



New extension of ordinal priority approach for multiple attribute decision-making problems: design and analysis

Mohamed Abdel-Basset¹ · Mai Mohamed¹ · Ahmed Abdel-monem¹ · Mohamed Abd Elfattah²

Received: 11 October 2021 / Accepted: 5 March 2022 / Published online: 29 April 2022
© The Author(s) 2022

Abstract

The selection and assessment process of appropriate robots became a more complex and complicated task due to various available alternatives and conflicting attributes which must take into consideration. Also, uncertainty which exists usually in the selection process is an unavoidable component that needs to be thoughtfully measured and traditional multi-attribute decision-making approaches failed to deal precisely with it. Since almost all decisions originate from subjective ordinal preferences, handling uncertainty using linguistic variables is also not enough. Thus, the objective of the current study is to present a new extended ordinal priority approach in the neutrosophic environment for the first time to select an appropriate robot. Since neutrosophic is one of the most effective and accommodating tools for handling uncertainty, thus, this method goes to transform linguistic information into triangular neutrosophic numbers using a new presented scale. This scale was used to determine the importance degree of attributes and alternatives regarding experts' opinions. Also, the score function of the triangular neutrosophic number is used for prioritizing attributes and alternatives. The experts in our proposed method have the same degree of importance, since each expert is a person with special skills and knowledge representing mastery of a particular subject. To measure the applicability and efficiency of the proposed approach, an experimental case study has been established for the robot selection problem of a new pharmaceutical city in Egypt for the first time. The source of data in this case study is experts, interviews, and questionnaires. Also, sensitivity and comparative analysis are further made for verifying the power of the proposed approach. The outcome of this study shows that the suggested approach for robot selection is quite helpful and has a great performance under uncertainty over classical and fuzzy ordinal priority approaches. Also, the suggested approach is less consumption of time and simpler than the fuzzy ordinal priority approach. Therefore, we recommend firms and governments to apply it for increasing product quality, hence the profitability of manufacturing industries and decrease needless costs.

Keywords Robot selection · Ordinal priority approach (OPA) · Neutrosophic sets · Triangular neutrosophic numbers · Uncertainty · Multi-attribute decision-making

✉ Mohamed Abdel-Basset
mohamedbasset@zu.edu.eg
Mai Mohamed
en_mai2011@yahoo.com
Ahmed Abdel-monem
aabdelmonem@zu.edu.eg
Mohamed Abd Elfattah
mohabdefatah8@gmail.com

¹ Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Sharqiyah, Egypt

² Misr Higher Institute for Commerce and Computers, Mansoura, Egypt

Introduction

As we know a robot is a power-driven self-controlled programmable machine. It is made with mechanical, micro-electronic, and electrical components. Robots can frequently perform complex and repetitive tasks. It also can be considered as a multi-functional structure, that can be well controlled by programs and commands [1]. The use of robots in commercial ventures and production units has been extended in the last decades to utilize resources well in time to enhance the efficiency and quality of products.

The robotic system can be used in many systems like auto manufacturing, firm manufacturing in the welding sector, large pharmaceutical companies, etc. As robots are very

expensive, then a detailed study for selecting the appropriate one for using it in the appropriate location must be made.

The selection process of an appropriate robot depends on multiple attributes that affect this selection such as accuracy, safety, security, performance, and speed or velocity of robot. This study takes into consideration the swarm intelligence, IoT, and big data attributes. We considered these attributes in the evaluation process, because they add value to the robot selection problem. For example, the robot should have big data processing that means capability and memory capacity for storing objects, maps, and images. Also, the cloud computing attribute is essential in this study, because robots can connect to cities in Europe and America to transfer many skills in the production of pharmaceutical. Selecting it also based on IoT means using sensors that are connected to others for doing different tasks as vehicles sensors which are used for vehicles' detection and measuring the amount of wetness of the road [2].

With these enormous attributes, it is not easy to select a suitable robot by decision-makers from among available robots in the marketplace. Therefore, decision-makers need to use a suitable model for the best selection of robots and then achieve the desired task.

Since the selection process of the appropriate robot is a multi-attribute decision-making (MADM) problem, several MADM techniques were applied to select the appropriate one [3]. However, there does not exist any research until now that used OPA for selecting appropriate robot. The OPA technique has several advantages such as (1) never needing a pairwise comparison matrix, (2) solving MADM problem using a mathematical model, (3) it also does not need normalization, and finally, it is simple and easy to understand. However, classical MADM techniques failed to handle uncertainty which exist usually in reality since in a classical set the element either belongs to a set or is excluded from it. Also, the fuzzy set considers only truth-membership degrees and is unable to handle indeterminacy degrees. Using a neutrosophic set in MADM make the decision-making process simulate reality via considering all aspect of decision (i.e., agree or truth, not sure or indeterminacy, and disagree or falsity degrees). Not only this, the neutrosophic set can handle paraconsistent information in contrast to the classical and fuzzy set. Also, in neutrosophic set, indeterminacy degree does not depend on truth and falsity degree and this can deal with various existing states. Also, using neutrosophic, we can distinguish between relative truth and absolute truth, and similarly relative falsehood and absolute falsehood. Due to this important role of the neutrosophic set, several researchers applied it in MADM as in [4]. However, in this study, we are the first to use the ordinal priority approach (OPA) in the neutrosophic

environment for selecting the appropriate robot for the new pharmaceutical city in Egypt. The proposed method exemplifies an intellectual MADM methodology that can handle the linguistic variables represented by neutrosophic numbers with many conveniences. Also, it is simple and with a lower computational cost. It can also deal with indeterminacy and simulate a natural decision-making process. Also, the proposed method is less consuming of time than fuzzy OPA. Table 1 illustrates a comparison of the suggested approach with some other multi-attribute decision-making techniques.

The remaining parts of this research consist of the following: In Sect. 2, we presented the literature review. The algorithm of the classical OPA model is presented in Sect. 3. Section 4 discusses the fundamental steps of the neutrosophic ordinal priority approach (OPA-N). In Sect. 5, the actual case study for the selection of an appropriate robot is implemented. A sensitivity analysis is presented in Sect. 6. In Sect. 7, a comparative study of the proposed method with the other existing methods is presented in detail. The managerial implications of the proposed method are presented in Sect. 8. Section 9 presents the conclusion, findings, and offers future work suggestions.

Literature review

The robot selection problem is solved by several MADM techniques, because it is a highly complex problem. Many past studies dealt with objective and subjective attributes. However, information on objective attributes is used more than subjective attributes.

Rashid et al. [5] used BW and EDAS methods for optimal industrial selection of robots. BW is used for calculating weights of the attribute, and EDAS used for ranking alternatives. They used four attributes, three objective attributes (Load Capacity, Repeatability, and Velocity Ratio), one subjective attribute (Degree of Freedom), and five alternatives with one expert. They concluded that their proposed model has advantages as fewer calculations and more consistency. The main limitations of their work are that they used small dimensions in calculations and failed to deal with vague, incomplete, and indeterminate information.

Also, Papakostas et al. [6] used the TOPSIS method for ranking fourteen alternatives with eight subjective attributes as (Multidimensional Learning, Flexibility, Cost, Resemblance of Human Abilities, Programmability, Autonomy, Hardware Performance, Factory Educational Abilities) for selecting appropriate social robot for education.

Table 1 Comparison of the suggested approach with some other MADM approaches

	AHP	VIKOR	COPRAS	TOPSIS	PROMETHEE	BWM	ANP	OPA	OPA_F	OPA_N
Require a pairwise comparison?	Yes	No	No	No	Yes	Yes	Yes	No	No	No
Require a decision-making matrix?	No	Yes	Yes	Yes	Yes	No	No	No	No	Yes
Require converting qualitative variables into quantitative numbers?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Require another method for ranking alternatives?	No	No	No	No	No	No	No	No	No	No
Determine weights of attributes?	Yes	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Construct a mathematical model?	No	No	No	No	No	Yes	No	Yes	Yes	Yes
Cost or benefits criteria can impact the process of decision-making?	No	Yes	Yes	Yes	Yes	No	No	No	No	No
Able to handle uncertainty?	No	No	No	No	No	No	No	No	In a small proportion	Yes
Able to consider Para consistency?	No	No	No	No	No	No	No	No	No	Yes
Simulate natural decision-making?	No	No	No	No	No	No	No	No	No	Yes

Besides key contributions of the suggested study, which was illustrated previously, we faced many challenges as follows: (1). The OPA method is new and there exist only a few research papers and never been presented in a neutrosophic environment. (2). In our study, we worked on a large scale of data. (3). In past research, there are a limited number of objective and subjective attributes for selecting an appropriate robot. However, in our study, we used 15 attributes and ten alternatives with five experts

Xue et al. [7] made a case study for evaluating robots in a manufacturing firm. They used six attributes: three subjective attributes (Man-machine Interface, Flexibility of Programming, and Contract Vendor Service), three objective attributes (Purchase Cost, Capacity, Accuracy of Positioning), and three available alternatives (robots). They used the numbers of hesitant 2-tuple for evaluating attributes and alternatives with incomplete and vague information. They used an integrated MADM with an extended QUALIFLEX method for the selection process of the best robot. The main

limitations of their work are that they did not consider indeterminacy degree; also, the number of attributes and alternatives is limited.

