Best Product End-of-Life Scenario Selection by a New Decision-Making Process Under Atanassov Fuzzy Uncertainty

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Abstract - Each year, larger amounts of worn out products are generated and their disposal has made the problem of best product end-of-life (EOL) scenario selection an important problem. Due to uncertain markets and technological advancements, uncertainty plays a vital role in any production related decision-making process. Here, EOL selection problem under uncertainty is addressed through introducing a new decision-making process based on the concept of preference selection index and Atanassov (intuitionistic) fuzzy sets. This model can effectively solve complex problems under uncertainty by allowing the decision makers and experts to express their hesitation and lack of knowledge as well as their expertise. To illustrate the presented approach, an example in the literature is solved; then, the results are presented and discussed.

Keywords - Product end-of-life scenario (EOL), Production uncertainty, Atanassov fuzzy sets, Preference selection index, Product life cycle (PLC)

I. INTRODUCTION

The complexity of product is continuously increasing and product life cycle (PLC) is consistently decreasing. This condition mostly happens to high-tech products with short PLCs that are delivered to markets to assist companies to reach goals, such as securing high profits, extending market share, and enhancing brand value. Production of high-tech products ensures that old ones would soon become obsolete and unable to compete in areas, such as functionality, design, and cost. Consequently, firms should establish a strategic product transition plan to consistently improve sales and market control [1].

On the other hand, how end-of-life (EOL) phase of a product is treated is an important problem for consumers, authorities and producers. Annually, more and more worn out products are generated and as a result, landfills are getting saturated. Expanding the landfills is not always possible, and it is actually not the best solution. In addition to the problem of finding new landfills to dispose worn out products, proper treatment of products with dangerous nature to environment should be also considered. Therefore, it is highly essential to consider alternative options to replace landfiling [2]. Due to more demanding legislations, manufacturers should develop new product EOL scenarios. Different aspects should be properly addressed in finding the best scenario among the available alternatives.

Uncertainty is one of the most important aspects of any products related decision-making process. For example, the process of determining the time of replacing an old product by a new one through reviewing the demand forecast of the old product has various uncertainties. Moreover, there are many complex production questions that have to be addressed by considering uncertainty. For instance, how long old products should be obtained in the market even if a new product has been released, or when is the right time to switch from an old product to a new one. Only few studies are available in the literature, addressing specifically the problem of finding the best product EOL scenario [1, 3].

Rahimifard et al. [4] presented a five-stage model to support product EOL management in manufacturing organizations. The modelling and design of appropriate product recovery information systems were also addressed. Kongar and Gupta [5] developed a genetic algorithm to consider disassembly sequencing of EOL products. The functionality of the proposed model was illustrated through a case example. Giudice et al. [6] in details addressed the aspects of product design for the environment by considering the life cycle approach.

Staikos and Rahimifard [7] developed the design and specification of a decision-making process to find the most appropriate reuse, recovery, and recycling alternative for post-consumer shoes. A decision-making framework based on the concept of analytic hierarchy process (AHP) was used in association with cost-benefit analysis and life cycle assessment (LCA). The method despite efficiently in dealing with objective as well as subjective attributes could sometimes face situations with unmanageable number of pair-wise comparisons. Chan and Tong [8] introduced an integrated approach of performing an order pair of materials and EOL product strategy to address material selection. Rao and Padmanabhan [9] focused on a methodology to find the best product EOL scenario by employing digraph and matrix methods. Their method was based on an EOL scenario selection index that evaluated and ranked the alternative product EOL scenarios. Their approach lacked enough consideration for addressing uncertainty. Rao and Rajesh [10] presented an improved compromise ranking method to select the best EOL scenario. Their approach was based on the concept of AHP and fuzzy logic. Oh et
al. [1], to consider uncertainty in the process, introduced a fuzzy based decision-making approach for assessing product discontinuing at the product transition point. Despite addressing uncertainty, the proposed method cannot fully address uncertainty since it is based on the concept of classical fuzzy sets that has its own shortcomings.

