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A Fuzzy Multi-Objective Mixed Integer Linear Programming Model for End of Life Use

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ABSTRACT

One of the main challenges of designing the effective reverse logistic network is to predict the amount of product which reach end of their useful life. Thus, in this study, we propose fuzzy multi-objective mixed integer linear programming (Fuzzy-MOMILP) model which the amount of returned product is considered as an uncertain parameter. In order to solve the proposed multi objective fuzzy mathematical programming model, a fuzzy solution approach is applied. The proposed Fuzzy-MOMILP model seeks to minimize the total reverse logistic network cost and minimize the total carbon emissions related to the transportation and processing of used products. To validate the model, a case study is examined. The results of this study indicate that the proposed model can be used to design a sustainable reverse logistic network for end-of-life (EOL) products.

Keywords: *Fuzzy approach, Multi-objective optimization, Emissions*

Kullanım Ömrü Tamamlanmış Ürünler için Bulanık Çok Amaçlı Karma Tamsayılı Doğrusal Programlama

ÖZ

Etkili bir tersine lojistik ağı tasarlamanın temel zorluklarından biri, kullanım ömrünü tamamlamış geri dönüşüm veya başka amaçlar için kullanılacak ürünlerin miktarını tahmin etmektir. Bu nedenle bu çalışmada, kullanım ömrünü tamamlamış ürünlerin geridönüşüm için veya başka maksatla kullanılacak olması sebebi ile geri dönüşüm döngüsünde ürün miktarının belirsiz bir parametre olarak kabul edildiği bulanık mantık çok amaçlı karma tamsayılı doğrusal programlama (Fuzzy-MOMILP) modeli önerilmiştir. Önerilen çok amaçlı bulanık mantık matematiksel programlama modelini çözmek için bir bulanık çözüm yaklaşımı uygulanmıştır. Önerilen Fuzzy-MOMILP modeli, toplam tersine lojistik ağ maliyetini en aza indirmeyi ve kullanılmış ürünlerin taşınması ve işlenmesiyle ilgili toplam karbon emisyonlarını en aza indirmeyi amaçlamaktadır. Önerilen modeli doğrulamak için bir vaka çalışması incelenmiştir. Bu çalışmanın sonuçları, önerilen modelin ömrünü tamamlamış ürünler için sürdürülebilir tersine lojistik ağı kurulurken fayda sağlayacağı gözlenmiştir.

Anahtar Kelimeler: *Bulanık yaklaşım, Çok amaçlı optimizasyon, Emisyon*

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I. INTRODUCTION

With rapid industrialization, environmental issues, such as increasing carbon emissions, are becoming huge concerns all over the world. To overcome some of these environmental problems, nations started to find alternative ways to reduce the environmental damages. Thus, using renewable energy resources, such as wind energy, have become one of the greenest alternative over the last two decades. However, considering the size of the wind turbines (WTs) and the amount of wind farms which is growing every year, it is obvious that more resources needed to build WTs[1]. Using the concept of the circular economy, after a turbine reaches its end-of-life (EOL), a WT should be either reused or recycled as much as possible to help reduce the need for virgin materials and waste quantities. Once a WT is manufactured its life expectancy is around 20 – 30 years, after that WTs usually get either repowered or decommissioned [2]. To apply circular economy concepts, reducing waste quantities and minimizing the need for virgin materials [3,4], there is a need to research an effective management of the WTs parts after their end-service-life. The purpose of this research is to evaluate the optimal handling procedures of EOL WTs in both environmental and economic level. Designing sustainable reverse logistic network may guarantees companies a level of circular economy. By implementing circular economy concept into reverse logistic operations for WTs, companies can reduce use of raw materials and can add value by reducing disposal costs by saving landfill space and energyas well as reducing carbon emissions [5,6].

The uncertainty in the EOL products quantity is one of the challenge that needs to be addressed while designing a sustainable reverse logistic networks [**7**]. In terms of uncertainty in return material, there is no exception for the WTs that reach their EOL. Therefore, we aim to develop a multi-period fuzzy multi-objective mixed integer linear programming (Fuzzy-MOMILP) model to handle the uncertainty in return quantity of EOL WTs. For the proposed model, we use two objectives, including minimizing the total costs and minimizing carbon dioxide emissions of the reverse logistic network. To handle the uncertainty, we use Zimmermann [8] multi-objective fuzzy linear programming approach. In literature, there are different methods that can be used to calculate the weights of each parameter such as fuzzy analytic hierarchy analysis. For the simplicity reason, in this study, different weights are assigned to each fuzzy objective function and a fuzzy constraint. By using a weighted additive approach, we convert the fuzzy multi-objective model into a single objective linear mathematical model.

Contributions of the proposed Fuzzy-MOMILP model are given below:

- In existing literature, despite potential EOL strategies to optimally manage WTs, the uncertainties both in remanufacturing and recycling processes, which may have huge impact on overall logistic cost and environmental effects were not considered.
- Based on the literature review, this is the first study consider multi products, multi period fuzzy approach, studying the multi-objective, including total cost and total carbon emissions for the WTs industry.

In section 2, we provide the literature review. In section 3, the details of the proposed mathematical model are given and in - section 4, the model results are given. In section 5, the effect of key parameters on model results are provided. Finally, in section 6, we summarize the study findings, conclusions and recommendations.

II. LITERATURE REVIEW

EOL reverse logistic networks design has been studies in a great details for the last two decades. For the most of the designed problems, mixed integer models, stochastic models and heuristic methods (such as Genetic Algorithm) have been used [9-15]. In addition, due to presence of uncertain parameters that add the complexity to design effective reverse logistic network, traditional methods have been used to forecast the quantity of returned products by examining available data. However, some of these methods are not effective to provide solutions when there is not enough data. As these methods are successful at certain capacity, other techniques such as fuzzy logic systems can be used to cover uncertainty issues in reverse logistic network design [16]. As we use a fuzzy approach to solve the proposed model, in the following section, we summarize the studies that use similar approach to address the uncertainties in reverse logistic network design in EOL products.

