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Determining rank in the market using a neutrosophic decision support system

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ABSTRACT

A company's rank vis-à-vis that of its competitors is an important metric in understanding its position in the market. For a company, being ranked below its competitors indicates that customers are dissatisfied with its products, signalling the need for a review of its strategies. Existing state-of-the-art methods for ascertaining a company's rank do not utilise the valuable data available on social media or most smart technologies such as the Internet of Things (IoT) and artificial intelligence. This study develops a new method to estimate a company's rank using company-deployed intelligent software agents and social IoT(SIoT) objects. The company objects collect real-time feedback about one or more of the company products from social networks for storage and analysis. These company objects are equipped with questionnaires with important metrics such as the Customer Happiness Index, opinion on features of competitive products, expectations in upcoming models of the product. Then neutrosophic numbers have been used to determine truthiness, falsity and indeterminacy of each opinion and based on such opinions, rank of a company is determined.

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KEYWORDS

Software agents;
neutrosophic sets; rank;
social networks; social
media; social IoT

1. Introduction

The rank of a company is an important metric for measuring its overall performance. A company ranking better than its competitors indicates that the customers are currently satisfied with the performance of its products and/or services (Neilson et al., 2008). This can provide confidence in the company's current business model and/or its strategies (McGee & Sammut-Bonnici, 2014). Conversely, if the rank is unsatisfactory, the company must review its plans based on the present market interests and its predicted future (Realzola, 1980). Thus the rank, as derived from customer perceptions, can help managers decide on the need for a review of the company's goals or a restructuring of its business model, strategy, procedures, and human resources (D'Aveni, 2007; Realzola, 1980). On the current literature on customer behaviour, a one of the common methods for soliciting customer opinion is via questionnaire. However, customers may often not be interested or motivated to complete such a questionnaire as when they are requested (Mathers et al., 2009). However, the same customers may be candidly providing such feedback across social media platforms. With the current technology, collating current product information and customer feedback from various sources instead of banking on the customer to actively contribute through a questionnaire survey is possible.

Internet of Things (IoT) has significantly transformed business processes for the better. They can search through, organise, and compare a huge amount

of data leading to prompt and efficient decision support systems (Attaran, 2017). According to Leemput (2014), the impact of IoT is felt most in the business world because it has not only changed the methods of different business operations but also the way information is collected and exchanged. Angelova et al. (2017) highlighted the ease of data exchange and object tracking amongst devices and users through built-in sensors and other technologies. IoT has found application in tracking the health of patients, the performance of various products and product parts, locating goods during transformation, monitoring facilities, and the list goes on (Whitmore, Agarwal & Xu, 2015). Ramachandran (2015) mentions the IDC's CIO Summit 2014, where it was stated that "IoT is no longer a buzzword; all participants in the study were at some stage of evaluation or implementation". IoT is thus expected to pervade across domains and be used everywhere.^{1,2,3} The current COVID-19 pandemic has further accelerated the adoption of IoT in automating society (Mishra, 2020). According to Deloitte (Mishra, 2020), 'the IoT units in India are expected to see rapid growth of ~32x to reach 1.9 billion units by 2020, from its current base of 60 million. As a result, the Indian IoT market is expected to grow ~7x to move from US\$ 1.3 billion in 2016 to US\$ 9 billion by 2020'.

Social Internet of Things (SIoT) is a social network of IoT devices. This paradigm enables IoT objects to communicate over their social networks and exchange

information to achieve certain objective(s) (Atzori et al., 2012). With the help of the SIoT Server, new software objects can be created as and when required. Emulating human behaviour, these new objects can be related to one or more existing objects through different relationships and be friends with each other, exchange information to achieve common goals, and update relationship status and their level of trustworthiness (Atzori et al., 2012; Basset, Gunasekaran, Mohamed et al., 2018; Basset et al., 2019). The various applications of SIoT include smart homes, cities, agriculture, classroom, health, industry automation of the industry, and so on. Some of these are collected from the literature are listed in Table 1. Wearable sensors and biochip transponders are being heavily used in health monitoring systems, farm animals, smart washing machines, remote monitoring in smart homes and cities (Basset, Gunasekaran, Mohamed et al., 2018; Basset et al., 2019). Among many others, SIoT is being used to implement smart retailing. For example, as a customer enters a supermarket, his smart phone may automatically communicate with a SIoT object to instal an app of the mart for auto-registration. This then lists the favourite products and corresponding brands associated with this customer identifier or suggests possible items based on the purchase behaviour of similar customers. Similarly, a phone can interact with a smart refrigerator at home to create a list of items that need restocking, which can then be sent to the customer as a reminder. According to The German Kraftfahrst-Bundesamt (KBA) report,⁴ around 2.3 million out of 43.9 million registered vehicles in Germany are involved in accidents yearly, which incurring an additional cost of €31 billion per year for the country. The deployment of IoT objects in vehicles to monitor their performance efficiency along with the expertise and attitude of their drivers has resulted in the avoidance of 90% of the accidents. IoT-based trace ability during manufacturing in food/medicine industries enables a high degree of quality control; any product could be traced back in case of customer complaints. Airtel has already built an independent IoT vertical as part of its Airtel Business, which totalled up to 1.7 USD billion in revenues for the fiscal year 2018–2019. Its rival Reliance Jio Infocomm is preparing to tap into the IoT market at the pan-India level through its NB-IoT network.⁵

According to a survey appearing in the study by Tomic (2017), 16.67% of the respondents indicated a major positive impact of IoT on almost all industries; 75% and 8.33% reported significant and limited impact, respectively. The estimated increase in productivity ranged from 15% to 72%, with an aggregate average of 36%. Among the respondents, 83.33% agreed that IoT has converted the product-centric industry culture into a customer-centric culture. As

per Wozniczka and Marek (2017), the potential impacts of IoT on business include providing proactive service to customers and strengthening relationships with them, keeping customers updated, predicting product failures, improving product performance, enhancing personalised services, and improving service processes. In determining company rank, IoT can play a significant effective role in obtaining customer feedback. Currently, even in developing countries, IoT-based customer feedback systems are being deployed across public platforms like petrol pumps, rail stations and the like, wherein a customer can provide feedback on their experience regarding hygiene, sanitation, and other such issues. IoT-enabled devices can also be configured to communicate granular and accurate feedback from customers to manufacturers in real-time. There are adapters developed for allowing a spontaneous exchange of messages between the customers and the company (Foroudi et al., 2018; Lo & Campos, 2018). These messages contain actionable product and customer data, thereby building closer relationships with “both larger demographic segments and individual customers”. IoT thus provides an exclusive “major data opportunity”. Using these data, often customers can be offered proactive services, enhancing customer delight (Foroudi et al., 2018).

Ranks among multiple competitor companies are usually decided based on factors such as sales, assets, earnings, and so on. This method is used by Fortune magazine to list the top 500 companies of the US.⁶ The Crunchbase Rank algorithm⁷ considers the level of community engagement, funding events, news articles, and acquisitions. However, none of these take care of the opinions of people on social media. Given the wide availability of information in social media, and technologies like IoT, a promising opportunity to review the methodologies for ranking companies exists.

In this paper, we endeavour to harness this opportunity and propose a methodology for ranking companies utilising SIoT objects to monitor product performance and company software objects to collect feedback from social media. The SIoT object can communicate with IoT sensors embedded in the products to obtain performance parameters, which constitutes a part of the customer feedback. The company objects are proposed to automatically complete questionnaires through product performance inputs from SIoT objects and customers’ social media contents and analyse these data to provide more accurate insights from the customers’ opinions. The customer feedbacks are then analysed by company objects and not SIoT objects, as the latter have limited processing power. The knowledge gained from such analysis can enable companies to develop an interpersonal

Table 1. Applications of SIoT available in literature.

Title of the Article	Author/Editor	Year	Application
Social IoT HealthCare	Zamanifar	2020	Describes the application of SIoT in healthcare
Challenges and Solutions of Using the Social Internet of Things in Healthcare and Medical Solutions – A Survey	Rahouma	2020	Describes the application of SIoT in healthcare
Social Networking with the Internet of Things Aid Bahraini Medical Professionals' Decisions Through Their Knowledge Sharing	Razzaque (a)	2020	Describes the application of SIoT in healthcare
Security Threats of Social Internet of Things in the Higher Education Environment	Mawgoud	2020	Describes the applications and potential threats of SIoT in higher education
Peak-End Rule Promotes Social Capital for Knowledge Management Through Social Internet of Things	Razzaque	2020	Describes the role of SIoT in Knowledge Management
Social Internet of Things in Agriculture: An Overview and Future Scope	Panda	2020	Describes the role of SIoT in agriculture
Social Internet of Things: Foundations, Thrust Areas, Systematic Review and Future Directions	Roopa et al.	2019	Describes the use of SIoT in smart parking, smart airport domain, object tracking, service locating, etc.
Social Internet of Things: Applications, Architectures, and Protocols	Rho&Chen	2018	Illustrates the applications of SIoT in multiple fields including healthcare, business, data analytics, energy harvesting, etc.
The Exploitation of Social IoT for Recommendation Services	Saleem et al.	2016	Discusses the utility of the SIoT network in determining the reusability of one IoT applications' data among various IoT applications
A Social Internet of Things Application Architecture: Applying Semantic Web Technologies for Achieving Interoperability and Automation Between the Cyber, Physical and Social worlds	Ali	2015	Discusses achieving situational integration among the cyber, physical, and social worlds

relationship with its customers based through social media as gleaned by these company objects, which can further be used to stimulate future purchase decisions. In our proposed Neutro-Know Your Rank (Neutro-KYR), we model the customer responses as a set of neutrosophic numbers and we assign each of the responses with three membership functions – truth membership degree, indeterminacy, and falsity membership degree. The responses are then analysed based on the weights assigned to each criterion of the questionnaire. Among the set of all possible solutions to the resulting neutrosophic functions, the best and the worst possible solutions are computed. If the best solution is hypothetical, then M-hamming distances of each solution are calculated from the best and the worst solutions. The solution which is closest to the best one, or is the farthest from the worst one, is accepted as optimal. From this, the company's product rank concerning competitors can be determined, and this can be used by the company to reposition its strategy accordingly. The proposed methodology for automated collection, collation, and analysis of customer responses to arrive at the company rank vis-à-vis its competitors is the contribution of this paper.