It can be concluded from the above that a number of decision-making methods have been developed to deal with EOL scenario selection problems. Considering uncertainty is a vital part of any method that can be applied in real-world problems. Classical fuzzy sets theory has been used to deal with uncertain environments. Through the years, necessity for improving fuzzy sets theory arose as it was more applied in real-world situations (e.g., [11-14]). One of classical fuzzy sets theory inadequacies can be observed when a DM is expected to give an exact opinion in a number in interval [0, 1]. Another problem is its inability in expressing hesitation and lack of knowledge.

In order to overcome the inadequacies of classical fuzzy sets in dealing with uncertain production environment, this paper presents a new model of decision making under uncertainty to select the best EOL scenario. To address uncertainty, Atanassov or intuitionistic fuzzy sets (IFSs) were used to develop a new preference selection index model. This approach helps decision makers to express their degree of knowledge, lack of knowledge and hesitation in the process. Moreover, IFSs enable the model to reflect the “disagreement” of the decision maker in addition to the fuzziness of “agreement” [15-17].

The remaining of this paper is organized as follows: in section II, the EOL scenario selection model is presented. An example from the literature is solved by the presented approach in section III, and section IV includes the conclusion remarks of the paper.

II. METHODOLOGY

This section presents an intuitionistic fuzzy preference selection index (IF-PSI) model aiming at solving the complex problem of product EOL scenario selection. In the introduced model the performance ratings of candidates are described by using the concept of the IFSs.

The concept of linguistic variable is very common in reasonably describing too complex or ill-defined environments [18]. Furthermore, expressing a phenomenon by applying the traditional linguistic approach is not clear enough since its presentation is based on the traditional fuzzy sets [19]. Additionally, in classical fuzzy sets theory, it is often difficult for decision makers to exactly represent his or her opinion as a number in interval [0, 1] (See Fig. 1). Therefore, this paper considers performance rating as linguistic variables and then converts them into intuitionistic fuzzy numbers, which are able to model membership degree, non-membership degree and hesitancy. Consequently, a seven-scale linguistic term based on the triangular intuitionistic fuzzy numbers (TIFNs) is presented in Table I. For the purpose of illustration, visual representation of a TIFN denoted as

\[ A = ([a_i, b_i, c_i]; u_A), ([a_1, b_1, c_1]; v_A) \]

is presented in Figure 1. The arithmetic operations of TIFNs is based on the studies of Shu et al. [20] and Li [21].

![Fig. 1. A triangular intuitionistic fuzzy number](image)

<table>
<thead>
<tr>
<th>Linguistic variables</th>
<th>Triangular intuitionistic fuzzy numbers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Poor (VP)</td>
<td>([((0.0,1);0.1], [(0,1.5);0.75]))</td>
</tr>
<tr>
<td>Poor (P)</td>
<td>([((0.5,1.25);0.25], [(0,1.35);0.6]))</td>
</tr>
<tr>
<td>Moderately Poor (MP)</td>
<td>([((1.5,3.45);0.4], [(0,3.5);0.5]))</td>
</tr>
<tr>
<td>Fair (F)</td>
<td>([((3.5,5,6.5);0.5], [(2.5,5,7.5);0.4]))</td>
</tr>
<tr>
<td>Moderately Good (MG)</td>
<td>([((5.5,7,9.5);0.6], [(4.5,7,9.5);0.3]))</td>
</tr>
<tr>
<td>Good (G)</td>
<td>([((7.5,9,10);0.7], [(5,5,9,10);0.2]))</td>
</tr>
<tr>
<td>Very Good (VG)</td>
<td>([((9.5,10,10);0.9], [(8.5,10,10);0.1]))</td>
</tr>
</tbody>
</table>

The introduced approach unlike other multiple attribute decision making (MADM) methods, e.g., TOPSIS, ELECTRE, SAW and VIKOR, does not need the provision of the weights for conflicting criteria. In this approach, linguistic variables are used to indicate the performance rating of potential candidates versus the selected criteria.