Olugu and Wong [17], studied fuzzy logic to assess the reverse logistic network in the automotive industry. Based on the results obtained, it was found that the approach adopted is appropriate to evaluate the reverse logistic performance of the automotive industry. According to this study, managers can assess the reverse logistic processes and identify areas which are deficient. Consequently, they can improve the overall performance of their reverse logistic network.

Tadic [18] investigated the management of the electronic waste problem in uncertain environment. Defined problem was considered as a fuzzy, non-convex optimization problem with linear objective function and a set of linear and nonlinear constraints. In their problem, the fuzzy rating of collecting point capacities and fix costs of recycling centers are modeled by triangular fuzzy numbers by using an illustrative example with real-life data. The results of this study suggested that initial study can be used an input for future research which is a good benchmark base for the tested reverse logistic network.

Govindana et al. [19] designed a multi objectives reverse logistic network that cost, environmental effect and social effects were selected as objective functions. To overcome the uncertain parameters, fuzzy mathematical programming with a particle swarm optimization algorithm was proposed. Comparing the proposed algorithm with epsilon-constraint method, it was concluded that proposed method gives better quality of the solution with less computational time.

Ergulen et al. [20] designed a reverse logistic network for recycling process as a form of recovery, to optimize reverse logistic costs by using fuzzy linear programming model in a real-time waste collection facility.

Ilgin [21] proposed a four-stage methods to select used product. During these four stage, the quantitative and qualitative selection criteria were determined first, then the weights of the criteria was determined by fuzzy analytic hierarchy process. During the last two stage, first, the values of quantitative criteria determined and then simulation were conducted to examine the applicability of the methodology.

Su [22] developed a fuzzy multi-objective linear programming. The objectives of the proposed model are minimize total costs, lead time and carbon emissions. The results of the study guide the decision maker to evaluate the importance of each objective function in recoverable remanufacturing planning.

Jeng and Lin [23] designed a green reverse logistic network by using fuzzy approach in recycled toner cartridge industry. In this study, by using fuzzy approach environmental inputs, such as law and regulations related to environmental issues and other environmental indicators as well as remanufacturing planning were determined to maximize the profits from green products.

Mavi et al. [24] analyzed sustainability and different risk factors for 3PL evaluation in plastic industry. For this purpose, first, fuzzy stepwise weight assessment ratio analysis was used to determine the weights for evaluation criteria. At the second step, fuzzy multi-objective optimization was used to rank the sustainable 3PL to overcome the uncertainties in the selected industry.

Colak and Boyaci [25], in their study assessed green performance of manufacturers which operate in the automotive sector by using a fuzzy multi criteria decision making (FMCDM) methods. In their model, 5 main criterias including green design, green energy, green material, green logistic and green management are selected, and 19 sub criteria are determined for the model. Based on the model results, , green energy as main criteria and low waste as sub criteria were determined as the most important criteria with weights of 0.268 and 0.1026 respectively. It is concluded that this modelcan be used as an effective tool for companies operating in the automotive industry for the purpose of measuring and following their green performance and selecting their suppliers.

Govindan et al. [26] studied supply chain network to examine the forward distribution partners and 3PL providers of electronic manufacturing firms was proposed. To evaluate the performance of the proposed network, fuzzy analytic hierarchy process was used. The multi objectives mixed integer programming, one objective is maximizing net profit manufacturing and the other objective maximizing the sustainable score of the forward and reverse logistic providers, was developed. The results of the study showed that integrated network can improve the sustainability performance and secure reasonable profits.

Doan et al. [27] employed a fuzzy theory which includes risk factors to overcome uncertain parameters in electronic industries. Based on the results, it was concluded that proposed approach provides flexibility during decision-making process.

Lu et al. [27] the proposed a fuzzy mixed integer linear programming model to examine the forward and reverse logistic network for multi-products in electronic assembly factory. In this study, uncertainties both in return and waste flow are examined. Model results including sensitivity analysis demonstrated that the proposed model provides effective solutions.

Zarbakhshnia et al. [28] developed a novel hybrid multiple attribute decision-making approach, which includes fuzzy analytic hierarchy process. Proposed method applied to a case study in car parts manufacturing industry to evaluate the effectiveness of the approach. The results showed that the proposed approach handles uncertain inputs well.

As listed above, most of these studies are addressing the uncertainty issues in logistic network for various industries, but to the best of our knowledge, there was not any study done in the field of WT EOL considering the uncertainties of the material recovery process which has a great environmental effect. By using Fuzzy-MILP, which integrate the uncertainty in recycling/remanufacturing of EOL WTs, we propose to close the research gap in the field of wind energy sector.

III. REVERSE LOGISTIC NETWORK MATHEMATICAL MODEL

In this study, we design our network which includes three wind farms (generating plants), three inspection centers, two recycling centers, two remanufacturing centers and one disposal center. The details of the network is given in Figure 1.

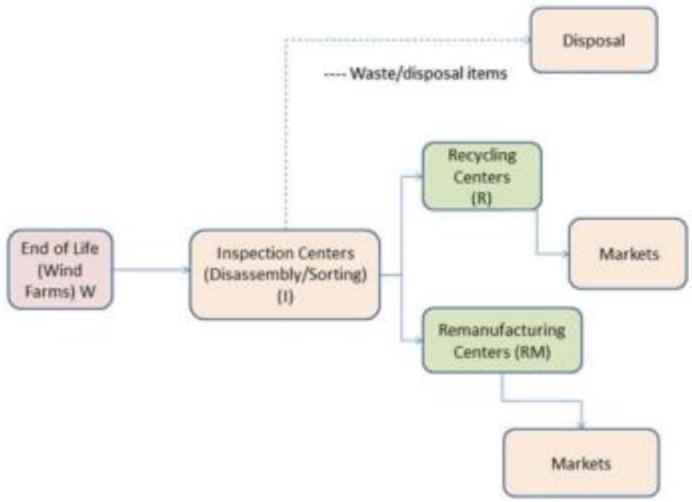

Figure 1. Reverse logistics of wind turbines

A. PROBLEM DEFINITION AND MILP MODEL FORMULATION

For the proposed Fuzzy-MOMILP used in this study, we use the mixed integer linear programing model (MILP) that was originally proposed by Cinar and Yildirim [29, 30]. As described in the original model, we have two objectives, including total network cost and carbon emissions. The network flow for EOL WTs starts at wind farms, which are considered as generation points. Dismantled WTs transferred from wind farm to inspection centers and from inspection centers, WTs parts either are sent to recycling or remanufacturing centers.

