{gk}{*}y_{cg} \quad \forall k \tag{19}$$

$$\sum_{k=1}^{K}\widetilde{De}_{gk} \leq U_g \leq Q \quad \forall g \tag{20}$$

$$0 \leq UU_t \leq Q \qquad \forall t \tag{21}$$

$$x_{ij},\, z_i,\, y_{cg},\, yy_{mt}\; F_j \in \{0,1\} \qquad \forall i, j, c, g. \tag{22}$$

The objective function (1) aims to minimize the total cost, including routing, workstation, product disassembly, and inventory costs, while accounting for the profit from satisfying demand.

Constraints (2) and (3) ensure the selection of exactly one OR-successor in the disassembly center. Constraint (4) specifies that each task must be allocated to only one workstation in the disassembly line. Constraint (5) enforces precedence relationships. The cycle time, as defined in Constraint (6), equals the total working time divided by the number of products disassembled. Constraint (7) ensures that the processing time at each disassembly workstation does not exceed the cycle time. Constraint (8) allows tasks to be assigned only if a workstation is active. Constraint (9) ensures that workstations are opened in order. Constraint (10) ensures that each remanufacturing center is visited exactly once. Constraint (11) defines the flow for the remanufacturing centers. Constraint (12) represents the vehicle capacity constraints. Constraint (13) indicates that visiting all collection centers is not mandatory. Constraint (14) ensures the flow associated with the collection centers. Constraints (15)–(17) represent capacity limitations. Constraint (18) ensures that the total supply from collection centers meets the demand of the remanufacturing centers. Constraint (19) maintains the inventory balance at the disassembly center. Constraints (20)–(22) specify the domain of the decision variables.

The proposed model contains constraints that include triangular fuzzy numbers requiring defuzzification. Various researchers have introduced methods for converting fuzzy mathematical models into crisp, deterministic models (Zimmermann, 2001; Jiménez et al., 2007). The method proposed by Jiménez et al. (2007) is used to handle uncertainty, as it efficiently performs defuzzification without adding extra inequality constraints. The defuzzification approach proposed by Jiménez et al. (2007) focuses on handling the feasibility of fuzzy constraints using α-feasibility coefficients and ranking methods. By applying these techniques, fuzzy constraints are converted into crisp deterministic constraints while maintaining a specific feasibility level. Based on the method proposed by Jiménez et al. (2007), defuzzification is applied to constraint (23). A triangular fuzzy parameter is described using three key values: pessimistic, likely, and optimistic, represented by *pes*, *mos*, and *opt*, respectively. Constraint (20) is replaced by Constraint (24), which allows the system to operate within a defined range while considering demand uncertainty.

$$\widetilde{De}_{gk} \leq \left[\alpha{*}\left(\frac{De_{gk}^{opt} + De_{gk}^{mos}}{2}\right) + (1-\alpha){*}\left(\frac{De_{gk}^{pes} + De_{gk}^{mos}}{2}\right)\right] \quad \forall g, k,\; g = 2, ..., N \tag{23}$$

$$\sum_{k=1}^{K} De_{gk}^{pes} \leq U_g \leq Q \quad \forall g \tag{24}$$

Results and Discussion

This section presents computational experiments for the proposed model. The generation of instances is described in Section 4.1, and an illustrative example is provided in Section 4.2 to test the model. Finally, Section 4.3 reports the results of the scenario analysis. All tests were run on a computer with an Intel Core i5-8250U 1.6 GHz dual-core processor and 8 GB of RAM. The solution was obtained using the GAMS/SCIP solver.

Data and benchmark instance generation

To create the sample case, we use well-known datasets from the literature. For DLB, the flashlight example presented by Tang (2002) is used, which includes 7 components and 10 tasks. The flashlight and its components are illustrated in Figure 2, whereas Figure 3 presents its transformed graph (TAOG), as introduced by Paksoy et al. (2013).

Figure 2

Components of a flashlight (Tang, 2002).