In an MADM problem with \(m\) possible candidates denoted as \(A_1, A_2, \ldots, A_m\) and \(n\) criteria denoted as \(c_1, c_2, \ldots, c_n\), an IF-decision matrix is denoted as \(\tilde{D} = [d_{ij}]_{mn} \). Obviously, \(d_{ij}\) describes the performance of alternative \(A_i\) with respect to criterion \(c_j\). In this group decision-making process with \(t\) experts, the performance rating of candidates versus each criterion is presented as:

\[ d_{ij} = \frac{1}{r} [d_{ij}^1 + d_{ij}^2 + \ldots + d_{ij}^t] \tag{1} \]
Steps of the proposed IF-PSI method are introduced as follows:

i. Considering

\[ \tilde{d}_{ij} = \frac{[(d_{ij1}, d_{ij2}, d_{ij3}); u_{ij}]; [(d_{ij1}, d_{ij2}, d_{ij3}); v_{ij}]]}{[(d_{ij1}, d_{ij2}, d_{ij3}); \mu_{ij}]; [(d_{ij1}, d_{ij2}, d_{ij3}); \nu_{ij}]],} \]

the normalized performance rating is obtained as follows:

\[ \tilde{E}_{ij} = \frac{[(d_{ij1}, d_{ij2}, d_{ij3}); \mu_{ij}]; [(d_{ij1}, d_{ij2}, d_{ij3}); \nu_{ij}]]}{[(d_{ij1}, d_{ij2}, d_{ij3}); \delta_{ij}]; [(d_{ij1}, d_{ij2}, d_{ij3}); \theta_{ij}]],} \]

\[ i = 1, 2, \ldots, m, \quad j \in B \]

\[ \tilde{E}_{ij} = \frac{[(d_{ij1}, d_{ij2}, d_{ij3}); \mu_{ij}]; [(d_{ij1}, d_{ij2}, d_{ij3}); \nu_{ij}]]}{[(d_{ij1}, d_{ij2}, d_{ij3}); \delta_{ij}]; [(d_{ij1}, d_{ij2}, d_{ij3}); \theta_{ij}]],} \]

\[ i = 1, 2, \ldots, m, \quad j \in C \]

where \( B \) denotes benefit and \( C \) denotes cost. Consequently, the normalized matrix \( \tilde{E} = [\tilde{E}_{ij}]_{m \times m} \) is calculated. The objective if the abovementioned step is to make sure that the ranges of numbers fall within \([0, 1]\).

ii. Calculate IF-preference variation \( (IF-PV) \) by the following Eq.

\[ IFPV_j = \sum_{i=1}^{m} \left( \left( \frac{e_{ij1} e_{ij2} e_{ij3}}{e_{ij1} e_{ij2} e_{ij3}}; u_{ij1} \right); \left( \frac{e_{ij1} e_{ij2} e_{ij3}}{e_{ij1} e_{ij2} e_{ij3}}; v_{ij1} \right) \right)^2 \]

where \( \tilde{E}_j = [(e_{ij1}, e_{ij2}, e_{ij3}); u_{ij1}]; [(e_{ij1}, e_{ij2}, e_{ij3}); v_{ij1}] \) is the mean of IF-normalized criterion \( j \) obtained as:

\[ \tilde{E}_j = \frac{1}{m} \sum_{i=1}^{m} \left( e_{ij1} e_{ij2} e_{ij3}; u_{ij1} \right) \left( e_{ij1} e_{ij2} e_{ij3}; v_{ij1} \right) \]

\[ (e_{ij1}, e_{ij2}, e_{ij3}; v_{ij1}) \]

iii. Calculate the IF-overall preference \( (IFOP) \) for each criterion. Calculating IFOP requires determining IF-deviation \( (IFD) \) in the \( IFPV \). The \( IFD \) is obtained as follows:

\[ IFD = \left( \left( 1 - IFPV_{j1}', 1 - IFPV_{j2}', 1 - IFPV_{j3}' \right); \mu_{jPV} \right) \left( \left( 1 - IFPV_{j1}', 1 - IFPV_{j2}', 1 - IFPV_{j3}' \right); \nu_{jPV} \right) \]