B. MODEL NOTATION

The proposed deterministic model components, sets, parameters, and variables are given as follows:

Sets:

a:	end-of-life product/component parts, $a \in A = \{1,\ldots,\|A\|\}$
j:	set possible locations $j \in J = \{1,\ldots,\|J\|\}$
t:	time periods, $t \in T = \{1,\ldots,\|T\|\}$
w:	set of collection centers, $w \in W = \{1,\ldots,\|J\|\}$
i:	set of inspection centers, $i \in I = \{1,\ldots,\|I\|\} \subseteq J$
m:	set of remanufacturing centers, $m \in M = \{1,\ldots,\|M\|\} \subseteq J$
r:	set of recycling centers, $r \in R = \{1,\ldots,\|R\|\} \subseteq J$
s:	set of secondary markets, $s \in S = \{1,\ldots,\|S\|\} \subseteq J$
ds:	set of disposal centers, $ds \in DS = \{1,\ldots,\|DS\|\} \subseteq J$

Parameters:

Q_{wat}: amount of selected product/component dismantled at collection centers *w* (ton) in period t

CPIit, CPRrt, CPMmt, CPDdst: capacity of i, r,m, ds in period t

α: percent of the selected product/component a sent from i to r

β: percent of the selected product/component a sent from i to ds

γ: percent of the selected product/component a sent from i to m

∇, μ: percent of the selected product/component a sent from r/m to s, respectively

Costs:

PRR_{rat}, PRM_{mat}: price of the selected product/component a sold to secondary market at r, rm at time period t ($/ton), respectively

FI_{it}, FM_{mt}, FR_{rt}, FA_{lt}: fixed cost for opening i, m, r, l in period t ($), respectively

POI_{ait}, POR_{art}, POM_{amt}, POA_{alt}: operating cost for one unit of end-of-life product/component a at i, r, m,l in period t ($/ton), respectively

CI_{ait}, CR_{art}, CM_{amt}, CA_{alt}: carbon emissions for processing one unit of the selected product/component a at each i, r, m, l in period t (gram), respectively

TR_{wiat}, TR_{irat}, TR_{imat}, TR_{rsat}, TR_{msat}, TR_{ilat}: transportation distance from w to i, i to r, i to m, r to s, m to s, or i to l (mile), respectively

Θ: transpiration cost factor ($/ton mile)

Ω: emissions factor (gram/unit-mile)

di: inflation rate

Decision Variables:

$X1_{wiat}$, $X2_{imat}$, $X3_{irat}$, $X4_{msat}$, $X5_{rsat}$, $X6_{ilat}$: product/component shipped from one center to another in period t, respectively

Binary Variables:

$$Y_{it}, Z_{mt}, U_{rt}, A_{lt} = \begin{cases} 1 & \text{if a center is operating in period } t \in T, \\ 0 & \text{otherwise} \end{cases}$$

C. MODEL FORMULATION

Here, (1) maximization of total profit and (2) minimization of total environmental impact (carbon emissions) are formulated as two conflicting objective functions.

C.1 First Objective (Total Cost)

The first objective is the total cost, which consists of total profit of selling product at remanufacturing and, recycling centers minus the total network cost. The breakdown for the total network cost is: transportation, operating, capital cost of opening each center. Our first objective is formulated as below:

Maximize profit Z_1=Z_{11} –(Z_{12}+ Z_{13} + Z_{14}) (1)

Profit of selling materials

$$Z_{11}=\sum_t \sum_a \sum_i \sum_m PRM_{mat} * X2_{imat} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_r PRR_{rat} * X3_{irat} * (1+di)^{-t} \quad (1a)$$

Fixed cost Z_{12}=

$$\sum_i \sum_t FI_{it} * (Y_{it} - Y_{i,t-1}) * (1+di)^{-t} + \sum_m \sum_t FM_{mt} * (Z_{mt} - Z_{m,t-1}) * (1+di)^{-t} + \sum_r \sum_t FR_{rt} * (U_{rt} - U_{r,t-1}) * (1+di)^{-t} + \sum_l \sum_t FA_{lt} * (A_{lt} - A_{l,t-1}) * (1+di)^{-t} \quad (1b)$$

Transportation cost Z_{13}=

$$\sum_t \sum_a \sum_w \sum_i TR_{wiat} * \Theta * X1_{wict} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_m TR_{imct} * \Theta * X2_{imct} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_r TR_{irat} * \Theta * X3_{irat} * (1+di)^{-t} + \sum_t \sum_c \sum_m \sum_s TR_{msct} * \Theta * X4_{msat} * (1+di)^{-t} + \sum_t \sum_a \sum_r \sum_s TR_{msat} * \Theta * X5_{rsat} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_l TR_{ilat} * \Theta * X6_{ilat} * (1+di)^{-t} \quad (1c)$$

Operations and disposal cost Z_{14}=

$$\sum_t \sum_a \sum_w \sum_i POI_{ait} * X1_{wiat} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_m POM_{amt} * X2_{imat} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_r POR_{art} * X3_{irat} * (1+di)^{-t} + \sum_t \sum_c \sum_i \sum_l POA_{ast} * X5_{ilat} * (1+di)^{-t} \quad (1d)$$

C.2 Second Objective (carbon emissions)

The total carbon emissions comes from the transportation activities. So, the second objective function can be formulated as follows.