Nasrollahi et al. [8] proposed a fuzzy Best Worst Method and PROMETHEE for obtaining the weights of attributes and ranking the robots. They used six attributes with four alternatives which include four objectives like (Velocity, Cost, Repeatedly, and Capacity) and two subjective attributes (Flexibility of Programming and Man–Machine Interface).

They used MATLAB software for ranking the robots. The main results of their work illustrated that their model is suitable and helpful for decision-makers in the selection process of appropriate robots. Also, they considered both quantitative and qualitative attributes. However, they failed to deal with uncertainty which exist usually in reality. They also did not compare their results with the other previous studies to show the difference between previous work methods and their method.

Rashid et al. [9] used the Best Worst Method, TOPSIS, and VIKOR methods integrated with Interval-Valued Trapezoidal fuzzy for selecting a suitable robot of a company. They used five robots and six attributes that include three subjective (Man–Machine Interface, Flexibility of Programming, and Vendor Contract of Vendor Service) and three objective attributes (Purchase Cost, Capacity of Load, and Accuracy of Positioning). The main outcome of their work is that they found the TOPSIS method which is more stable than the VIKOR method.

Kavita Devi [10] used the extension of the VIKOR method under an intuitionistic fuzzy environment for robot selection problems. He used three alternatives with three subjective (Man–Machine Interface, Programming Flexibility, and Vendor’s Service Contract) and three objective attributes (Purchase Cost, Load Capacity, and Positioning Accuracy).

Narayanamoorthy et al. [11] used Interval-valued intuitionistic hesitant fuzzy with entropy and VIKOR methods. The entropy method is used for calculating weights of attributes and the VIKOR method is used for rank alternatives. They used three alternatives, three subjective attributes (Programming, Performance, and Flexibility), and two objective attributes (Cost and Capacity).

Irfan Deli [12] used generalized trapezoidal hesitant fuzzy numbers with the TOPSIS method for the robot selection problem. He made his model for Auto Company. He used six subjective attributes (Inconsistency with infrastructure, Man-machine interface, Programming flexibility, Vendor’s service contract, Supporting channel partner’s performance, and Compliance) and five alternatives with one expert.

Also, Ghorabae [13] used interval type-2 fuzzy sets with the VIKOR method for the robot selection problem. He used eight alternatives with seven subjective attributes (Inconsistency with infrastructure, Man-machine interface, Programming flexibility, Vendor’s service contract, Supporting channel partner’s performance, Compliance, and Stability) and one expert. He made his study for an auto company that wants to select an appropriate robot for the productions process.

Although several researchers used different MADM techniques for the robot selection process, they all failed to deal effectively with uncertainty which exist usually in reality. Also, the OPA technique was never used until now for robot

selection problems and this motivated us to use it in this important problem.

Since OPA is a new technique, there exist few research papers until now which applied this technique. The ordinal priority approach (OPA) was proposed by Ataei et al. [14] to handle various drawbacks of traditional multi-attribute decision-making techniques. Also, a novel project portfolio selection framework toward organizational resilience based on robust OPA has been presented by Mahmoudi et al. [15]. A hybrid DEA-OPA Model has been presented also by Mahmoudi et al. [16] for evaluating the performance of the suppliers. Not only this, the OPA has been deployed by Mahmoudi and Javed [17] for evaluating the performance of construction subcontractors. The OPA was also used by Sadeghi et al. [18] for evaluating barriers to the sustainable construction industry.

Although the traditional OPA succeeded in handling the existing drawbacks of MADM, it failed to consider the situations in which experts are not sure about his/her opinion. To handle these drawbacks, a grey ordinal priority approach has been presented for selecting a sustainable supplier [19]. Since fuzzy sets are applied in various fields due to their important role [20], a fuzzy OPA has been presented also for selecting the resilient supplier and making a decision in the post-COVID era [21]. Not only this, the OPA was integrated with TOPSIS for large-scaled multiple attribute decision-making with missing values [22].

Due to the important role of the neutrosophic set in handling uncertainty via considering truth, indeterminacy, and falsity degrees [23–31], and hence simulating the natural decision-making process, we integrated it with OPA in this research for the first time to select appropriate robot for a new pharmaceutical city in Egypt. In this research, 15 attributes and ten alternatives are selected and used by experts for the evaluation process of the presented case study. The 15 attributes consist of subjective and objective attributes.

The ordinal priority approach (OPA)

In 2020, the ordinal priority approach (OPA) was proposed by Ataei et al. [14] to determine the alternative weights based on a set of attributes and as well to deal with both single and group decision-making. We can summarize the steps of OPA with details using this pseudocode as follows:

```

// OPA Algorithm
BEGIN
Inputs:  $i, j,$  and  $k$  //  $i$  - index of the experts  $(1, \dots, p)$ 
           //  $j$  - index of preference of the attributes  $(1, \dots, n)$ 
           //  $k$  - index of the alternatives  $(1, \dots, m)$ 
Output:  $W_{ijk}^r$  // weight (importance) of  $k$ th alternative based on  $j$ th criterion by  $i$ th expert at  $r$ th rank
Determine attribute  $j,$  sub-attribute  $s$  // the decision-maker should identify essential attributes and sub-attribute.
// If there is more than one expert
IF ( $i > 1$ )
  Rank experts  $i$  // to identify the priority of the experts; the years of experience or academic degree can be
  considered.
  Rank attribute  $j,$  sub-attribute  $s$  // the priority of attribute /sub-attribute should be determined by the
  experts.
  Rank alternatives  $k$  // the experts should specify the priorities of alternatives regarding each criterion.

  // Construct OPA model and solve it using LINGO, Excel, ...etc., to find weights of the attribute, and rank
  the alternatives
  Max  $Z;$  //  $Z$  is the objective function and unrestricted in sign
  Subject to:
   $i \left( j \left( r \left( W_{ijk}^r - W_{ijk}^{r+1} \right) \right) \right) \geq Z \quad \forall i, j$  and  $r$ 
   $ijmW_{ijk}^m \geq Z \quad \forall i, j$ 

   $\sum_{i=1}^p \sum_{j=1}^n \sum_{k=1}^m W_{ijk}^r = 1 \quad \forall r$ 

   $W_{ijk}^r \geq 0$ 

//The weights of alternatives
FOR  $i = 1$  to  $P$ 
  FOR  $j = 1$  to  $n$ 
     $W(k) = \sum W_{ijk}^r \quad \forall k$ 
  ENDFOR
ENDFOR

// The weights of attributes
FOR  $i = 1$  to  $P$ 
  FOR  $k = 1$  to  $m$ 
     $W(j) = \sum W_{ijk}^r \quad \forall j$ 
  ENDFOR
ENDFOR

// the weights of experts
FOR  $j = 1$  to  $n$ 
  FOR  $k = 1$  to  $m$ 
     $W(i) = \sum W_{ijk}^r \quad \forall i$ 
  ENDFOR
ENDFOR

ELSE
  Rank attribute  $j,$  sub-attribute  $s$  // the priority of attribute /sub-attribute should be examined by the expert.
  Rank alternatives  $k$  // the expert should specify the priorities of alternatives in each criterion.
// Solving the OPA model to find the weights of the attribute, and rank the alternatives
Max  $Z,$  //  $Z$  is the objective function and unrestricted in sign
Subject to
 $\left( j \left( r \left( W_{ijk}^r - W_{ijk}^{r+1} \right) \right) \right) \geq Z \quad \forall j, r$ 

 $jmW_{jk}^m \geq Z \quad \forall j$ 

 $\sum_{j=1}^n \sum_{k=1}^m W_{ijk}^r = 1 \quad \forall r$ 

 $W_{jk}^r \geq 0$ 

//The weights of alternatives
FOR  $i = 1$  to  $P$ 
  FOR  $j = 1$  to  $n$ 
     $W(k) = \sum W_{jk}^r \quad \forall k$ 
  ENDFOR
ENDFOR

// the weights of attributes
FOR  $i = 1$  to  $P$ 
  FOR  $k = 1$  to  $m$ 
     $W(j) = \sum W_{jk}^r \quad \forall j$ 
  ENDFOR
ENDFOR

ENDIF
Return weights and ranks of alternatives.
END OPA

```

Neutrosophic ordinal priority approach (OPA-N)

In the current section, the important concepts of the ordinal priority approach in a neutrosophic environment are introduced.