The rest of this paper is organised as follows. A review of related literature appears in [Section 2](#); overview of the methodology of Neutro-KYR is presented in [Section 3](#). The detail of the scheme is presented in [Section 4](#). An illustrative example appears in [Section 5](#). Finally, [section 6](#) concludes the paper.

2. Literature review

In this paper, we have used SIoT objects to collect and collate data and utilised artificial intelligence (AI) techniques to analyse and extract meaning out of the data. AI is expected to be the key propellant to the growth of the IoT revolution. Therefore, in related work, we have examined the impact of both AI and IoT on business.

AI has made its presence felt across business domains. Certain companies and retail stores have started experimenting with this technology. AI has been used to retrieve information about customer concerns regarding a company's products and similar products launched by their competitors (Balaji & Roy, 2017; Desai & Mahalakshmi, 2018; Jie et al., 2015; Yerpude & Singhal, 2018). Customer concerns help the business to re-examine their process and products or services. However, the process of manually collecting and collating such customer data and feedback is time-consuming and error-prone. AI tools can assume such tasks and play a significant role in enhancing product quality and in providing an optimal solution for enhancing customer satisfaction (Desai & Mahalakshmi,

2018; Jie et al., 2015). Canhoto and Arp (2017) theoretically model the advantages and difficulties of adopting AI in monitoring the health of individuals through wearable sensors and concludes that it helps in promoting and maintaining the brand name.

Jie et al. (2015) studied the process of e-retailing, which aims at ensuring timely and efficient delivery of services and products to customers using IoT technology. The case of the electricity distribution centre of Bangalore Electricity Supply Company (BESCOM) is modelled in (Desai & Mahalakshmi, 2018). The study aimed to find the gap between customer service expectations and actual delivery. The results indicate that there were significant differences between expected and perceived service and emphasised that IoT can greatly help in filling this gap. Moreover, BESCOM customers were shown to be willing to use IoT if they are introduced. Yerpude and Singhal (2018) focused on the utility of IoT in promoting business, and they proposed a scheme for facilitating IoT-based vehicle assistance on-road and elaborated on its impact on customer service enhancement. The analysis generates insights on the positive impacts of IoT on vehicle assistance solutions and the customers' relationship with the company. Desai and Mahalakshmi (2018) investigated value co-creation with IoT technology, especially in the retail business as “the retail industry is at the forefront in embracing IoT which is expected to change the way customers experience shopping”. Their results reveal that better functionality, user-friendliness, accuracy, and aesthetics are key advantages of IoT in this sector.

Discussion on IoT-based customer relationship management appears in Abdel-Basset et al. (2018), Ziemba et al. (2018), Chaffey et al. (2009), Karczmarczyk et al. (2018), and Abdel-Basset et al. (2018) emphasised that sensors can be integrated with the products so that the company can track their performance post-sale. In case of a problem, the company representatives can proactively intervene for better customer experience and enhanced bonding between customer and company. According to Chaffey et al. (2009), “the strength of IoT in CRM lies in how to make sense of historical enterprise data, connect it with real-time data from things and generate insights to take action. It is all about data and technologies, and how CRM can make use of it”. Sensors can provide real-time data, which in turn can generate great opportunities to analyse customers' opinions based on their behaviour, attributes, requirements as well as purchase patterns. According to Karczmarczyk et al. (2018), IoT-based CRM provides a higher degree of personalisation based on a deep analysis of customer behaviour and through friendly interactions. It helps design highly targeted and quick campaigns to influence purchase decisions in real-time.

AI and/or IoT/SIoT can also allow for new customer service options. Wu et al. (2017) emphasise that friend-like interactions promoted using IoT technology can produce enhanced positive brand attachment and brand competence. Objects are becoming increasingly smart and connected and, as far as performances of products are concerned, are facilitating proactive communication with customers and thereby spreading brand warmth and concern in the grievance redressal process. Mani and Chouk (2017) focus on the difficulties involved in adopting IoT technology: inertia against accepting and adopting something new remains prominent because of the lack of technical ability. Proper training and psychological openness is also a challenge. In a general context of industry and business models, certain productivity advantages and threats imposed by AI arise as illustrated in (Aksu et al., 2018; De Cremer et al., 2017; Rajabi & Hakim, 2015, 2015). Celik (2016) proposes a smart framework, particularly for shopping malls. Đurđević et al. (2017) propose a model to analyse the immense possibilities of IoT technology in marketing and retail from the perspectives of manufacturers, retailers, and customers. They also advocate for the intelligent use of sensors “for consumer activation to generate incremental commercial results above and beyond standard promotional practices”. This is important both from the perspective of influencing product purchase decisions and grievance redressal. IoT technologies can also be integrated with smart software objects to narrow the gap between companies and customers. Useful apps provide real-time, location-aware, integrated, and updated information to the customers users can make wiser and more effective purchase decisions (Tsai et al., 2017). The propensity to remain updated and adopt new things is different in among people, and the use of apps requires user’s acceptance and willingness to download, store, and use them. The authors investigate the behavioural characteristics of customers in this respect. Smart interactions of customers and shopping malls are discussed in Nallakaruppan and Kumaran (2018).

Customer involvement means a lot to companies. According to Burns and Hulliburton (1990), customers should continuously be involved not only in the evaluation of final products but also during acceptance/rejection of initial ideas and subsequent evaluation of prototypes, if the idea gets accepted. Chen et al. (2011) concentrate not only on customer responses about products but also the used data about the customers themselves. This data about customers include “demographic, psychographic as well as behavioural data”. This allows understanding the importance of various features of a given product across different classes of customers. Bhatia et al. (2013) emphasise the utilisation of social networks in the collection of customer feedback. According to him, “social network

and crowd-funding platforms like Kickstarter, provide a source of data that reveals whether a product succeeded or failed in gathering community support”. Martin and Woodside (2017) advocate for promoting interactions among customers with similar experiences. Such pairing of customers is not only beneficial for feedback collection but also helps inefficient management of their relationships with the concerned company. The article⁸ supports nonformal feedback collection to retrieve useful and truthful responses from the market. Nonformal feedback includes comments or complaints regarding the quality of products and services as well as suggestions for improvement. Both the attitude and behaviour of customers are also important in this context. Different customer feedback techniques are discussed in Fabijan et al. (2015).

Opoku (2006) describes certain tools for online collection and analysis of customer feedback, applicable especially for small and medium-sized enterprises (SMEs). He encourages SME managers to collect customer feedback from the internet and scrutinise those based on the behavioural aspects (“nature and habits”) of the customers. All these provide strong evidence for analysing individual customer’s attributes before considering their responses seriously. Davenport (2018) describes the application of AI over business analytics. It details the eras of analytical focus, with AI appearing in the fourth era. Delen and Ram (2018) discuss the difference between analysis and analytics and explain the role of AI and the associated research challenges.

While pointers for using of IoT/SIoT to collect product information are available, and social networks collect personal information about the user and the user experiences, we did not encounter comprehensive methodology which used all of these in an integrated fashion to provide intelligence regarding a product or service and extend such information to rank a company against its competitors. In our current proposal, we propose providing a unified methodology to achieve the above.

3. Overview of the proposed methodology

The proposed Neutro-KYR methodology captures feedback from both customers and non-customers, without having them directly completing a questionnaire. Certain advantages of feedback collection and analysis procedure of Neutro-KYR compared to the standard practice of completing questionnaires directly by customers/non-customers. Completing feedback forms are sometimes considered to be a waste of time by responders. Thus, the views expressed in these feedbacks are often casual and may not reflect the respondents’ truthful responses concerning the product/service.