Minimize carbon emissions Z_2=

$$\sum_t \sum_w \sum_a \sum_i TR_{wiat} * \Omega * X1_{wiat} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_r TR_{irat} * \Omega * X3_{irat} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_m TR_{imat} * \Omega * X2_{imat} * (1+di)^{-t} + \sum_t \sum_a \sum_m \sum_s TR_{msat} * \Omega * X4_{msat} * (1+di)^{-t} + \sum_t \sum_a \sum_r \sum_s TR_{rsat} * \Omega * X5_{rsat} * (1+di)^{-t} + \sum_t \sum_w \sum_a \sum_i CI_{ait} * X1_{wiat} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_m CM_{amt} * X2_{imat} * (1+di)^{-t} + \sum_t \sum_a \sum_i \sum_r CR_{art} * X3_{irat} * (1+di)^{-t} + \sum_t \sum_l \sum_a \sum_i CA_{alt} * X6_{ilat} * (1+di)^{-t} \quad (2)$$

The constraints of the deterministic model are given below:

$$Q_{wat} = \sum_{i \in I} X1_{wiat} \qquad w \in W, a \in A, t \in T \quad (3)$$

$$\alpha+\beta+\gamma = 1 \tag{4}$$

$$\sum_{w\in W} \alpha * X1_{wiat} = \sum_{m\in M} X2_{imct} \qquad i \in I, a \in A, t \in T \tag{5}$$

$$\sum_{w\in W} \beta * X1_{wiat} = \sum_{r\in R} X3_{irat} \qquad i \in I, a \in A, t \in T \tag{6}$$

$$\sum_{a\in A} \gamma * X1_{wiat} = \sum_{l\in L} X6_{ilat} \qquad i \in I, a \in A, t \in T \tag{7}$$

$$\sum_{i\in I} \nabla * X2_{imat} = \sum_{s\in S} X4_{msat} \qquad m \in M, a \in A, t \in T \tag{8}$$

$$\sum_{i\in I} \mu * X3_{irct} = \sum_{s\in S} X5_{rsat} \qquad r \in R, a \in A, t \in T \tag{9}$$

$$\sum_{w\in W} \sum_{a\in A} X1_{wiat} \leq CAPI_{it} * Y_{it} \qquad i \in I, t \in T \tag{10}$$

$$\sum_{i\in I} \sum_{a\in A} X3_{irat} \leq CAPR_{rt} * U_{rt} \qquad r \in r, t \in T \tag{11}$$

$$\sum_{i\in I} \sum_{a\in A} X2_{imat} \leq CAPM_{mt} * Z_{mt} \qquad m \in M, t \in T \tag{12}$$

$$\sum_{i\in I} \sum_{a\in A} X6_{ilat} \leq CAPD_{lt} * A_{lt} \qquad l \in L, t \in T \tag{13}$$

$$X1_{wiat}, X2_{imat}, X3_{irat}, X4_{msat}, X5_{rsat}, X6_{ilat} \geq 0 \quad (14)$$

$$Y_{it} \in \{0,1\},\ Z_{mt} \in \{0,1\},\ U_{rt} \in \{0,1\}, A_{lt} \in \{0,1\} \quad i \in I, r \in R, M \in M, t \in T, l \in L \quad (15)$$

$$Y_{it} \leq Y_{i,t+1} \qquad i \in I, t \in T \quad (16)$$

$$U_{rt} \leq U_{r,t+1} \qquad r \in R, t \in T \quad (17)$$

$$Z_{mt} \leq Z_{m,t+1} \qquad m \in M, t \in T \quad (18)$$

$$A_{lt} \leq ZA_{l,t+1} \qquad l \in L, t \in T \quad (19)$$

The first constraint (3) is a flow balance which provides flow from wind farm (the number of disassemble wind turbines) to inspection centers. The second constraint (4) satisfy the ratio of products/components sent to each center. The constraints (5) through (8) are flow balance constraints for each center. Constraint (9) represents the demand constraint which satisfy demand for the remanufactured WTs at each time period. Constraints (10) through (13) are the capacity constraint for each center. Constraint (14) represent the non-negativity constraint, and constraint (15) represent the integrality constraint, respectively. Constraints (16 to 19) are binary variables.

D. FUZZY MULTI-OBJECTIVE MIXED INTEGER LINEAR PROGRAMING (FUZZY-MOMILP) MODEL

It is not certain exactly how many WTs will be dismantled after they reach their end of life span, which is around 20-30 years. Due to extensive preventive maintenance and possible retrofitting, it is very likely that some of the WTs that are expected to retire could be in service further at least 5-10 more years. Therefore, this may cause uncertainty in WTs reverse logistic network design. We assume that the number of WTs retired at wind farms is a fuzzy parameter and we propose using fuzzy theory developed by Zimmermann [8]. As a result, in our initial model , the parameter Q_{wt} number of WTs collected from wind farms was replaced with a fuzzy parameter $\widetilde{Q_{wt}}$.

Using Zimmermann approach, the membership functions are calculated and then the linear programming model is converted to fuzzy model by adding fuzzy objective functions and fuzzy constraints as new constraints. In this study, based on the method developed by Tiwari et al. [31], a weighted additive method used to assign appropriate weights to each fuzzy objective and fuzzy constraints. For the simplicity reason, in this study, we assigned the weight based on the expert opinion. Newly added model variables, fuzzy parameter, new fuzzy objective functions, and fuzzy constraints are provided below.

Newly added variables:

$\lambda_1, \lambda_2, \lambda_3$: membership degrees of intersections of fuzzy sets

Fuzzy parameter:

$\widetilde{Q_{wt}}$: amount of WT dismantled by wind farm operator *w* (ton) in period t
λ_1, λ_2: weights for the objective functions
γ_1: weights for the constraints

The fuzzy objective functions:

$$\widetilde{Z_1}.=Z_{11} - (Z_{12} + Z_{13} + Z_{14}) < Z_1 \tag{20}$$

$$\widetilde{Z_2}=\sum_t \sum_w \sum_a \sum_i \mathrm{TR}_{wiat} * \Omega * \mathrm{X1}_{wict} * (1+\mathrm{di})^{-t} + \sum_t \sum_a \sum_i \sum_r \mathrm{TR}_{irat} * \Omega * \mathrm{X3}_{irct} * (1+\mathrm{di})^{-t} + \sum_t \sum_a \sum_i \sum_m \mathrm{TR}_{imat} * \Omega * \mathrm{X2}_{imat} * (1+\mathrm{di})^{-t} + \sum_t \sum_a \sum_m \sum_s \mathrm{TR}_{msat} * \Omega * \mathrm{X4}_{msat} * (1+\mathrm{di})^{-t} + + \sum_t \sum_w \sum_a \sum_i \mathrm{CI}_{ait} * \mathrm{X1}_{wiat} * (1+\mathrm{di})^{-t} + \sum_t \sum_a \sum_i \sum_m \mathrm{CM}_{amt} * \mathrm{X2}_{imat} * (1+\mathrm{di})^{-t} + \sum_t \sum_a \sum_i \sum_r \mathrm{CR}_{art} * \mathrm{X3}_{irat} * (1+\mathrm{di})^{-t} + + \sum_t \sum_l \sum_a \sum_i \mathrm{CA}_{alt} * \mathrm{X5}_{ilct} * (1+\mathrm{di})^{-t} \tag{21}$$