The most significant feature which distinguishes the ordinal priority approach over other existing decision-making techniques is its simplicity. Since every decision is a product of human efforts usually a certain degree of incompleteness and imprecision does exist due to vague and inconsistent information which exist usually in reality. Also, almost all decisions originate from subjective ordinal preferences. As an example, when someone wants to buy a new car, he/she does not construct any comparison matrix or make any normalization of data, he/she should only prioritize all available cars regarding the desired attributes such as price, speed, etc. Since almost all decisions based on linguistic variables as high, very high these values have vague information also. For example, when a father says that he bought a very good bike for his daughter, but his daughter's opinion about the bike is not very good. Therefore, handling uncertainty using linguistic variables is also not enough. Also, decision-makers usually in reality when they give their opinions about a statement may say that this statement is 60% true, 50% false, and 20% not sure.

Therefore, the neutrosophic set is the best concept for handling all the previous problems, since it is able to handle vague and inconsistent information which exists usually in the decision-making process [32], and is also able to deal with paraconsistent information in contrast to classical and fuzzy sets. Since OPA has not yet been presented using neutrosophic, we were motivated to extend it in the neutrosophic environment (OPA-N) for the first time.

The OPA-N goes to transform linguistic information into triangular neutrosophic numbers using a newly presented neutrosophic scale. We should note that this approach can be used for group and individual decision-making problems.

The flowchart of the OPA-N is presented in Fig. 1. Also, the suggested OPA-N involves some simple steps that have been delineated in the following steps:

Step 1: Select experts according to the problem domain. Since experts are persons with both knowledge and experience in a very high-level domain, in our algorithm, we considered all experts to have the same important degree and then does not prioritize them. Also, the process in which classical OPA prioritizes experts based on the organizational chart may be not sufficient in some cases in reality, and if the prioritization process is not precise, then the outcome decision will be affected.

Step 2: Let experts begin to determine attributes regarding their opinions and also available alternative alternatives.

Step 3: To calculate the relative importance of attributes, use the scale presented in Table 2.

Step 4: If we have more than one expert make an aggregation of their opinions. The aggregation operator (G) means a mapping function denoted as $G : \psi^n \rightarrow \psi$. Here, in this aggregation method, we calculate the average value of the importance degree of each attribute via the dividing sum of the relative importance of the j attribute by the k expert or decision-maker on n . Since n is the number of experts or decision-makers.

From Table 2, the expert or decision-maker must make the rank of attributes and alternatives in the form of triangular neutrosophic numbers ($L, M, U; CD$); as an example, if the expert will rank the first alternative as the best one and give it an "Absolutely important" linguistic variable and the degree of confirmation of her/his opinion about the rank of the first alternative is very strongly sure, then the final evaluation value will take the following form of the triangular neutrosophic number $\langle (7, 8, 9); 0.90, 0.10, 0.10 \rangle$, where the first part (7, 8, 9) is lower, median, and upper bound for triangular neutrosophic number, (0.90, 0.10, 0.10) is the confirmation degree which consists of maximum truthiness value, minimum indeterminacy, and falsity degrees of a triangular number.

Step 5: After making an aggregation of experts' opinions about the importance of attributes uses the score function equation for obtaining the final rank or priority of aggregated values as follows:

Let $\tilde{A}_1 = \langle (A_1, A_2, A_3); \mu_{\tilde{A}_1}, \gamma_{\tilde{A}_1}, \lambda_{\tilde{A}_1} \rangle$ be a triangular neutrosophic number then the score function equals

$$S(\tilde{A}_1) = \frac{1}{12} (A_1 + 2A_2 + A_3) * [2 + \mu_{\tilde{A}_1} - \gamma_{\tilde{A}_1} - \lambda_{\tilde{A}_1}]. \quad (1)$$

From obtained score function of the attribute, if $S(\tilde{C}_1) > S(\tilde{C}_2)$, then $\tilde{C}_1 > \tilde{C}_2$, which means that \tilde{C}_1 will take the first priority and \tilde{C}_2 will take second priority. Also, if $S(\tilde{C}_1) < S(\tilde{C}_2)$, then $\tilde{C}_1 < \tilde{C}_2$, and if $S(\tilde{C}_1) = S(\tilde{C}_2)$, then $\tilde{C}_1 = \tilde{C}_2$.

Step 6: After determining the final rank of attributes via considering all aspects of uncertainty and simulating the real decision-making process, use Table 2 also to determine the relative importance of alternatives according to each criterion and also the previous score function for prioritizing them. If your system has more than one expert, repeat step 4 and use Eq. (1) for obtaining the final rank of aggregated value.

Step 7: Now, we can traditionally present variables, sets, and indexes of the OPA model as appeared in Table 3 and solve it as follows:

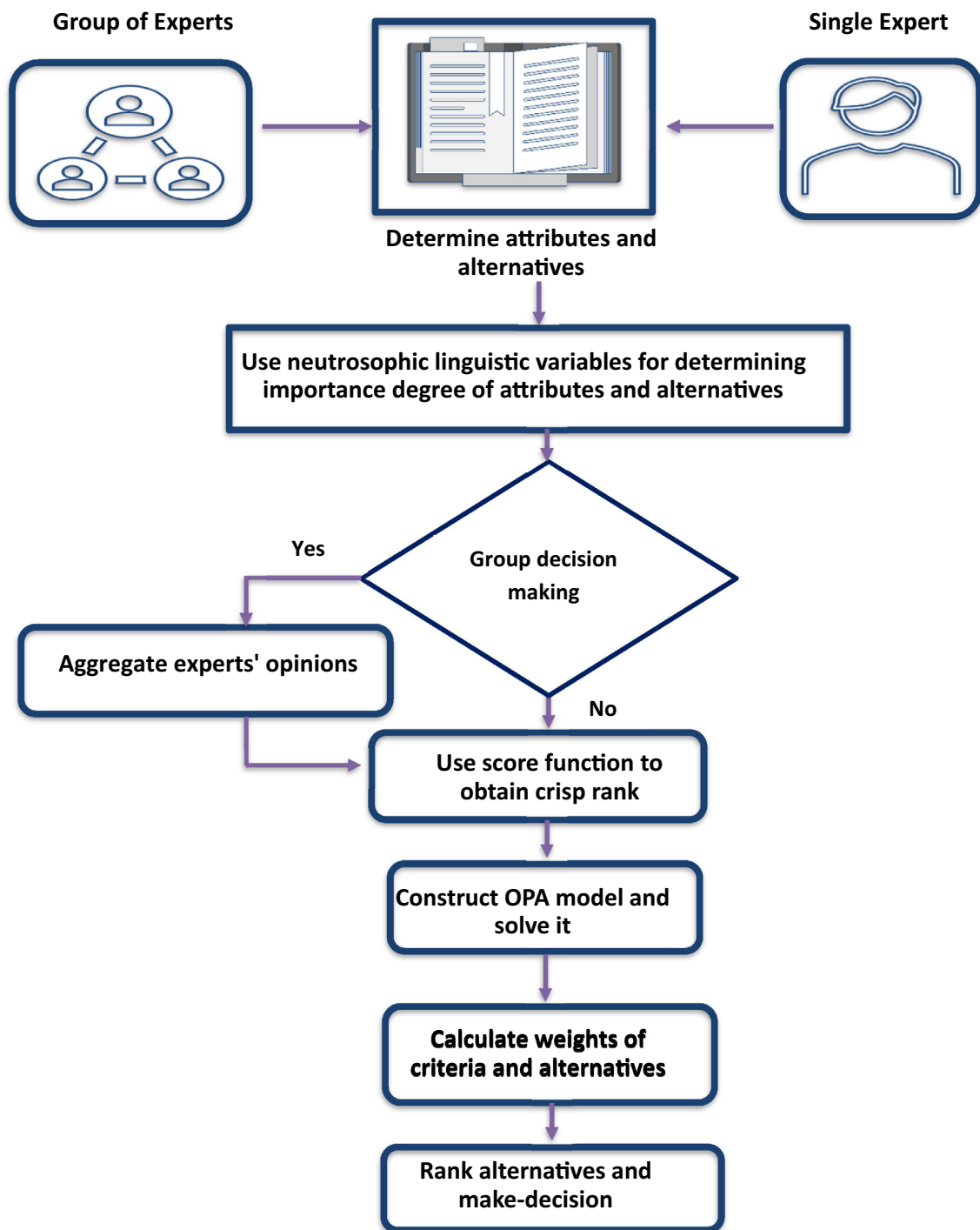


Fig. 1 Flowchart of neutrosophic OPA

For expressing rank of alternatives based on various values of c , the equation will take this form