The Neutro-KYR scheme is based on a three-tier communication architecture with customers, SIoT

object, and company objects at different levels, as shown in Figure 1(a). At the lowest level (level 0), we consider n different customers in a social network along with other users who are non-customers. In addition to those of their customers, the opinions of non-customers also matter because they may be the customers of competitor companies. Extracting customer feedback and relating it with product performance are easier as the company is already aware of the performance of products through sensors/IoT objects (Ramachandran & Mishra, 2020). Further, identifying customers' profiles and their social media accounts is not difficult; customers' names, photos, and emails are generally available to companies (Srivastava & Roychoudhury, 2020). These social media accounts can provide access to publicly displayed comments. In contrast, to collect views from noncustomers, one needs to search social media extensively and determine the publicly displayed comments related to the company, its products, or competitors. While certain legal and ethical issues there exist in this context (Sormanen & Lauk, 2016), this study limits to publicly available social media comments. Neuro-KYR proposes completing questionnaires based on the collected data and subsequently analysing them using neutrosophic numbers. Neutrosophic numbers are used as they allow for the recording of three components for each response – truthiness, falsity, and indeterminacy index. The feedbacks obtained as above may have some falsity and indeterminacy in them which need to be addressed.

The IoT sensors fitted into products like a vehicle, hearing aid, microwave, and the like, can provide their position, while product performance can be tracked by the SIoT object of the company through their social network of devices in real-time. Device performance data, as collected by these SIoT objects, are forwarded to software agent or company object (at level-2) for analysis. The company object also searches for comments related to its own company and product(s) in social media, including those mentioning the collaborator/competitor companies and their products. Once it gets such social media posts, the company object performs lexicon-oriented sentiment analysis on these social media data to determine whether these mentions are positive (favourable) or otherwise.

For example, let us consider a system with five companies – CMP1, CMP2, CMP3, CMP4, and CMP5. In this example, CMP1 and CMP2 collaborate with CMP3, CMP4, and CMP5, who supply to the former. All companies have their software agents or company objects; however, as far as SIoT objects are concerned, only CMP1 and CMP2 sell their products to the end customers have deployed them for product performance data collection. The rest, CMP3, CMP4, and CMP5, sell their products to CMP1; thus, they share the SIoT object of CMP1. If the SIoT object

observes performance issues involving a product sold by CMP1, wherein the concerned part is manufactured by CMP4, the SIoT object of CMP1 will pass this observation to the company objects of both CMP1 and CMP4. This communication will include a unique product identifier, model number, and both customer and purchase details. To complete the questionnaire, the company object of CMP1 will search social networks to find further information related to the company and/or the product posted by that customer. If any comment is found to be related to a product part produced by, for example, CMP4, then the profile information and comment will be sent to the company object of CMP4, so that it can fill up its questionnaire. Both these company objects will analyse, record, and preserve the sentiments hidden in the social media posts of the customer in the questionnaire corresponding to him. In contrast, the social media posts of persons who are not customers of CMP1 but still provide opinions about the products of CMP1 or its competitor(s) are included. The company object will also collect such information to aid an overall understanding of the environment.

Figures 1(b) and 1(c) illustrate the functioning of SIoT objects of CMP1 and CMP2, respectively. Similarly, Figures 1(d) and 1(e) demonstrate the working of the company objects of CMP1 and CMP2. Company objects CMP3, CMP4, and CMP5 behave similarly to that of CMP2. They only use their own company objects, while depending on CMP1 for SIoT-collated information.

While populating the neutrosophic sets from the filled in questionnaires, we consider a set of product-criterion pair. The weight of each pair is represented by a triangular neutrosophic number comprising six components. Each of these components has a specific meaning. The first one may relate to the product's efficiency, the second to neutrality, and the third component for inefficiency. It must be noted that opinions must contain a certain degree of truth, uncertainty, and falsity. These constitute the last three components of the neutrosophic number, which are computed based on qualification, experience gathered by past usage of the same or alternative products, and customer age. In our illustration in the later part of this paper, different customer age groups are given different priorities: we give more priority to the opinions of a person aged between 25 and 50 than those of somebody in their teens or a very old person aged about 75 or more. As placed in Ratcliff et al. (2011), intelligence and emotional quotient, as well as recall capability of a person, exhibit a monotonically increasing trend up to the age of 50, but then starts decreasing gradually and becomes almost half after the age of 75.⁹ Answering individual questions in the feedback form about the concerned product/service is a measure of the efficiency of that product/service concerning the

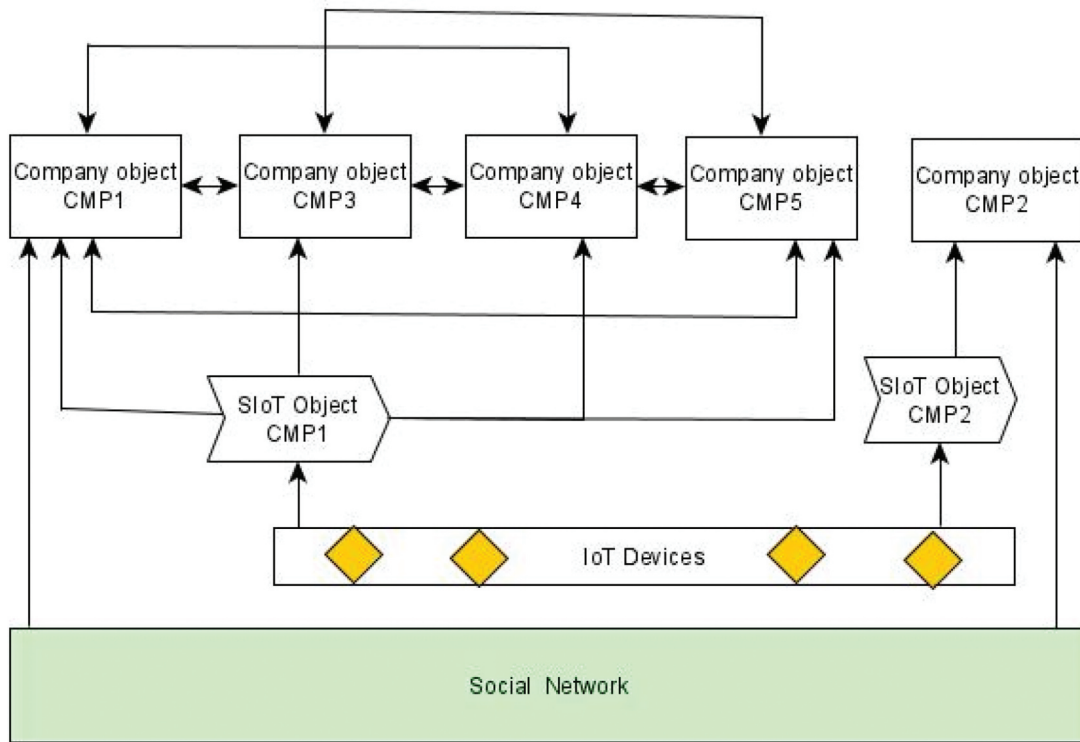


Figure 1. Three-tier architecture of Neuro-KYR.

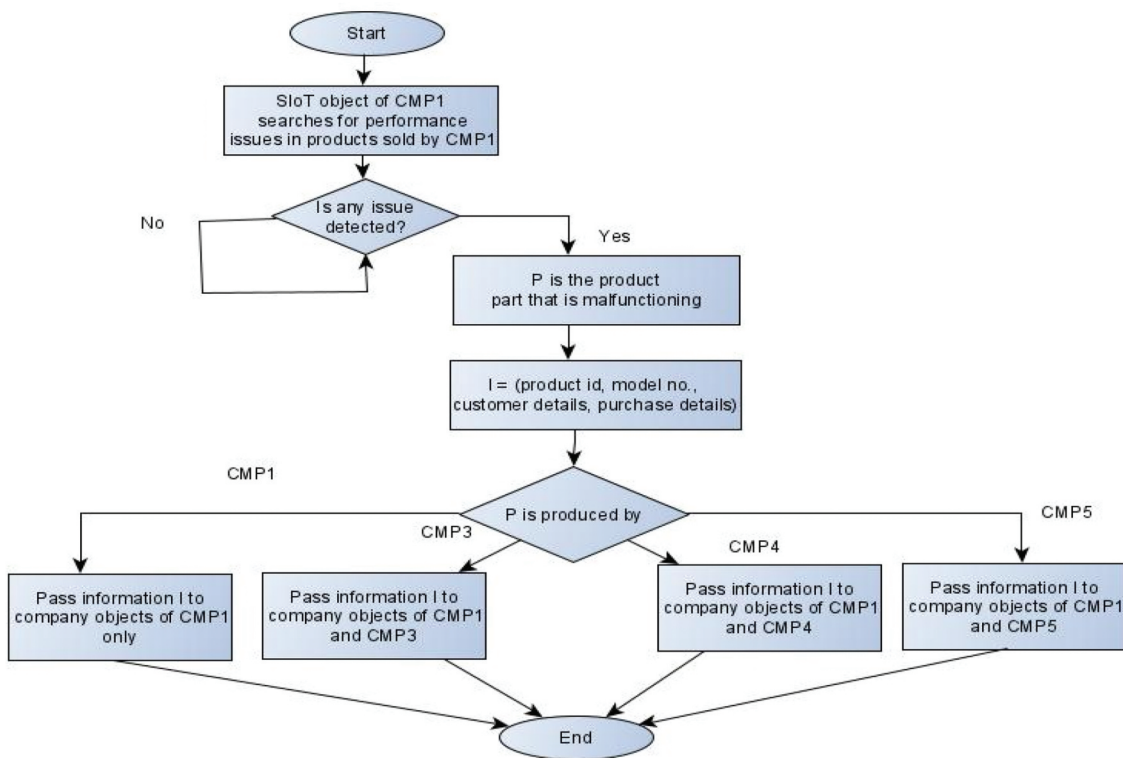


Figure 1. Figures 1(b) and 1(c) illustrate the functioning of SlIoT objects of CMP1 and CMP2, respectively. Similarly, Figures 1(d) and 1(e) demonstrate the working of the company objects of CMP1 and CMP2. Company objects CMP3, CMP4, and CMP5 behave similarly to that of CMP2. They only use their own company objects, while depending on CMP1 for SlIoT-collated information.