Fuzzy constraints:

$$\widetilde{\mathrm{Q}_{wct}} = \sum_{i \in I} \mathrm{X1}_{wiat} \qquad \mathrm{w} \in \mathrm{W}, \mathrm{a} \in \mathrm{A}, \mathrm{t} \in \mathrm{T} \tag{22}$$

The linear membership functions of fuzzy objective functions and fuzzy constraint are calculated using the following formulas. For the maximization problem (positive targets) we use equation (23), and for the minimization problem (fuzzy negative targets) we use equation (24), and for the fuzzy constraints we use equation (25).

$$\mu_{zmx}(x) = \begin{cases} 1, & Z_{mx} \leq \bar{Z}_{mx} \\ \dfrac{Z_{mx}^{+} - Z_{mx}(x)}{Z_{mx}^{+} - Z_{mx}^{-}} & Z_{mx}^{-} \leq Z_{mx} \leq Z_{mx}^{+} \quad mx = 1,2,\dots,s \\ 0 & Z_{mx} \geq Z_{mx}^{+} \end{cases} \tag{23}$$

$$\mu_{zm}(x) = \begin{cases} 1, & Z_m \geq Z_m^{+} \\ \dfrac{Z_m(x) - Z_m^{-}}{Z_m^{+} - Z_m^{-}} & Z_m^{-} \leq Z_m(x) \leq Z_m^{+} \quad m = s+1, s+2, \dots, t \\ 0 & Z_m \leq Z_m^{-} \end{cases} \tag{24}$$

$$\mu_{gp}(x) = \begin{cases} 1, & g_p(x) \le b_p \\ 1 - \dfrac{g_p(x) - b_p}{t_p} & b_p \le g_p(x) \le b_p + t_p \quad p = 1,2,\dots,y \\ 0 & g_p(x) \ge b_p + t_p \end{cases} \tag{25}$$

To be able to calculate the membership function values, we need the lower and upper limits for each objective function and constrain. Therefore, we solve the deterministic model for each objective function and constraint. The lower and upper limit values are given in Table 1.

Table 1. *Membership Functions*

Fuzzy Objectives	**μ=0**	**μ=1 (min)**	**μ=0 (max)**
Z_1	-	-134,757,000	-18,833,760
Z_2	-	29,012.67	128,010.0
Constraints	**μ=0**	**μ=1 (min)**	**μ=0 (max)**
Fuzzy constraint	46	1500	2803

After the membership functions are calculated, the fuzzy model is converted to the linear programming model. The target weights for objective functions is assumed to be 0.6, and 0.3, respectively. The weight for the fuzzy constraint is taken as 0.10. Based on these weights, new objective function is formulated as below.

New objective function:

$$Max\ 0.6\lambda_1 + 0.3\lambda_2 + 0.1\gamma_1 \tag{26}$$

$$\lambda_1 \le \frac{1.34757\text{E} + 8 - Z_1}{1.34757\text{E} + 8 - 1.88338\text{E} + 7} \tag{27}$$

$$\lambda_2 \le \frac{Z_2 - 29012.671}{128010.077 - 29012.671} \tag{28}$$

$$\gamma_1 \le \frac{46 - Q_{wict}}{2803 - 46} \tag{29}$$

Subject to: constraints (4)-(19).

E. INPUT PARAMETER

In this study, the percent composition of each WT component and the weight data is taken from the Vestas V82 1.65-MW WT. The composition of the selected turbine type is given in Table 2. We assumed that at recycling centers, we sell the ferrous metals based on their weight % and at remanufacturing center, we assumed that, we sell whole WT parts (tower, gearbox, and nacelle) as remanufactured products. The cost value of each component at recycling centers, the current market price ($/ton) of the metals is used. For remanufacturing facility, we use the average market price for each WT part. The total disposal cost of a turbine is calculated based on the expert opinions. The market prices of remanufactured components and recycled metals extracted in WTs are listed Table 3 and Table 4, respectively. The weight of a WT is assumed as 245 tons [32].

Table 2: *Composition of Vestas V82 1.65-MW Wind Turbine [32]*

Materials	**Weight of recycled material per Turbine** *(ton)*	**Percentage of recycled material** *(%)*
Steel	159.4	59
Iron	29.3	11
Copper	4.38	2
Aluminum	8.69	3
Disposable materials (epoxy, oil and etc.)	42.77	16
Total weight of a WT *(ton)*	**245**	

Table 3: *Market value of Reusable/Remanufactured Materials for 1.65-MW Wind Turbine [33]*

	WT Compound	**Main Material**	**Quantity of the Material** *(Ton)*	**Average Market price for remanufactured WT compounds** *($)*	**Cost of material** *($/ton)*
Remanufacturing	Tower	Steel	135	$125,000	$1,000
	Nacelle	Stainless	8	$50,000	$7,000
	Gearbox	Iron	11	$75,000	$4,800

Table 4: *Market value of Recyclable Materials and Disposal Cost for 1.65-MW Wind Turbine [33,34]*

Material	**Quantity of the Material** *(Ton)*	**Cost** *($/ton)*
Steel	159.4	$522

Recycling	Iron	29.3	$300
	Aluminum	20	$1,482
Disposal	Epoxy, plastic, fiber	42.77	$33.35

The operation and installation costs for each center are given in Table 5.