Consequently, \( IFOP \) is determined as follows:

\[ IFOP_j = \left( \left( 1 - IFPV_{j1}', 1 - IFPV_{j2}', 1 - IFPV_{j3}' \right); \mu_{jPV} \right) \left( \left( 1 - IFPV_{j1}', 1 - IFPV_{j2}', 1 - IFPV_{j3}' \right); \nu_{jPV} \right) \]

\[ \sum_{j=1}^{n} \left( \left( 1 - IFPV_{j1}', 1 - IFPV_{j2}', 1 - IFPV_{j3}' \right); \mu_{jPV} \right) \left( \left( 1 - IFPV_{j1}', 1 - IFPV_{j2}', 1 - IFPV_{j3}' \right); \nu_{jPV} \right) \]

iv. IF-preference selection index \( (IFPSI) \) is calculated as follows:

\[ IFPSI_i = \sum_{j=1}^{n} \left( e_{ij1}, e_{ij2}, e_{ij3}; u_{ij} \right) \left( e_{ij1}, e_{ij2}, e_{ij3}; v_{ij} \right) \left( e_{ij1}, e_{ij2}, e_{ij3}; \mu_{ij} \right) \left( e_{ij1}, e_{ij2}, e_{ij3}; \nu_{ij} \right) \]

\[ \left( e_{ij1}, e_{ij2}, e_{ij3}; \delta_{ij} \right) \left( e_{ij1}, e_{ij2}, e_{ij3}; \theta_{ij} \right) \]

\[ \left( e_{ij1}, e_{ij2}, e_{ij3}; \chi_{ij} \right) \left( e_{ij1}, e_{ij2}, e_{ij3}; \psi_{ij} \right) \]

v. The alternatives are ranked in decreasing order of \( IFPSI \). In other words, an alternative with the highest value is ranked first and a candidate with the lowest value is ranked last.

### III. ILLUSTRATIVE EXAMPLE

In order to display model’s effectiveness in finding the best product EOL scenario, an existing example in the literature [3, 21] is presented and solved in this section.

The product considered in the example is telephone with its various elements, such as handset, base, mainboard, buzzer speaker, buzzer case, keys, silicon contacts, screws and cables. Candidate EOL scenarios considering the aforementioned components are:

- Functional reclamation (FNC), reusing/remanufacturing (REM), recycling (REC), incineration with energy recovery (INC1), incineration without energy recovery (INC2), and disposal to landfill (LND). Since different components require different possible scenarios, the example has stated five different EOL scenarios as a result of combining EOL options and telephone components. The first scenario \((S_1)\) is to landfill the entire product. Due to legislation restrictions, the first scenario is not practical and therefore it is eliminated. The second scenario \((S_2)\) is to use REC for certain elements and LND for the remaining elements. The third scenario \((S_3)\) is to use INC1 majority of elements and LND a few of them. The fourth scenario \((S_4)\) considers REC for most of the elements and INC1 for the remaining.
scenario \( (S_5) \) suggests REM, REC, LND and FNC for different elements of the product.

In order to address sustainability in the process, the example has provided different criteria in economic, social and environmental areas. The economic criteria are: logistics cost, disassembly cost, product value and product cost. Social attributes are: number of employees and exposure to dangerous materials. Environmental criteria are: \( CO_2 \) emissions, \( SO_2 \) emissions and energy consumption. Product value and number of employees are considered to be of beneficial nature while the rest are non-beneficial (cost related).