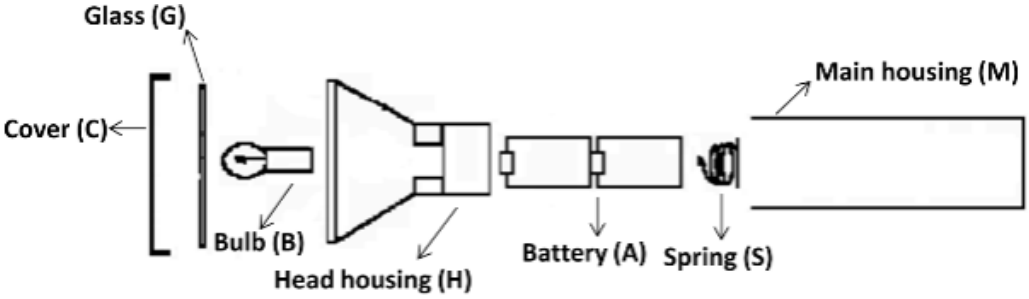
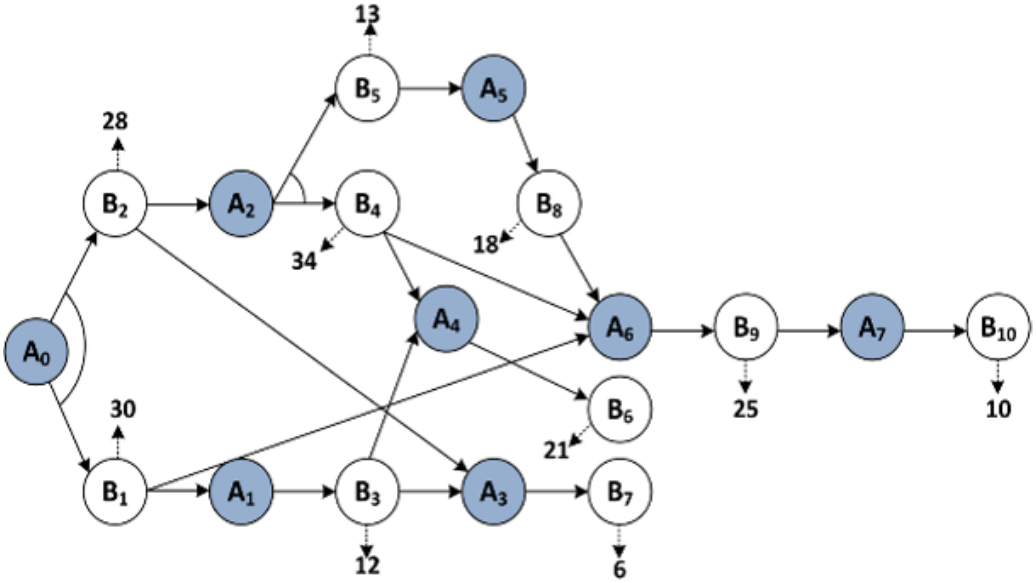


Figure 3

TAOG for the flashlight (Paksoy et al., 2013).



The VRP phase employs the smallest dataset from Set P of Augerat et al. (1995) and modifies classical VRP instances to create our test cases. We adapt the smallest dataset (P_n16_k8) from Set P by designating the first node as the disassembly center, five nodes as remanufacturing centers, and five nodes as collection centers, keeping their coordinates unchanged. Distinct uniform distributions are used to generate supply and demand parameters within defined ranges [10-20] and [1-6], respectively. Table 2 displays the demand values, where C1 through C7 represent components 1–7 and RC stands for the remanufacturing center. Table 3 presents the supply data, where CC denotes collection centers.

Table 2

The most likely demands for remanufacturing centers

	C1	C2	C3	C4	C5	C6	C7
RC1	3	1	4	3	2	1	2
RC2	2	4	3	2	3	1	2
RC3	1	1	6	2	2	1	3
RC4	2	1	2	3	4	3	4
RC5	1	1	5	2	1	2	1

Table 3

Supply for the collection centers

CC	1	2	3	4	5
Supply	11	12	10	15	20

The most optimistic and pessimistic values are calculated by randomly multiplying the most likely values by the intervals [0.6–0.8] and [1.2–1.4], respectively. As demand values are integers, the pessimistic values are rounded down, whereas the optimistic values are rounded up.