***Table 5**: Operation and Installation Cost [35]*

	Iteming	Cost*
Operating Cost	remanufacturing center	[$10,000–$50,000]
	inspection center + dismantling cost	[$1,000–$5,000] [$35,000 added dismantling cost]
	recycling center	[1,000-5,000]
Installation cost of centers	Inspection, remanufacturing, and recycling centers	[15,000 - 70,000]

*Each cost is estimated based on expert opinion

IV. MODEL RESULTS

In this study, Generic Algebraic Modeling System (GAMS) is used to code the model and CPLEX optimizer was used as solver tool. Three time period is used for the model runs.

Based on the model results, the value of the first objective function, which is the total cost, is found to be $11,866,313.38. The total amount of carbon emitted to the environment due to transports is approximately 38.8 tons. The objective function of the Fuzzy-MOMILP model is found to be 0.802. In other words, the probability of these values we obtain under uncertainties is 0.802. The degree of achievement of fuzzy objective 1 and fuzzy objective 2 is calculated to be 0.86 and 0.901, respectively. The degree of achievement of fuzzy constraint is found to be 1.0. Based on the optimum solution of the fuzzy approach, all of the five inspection centers and 4 recycling centers, one disposal center and two remanufacturing centers must be open at all time. Summary of the model results is given in Table 6 and cost data is depicted in Figure 2.

***Table 6.** Fuzzy Multi-Objective Mixed Integer Linear Programing (*Fuzzy-MOMILP*) Model Results*

Parameters	**Fuzzy model results**
λ	0.802
Objective function 1	$3,771,939
Objective function 2	38,8 ton
# recycling, remanufacturing and disposal centers opened	5 Inspection centers 3 recycling centers 1 disposal centers and

	2 remanufacturing centers
Recycled material	6.40 ton
Remanufacturing material	9.87 ton
Disposed material	1.14 ton

The total cost breakdown of the model is presented in Figure 2. Based on the cost data, it can be seen that remanufacturing revenue is higher that the recycling revenue, but due to the high operating and installation costs, the total profit is still below the total cost of the whole reverse logistic network.

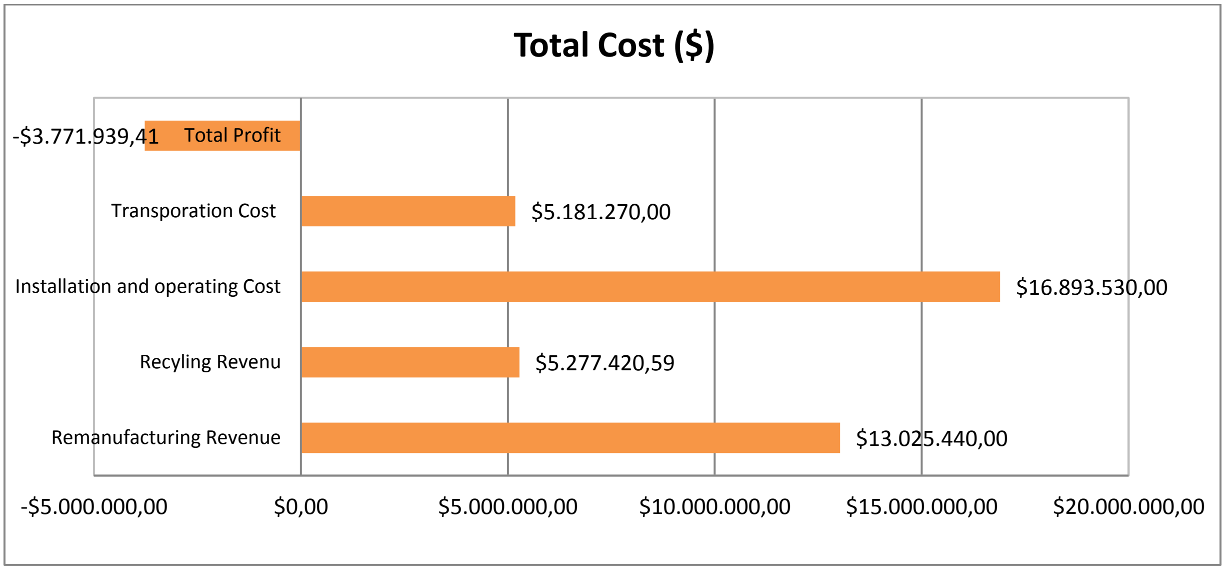

Figure 2. *Cost of each component of reverse logistic network*

V. SENSITIVITY ANALYSIS

Here, the effect of the change in the weights of the two different fuzzy objectives and the fuzzy constraint is examined. The weights of the fuzzy objectives and fuzzy constraint are changed incrementally to observe the relationship between each fuzzy objective and the fuzzy constraint. The weights that we use for the sensitivity analysis are to be in the range of [0.10; 1.0]. In the first analysis, starting from the first objective, the weight is changed with an incremental increase of 0.10 while the weight of the second objective is changed proportionally and the fuzzy constraint is kept constant. In the second analysis, the weight of the fuzzy constraint is changed in increments of 0.1 while, the weight of the first objective is changed proportionally and the second objective is kept constant. In the third analysis, similar to the second analysis, the weight of the fuzzy constraint is changed in increments of 0.1 and the weight of second objective is changed proportionally while the weight of first objective is kept constant. The results of each analysis are presented in the following sections.

A. CHANGES IN CARBON EMISSIONS WHILE CHANGING THE WEIGHT OF TOTAL COST OBJECTIVE

In the first analysis, to examine the effect of each fuzzy objective weight, the weight of fuzzy constraint is kept constant while the weight of each fuzzy objective is changed incrementally. In this first analysis, for each 0.10 incremental increase in the weight of total cost objective, the total carbon emissions weight is arranged so that the total weight of all the fuzzy objectives and fuzzy constraints is equal to 1. Table 9 shows the objective function value of Fuzzy-MOMILP model, the breakdown of the total cost, total revenue, total profit and the total carbon emissions calculated for different weights of the objective function 1.