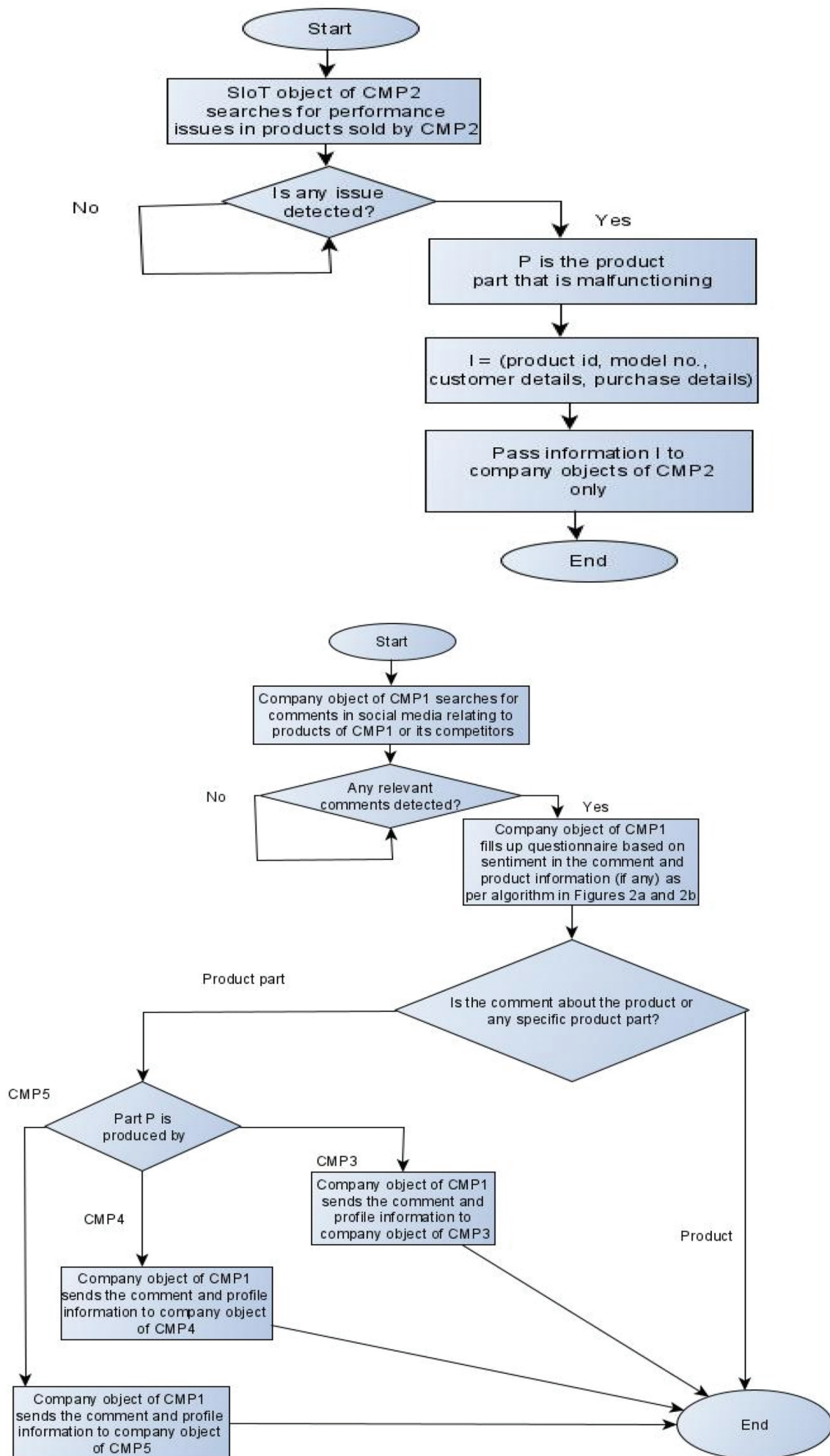


Figure 1. (Continued).

particular criterion targeted in the question. If most of customers certify a product as efficient, then the efficiency index of the product will be high, and inefficiency and neutrality indices will be low. However, these are only for illustration, and these might vary depending on the wisdom of the analyst. These parameters are combined using a fuzzy controller named FUZZ-MARK. Figures 2(a) and 2(b) illustrate the computation of company rank based on feedbacks collected by SIoT and/or company objects.

Thus, every answer of each customer has a truthiness, falsity, and indeterminacy factor associated with it. Combining these factors for all criteria, the overall competency of the current product and all its alternatives are computed using neutrosophic set theory. Using this overall competency as the measure, the product rank concerning its alternatives can be obtained.

Mathematically, if X is the universe of discourse, then a single valued neutrosophic set A , defined over X , is modelled as follows:

$$A = \{ \langle x, \alpha_A(x), \beta_A(x), \gamma_A(x) \rangle : x \in X \} \quad (1)$$

such that the attributes $\alpha_A(x) : X \rightarrow [0, 1]$, $\beta_A(x) : X \rightarrow [0, 1]$, $\gamma_A(x) : X \rightarrow [0, 1]$

where $\alpha_A(x)$ denotes truthiness-index of x to A based on the level of confidence reported in the feedback form corresponding to each response and

output of the fuzzy controller FUZZ-MARK (illustrated in subsection 4.2). $\beta_A(x)$ and $\gamma_A(x)$ represent indeterminacy index and falsity index of the same object x which belongs to the universe of discourse.

4. Description of Neuro-KYR

This section illustrates the function of the Neuro-KYR scheme using an illustration of car company.

4.1. Communication model of Neuro-KYR and analysis of the questionnaire

The company needs to complete the questionnaire to collect responses from its customers as well as non-customers to determine its rank against its competitors, and the Neuro-KYR scheme is used for this.

For example, the company deployed software agents of the concerned car company has a similar questionnaire presented in Figure 3(a). These agents help in storing customer responses in a well-defined format for the convenience of the analysis. As shown in the figure, the SIoT object of the company scans social media for comments about its products. After finding such comments, the SIoT object forwards these to company object along with associated user id. Then, the company object searches the social media for full profile information of the customer who left