The total working time (W_{time}) is defined as 1250 seconds, with a maximum of 10 workstations (*J*). Each workstation in the disassembly line incurs an operational cost *(O)* of $100. For a standard truck, the shipping cost *(Ct)* is set at 5.23 cents per ton-km. Vehicle capacities are fixed at 35 and 70 for the collection and distribution processes, respectively.

Results of an illustrative example

To test the model, a small dataset was used, considering five collection and five remanufacturing centers. α = 0.3 was applied in the computational experiments, and the optimal results are presented in Table 4. Optimal component distribution results are presented in Table 5. Optimal distribution routes are shown in Figure 4.

Table 4

Optimal results of an illustrative example

Obj ($)	Inv	CT (sec)	CPU (sec)
72.057	1	178.571	809.85

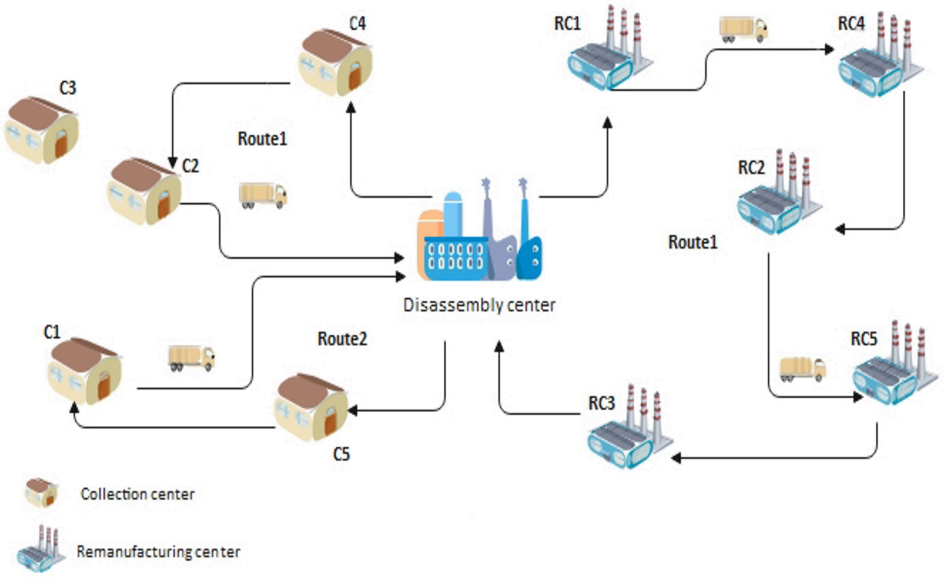
Table 5

Optimal component distribution for the sample case

	C1	C2	C3	C4	C5	C6	C7
RC1	2	1	3	2	2	1	1
RC2	1	3	2	2	1	1	1
RC3	1	1	1	0	1	1	2
RC4	1	1	1	2	3	2	3
RC5	1	1	0	1	0	2	0

Figure 4

Optimal distribution routes for the sample case



Managerial insights

Regarding managerial insights, the analysis is conducted across multiple dimensions. Initially, it examines the effects of different α-levels on the solutions. In the second phase, it analyses the impacts of varying working times on the results. It then investigates how different disassembly costs affect the solutions. Finally, it assesses the effects of varying profit margins on the results. The aim of this multi-dimensional analysis is to provide a comprehensive guide for managers to support their decision-making processes.

α-feasibility coefficient analysis

This section examines how the fuzzy model performs. To evaluate the performance of the fuzzy model, α-levels of 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, and 0.6 are considered. All results are presented in Table 6 and Figure 5.