***Table 9**. Sensitivity by changing the weights of the total cost objective*

Weight obj. 1	Weight obj. 2	Weight of fuzzy constraint	Fuzzy objective function	Total Profit *($)*	Total Cost *($)*	Total Revenue *($)*	Carbon emissions *(kg)*
0.1	0.8	0.1	0.828	$-4,049,024	29,267,218	25,218,194	128010.1
0.2	0.7	0.1	0.737	$-4,049,024	29,267,218	25,218,194	128010.1
0.3	0.6	0.1	0.731	$-3,771,939	22074800	25,218,194	38800.65
0.4	0.5	0.1	0.763	$-4,108,944	16,864,554	12,755,610	38800.65
0.5	0.4	0.1	0.709	$-4,311,844	14,878,136	10,566,292	38800.65
0.6	0.3	0.1	0.779	$-4,311,844	14,878,136	10,566,292	38800.65
0.8	0.1	0.1	0.918	$-4,311,844	14,878,136	10,566,292	38800.65

Figure 3 shows the change in total profit for the changing weights of the fuzzy objective 1 (cost objective). As seen in the Figure 3, when the target's weight of fuzzy objective 1 is increased, the total profit decreases. When the results of the model are examined, it is seen that the material recycling rate has increased from 65% to 85%. Therefore, it can be said that the model reduces the material remanufacturing rate in order to reduce the total carbon emissions comes from remanufacturing centers as the carbon emissions rate at remanufacturing center is higher than recycling centers. Therefore, this outcome is highly predictable. It is also observed that while the target's weight of objective 1 is between 0.50 and 0.80, the total cost values are similar.

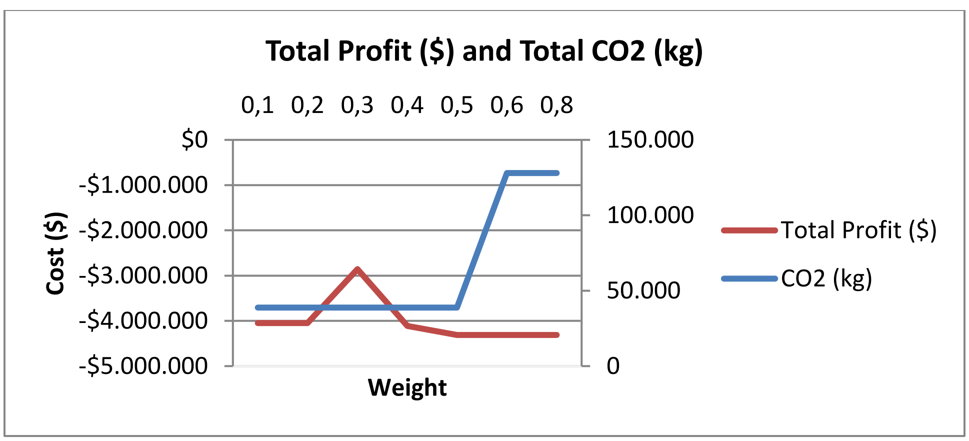

***Figure 3.** Changes in carbon emissions and total profit while changing the weight of fuzzy objective 1*

B. CHANGES IN TOTAL COST WHILE CHANGING THE WEIGHT of FUZZY CONSTRAINT

The analyzes performed in this section are similarly designed in section 5.2. To be able to see the effect of different weights, here, we change the fuzzy constraint weight while keeping the objective function 2 (carbon emissions) weight constant. The results of the first analysis are given Table 10, and Figure 4.

Table 10. *Sensitivity by changing the weights of the total cost objective*

Weight obj. 1	**Weight obj. 2**	**Weight of fuzzy constraint**	**Fuzzy objective function**	**Total Profit** *($)*	**Total Cost** *($)*	**Total Revenue** *($)*	**Carbon emissions** *(kg)*
0.8	0.1	0.1	0.928	$-8,700,926	29,267,218	10,566,292	128010.08
0.7	0.1	0.2	0.926	$-18,700,926	29,267,218	10,566,292	128010.08
0.6	0.1	0.3	0.925	$-18,700,926	29,267,218	10,566,292	128010.08
0.5	0.1	0.4	0.924	$-18,700,926	29,267,218	10,566,292	128010.08
0.4	0.1	0.5	0.922	$-12,045,686	22,611,978	10,566,292	128010.08
0.3	0.1	0.6	0.921	$-4,311,844	14,878,136	10,566,292	128010.08
0.2	0.1	0.7	0.919	$-4,311,844	14,878,136	10,566,292	128010.08
0.1	0.1	0.8	0.918	$-4,311,844	14,878,136	10,566,292	128010.08

Figure 4 depicts the change in the weight of the fuzzy constraint and the change in the total cost. As can see from the figure, when the target's weight reaches from 0.10 to 0.40, the total profit does not change and at point 0.5, the total profit start decreasing. This can be due to sending more product to recycling centers where the recycled product market price is lower than remanufactured products. For this reason, total revenue cost decrease, accordingly. When the weight reaches 0.60, the cost stays the same as the model reaches an optimal point.

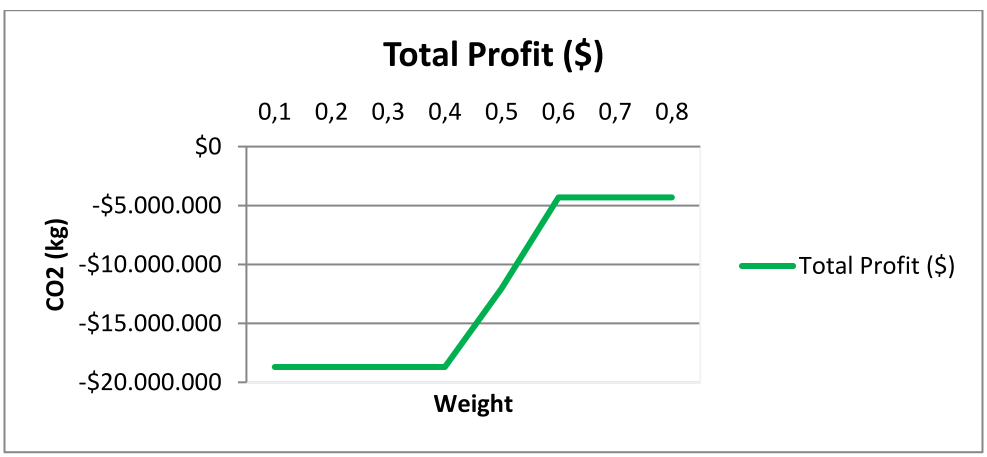

Figure 4. *Changes in carbon emissions while changing the weight of fuzzy constraint*

C. CHANGES IN CARBON EMISSIONS WHILE CHANGING THE WEIGHT of FUZZY CONSTRAINT

In this analysis, the weight of objective function 1 (total cost) is kept constant and fuzzy constraint and the total carbon objective 2 are changed, accordingly. The each 0.10 increase in the weight of the fuzzy constraint is investigated to observe the changes in total carbon emissions. The results of the analysis are given Table 10, and Figure 5, respectively.