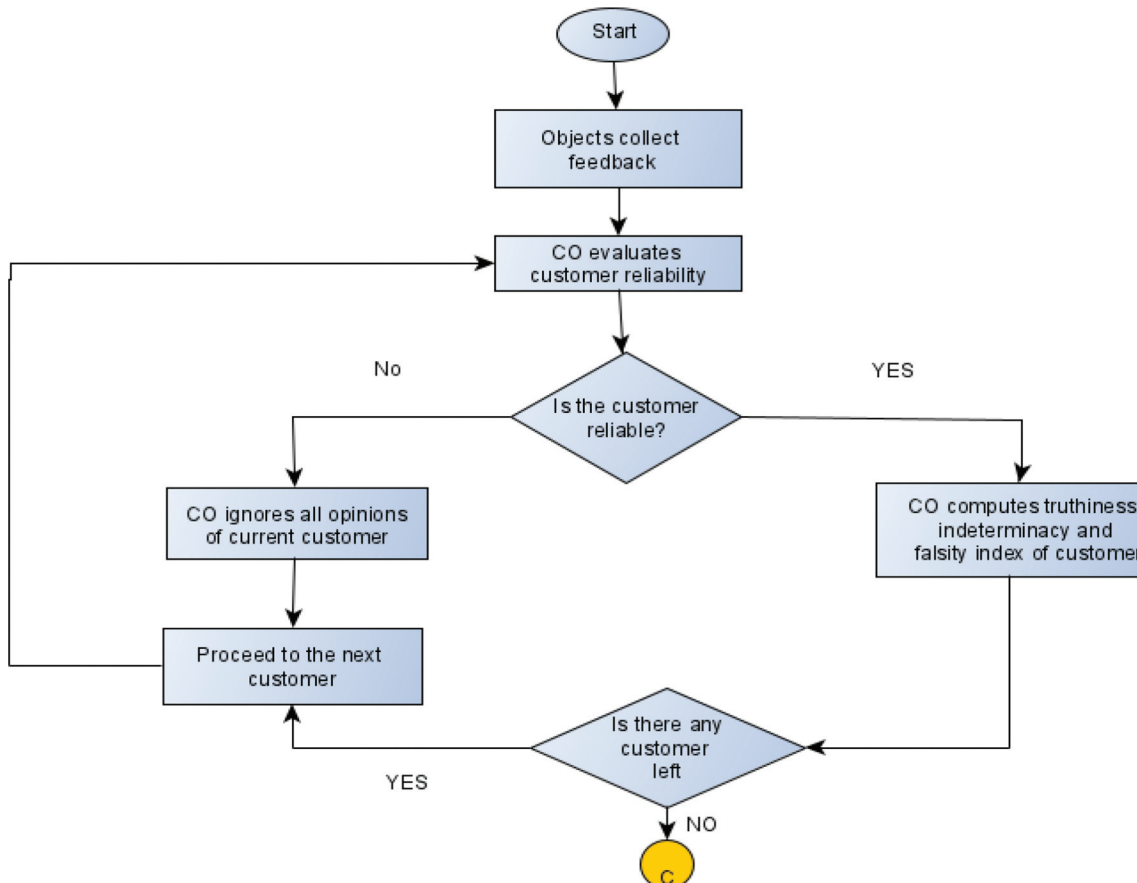


Figure 2a. First part of flowchart of neuro-KYR.

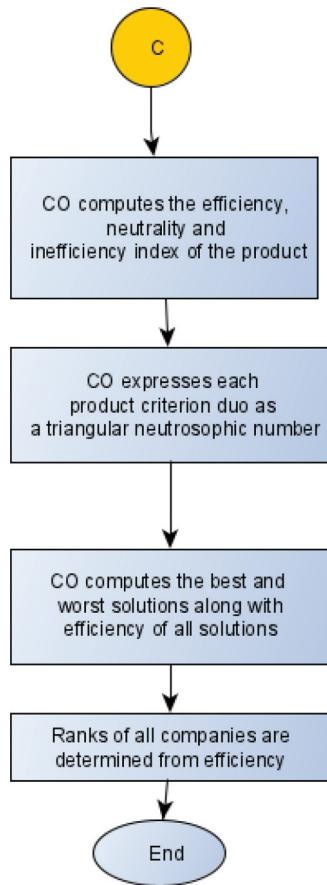


Figure 2b. Second part of the Neutro-KYR flowchart

the comment. After obtaining the profile information, its reliability is checked by a fuzzy controller, referred to as FUZZ-MARK, which is embedded in the company object. If the customer is found reliable, then the company object starts to complete a questionnaire based on his or her profile and comments. In case any additional information is required, the company object communicates with the customer and attempt to conveniently extract necessary information from him or her through informal message exchange.

The example car company questionnaire in Figure 3 (a) has three parts – A, B, and C. The first part records basic information about the driving and riding experience of a customer. This helps the company object assess the confidence level of a customer in answering certain questions of the second part. For example, if a customer owns at least two cars (indicating his experience with cars), he or she is expected to have decent knowledge about their resale values, after-sales service, etc. Similarly, anybody who has seen the car can only be very confident only about its looks. Questions 1 and 2 do not require any technical or user expertise. In addition, the answers in questions 3, 4, 5, and 7 of those who have driving licences are expected to be more reliable. This is because these questions are concerned with engine quality, fuel efficiency, etc. The third part probes the importance of different features in influencing the purchase decision of a customer and can quite vary per customer. For some,

cost may be the most important factor; someone else may rank safety features as more important. For some, looks may be the decision points, while others may value the brand name and might be ready to compromise with cost, look, efficiency, etc. The questionnaire herein is an illustration of this study, and the questions and assumptions regarding reliability can vary depending on the company and the product.

How the questionnaire is filled in can proceed differently depending on whether the person being analysed is a customer of the company or not. If he or she is a customer, the SIoT object can obtain answers to many of the questions from sensors attached to the product, as well as from customer data available from the company. As some of the customers are expected to be active in social media, further information can be collected from their social media content. Meanwhile, non-customers responses will need to be obtained entirely from social media content. Based on people's comments about different car models and car manufacturing companies in social media, the company object can extract meaningful information for the questionnaire through sentiment analysis of such contents. Such persons' information may be scattered across several social media platforms they use, and their identities should be known across multiple social media platforms to gather all relevant information regarding them to properly fill the questionnaire with their implicit feedback (Srivastava & Roychoudhury, 2020).

4.2. Computing reliability of responses

FUZZ-MARK is a fuzzy controller embedded in the company object which evaluates the reliability of a customer based on, from our example, age, qualification, and driving experience; this information is available from customer profile and unofficial conversations with the customer. For non-customers, such information will have to be collated from across social media accounts of the concerned persons. The input parameters for the fuzzy controller are as follows:

- (i) Age – Age of a customer is divided into four parts (0–20 denoted as fuzzy premise variable a' , 20–40 as b' , 40–70 as c' , and 70–100 as d'). As quoted previously from Ratcliff et al. (2011), we mostly rely on the feedback of 20–40 and 40–70 and less on the higher ones.
- (ii) Qualification – We assume that the higher the qualification, the more desirable the feedback from the responders. It is assumed that the responses of those with higher qualifications will be more thought about, compared to the responses of those with lesser qualifications. We divide this parameter into four educational

<p>1. How many cars you have purchased until now? <input type="radio"/> 0 <input type="radio"/> 1 <input type="radio"/> 2 <input type="radio"/> More than 2</p> <p>2. Do you have a driving license? <input type="radio"/> Yes <input type="radio"/> No</p>	Part A																																													
<p>1. Is CR your favorite car? <input type="radio"/> Yes <input type="radio"/> No</p> <p>2. Do you like any other cars from PN? <input type="radio"/> Yes <input type="radio"/> No</p> <p>3. Do you consider safety measures to be sufficient? <input type="radio"/> More than sufficient <input type="radio"/> Just satisfactory <input type="radio"/> Ordinary <input type="radio"/> Not sufficient</p> <p>4. Are you satisfied with the fuel efficiency? <input type="radio"/> Really good <input type="radio"/> Good <input type="radio"/> Ordinary <input type="radio"/> Very bad</p> <p>5. Do you like the overall design (interior, exterior, colour etc.) of the car? <input type="radio"/> Really good <input type="radio"/> Good <input type="radio"/> Ordinary <input type="radio"/> Very bad</p> <p>6. How do you rate the resale value of the car with respect to its competitors? <input type="radio"/> Far better <input type="radio"/> Better <input type="radio"/> Comparable <input type="radio"/> Worse</p> <p>7. Are you satisfied with engine quality? <input type="radio"/> Really good <input type="radio"/> Good <input type="radio"/> Ordinary <input type="radio"/> Very bad</p> <p>8. Is the size sufficient for your family? <input type="radio"/> More than sufficient <input type="radio"/> Sufficient <input type="radio"/> Neutral <input type="radio"/> Not sufficient</p> <p>9. Are you satisfied with the service after delivery? <input type="radio"/> Really good <input type="radio"/> Good <input type="radio"/> Ordinary <input type="radio"/> Very bad</p> <p>10. Overall, how do you rate the car to its competitors? <input type="radio"/> Far better <input type="radio"/> Better <input type="radio"/> Comparable <input type="radio"/> Worse</p> <p>Rate your confidence for answers in the second part: Write 'r' for Really confident (RC), 'b' for A bit confident (AbC), and 'n' for Not confident (NC).</p> <p>1. <input type="checkbox"/> 2. <input type="checkbox"/> 3. <input type="checkbox"/> 4. <input type="checkbox"/> 5. <input type="checkbox"/> 6. <input type="checkbox"/> 7. <input type="checkbox"/> 8. <input type="checkbox"/> 9. <input type="checkbox"/> 10. <input type="checkbox"/></p>	Part B																																													
<p>Select the importance level of the following factors that might have an impact on car purchase decision (put \checkmark in appropriate place).</p> <table border="1" style="width: 100%; border-collapse: collapse; text-align: center;"> <thead> <tr> <th style="padding: 5px;">Importance →</th> <th style="padding: 5px;">Not important</th> <th style="padding: 5px;">Neutral</th> <th style="padding: 5px;">Important</th> <th style="padding: 5px;">Very important</th> </tr> </thead> <tbody> <tr> <td style="padding: 5px;">Attribute ↓</td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td style="padding: 5px;">Brand</td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td style="padding: 5px;">Cost</td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td style="padding: 5px;">Look</td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td style="padding: 5px;">Fuel efficiency</td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td style="padding: 5px;">Engine quality</td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td style="padding: 5px;">Resale value</td> <td></td> <td></td> <td></td> <td></td> </tr> <tr> <td style="padding: 5px;">Safety measures</td> <td></td> <td></td> <td></td> <td></td> </tr> </tbody> </table>	Importance →	Not important	Neutral	Important	Very important	Attribute ↓					Brand					Cost					Look					Fuel efficiency					Engine quality					Resale value					Safety measures					Part C
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Safety measures																																														

Figure 3a. Example questionnaire.

levels – illiterate, undergraduate, graduate, and postgraduate.