Table 6

The effects of varying α levels on the model results

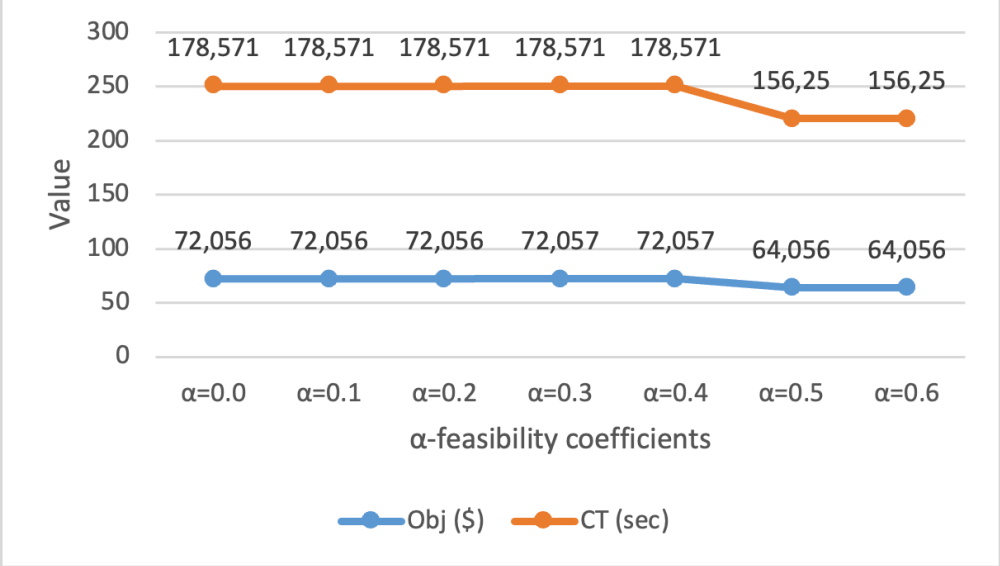
	α=0.0	α=0.1	α=0.2	α=0.3	α=0.4	α=0.5	α=0.6
Obj ($)	72.056	72.056	72.056	72.057	72.057	64.056	64.056
CT (sec)	178.571	178.571	178.571	178.571	178.571	156.25	156.25
P	7	7	7	7	7	8	8
Inv	1	1	1	1	1	0	0
CPU (sec)	402.95	659.72	850.03	809.85	894.13	1504.07	2404.14

Table 6 illustrates the effects of varying α levels on the model results. As α ranges from 0.0 to 0.4, the objective value remains nearly constant, indicating that the model is relatively insensitive to lower α values. However, when α reaches 0.5 and above, the objective value decreases sharply to $64.056, suggesting a significant cost improvement. Similarly, the CT remains stable at approximately 178.57 seconds for $\alpha \leq 0.4$, then decreases to 156.25 seconds as α increases to 0.5, reflecting a notable improvement in processing efficiency. Finally, the CPU time ranges between 402 and 895 seconds for lower α levels but sharply increases to approximately 1504–2404 seconds for $\alpha \geq 0.5$, underscoring the significant computational effort required for higher α values. Figure 5 illustrates the relationship between the objective

function and cycle time values for different α-feasibility coefficients. These results demonstrate the critical role of the α parameter in shaping both the decision variables and the computational performance of the model.

Figure 5

Relationship between cycle time and objective function values according to α-feasibility coefficients



Working time analysis

In this section, the effects of varying working times (250–1500) on the results of the proposed model are analyzed (see Table 7 and Figure 6). At a working time of 250, the objective value is relatively high at $96.34, but it decreases sharply to $79.65 when the working time increases to 500 and reaches its lowest point of approximately $72.057 for working times of 750 and above, indicating that longer working times enable more cost-efficient solutions. The CT shows a similar trend, dropping from 125 seconds at the shortest working time to roughly 100 seconds at 500, before gradually rising to 178.57 and 214.28 seconds as working times extend to 1250 and 1500, respectively. Interestingly, CPU times fluctuate significantly, rising sharply from 136.81 seconds at 250 to 374.75 seconds at 500, then dropping to 231.83 seconds at 750, peaking at 809.85 seconds at 1250, before decreasing to 225.41 seconds at 1500.