$$A_{ca}^1 \geq A_{ca}^2 \geq \dots \geq A_{ca}^r \geq A_{ca}^{r+1} \geq \dots \geq A_{ca}^m \forall c, a. \quad (2)$$

For the superiority of i^{th} alternative over l^{th} alternative, we also have the relationship as follows:

$$W_{ca}^1 \geq W_{ca}^2 \geq \dots \geq W_{ca}^r \geq W_{ca}^{r+1} \geq \dots \geq W_{ca}^n \forall c, a. \quad (3)$$

From Eq. (3) we can obtain relation among W_{ca}^r and W_{ca}^{r+1} as follows:

$$W_{ca}^1 - W_{ca}^2 \geq 0,$$

Table 2 Linguistic variables for determining the importance degree of attributes and alternatives

Linguistic terms	The lower, median, upper values of triangular numbers (L, M, U)	Confirmation degree of expert opinion (CD)
Absolutely not important	((0, 0, 0))	Absolutely not sure (0,1,1)
Not important	((0, 0, 1))	Not sure (0.25,0.75, 0.75)
Slightly important	((1, 2, 3))	Slightly sure (0.45, 0.60, 0.60)
Median important	((2, 3, 4))	Median sure (0.50, 0.50, 0.50)
Important	((3, 4, 5))	Sure (0.75, 0.20, 0.20)
Strongly important	((5, 6, 7))	Strongly sure(0.85, 0.15, 0.15)
Very strongly important	((6, 7, 8))	Very strongly sure (0.90, 0.10, 0.10)
Absolutely important	((7, 8, 9))	Absolutely sure (1.00, 0.00, 0.0)

Table 3 Ordinal priority approach’s sets, indexes, and variables

Sets	
C	Set of attributes
A	Set of alternatives (robots)
Indexes	
c	Index of attributes preferences (1, 2, . . . , n)
a	Index of alternatives (1, 2, , m)
Variables	
Z	Objective function
A_{ca}^r	The a th alternative is based on attribute c at rank r
W_{ca}^r	Weight of alternative a th based on attribute c th at the rth rank

$$W_{ca}^2 - W_{ca}^3 \geq 0, \tag{4}$$

$$W_{ca}^r - W_{ca}^{r+1} \geq 0,$$

$$W_{ca}^{m-1} - W_{ca}^m \geq 0.$$

For presenting the degree of importance of alternatives weights, we will multiply both sides of Eq. (4) by c with rank r as follows:

$$c \left(r \left(W_{ca}^r - W_{ca}^{r+1} \right) \right) \geq 0. \tag{5}$$

To determine alternative weights, we should solve the following model, in which we want to maximize alternative preference for each attribute:

$$Max \left\{ c \left(r \left(W_{ca}^r - W_{ca}^{r+1} \right) \right), cm W_{ca}^m \right\}$$

Subject to:

$$\sum_{c=1}^n \sum_{a=1}^m W_{ca} = 1 \tag{6}$$

$$W_{ca} \geq 0.$$

Since we want to maximize the minimization objectives of the model (6), because it is a multi-objective and nonlinear model and then it is as follows:

$$Max Min \left\{ c \left(r \left(W_{ca}^r - W_{ca}^{r+1} \right) \right), cm W_{ca}^m \right\}$$

subject to:

$$\sum_{c=1}^n \sum_{a=1}^m W_{ca} = 1 \tag{7}$$

$$W_{ca}^r \geq 0.$$

For transforming model (7) to its linear form, it will be as follows:

$$Max Z$$

subject to:

$$c \left(r \left(W_{ca}^r - W_{ca}^{r+1} \right) \right) \geq Z \tag{8}$$

$$cm W_{ca}^m \geq Z$$

$$\sum_{c=1}^n \sum_{a=1}^m W_{ca} = 1$$

$$W_{ca} \geq 0,$$

where $Z = Min \{ c \left(r \left(W_{ca}^r - W_{ca}^{r+1} \right) \right), cm W_{ca}^m \}$, and unrestricted in sign.

The obtained model can be solved by different software such as LINGO, Excel, etc.

The weights of alternatives and attributes are determined as follows:

$$W_a = \sum_{c=1}^n W_{ca} \forall a, \tag{9}$$

$$W_c = \sum_{a=1}^m W_{ca} \forall c. \tag{10}$$



Fig. 2 Decision-making methodology

Table 4 Information about experts

Expert	Degree	Field
E1	PhD	Artificial intelligence
E2	PhD	Data science
E3	M.Sc	Management consultant
E4	M.Sc	Medicine
E5	PhD	Mechanical engineering

Step 8: Finally rank alternatives and take a suitable decision.

Case study: results and analysis

For evaluating the validity of the neutrosophic OPA model, a real case study for selecting the best robot for a new pharmaceutical city “Gypto pharma” in Qalyubia, Egypt is presented and solved.

This city in our case study desires to increase productivity and makes the process of production simpler and empty from human errors by adopting a robotic system. The process of production includes a sequence of cycle elements and tasks. Therefore, this city needs a robot for doing a repetitive job. The robot will do various operations such as producing medicines and vaccines for patients with cancer, coronavirus, brain, nerves, etc. It also will load and unload machines and materials. This city will produce 150 types of drugs and 150 million packages. This number of packages will increase more and more by implementing a suitable robot for this city. This city will produce a new drug that did not produce before in Egypt. Using a suitable robot, this city will become more important in the Middle East and Africa. This new city aims to export pharmaceuticals to cities in Africa. Therefore, selecting the best robots is an essential and difficult task here.

The methodology of the decision-making process consists of the following steps, as shown in Fig 2.

By applying the proposed method in this research for selecting an appropriate robot, the steps are as follows:

Step 1: The group of experts is selected by domain problem as in Table 4:

Table 5 Attributes and its description

Attribute	Description
C ₁ : Man–machine interface	More flexible programming and control robots
C ₂ : Work independently	Capable to work independently
C ₃ : Programming flexibility	Flexible of function programming
C ₄ : Big data	Big data processing capability/memory capacity
C ₅ : Velocity	Speed of work
C ₆ : Performance	Environment performance
C ₇ : Robot structure	Robot size, weights, materials
C ₈ : Repeatability	Perform some tasks many times
C ₉ : Life expectancy	Life expectancy robot
C ₁₀ : Security and safety	Safety of robot and less risk for preventing control by a hacker
C ₁₁ : Accuracy	Accuracy for doing the task
C ₁₂ : Communication and behavior interaction	Communication with environment
C ₁₃ : Sensor	Use sensor fashion for IoT system
C ₁₄ : Total cost	Purchase, the initial cost
C ₁₅ : Cloud	Robot manipulating and can use cloud during operation

Step 2: The attributes are collected from previous research by experts [2, 33–35]. Fifteen attributes and ten robots (alternatives) are selected in this work. Table 5 shows the attributes and their description. As shown in Table 5, there are four objective attributes (C₅, C₈, C₁₁, and C₁₄) and all others are subjective attributes (11 subjective attributes).

Step 3: Let five experts begin to assess the attributes listed in Table A.1 by using the presented scale in Table 2.