- (iii) Driving experience – We divide this into three ranges (0–3) denoted as fuzzy premise variable (a', 3–6 as b', 6–10 as c', and >10 as d'). Higher experience of the responders is preferred.

In Table 2, we combine age and qualification to form a temporary variable *temp*, and we assign it values a', b', c', and d', which are in ascending order of their

magnitude. Based on the desirability of the responders' profile as a function of age and qualification, these values are assigned to each {age, qualification} tuple. We prefer to have responses from those who are, at least, undergraduate and are aged 20 or above while also discounting the opinion of those at a high age group.

temp (from Table 2) is a component of reliability; the higher the value, the higher its reliability. Table 2 combines *temp* and the driving experience response; the higher driving experience, the better.

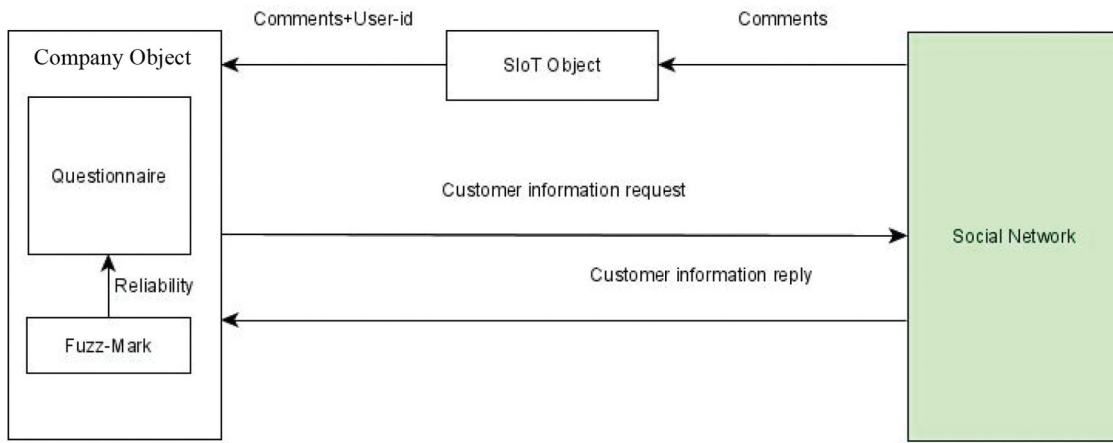


Figure 3b. Communication model of Neuro-KYR.

Table 2. Combination of age and qualification producing temporary variable *temp*.

Age→ Qualification ↓	a'	b'	c'	d'
illiterate	a'	a'	a'	a'
undergraduate	a'	b'	b'	a'
graduate	a'	b'	c'	b'
postgraduate	b'	c'	d'	c'

Table 3 further shows the measure of the reliability of responses; reliability increases with an increase in *temp* and driving experience.

The Neuro-KYR model measures reliability as a fraction between 0 and 1 such that a', b', c', and d' denote crisp ranges (0–0.25), (0.25–0.50), (0.50–0.75), and (0.75–1.00), respectively. Therefore, pivot values of fuzzy variables a', b', c', and d' are (0 + 0.25)/2 or 0.125, (0.25 + 0.50)/2 or 0.375, (0.50 + 0.75)/2 or 0.625, and (0.75 + 1.00)/2 or 0.875, respectively. These pivot values will be used in Table 4 to assess the truthiness of responses.

Table 3. Combination of temp and driving experience resulting in ultimate output reliability.

temp→ driving experience ↓	a'	b'	c'	d'
a'	a'	a'	a'	a'
b'	a'	b'	b'	b'
c'	a'	b'	c'	c'
d'	a'	b'	c'	d'

Table 4. Combination of reliability and confidence.

Reliability → Confidence level ↓	a'	b'	c'	d'
Not confident or NC	$\text{pivot}(a') / (1 - \text{pivot}(\text{NC}))$ = 0.125 / (1 - 0.165) = 0.149	$\text{pivot}(b') / \{1.5(1 - \text{pivot}(\text{NC}))\}$ = 0.375 / {1.5(1 - 0.165)} = 0.299	$\text{pivot}(c') / \{2(1 - \text{pivot}(\text{NC}))\}$ = 0.625 / {2(1 - 0.165)} = 0.374	$\text{pivot}(d') / \{2.5(1 - \text{pivot}(\text{NC}))\}$ = 0.875 / {2.5(1 - 0.165)} = 0.419
A bit confident or AbC	$\text{pivot}(a') / (1 - \text{pivot}(\text{AbC}))$ = 0.125 / (1 - 0.495) = 0.247	$\text{pivot}(b') / \{1.5(1 - \text{pivot}(\text{AbC}))\}$ = 0.375 / {1.5(1 - 0.495)} = 0.495	$\text{pivot}(c') / \{2(1 - \text{pivot}(\text{AbC}))\}$ = 0.625 / {2(1 - 0.495)} = 0.619	$\text{pivot}(d') / \{2.5(1 - \text{pivot}(\text{AbC}))\}$ = 0.875 / {2.5(1 - 0.495)} = 0.693
Really confident or RC	$\text{pivot}(a') / \{2(1 - \text{pivot}(\text{RC}))\}$ = 0.125 / {2(1 - 0.83)} = 0.367	$\text{pivot}(b') / \{2^2(1 - \text{pivot}(\text{RC}))\}$ = 0.375 / {2 ² (1 - 0.83)} = 0.551	$\text{pivot}(c') / \{2^2(1 - \text{pivot}(\text{RC}))\}$ = 0.625 / {2 ² (1 - 0.83)} = 0.912	$\text{pivot}(d') / \{2.3^2(1 - \text{pivot}(\text{RC}))\}$ = 0.875 / {2.3 ² (1 - 0.83)} = 0.973

4.3. Determining truthiness, falsity, and indeterminacy index

Considering Z number of total feedback received, let us assume the distribution of responses to criterion C1 (e.g., regarding the space in the car, corresponding to question number 8 in Part B of the questionnaire in Figure 3(a)) as Ψ1 opted for the first option (A1), Ψ2 for the second option (A2), Ψ3 for the third option (A3), and Ψ4 for the fourth option (A4). Specifically, for this illustration, Ψ1 gave an opinion as “more than sufficient”, Ψ2 opted for the option “sufficient”, Ψ3 were neutral, and Ψ4 commented on “not sufficient” such that

$$0 \leq \psi_1, \psi_2, \psi_3, \psi_4 \leq Z. \tag{2}$$

$$(\psi_1 + \psi_2 + \psi_3 + \psi_4) = Z. \tag{3}$$

Based on (2), (3), the responses for the CI criteria can be represented by a triangular neutrosophic number TN(C1) defined as

$$\text{TN} = \langle ((\psi_1 + \psi_2)/Z, \psi_3/Z, \psi_4/Z; \text{tru}, \text{indet}, \text{fls}) \rangle, \tag{4}$$

where *tru* specifies the central tendency of approximate truthiness of opinion of all customers in terms of current alternative A1 of criterion C1. Similarly, *indet* and *fls* are central tendencies of apparent indeterminacy and falsity of opinions, respectively.

Approximate truthiness is the composition of reliability and confidence. Truthiness increases with an increase in reliability as well as confidence. Reliability specifies the worthiness of a customer according to FUZZ-MARK, whereas confidence denotes the worthiness of the customer in his own opinion. In the feedback form, there are three levels of confidence – “not confident”, “a bit confident”, and “really confident”. These linguistic variables are represented by three ranges of fractions (0–0.33 as “not confident”, 0.33–0.66 as “a bit confident”, and 0.66–1.00 as “really confident”). The pivot value of range 0–0.33 is $(0 + 0.33)/2$ (i.e. 0.165). Similarly, the pivot values of range 0.33–0.66 is 0.495, and that of range 0.66–1.00 is 0.83. A combination of reliability and confidence is presented in Table 4. The computations are based on the pivot values of reliability parameters a' , b' , c' , and d' and those of confidence parameters explained herein. As observed in Table 4, the maximum value of truthiness is 0.973. We scale all the values in range 0–1, and the resulting values are presented in Table 5. An extra parameter included in addition to the scaled values. Thus, each entry in Table 5 is an ordered pair of the form $(g', fz(g'))$, where g' is an integer and fz is a function that “fuzzifies” it according to the logic of FUZZ-MARK. For example, in the entry at row NC and column a' , the scaled value of 0.153 is between 0 and 0.25; therefore, the corresponding fuzzy premise variable is a' . This follows from what we mentioned previously; that is, a' , b' , c' , and d' denote crisp ranges (0–0.25), (0.25–0.50), (0.50–0.75), and (0.75–1.00), respectively. The other cells in Table 5 are filled in accordingly to provide the rule set.

From Table 5, the truthiness of cell cl is given by a fraction $f(cl)$. Subsequently, fractional values $g(cl)$ and $h(cl)$ representing falsity and indeterminacy, respectively, should be determined for the same cell cl . These are computed according to the following rule set:

Rule set

- (i) If $f(cl) = 1.000$, $g(cl) = h(cl) = 0.00$.