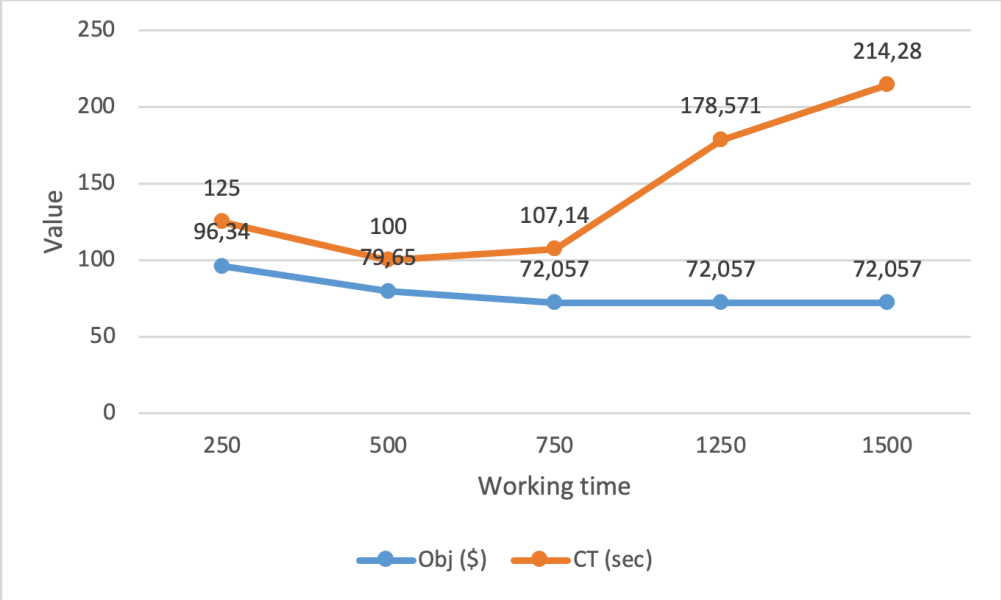
Table 7

Optimal results for the working time analysis

	250	500	750	1250	1500
Obj ($)	96.34	79.65	72.057	72.057	72.057
CT (sec)	125	100	107.14	178.571	214.28
P	2	5	7	7	7
Inv	0	0	1	1	1
CPU (sec)	136.81	374.75	231.83	809.85	225.41

Figure 6

Relationship between cycle time and objective function values according to working time



Cost analysis

In this section, the effects of disassembly cost and profit on the solution is analyzed. Table 8 presents the optimal results for the disassembly cost analysis across varying fixed disassembly cost levels. As the fixed cost increases from \$0.25 to \$0.75, the number of production (P) remains constant at 8, the CT is fixed at 156.25 seconds, and the inventory level stays at 4 units, indicating that in this cost range, both production and inventory policies remain unchanged despite rising fixed disassembly costs. Meanwhile, the objective value (OBJ) gradually increases from \$66.057 to \$70.057, reflecting the direct cost impact. At a fixed disassembly cost of \$1.00, a shift occurs: the number of production batches decreases to 7, CT increases to 178.57 seconds, and the inventory level drops to 1 unit. As the cost continues to rise from \$1.25 to \$1.75, the Objective value steadily increases from \$73.80 to \$77.30, while the production batch quantity and inventory level remain unchanged. Notably, the CPU times fluctuate across the cost levels, ranging from 104.63 seconds at the lowest cost level to a peak of 1858.72 seconds when the cost is \$1.75, indicating the growing computational effort required for higher fixed disassembly cost scenarios. These results highlight the significant interplay between fixed disassembly cost, operational decisions, and computational performance.