Step 4: After assessing attributes by experts, there are five opinions. After that those five opinions were combined to obtain an aggregated opinion by applying the aggregation method.

Step 5: After aggregating the five opinions of experts and applying the score function using Eq. (1), the final rank of attributes according to score value is presented in Table 6.

Experts assess attributes and alternatives in Table A.2.

The combined opinions of experts’ data for alternatives (robots) regarding each attribute are presented in Table A.3. Based on Table A.3, we will take the average of these combined values by dividing it by the number of experts. For determining the final rank of alternatives, we will apply

Table 6 The neutrosophic computations of attributes for the ranking process

Attribute	Sum of the relative importance of attributes	Score value of average relative importance of attributes	Rank
C ₁	((18,23,28);0.50,0.50,0.50)	2.30	6
C ₂	((19,24,29);0.45,0.60,0.60)	2.00	10
C ₃	((22,27,32);0.45,0.60,0.60)	2.25	7
C ₄	((15,20,25);0.45,0.60,0.60)	1.66	13
C ₅	((21,26,31);0.45,0.60,0.60)	2.17	8
C ₆	((19,24,29);0.50,0.50,0.50)	2.40	5
C ₇	((12,17,22);0.45,0.60,0.60)	1.42	14
C ₈	((24,29,34);0.50,0.50,0.50)	2.90	4
C ₉	((9,14,19);0.45,0.60,0.60)	1.17	15
C ₁₀	((26,31,36);0.75,0.20,0.20)	4.86	2
C ₁₁	((23,28,33);0.75,0.20,0.20)	4.39	3
C ₁₂	((16,21,26);0.45,0.60,0.60)	1.75	12
C ₁₃	((18,23,28);0.45,0.60,0.60)	1.92	11
C ₁₄	((29,34,39);0.85,0.15,0.15)	5.78	1
C ₁₅	((20,25,30);0.45,0.60,0.60)	2.08	9

Table 7 The final rank of alternatives and attribute

Attribute	Rank attribute	Rank of robots									
		A ₁	A ₂	A ₃	A ₄	A ₅	A ₆	A ₇	A ₈	A ₉	A ₁₀
C ₁₄	1	5	8	1	9	3	10	4	2	7	6
C ₁₀	2	10	2	7	8	9	3	5	1	6	4
C ₁₁	3	10	9	1	7	2	6	5	3	4	8
C ₈	4	1	10	5	3	6	9	8	7	4	2
C ₆	5	3	5	10	1	7	8	9	4	2	6
C ₁	6	6	4	7	2	10	3	1	9	5	8
C ₃	7	8	6	5	2	7	3	10	4	1	9
C ₅	8	8	5	3	10	1	4	7	6	9	2
C ₁₅	9	10	1	5	4	2	8	6	3	9	7
C ₂	10	1	2	5	7	4	6	8	10	9	3
C ₁₃	11	10	2	9	1	8	6	5	3	7	4
C ₁₂	12	4	2	8	6	1	7	5	3	9	10
C ₄	13	4	8	5	7	2	9	1	10	6	3
C ₇	14	5	8	9	4	2	7	1	10	3	6
C ₉	15	9	6	5	8	4	10	3	1	7	2

Eq. (1) to the average values of these alternatives. The alternative with the biggest score value will take rank 1, and so on. The final rank of attributes and alternatives are presented in Table 7.

The model of OPA_N in Appendix B.

The weights of attributes and alternatives can obtain using the LINGO or MATLAB software. In this work, the results were obtained by the LINGO software.

Obtained results show that C14 (i.e., Total Cost) is the attribute with the highest weight and the C9 (i.e., Life Expectancy) is the attribute with the least weight, as shown in Fig. 3.

According to the final rank of robots (alternatives), A₃ is the best robot and A₆ is the worst robot as appears in Fig. 4.

Fig. 3 Final weights of attributes

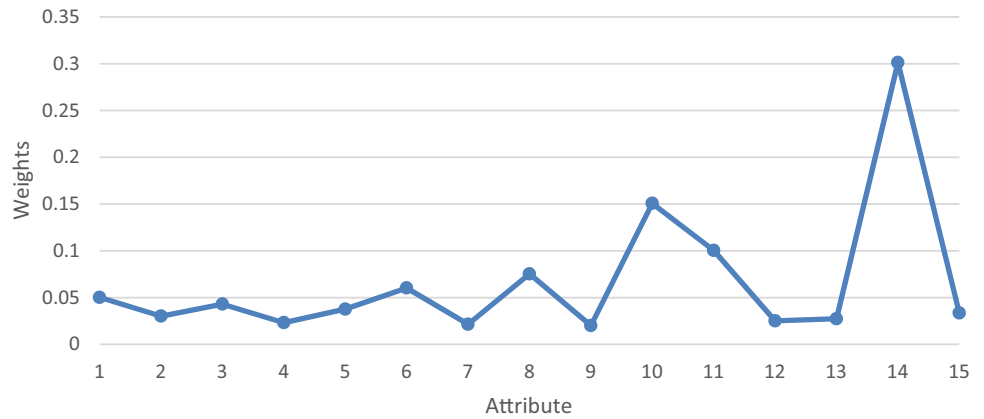


Fig. 4 Final Weights of alternatives

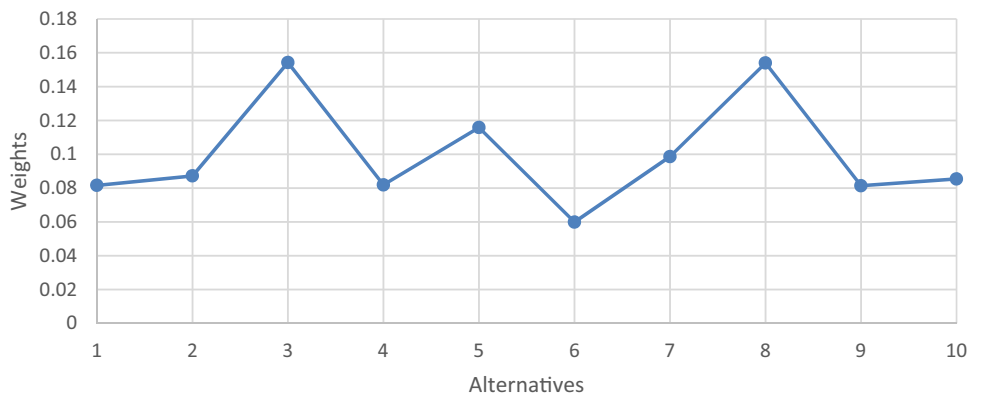
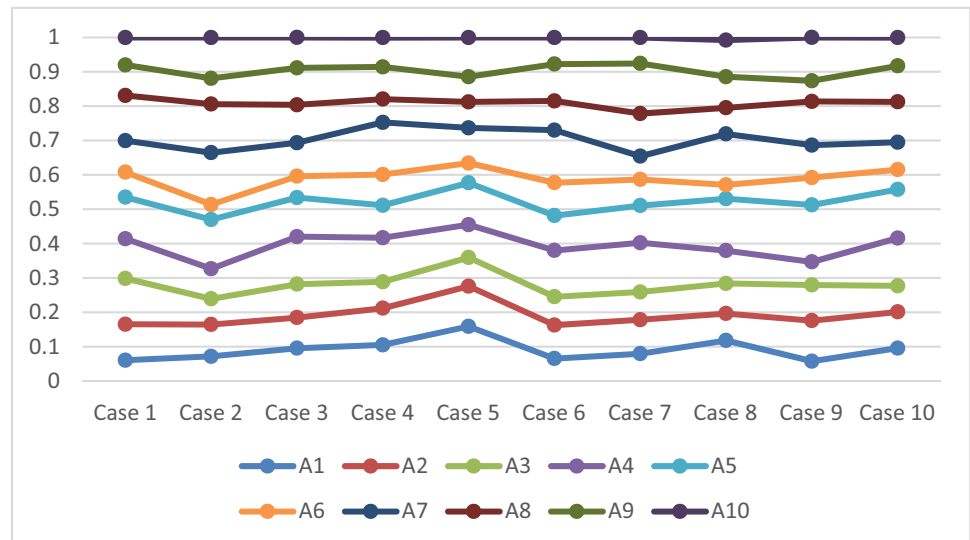