Explanation: $f(cl) = 1.00$ implies that the responder is reliable and confident to the highest possible degree; the index of falsity and indeterminacy is thus 0.

- (ii) Case: $fz(f(cl)) = a'$

- a. If $fz(f(cl)) = a'$, then $g(cl) = \text{rand-fr}(0.001,1)$. However,
- b. If $fz(g(cl)) = a'$ or b' then $h(cl) = \text{rand-fr}(0.75,1)$, or
- c. If $fz(g(cl)) = c'$ then $h(cl) = \text{rand-fr}(0.50,1)$, or
- d. If $fz(g(cl)) = d'$ then $h(cl) = \text{rand-fr}(0.001,0.50)$,

where $\text{rand-fr}(e,1)$ returns a value greater or equal to e and less than 1.

Explanation: The truthiness index of $fz(f(cl)) = a'$ indicated that the responder is reliable and confident to the least possible degree. Thus, there is a very high chance that the index of at least 1 for falsity or indeterminacy is high. Therefore, the range of falsity index $g(cl)$ allows the maximum range from 0.001 to 1.

However,

- If $fz(g(cl))$ has low-to-moderate value (denoted by a' or b'), the indeterminacy index will be high, in the range between 0.75 and 1, or
- If $fz(g(cl))$ is moderately high (denoted by c'), then we allow indeterminacy index to be moderately high, in the range of 0.50 and 1, or
- The other alternative is $fz(g(cl))$ is high (denoted by d'). In this case logically, at least one of the truthiness index or indeterminacy index should be low, while the other one should be either low or moderately low. This is very practical as when $fz(f(cl))$ is low (or a') and $fz(g(cl))$ is high, the responder is inclined to opine that truthiness of his opinion is low and falsity is high. High falsity with low truthiness, thus, indicates a lower state of confusion or indeterminacy. Hence, indeterminacy of the statement should be low or moderately low (i.e. union of the two ranges 0.001–0.25 and 0.25–0.50, i.e. 0.001–0.50).

- (iii) Case: $fz(f(cl)) = b'$

- a. If $fz(f(cl)) = b'$, then $g(cl) = \text{rand-fr}(0.001,1)$. However,
- b. If $fz(g(cl)) = a'$, then $h(cl) = \text{rand-fr}(0.75,1)$, or
- c. If $fz(g(cl)) = b'$, then $h(cl) = \text{rand-fr}(0.50,1)$, or
- d. If $fz(g(cl)) = c'$ or d' , then $h(cl) = \text{rand-fr}(0.001, 0.50)$.

Explanation: $fz(f(cl)) = b'$ indicates that the responder is not being that reliable and confident. Hence, there is

Table 5. Scaled combination of reliability and confidence.

Reliability → Confidence level ↓	a'	b'	c'	d'
Not confident or NC	(0.153, a')	(0.308, b')	(0.385, b')	(0.432, b')
A bit confident or AbC	(0.254, b')	(0.509, c')	(0.638, c')	(0.714, c')
Really confident or RC	(0.378, b')	(0.568, c')	(0.939, d')	(1.00, d')

a high chance that either falsity or indeterminacy is high. Therefore, range of falsity index $g(cl)$ is allowed the maximum range of 0.001–1.0.

However,

- If $fz(g(cl))$ is also low (denoted by a'), then we can allow indeterminacy index to be high, giving it the range of values between 0.75 and 1.
- If $fz(g(cl))$ is moderately low, then $fz(h(cl))$ will be on the higher side of medium (i.e. in the range of 0.50–1.00).
- Meanwhile, when $fz(g(cl))$ is medium (denoted by c') or high (i.e. d'), then indeterminacy index will be at the lower side of medium, in the range of 0.001–0.50.

(iv) Case: $fz(f(cl)) = c'$

a. If $fz(f(cl)) = c'$, then $g(cl) = \text{rand-fr}(0.001, 0.50)$.

However,

b. If $fz(g(cl)) = a'$, then $h(cl) = \text{rand-fr}(0.75, 1)$, or

c. If $fz(g(cl)) = b'$, then $h(cl) = \text{rand-fr}(0.001, 0.50)$.

Explanation: $fz(f(cl)) = c'$ implies that the responder seems to be more or less reliable and confident (medium level of confidence). Thus, falsity or indeterminacy must be low or moderately low, in the range of 0.001–0.50.

However,

- If $fz(g(cl))$ is low (denoted by a'), then indeterminacy index will be high, in the range of 0.75–1, or
- If $fz(g(cl))$ is medium–low (denoted by b'), then the indeterminacy index will be low or medium–low, within the range of 0.001 and 0.50. No other alternative is possible for $fz(g(cl))$.

(v) If $fz(f(cl)) = d'$, then $g(cl) = h(cl) = \text{rand-fr}(0.001, 0.50)$;

Explanation: $(f(cl)) = d'$ implies that the responder is reliable and confident about his statement. Hence, falsity or indeterminacy must be low or medium–low, within the range of 0.001–0.50.

Similarly, for each criterion, one can quantify the response of individual responders along with their

truthiness, falsity, and indeterminacy values. The overall response of all the responders for a product, corresponding to each criterion, will be the mean of opinions of all responders.

4.4. Illustration of product-wise determination of truthiness, falsity, and indeterminacy values

For a simple illustration, only two criteria, C1 and C2, with 10 customer responses (Table 6), were considered. Age, qualification, and experience of customers are shown in Table 7. Let C1 be the space inside a car and C2 its resale value.

To generate the neutrosophic set based on the above table, we should compute the central tendencies:

- (i) The central tendency of truthiness series (0.568, 0.254, 0.378, 0.638, 0.638, 0.378, 0.378, 0.509, 0.939, 0.939) is mean = 0.562 and standard deviation = 0.235.
- (ii) The central tendency of indeterminacy (0.367, 0.216, 0.681, 0.889, 0.227, 0.463, 0.215, 0.489, 0.389, 0.256) is mean = 0.419 and standard deviation = 0.223.
- (iii) The central tendency of falsity series (0.412, 0.783, 0.435, 0.112, 0.467, 0.999, 0.801, 0.467, 0.412, 0.352) is mean = 0.524 and standard deviation = 0.260.

Hence, (0.562, 0.419, and 0.524) is the trio that represents truthiness, indeterminacy, and falsity of responses, respectively, with respect to the product. As the actual response values are considered, among all the responders, 3 responded “more than sufficient” (A1), 6 “sufficient” (A2), and 1 “neutral” (A3), and no one responded “not sufficient” (A4). This implies that, for the current product and criterion C1, the triangular neutrosophic number would be

$$\langle (3 + 6)/10, 1/10, 0/10; (0.562, 0.524 \text{ and } 0.419) \rangle, \text{ or } \langle (0.9, 0.1, 0.0); (0.562, 0.419, 0.524) \rangle.$$

Similarly, we can calculate for the criterion C2.

Table 6. Customer feedback sample.

Criteria → Customer ↓	C1	C2
Cust1	(sufficient, important, really confident)	(better, neutral, really confident)
Cust2	(sufficient, important, a bit confident)	(comparable, neutral, really confident)
Cust3	(more than sufficient, important, really confident)	(better, important, really confident)
Cust4	(more than sufficient, important, a bit confident)	(far better, important, really confident)
Cust5	(neutral, important, a bit confident)	(better, important, really confident)
Cust6	(sufficient, important, really confident)	(far better, neutral, really confident)
Cust7	(more than sufficient, important, really confident)	(better, important, really confident)
Cust8	(sufficient, important, a bit confident)	(better, important, really confident)
Cust9	(sufficient, important, really confident)	(better, important, really confident)
Cust10	(sufficient, important, really confident)	(better, neutral, really confident)

Table 7. Components of reliability of a customer; reliability (computed using rule bases of FUZZ-MARK) and (truthiness, falsity, and indeterminacy indices) trio.

Components of reliability and reliability itself → Customer ↓	Age	Qualification	Experience	Reliability	Scaled combination of confidence and reliability or truthiness	Falsity index	Indeterminacy index
Cust1	36 (b')	Postgraduate	5 (b')	(b')	0.568 (c')	0.412	0.367
Cust2	45 (c')	Graduate	0 (a')	(a')	0.254 (b')	0.783	0.216
Cust3	43 (c')	Postgraduate	0 (a')	(a')	0.378 (b')	0.435	0.681
Cust4	51 (c')	Graduate	11 (d')	(c')	0.638 (c')	0.112	0.889
Cust5	27 (b')	Postgraduate	9 (c')	(c')	0.638 (c')	0.467	0.227
Cust6	19 (a')	Undergraduate	7 (c')	(a')	0.378 (b')	0.999	0.463
Cust7	35 (b')	Postgraduate	0 (a')	(a')	0.378 (b')	0.801	0.215
Cust8	73 (d')	Graduate	8 (c')	(b')	0.509 (c')	0.467	0.489
Cust9	58 (c')	Postgraduate	8 (c')	(c')	0.939 (d')	0.412	0.389
Cust10	48 (c')	Postgraduate	9 (c')	(c')	0.939 (d')	0.352	0.256

4.5. Assigning weight to each criterion

In addition to providing feedback on various criteria, the responder assigns different weights to different criteria. For example, let us go back to the feedback form in Fig. 5a. The importance of the criteria is categorised as “not important”, “neutral”, “important”, and “very important”. These linguistic variables are categorised into ranges as “not important” (0–0.25), “neutral” (0.25–0.50), “important” (0.50–0.75), and “very important” (0.75–1.00). The pivotal value of “not important” is $(0 + 0.25)/2$ (i.e. 0.125). Similarly, the pivotal values of the other ranges are 0.375 for neutral, 0.625 for important, and 0.875 for very important. For each customer criteria duo, a fractional value exists (one of the abovementioned pivotal values) representing the utility. Hence, the central tendency for each criterion should be computed to determine its importance for all customers in general.