Table 8

Optimal results for the disassembly cost analysis

fixed cost to disassemble a product	P (unit)	CT (sec)	OBJ ($)	Inv (unit)	CPU
0.25	8	156.25	66.057	4	104.63
0.5	8	156.25	68.057	4	308.75
0.75	8	156.25	70.057	4	148.58
1	7	178.571	72.057	1	402.95
1.25	7	178.571	73.80	1	597.79
1.5	7	178.571	75.55	1	448.46
1.75	7	178.571	77.3	1	1858.72

Figure 7

Relationship between cycle time and objective function values according to disassembly cost

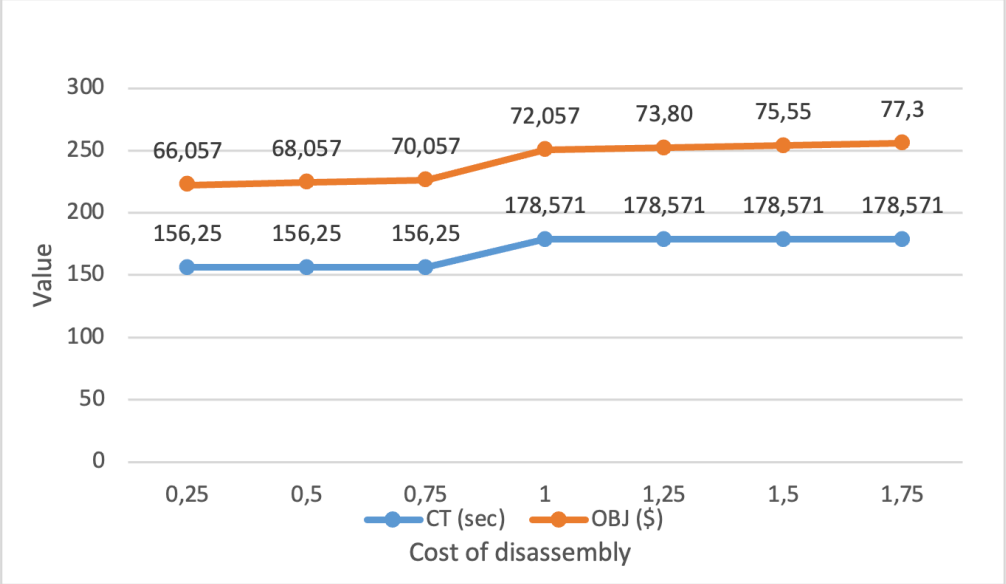


Table 9 summarizes the effects of varying profit levels from satisfying demand on the model results. As profit increases from 0.25 to 1.75, the number of production units increases from 4 to 9, while cycle time decreases from 312.5 to 138.89 seconds, indicating improved production efficiency. The objective value drops significantly—from $105.87 to $32.807—demonstrating better cost-effectiveness at higher profit margins. Although CPU time fluctuates, a notable spike at 0.5 profit suggests greater complexity at low profit levels. Overall, higher demand-related profit leads to more efficient, inventory-driven solutions.