Table 8 The case of change in priority of attributes

Case #	C ₁₄	C ₁₀	C ₁₁	C ₈	C ₆	C ₁	C ₃	C ₅	C ₁₅	C ₂	C ₁₃	C ₁₂	C ₄	C ₇	C ₉
1	C ₁₁	C ₁₃	C ₁₀	C ₂	C ₆	C ₁	C ₃	C ₅	C ₁₅	C ₁₄	C ₈	C ₁₂	C ₄	C ₇	C ₉
2	C ₉	C ₇	C ₄	C ₁₂	C ₁₃	C ₂	C ₁₅	C ₅	C ₃	C ₁	C ₆	C ₈	C ₁₁	C ₁₀	C ₁₄
3	C ₁₀	C ₆	C ₁₁	C ₁	C ₈	C ₉	C ₅	C ₃	C ₂	C ₁₅	C ₁₂	C ₄	C ₁₃	C ₁₄	C ₇
4	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀	C ₁₁	C ₁₂	C ₁₃	C ₁₄	C ₁₅
5	C ₂	C ₄	C ₆	C ₈	C ₁₀	C ₁₂	C ₁₄	C ₁	C ₃	C ₅	C ₇	C ₉	C ₁₁	C ₁₃	C ₁₅
6	C ₁	C ₃	C ₅	C ₇	C ₉	C ₁₁	C ₁₃	C ₁₅	C ₂	C ₄	C ₆	C ₈	C ₁₀	C ₁₂	C ₁₄
7	C ₃	C ₆	C ₉	C ₁₂	C ₁₅	C ₂	C ₅	C ₈	C ₁₁	C ₁₄	C ₁	C ₄	C ₇	C ₁₀	C ₁₃
8	C ₄	C ₈	C ₁₂	C ₃	C ₇	C ₁₁	C ₁₅	C ₂	C ₆	C ₁₀	C ₁₄	C ₁	C ₅	C ₉	C ₁₃
9	C ₅	C ₁₀	C ₁₅	C ₄	C ₉	C ₁₄	C ₃	C ₈	C ₁₃	C ₂	C ₇	C ₁₂	C ₁	C ₆	C ₁₁
10	C ₆	C ₁₂	C ₅	C ₁₁	C ₄	C ₁₀	C ₃	C ₉	C ₁₅	C ₂	C ₈	C ₁₄	C ₁	C ₇	C ₁₃
11	C ₇	C ₁₄	C ₆	C ₁₃	C ₅	C ₁₂	C ₄	C ₁₁	C ₃	C ₁₀	C ₂	C ₉	C ₁	C ₈	C ₁₅
12	C ₈	C ₇	C ₁₅	C ₆	C ₁₄	C ₅	C ₁₃	C ₄	C ₁₂	C ₃	C ₁₁	C ₂	C ₁₀	C ₁	C ₉
13	C ₉	C ₈	C ₇	C ₆	C ₁₅	C ₅	C ₁₄	C ₄	C ₁₃	C ₃	C ₁₂	C ₂	C ₁₁	C ₁	C ₁₀
14	C ₁₀	C ₉	C ₈	C ₇	C ₆	C ₅	C ₁₅	C ₄	C ₁₄	C ₃	C ₁₃	C ₂	C ₁₂	C ₁	C ₁₁
15	C ₁₁	C ₁₀	C ₉	C ₈	C ₇	C ₆	C ₅	C ₄	C ₁₅	C ₃	C ₁₄	C ₂	C ₁₃	C ₁	C ₁₂
16	C ₁₂	C ₁₁	C ₁₀	C ₉	C ₈	C ₇	C ₆	C ₅	C ₄	C ₃	C ₁₅	C ₂	C ₁₄	C ₁	C ₁₃
17	C ₁₃	C ₁₂	C ₁₁	C ₁₀	C ₉	C ₈	C ₇	C ₆	C ₅	C ₄	C ₃	C ₂	C ₁₅	C ₁	C ₁₄
18	C ₁₄	C ₁₃	C ₁₂	C ₁₁	C ₁₀	C ₉	C ₈	C ₇	C ₆	C ₅	C ₄	C ₃	C ₂	C ₁	C ₁₅
19	C ₁₅	C ₁₄	C ₁₃	C ₁₂	C ₁₁	C ₁₀	C ₉	C ₈	C ₇	C ₆	C ₅	C ₄	C ₃	C ₂	C ₁

Fig. 5 Different weights of alternatives under sensitivity analysis from cases 1–10



Case #	A ₁	A ₂	A ₃	A ₄	A ₅	A ₆	A ₇	A ₈	A ₉	A ₁₀
1	10	5	1	4	3	9	6	2	7	8
2	9	5	8	6	2	10	1	3	7	4
3	7	8	6	1	2	10	5	3	4	9
4	4	3	9	2	5	7	1	10	6	8
5	1	3	7	6	2	10	5	8	9	4
6	10	5	8	2	4	6	1	7	3	9
7	7	5	6	2	4	8	10	3	1	9
8	3	8	7	5	1	10	2	9	6	4
9	10	4	5	8	1	7	6	2	9	3
10	6	4	9	2	1	10	8	3	5	7

Sensitivity analysis

The sensitivity analysis of the OPA-N results is conducted to assess the persistence of the priority rating and it can be an efficient way to determine the proposed approach’s efficiency.

The rank of attributes was subjected to a sensitivity analysis. Therefore, we will show how various priorities of attributes will impact on final rank of alternatives.

As we have 15 attributes, there are many cases, so we take only 19 random cases as in Table 8.

Figures 5 and 6 show the weights of alternatives based on various ranks of attributes. As seen in the figures, adjusting the ranking of the attributes has a direct influence on the weights of the alternatives.

The findings of the sensitivity analysis indicate that in cases 8, 10, 12, and 16, A₅ is the best alternative, and A₆ is the worst one. In cases 2 and 11, A₇ is the best robot and A₆ is the worst, and also, in cases 13 and 18, A₈ is the best alternative and A₆ is the worst one. Also, in cases 14, and 15, A₈ is the best alternative, and A₁ is the worst one. Therefore, we can conclude that A₅ appeared five times as the best alternative. Also, A₇ and A₈ appeared four times as

the best alternative. A₄ appeared also two times as the best. Finally, A₃, A₁, A₉, A₂ appeared only one time as the best alternative in the nineteen cases. However, as the lowest rank, A₆ appeared eleven times, A₁ appeared six times, A₇ and A₈ appeared one time as the lowest rank in 19 cases.

Comparative analysis

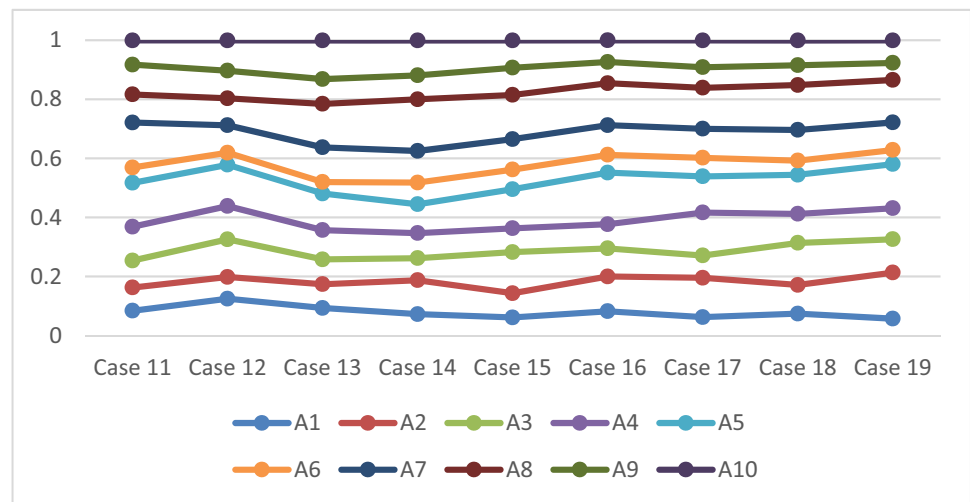
In this section, we mutually compared the obtained results of the proposed algorithm (OPA-N) with obtained results of fuzzy OPA (OPA-F) which was presented in [21].

By solving our case study using (OPA-F) which was presented in [21], the results showed that alternative 8 is the best one as appears in Table 9 and Fig. 7. The total rank of alternatives is as follows: A₈ > A₃ > A₁₀ > A₅ > A₇ > A₂ > A₄ > A₉ > A₁ > A₆.