Table 11. *Sensitivity by changing the weights of the total cost objective*

Weight obj 1	**Weight obj 2**	**Weight of fuzzy constraint**	**Fuzzy objective function**	**Total Profit** *($)*	**Total Cost** *($)*	**Total Revenue** *($)*	**Carbon emissions** *(kg)*
0.1	0.1	0.8	0.928	4,311,844	14,878,136	10,566,292	30351.096
0.1	0.2	0.7	0.926	4,311,844	14,878,136	10,566,292	30351.096
0.1	0.3	0.6	0.925	4,311,844	14,878,136	10,566,292	30351.096
0.1	0.4	0.5	0.924	4,311,844	14,878,136	10,566,292	30351.096
0.1	0.5	0.4	0.922	4,311,844	14,878,136	10,566,292	30351.096
0.1	0.6	0.3	0.921	4,311,844	14,878,136	10,566,292	30351.096
0.1	0.7	0.2	0.919	4,311,844	14,878,136	10,566,292	30351.096
0.1	0.8	0.1	0.918	4,311,844	14,878,136	10,566,292	30351.096

In Figure 5, the change in the weight of the fuzzy constraint and the change in the total carbon emissions is given graphically. It is observed that changing the weight of the fuzzy constraint does not change the amount of carbon emissions. This shows that the fuzzy constraint weight does not play importance on the objective function 2.

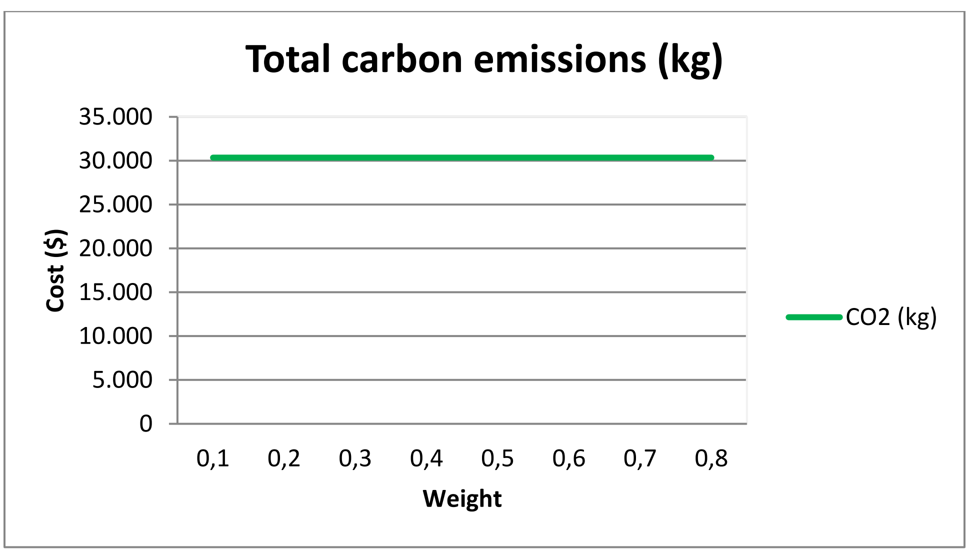

Figure 5. *Changes in carbon emissions while changing the weight of fuzzy constraint*

As sum, the results of each scenario represent that the proposed model fits all scenarios quite well. The key issue here is not knowing the physical conditions of WTs. If there is not enough data about the condition of the WTs, it is hard to decide which WTs need to be sent to recycling or remanufacturing center. Therefore, model results can provide guidance to address the potential challenges, which are led due to uncertainties in the EOL material amounts of WTs.

VI. CONCLUSION

To be able to overcome issues may arise due to uncertainty in EOL products' reverse logistic networks, in this paper, we developed a fuzzy multi objective programming model for EOL WTs. The uncertainty in a reverse logistic network may result in a lower/higher recycling or remanufacturing rate of the EOL products, which may cause loss of profit or cause more emissions release due to improper network design. Therefore, in this paper, we build a Fuzzy-MOMILP model which take the uncertainty of the return EOL products quantity into account.

The results of the numerical experiments indicated that the value of the first objective function, total cost, is $11,866,313.38 and the total amount of carbon emissions due to transportation activities is approximately 38.8 tons. The objective function of the FMODP model was found to be 0.802. Thus, under uncertainties, the probability of these values is calculated to be 0,802. In addition, the degree of achievement of fuzzy objective 1, fuzzy objective 2 and fuzzy constraint is calculated to be 0.86, 0.901, and 1.0.

The paper has provided important insights to decision makers while designing reverse logistic network under uncertainty. Even though, WTs operators/decision makers may not know how many WTs may be dismantled at each wind farm, using the proposed model, different EOL product, considered as supply, can be predicted. In future studies, it will be worthy of investigation for the followings:

- To validate the results from the proposed model, more parameters may be examined. For example, in future study, the cost increase in recycling and remanufacturing operations may be examined to analyze the effect of these parameters on the model results.
- Future works may include more uncertain parameters, such as secondary market demand. Adding more uncertain parameters may change the complexity of the model that may require building different solution methods/algorithm.
- In the solution method, for the simplicity reason, different weights are assigned to each fuzzy objective function and fuzzy constraint, randomly. For the accuracy, the weights of each parameter can be calculated by using different methods such as fuzzy analytic hierarchy analysis.

In terms of managerial implications, due to the technical and economic aspect, the designing a sustainable reverse logistic network for EOL WTs can be more complicated. Such as, with new technologies, there may not be a need for remanufactured WTs due to low energy production capacity, reliability issues and etc. Therefore, based on technological improvement in the sectors such as retrofitting WTs, which is not considered in the model presented here can be evaluated as managerial implications.

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