The existing data is adopted and changed into the seven-scale linguistic variable presented in this paper. Table II presents the adopted data.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>( S_1 )</th>
<th>( S_2 )</th>
<th>( S_3 )</th>
<th>( S_4 )</th>
<th>( S_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( CO_2 ) emissions</td>
<td>VP</td>
<td>P</td>
<td>P</td>
<td>P</td>
<td>P</td>
</tr>
<tr>
<td>( SO_2 ) emissions</td>
<td>VP</td>
<td>F</td>
<td>P</td>
<td>VP</td>
<td></td>
</tr>
<tr>
<td>Energy consumption</td>
<td>VP</td>
<td>P</td>
<td>P</td>
<td>MP</td>
<td></td>
</tr>
<tr>
<td>Logistics cost</td>
<td>P</td>
<td>VP</td>
<td>VP</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Disassembly cost</td>
<td>VP</td>
<td>VP</td>
<td>VP</td>
<td>VP</td>
<td></td>
</tr>
<tr>
<td>Product value</td>
<td>VG</td>
<td>MP</td>
<td>G</td>
<td>VG</td>
<td></td>
</tr>
<tr>
<td>Product cost</td>
<td>P</td>
<td>VP</td>
<td>VP</td>
<td>P</td>
<td></td>
</tr>
<tr>
<td>Number of employees</td>
<td>G</td>
<td>F</td>
<td>G</td>
<td>VG</td>
<td></td>
</tr>
<tr>
<td>Exposure to dangerous materials</td>
<td>VG</td>
<td>MG</td>
<td>VG</td>
<td>VG</td>
<td></td>
</tr>
</tbody>
</table>

The following steps are taken to rank the candidate projects and select the best scenario.

1. The TIFNs described in Table I are used to convert linguistic variables of Table II into fuzzy numbers. The resulting numbers are normalized to be in range of [0, 1].
2. Eq. (4) is applied to calculate IF-preference variation for each criterion.
3. Eq. (6) is used to find the IF-deviation of each criterion and then Eq. (7) is applied to calculate the IF-overall preference of each criterion.
4. To reach an understanding of the alternatives, IF-preference selection index of each alternative is calculated by using Eq. (8).
5. The final results of step 4 are used to rank the candidate projects.

In order to display the validation of the proposed model, the final results achieved from the presented method are compared with the results of the existing literature in Table III. It can be observed that the results verify the developed method. Additionally, the proposed method outperforms the existing methods in the literature since it is able to explain and calculate uncertainty better and with more flexibility. This enhancement in modelling and calculating uncertainty is the result of the model’s ability to express membership, non-membership and hesitation degrees. Using Atanassov fuzzy sets in this method gives it privilege over similar triangular fuzzy, trapezoidal fuzzy and interval-valued fuzzy-based methods since IFS can reflect the disagreement of the DM in addition to the fuzziness of agreement. However, this feature requires careful considerations in defining and using Atanassov sets [22-24].

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>The proposed method ranking</th>
<th>The ranking results of Rao [3]</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_2 )</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>( S_3 )</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>( S_4 )</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>( S_5 )</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

As rapid technological advancements make more modern products available every day, the way the old products need to be treated gets more vital. In other words, more and more products are out of use on a daily basis and these products cannot be all landfilled for a number of reasons such as legislation restrictions and environmental impacts. As a result, different scenarios are proposed to treat products at the end of their lives. Finding the best possible end of life (EOL) product scenario is an interesting and practical subject for manufacturing firms. Since the existing literature on this subject is poor and this manufacturing decision-making process takes place in an uncertain environment, this paper offers a novel approach is finding the best EOL scenario under uncertainty. To model the highly uncertain environment of manufacturing, Atanassov fuzzy sets or intuitionistic fuzzy sets were applied in this process. This approach not only considered the degree of membership in the process, but also addressed the degree of
disagreement and hesitation. Moreover, an intuitionistic fuzzy preference index was developed in this paper. To display the applicability of the presented model, an existing example from the literature was adopted and solved. The algorithm was illustrated step by step for the example, and the results were presented. To verify the model, the results were compared with the existing results in the literature. Eventually, the finer points of the presented model in comparison with similar studies on the subject of best product EOL scenario selection were pointed out. For further researches, developing a decision support system to address this problem could be a practical and interesting subject.

REFERENCES