For comparing ranks of the proposed approach (OPA-N) with fuzzy OPA (OPA-F), we used the following statistical methods as follows:

- *Spearman’s correlation*: it is one of the most important methods for finding whether there is a correlation between

Fig. 6 Different weights of alternatives under sensitivity analysis from cases 11–19



Case #	A ₁	A ₂	A ₃	A ₄	A ₅	A ₆	A ₇	A ₈	A ₉	A ₁₀
11	7	9	6	3	2	10	1	5	4	8
12	3	9	2	4	1	10	7	8	6	5
13	6	9	7	5	3	10	4	1	8	2
14	10	3	8	6	5	9	4	1	7	2
15	10	7	2	8	3	9	4	1	6	5
16	6	3	5	7	1	10	4	2	9	8
17	10	3	7	1	4	9	5	2	8	6
18	8	6	2	5	3	10	4	1	9	7
19	9	1	4	5	2	10	6	3	8	7

Table 9 Total fuzzy score of each alternative

Alternatives	L	M	U	R(TS)	Rank
A1	0.0005419376	0.0006777076	0.0009085798	0.000694	9
A2	0.0008219997	0.0010786460	0.0011490333	0.001048	6
A3	0.0009490061	0.0012981143	0.0014115375	0.001259	2
A4	0.0007755645	0.0009122549	0.0010336042	0.00091	7
A5	0.0009542543	0.0011288226	0.0012877669	0.001126	4
A6	0.0004783107	0.0006179901	0.0007868482	0.000623	10
A7	0.0009271659	0.0010670592	0.0011796840	0.001063	5
A8	0.0011350590	0.0013732713	0.0019678994	0.001433	1
A9	0.0006663868	0.0008009228	0.0010163652	0.000814	8
A10	0.0009077259	0.0011758927	0.0012348042	0.001141	3

two ordinal variables or there isn't. The Spearman's correlation is calculated as follows:

$$S_C = 1 - \left[\frac{6 \cdot \sum_{m=1}^A (d_m)^2}{A \cdot (A^2 - 1)} \right], \tag{11}$$

where A is the number of alternatives and d_m is the difference between the two ranks of alternatives. If S_C has value close to $+1$ or -1 , it means that it is a strong correlation. However, if the value of S_C is close to 0 , it means that it is a weak correlation.

- *Person's correlation*: shows the extent to which two variables are linearly correlated. If the correlation coefficient is 1 , then there is a total positive linear correlation. However, if the correlation coefficient is -1 , then there is a total negative linear correlation. Finally, if the correlation coefficient is 0 , then there is no linear correlation. The formula of Person's correlation coefficient is as follows:

$$p_{cor}(b, c) = \frac{cov(b, c)}{\sigma_b \sigma_c}, \tag{12}$$

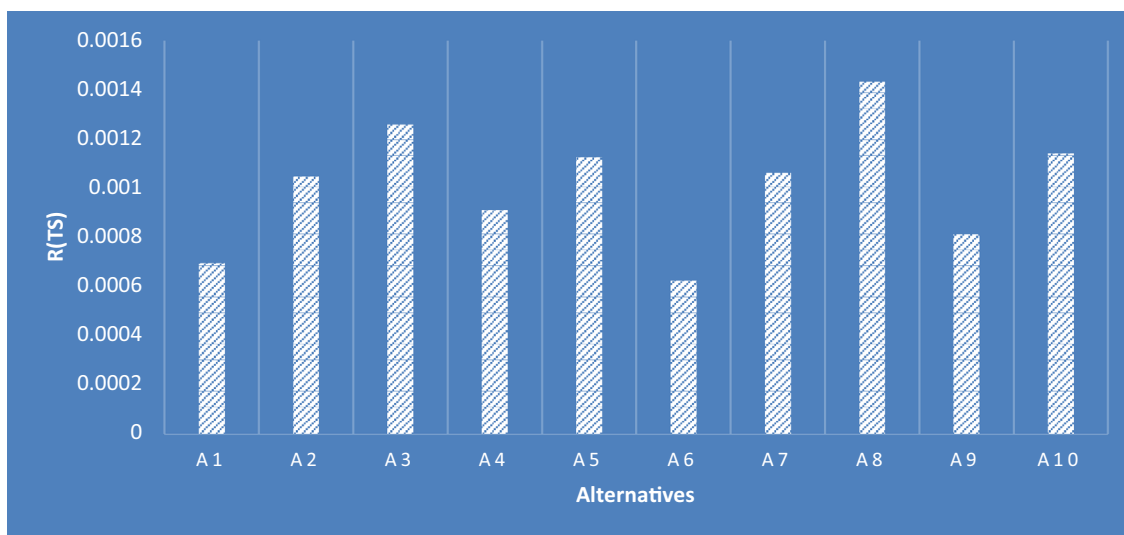


Fig. 7 The rank of alternatives based on defuzzification formula R (TS)

Table 10 Rank of alternatives based on OPA-N and OPA-F

Alternatives	OPA-N	OPA-F
A1	8	9
A2	5	6
A3	1	2
A4	7	7
A5	3	4
A6	10	10
A7	4	5
A8	2	1
A9	9	8
A10	6	3

where $cov(b, c)$ is the covariance among b, c , and σ_b, σ_c is the standard deviation of b and c , respectively.

The final rank of alternatives using the proposed neutrosophic OPA (OPA-N) approach and fuzzy OPA (OPA-F) approach is presented in Table 10.

Firstly, we calculated Spearman's correlation coefficient for comparing obtained ranks from two approaches. Spearman's correlation coefficient is equal to 0.90303 which shows the strong correlation between the two approaches.

Also, we calculated the Person's correlation coefficient for showing linear relation among two approaches. The Pearson's correlation coefficient is also equal to 0.90303 which shows a strong linear correlation among the two approaches. By considering $\alpha = 0.05$, then.

$$t = 0.90303 \frac{\sqrt{10-2}}{\sqrt{1-0.90303^2}} = 5.94.$$

Since $t = 5.94 > t_{0.05}(10-2) = 1.8$, then the hypothesis test shows that there is a strong positive correlation among alternative weights of the proposed method and OPA-F.

Finally, the finding from the comparative study of OPA-F and OPA-N for measuring and ranking the weights of attributes/alternatives are as follows:

- Even though both methods produced near results, the suggested model (OPA-N) is simpler and more useful than the OPA-F for the following reasons:
- To calculate the weights of attributes/alternatives, a crisp model must be generated from the fuzzy model. However, the conversion process from fuzzy model to crisp increases the number of equations by three times. The increase in the number of equations makes the OPA-F model more complex, time, and storage-consuming compared with (OPA-N). Table 11 shows the number of constraints, variables, and iterations for OPA_N and OPA_F.
- To solve this case study using the OPA-F model, we constructed a total of 7452 crisp equations which were needed to obtain the ranks for the alternatives only, so in large-scale problems, the OPA-F model will be more complex, and time-consuming than the proposed OPA-N model.
- Finally, the OPA-F model cannot deal efficiently with vague and inconsistent information which exist usually in the decision-making process, since it considers only the truth-membership degree, while the proposed model is capable of handling vague and inconsistent information efficiently and simulating natural human thinking during the decision-making process via considering truth, indeterminacy, and falsity membership degrees.

Table 11 Difference between OPA_N and OPA-F at solving the same case study

Case study components	OPA_N	OPA_F [21]
Number of experts	5	5
Number of attributes	15	15
Number of alternatives	10	10
Number of total variables	178	4966
Number of total constraints	329	7452
Number of iterations	0	2107

The difference between OPA-N and OPA-F at solving the same case study is presented in Table 11.

Managerial implications

Since companies need robots for doing complex and repetitive tasks, they need to select appropriate types for fulfilling their missions in the best manner. As the selection process is a hard task due to several conflicting attributes which exist nowadays, then we need an ordering technique that commonly contains various extents of selection. In this research, we presented for the first time the ordinal priority approach in the neutrosophic environment for handling uncertainty which exist usually in the selection process. The proposed OPA_N proved its applicability to deal with subjective and objective attributes under uncertainty for evolving a strong decision.

The suggested model can be a powerful guide for companies or organization that desire to use a robotic system in hospitals, pharmacy, manufacturing company, and companies that wishes to robotize the welding section on their manufacturing units. In addition, governments can use the suggested model for making precise decisions about any social, economic, and environmental problems.