Table 9

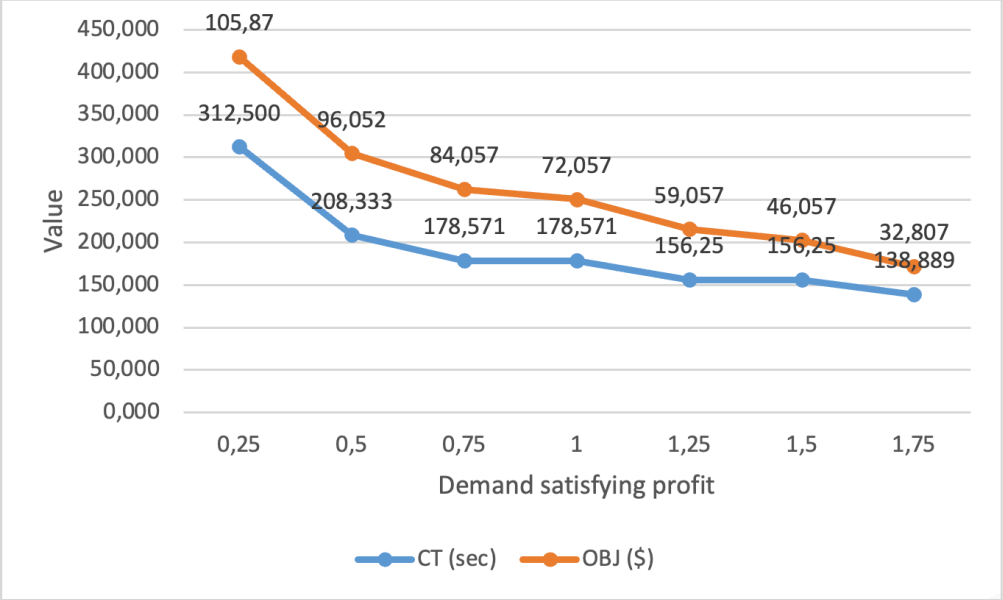
Optimal results for profit analysis

demand satisfying profit	P (unit)	CT (sec)	OBJ ($)	Inv (unit)	CPU
0.25	4*	312.500*	105.87*	0*	TL
0.5	6	208.333	96.052	0	4120.68
0.75	7	178.571	84.057	1	447.09
1	7	178.571	72.057	1	402.95
1.25	8	156.25	59.057	4	635.70
1.5	8	156.25	46.057	4	648.58
1.75	9	138.889	32.807	7	466.01

TL= time limit reached *=integer solution

Figure 8

Relationship between objective function and cycle time values according to demand profit



The results provide useful managerial insights for decision-makers working under demand uncertainty. First, the α-feasibility analysis shows that higher α levels lead to lower cycle times and better objective values, but they also require more computational time. This means that managers can choose higher α levels when they want more reliable and cautious decisions, while lower α levels can be used when faster decisions are needed.

Second, the working time analysis shows that increasing working time improves cost performance up to a certain point. After this point, the improvement becomes limited. Therefore, managers should provide enough capacity but avoid excessive working time since it does not always lead to better results.

Third, the cost analysis shows that disassembly cost strongly affects decisions. When disassembly costs are low, higher disassembly and inventory levels can be maintained. However, when costs increase, the system moves toward lower disassembly and less inventory. For this reason, managers should closely monitor disassembly costs and adjust operation plans accordingly.

Finally, the profit analysis shows that higher profit levels support more aggressive production strategies. When profit increases, managers should increase production and reduce cycle times, even if inventory levels increase. In contrast, when profit is low, a more conservative strategy should be followed, where disassembly activities are reduced and excess inventory is avoided to lower costs.

Conclusion

In this study, the integrated collection–disassembly–distribution problem under fuzzy demand (I-CDDP-FD) was investigated. With the increase in electronic waste, the importance of sustainable waste management has also increased. In this research, the importance of balancing the disassembly line and vehicle routing in the transportation of EOL products is emphasized, and uncertainty is also considered. In this study, uncertain demand is modeled using fuzzy logic, and the limitations of classical probabilistic approaches are addressed, especially in cases with insufficient data. The proposed model contributes to the literature by providing a more realistic and flexible decision-support tool for manufacturers facing uncertainty in reverse supply chains.

For the proposed problem, a nonlinear mixed-integer mathematical model is formulated, and several analyses have been conducted using the model. Accordingly, as α-levels increase, the objective function value and cycle time decrease,

CPU time rises for higher α values, and the disassembled product numbers also increases. Increasing working times initially reduces the objective value and cycle time, while CPU times fluctuate, and inventory levels and the number of disassembled products increases. As disassembly costs increase, production batches and inventory levels remain stable up to a threshold, after which production decreases, cycle time, objective function value, and CPU time increase. Higher profit levels from satisfying demand lead to increased production, reduced cycle time, and lower objective function value, reflecting improved cost effectiveness.

The results demonstrate that cost efficiency and resource optimization can be achieved even under demand uncertainty, demonstrating the significant importance of this approach for industries operating in dynamic and unpredictable markets. Future studies could expand on this research by incorporating additional uncertainties into the model or applying the model to different product categories within the context of a circular economy.

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