Conclusions and future directions

In this research, a new extension of the OPA method is presented in the neutrosophic environment for robot selection problems. This research presented for the first time a case study of a new pharmaceutical city in Egypt for selecting the best robot from among available alternatives for increasing productivity of pharmaceutical and to serve Egyptian people. In this case, we selected five experts from various specialties. The experts constructed the evaluation process of robots based on 15 attributes and 10 alternatives.

The finding of the outcomes illustrated that the proposed method is able to handle uncertainty efficiently. Also, the proposed method is simpler and more helpful than the classical

and fuzzy model of OPA. Not only this, but by comparing OPA_N with OPA-F, we concluded that OPA-N is less time-consuming than OPA-F as fuzzy OPA produces a huge number of equations on a large scale. On the other hand, some limitations must be enhanced in the further study such as considering interrelationships among attributes and not only independent attributes. Also, we need to develop a proposed method to consider in detail the impact of positive and negative attributes on the final decision.

In the future, we plan to use various multi-attribute decision-making methods and present them in a neutrosophic environment using the alpha cut method to solve the problem of selecting the robot with more difficult and complex dependencies between attributes.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s40747-022-00721-w>.

Author contributions All authors have contributed equally to this research.

Funding This research has no funding source.

Declarations

Conflict of interest The authors declare that there is no conflict of interest about the research.

Ethical approval None of the authors' experimented with human subjects or animals during this research.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

1. Mondal S, Chakraborty S (2013) A solution to robot selection problems using data envelopment analysis. *Int J Ind Eng Comput* 4(3):355–372
2. Roy Chowdhury A (2017) IoT and Robotics: a synergy, *PeerJ Prepr*, 5: e2760v1
3. Sen DK, Datta S, Patel SK, Mahapatra SS (2015) Multi-criteria decision making towards selection of industrial robot, *Benchmarking An Int J*.
4. Mahmood T, Ali Z (2022) Prioritized Muirhead mean aggregation operators under the complex single-valued neutrosophic settings

- and their application in multi-attribute decision making, *J Comput Cogn Eng*
5. Rashid T, Ali A, Chu Y-M (2021) Hybrid BW-EDAS MCDM methodology for optimal industrial robot selection, *PLoS One*, 16(2): e0246738
 6. Papakostas GA, Strolis AK, Panagiotopoulos F, Aitsidis CN (2018) Social robot selection: a case study in education. In: 2018 26th international conference on software, telecommunications and computer networks (SoftCOM), pp 1–4.
 7. Xue Y-X, You J-X, Zhao X, Liu H-C (2016) An integrated linguistic MCDM approach for robot evaluation and selection with incomplete weight information. *Int J Prod Res* 54(18):5452–5467
 8. Nasrollahi M, Ramezani J, Sadraei M (2020) A FBWM-PROMETHEE approach for industrial robot selection, *Heliyon* 6(5):e03859.
 9. Rashid T, Ali A, Guirao JLG, Valverde A (2021) Comparative analysis of hybrid fuzzy MCGDM methodologies for optimal robot selection process. *Symmetry (Basel)* 13(5):839
 10. Devi K (2011) Extension of VIKOR method in intuitionistic fuzzy environment for robot selection. *Expert Syst Appl* 38(11):14163–14168
 11. Narayanamoorthy S, Geetha S, Rakkiyappan R, Joo YH (2019) Interval-valued intuitionistic hesitant fuzzy entropy based VIKOR method for industrial robots selection. *Expert Syst Appl* 121:28–37
 12. Deli I (2020) A TOPSIS method by using generalized trapezoidal hesitant fuzzy numbers and application to a robot selection problem. *J Intell Fuzzy Syst* 38(1):779–793
 13. Ghorabae MK (2016) Developing an MCDM method for robot selection with interval type-2 fuzzy sets. *Robot Comput Integr Manuf* 37:221–232
 14. Ataei Y, Mahmoudi A, Feylizadeh MR, Li DF ordinal priority approach (OPA) in multiple attribute decision-making, *Appl. Soft Comput J* 86 December, 2020, <https://doi.org/10.1016/j.asoc.2019.105893>.
 15. Mahmoudi A, Abbasi M, Deng X (2022) A novel project portfolio selection framework towards organizational resilience: robust ordinal priority approach, *Expert Syst Appl* 188:116067
 16. Mahmoudi A, Abbasi M, Deng X (2021) Evaluating the performance of the suppliers using hybrid DEA-OPA model: a sustainable development perspective, *Gr Decis Negot* pp 1–28.
 17. Mahmoudi A, Javed SA (2021) Performance Evaluation of Construction Sub-contractors using Ordinal Priority Approach, *Eval Program Plann*, 102022
 18. Sadeghi M, Mahmoudi A, Deng X (2021) Adopting distributed ledger technology for the sustainable construction industry: evaluating the barriers using Ordinal Priority Approach, *Environ Sci Pollut Res* pp 1–26.
 19. Mahmoudi A, Deng X, Javed SA, Zhang N (2020) Sustainable supplier selection in megaprojects: grey ordinal priority approach, *Bus Strateg Environ*.
 20. Ünver M, Olgun M, Türkarslan E (2022) Cosine and cotangent similarity measures based on Choquet integral for Spherical fuzzy sets and applications to pattern recognition, *J Comput Cogn Eng*
 21. Mahmoudi A, Javed SA, Mardani A (2021) Gresilient supplier selection through fuzzy ordinal priority approach: decision-making in post-COVID era. *Oper Manag Res*. <https://doi.org/10.1007/s12063-021-00178-z>
 22. Mahmoudi A, Deng X, Javed SA, Yuan J (2020) Large-scale multiple criteria decision-making with missing values: project selection through TOPSIS-OPA. *J Ambient Intell Humaniz Comput* pp 1–22.
 23. Ye J, Du S, Yong R (2021) Correlation coefficients of credibility interval-valued neutrosophic sets and their group decision-making method in single-and interval-valued hybrid neutrosophic multi-valued environment. *Complex & Intelligent Systems*: 1–15.
 24. Ye J, Türkarslan E, Ünver M, Olgun M (2021) Algebraic and Einstein weighted operators of neutrosophic enthalpy values for multi-criteria decision making in neutrosophic multi-valued set settings. *Granular Comput*: 1–9.
 25. Ye J, Du S, Yong R, Zhang F (2021) Arccosine and arctangent similarity measures of refined simplified neutrosophic indeterminate sets and their multicriteria decision-making method. *J Intell Fuzzy Syst Preprint*: 1–13.
 26. Ye J, Du S, Yong R Orthopair indeterminate information expression, aggregations and multiattribute decision making method with indeterminate ranges. *J Control Decision* (2021): 1–9.
 27. Ye J (2021) Entropy measures of simplified neutrosophic sets and their decision-making approach with positive and negative arguments. *J Manag Anal* 8(2):252–266
 28. Ye J, Song J, Du S (2020) Correlation coefficients of consistency neutrosophic sets regarding neutrosophic multi-valued sets and their multi-attribute decision-making method. *Int J Fuzzy Syst*: 1–8.
 29. Ye J, Cui W (2020) Modeling and stability analysis methods of neutrosophic transfer functions. *Soft Comput* 24(12):9039–9048
 30. Ye J (2020) Generalized ordered weighted simplified neutrosophic cosine similarity measure for multiple attribute group decision making. *Int J Cognit Inform Nat Intell (IJCINI)* 14(1):51–62
 31. Ye J (2019) Hesitant interval neutrosophic linguistic set and its application in multiple attribute decision making. *Int J Mach Learn Cybern* 10(4):667–678
 32. Abdel-Basset M, Mohamed M, Hussien A-N, Sangaiah AK (2018) A novel group decision-making model based on triangular neutrosophic numbers. *Soft Comput* 22(20):6629–6643
 33. Sen DK, Datta S, Mahapatra SS (2016) Extension of PROMETHEE for robot selection decision making, *Benchmarking An Int J*.
 34. Liu H, Quan M, Shi H, Guo C (2019) An integrated MCDM method for robot selection under interval-valued pythagorean uncertain linguistic environment. *Int J Intell Syst* 34(2):188–214
 35. Zhou F, Wang X, Goh M (2018) Fuzzy extended VIKOR-based mobile robot selection model for hospital pharmacy. *Int J Adv Robot Syst* 15(4):1729881418787315

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.