4.6. Finding your product rank

After determining truth, indeterminacy, and falsity membership indices, an alternative criteria (AC) matrix is formed, where all cells at the intersection of a row or column contain a triangular neutrosophic number. However, a different priority of various criteria exists as specified by the responder. Therefore, each cell of AC is multiplied by a weight factor to form the ultimate decision matrix (UDM). UDM helps in finding the current product rank in relation to other alternatives or similar products offered by competitors in the market. Specifically, q alternatives (A1, A2, A3, ..., Aq) and r criteria (C1, C2, C3, ..., Cr) are assumed.

AC = $\langle \Phi_{ij} \rangle_{q \times r}$	C1	C2	C3 ... Cr
A1	Φ_{11}	Φ_{12}	$\Phi_{13} \dots \Phi_{1r}$
A2	Φ_{21}	Φ_{22}	$\Phi_{23} \dots \Phi_{2r}$
A3	Φ_{31}	Φ_{32}	$\Phi_{33} \dots \Phi_{3r}$
...	...		
...	...		
Ar	Φ_{q1}	Φ_{q2}	$\Phi_{q3} \dots \Phi_{qr}$

Let ω_j be the weight of criterion $C_j (1 \leq j \leq r)$. The ultimate decision matrix $UDM_{q \times r}$, consisting of alternative options and weighted criteria, is mathematically expressed as

UDM $_{q \times r}$ =	C1	C2	C3 ... Cr
A1	$\omega_1 \Phi_{11}$	$\omega_2 \Phi_{12}$	$\omega_3 \Phi_{13} \dots \omega_r \Phi_{1r}$
A2	$\omega_1 \Phi_{21}$	$\omega_2 \Phi_{22}$	$\omega_3 \Phi_{23} \dots \omega_r \Phi_{2r}$
A3	$\omega_1 \Phi_{31}$	$\omega_2 \Phi_{32}$	$\omega_3 \Phi_{33} \dots \omega_r \Phi_{3r}$
...	...		
...	...		
Ar	$\omega_1 \Phi_{q1}$	$\omega_2 \Phi_{q2}$	$\omega_3 \Phi_{q3} \dots \omega_r \Phi_{qr}$

All $\omega_j \Phi_{ij}$ are triangular neutrosophic number of the form $\omega_j \Phi_{ij} = (vl_{ij}(1), vl_{ij}(2), vl_{ij}(3); \tau_{ij}, dn_{ij}, fl_{ij})$

The next task is to find neutrosophic best possible solution (BS) and neutrosophic worst possible solution (WS).

To determine the best solution, we extract the maximum of all possible values corresponding to benefit type attributes, except for the components in triangular neutrosophic sets that indicate indeterminacy and falsity, for which we consider the minimum values. Similarly, we extract the minimum for all possible values corresponding to cost type attributes, except for the components of neutrosophic sets that signify indeterminacy and falsity, for which we consider the maximum values. Let sets ADVN and ACST represent benefit and cost type attributes, respectively. Further, BS and WS are assumed to be formulated as follows:

$$BS = (\text{best-soln}_1, \text{best-soln}_2, \dots, \text{best-soln}_r)$$

$$WS = (\text{worst-soln}_1, \text{worst-soln}_2, \dots, \text{worst-soln}_r).$$

Here, $\text{best-soln}_i = (val_j(1), val_j(2), val_j(3); \text{truth}_j, \text{indetr}_j, \text{falsity}_j)$ such that $1 \leq j \leq r$, and

$$val_j(k) = \begin{cases} \max (vl_{ij}(k) \text{ if } C_j = ADVN \\ \min (vl_{ij}(k) \text{ if } C_j = ACST \end{cases} \quad (7)$$

$$truth_j = \begin{cases} \max(\tau u_{ij} \text{ if } C_j = ADVN \\ \min(\tau u_{ij} \text{ if } C_j = ACST \end{cases} \quad (8)$$

$$indet_r_j = \begin{cases} \min(dn_{ij} \text{ if } C_j = ADVN \\ \max(dn_{ij} \text{ if } C_j = ACST \end{cases} \quad (9)$$

$$falsity_j = \begin{cases} \min(fl_{ij} \text{ if } C_j = ADVN \\ \max(fl_{ij} \text{ if } C_j = ACST \end{cases} \quad (10)$$

Here, $1 \leq k \leq 3$, $1 \leq i \leq q$, and vl represent the first three components of the neutrosophic number. Moreover, τu indicates the truthiness, dn is the indeterminacy, and fl is the falsity components.

Similarly, $worst\text{-}soln_2 = (wval_j(1), wval_j(2), wval_j(3); wtruth_j, windetr_j, wfalsity_j)$ such that $1 \leq j \leq r$ and \forall .

$$wval_j(k) = \begin{cases} \min(vl_{ij}(k) \text{ if } C_j = ADVN \\ \max(vl_{ij}(k) \text{ if } C_j = ACST \end{cases} \quad (11)$$

$$wtruth_j = \begin{cases} \min(\tau u_{ij} \text{ if } C_j = ADVN \\ \max(\tau u_{ij} \text{ if } C_j = ACST \end{cases} \quad (12)$$

$$windetr_j = \begin{cases} \max(dn_{ij} \text{ if } C_j = ADVN \\ \min(dn_{ij} \text{ if } C_j = ACST \end{cases} \quad (13)$$

$$wfalsity_j = \begin{cases} \max(fl_{ij} \text{ if } C_j = ADVN \\ \min(fl_{ij} \text{ if } C_j = ACST \end{cases} \quad (14)$$

Here, $1 \leq k \leq 3$, $1 \leq i \leq q$, and vl also represent the first three components of the neutrosophic numbers. Further, τu indicates the truthiness, dn is the indeterminacy, and fl is the falsity components.

Let $sl\text{-}cur$ be the current solution under consideration and $dist\text{-}ham(sl\text{-}cur, BS)$ specify the hamming distance between $sl\text{-}cur$ and BS. Similarly, $dist\text{-}ham(sl\text{-}cur, WS)$ specifies the hamming distance between $sl\text{-}cur$ and WS. Thus, the efficiency $eff(sl\text{-}cur)$ of the current solution $sl\text{-}cur$ is mathematically modelled in (28) as follows:

$$eff(sl - cur) = \frac{dist - ham(sl - cur, WS) + 1}{dist - ham(BS, WS) + 1} \times \left(1 - \frac{dist - ham(sl - cur, WS) + 1}{dist - ham(BS, WS) + 2} \right) \quad (15)$$

5. Examples of worst, best, and optimal solutions

Table 8 presents a hypothetical UDM. For every product, the values of $\omega_j \Phi_{ij}$ as mentioned in equation 6 are included in this Table.

C1 and C3 belong to benefiting type criterion, whereas C2 is cost type. For BS, we compute the maximum for the first four attributes and the minimum for the last two for every triangular neutrosophic sets, while, for C2, we compute minimum for the first four attributes and the maximum for the last two. Conversely, for WS, we compute the minimum for the first four attributes and the maximum for the last two, while, for C2, we compute the maximum for the first four attributes and the minimum for the last two for each triangular neutrosophic set.

$$\text{Best Solution BS} = \{0.4, 0.5, 0.7; 0.91, 0.1, 0.2, 0.1, 0.1, 0.3; 0.5, 0.5, 0.5, 0.3, 0.8, 0.7; 1, 0, 0\}$$

$$\text{Worst Solution WS} = \{0.2, 0.1, 0.2; 0.5, 0.5, 0.5, 0.5, 0.2, 0.8; 1.0, 0, 0.1, 0.1, 0.1; 0.5, 0.5, 0.5\}$$

$$dist - ham(BS, WS) = K1 + K2 + K3 \quad (16)$$

and

$$K1 = (|0.4-0.2|+|0.5-0.1|+|0.7-0.2|+|0.91-0.5|+|0.1-0.5|+|0.2-0.5|)$$

$$K2 = (|0.1-0.5|+|0.1-0.2|+|0.3-0.8|+|0.5-1.0|+|0.5-0|+|0.5-0|)$$

$$K3 = (|0.4-0.2|+|0.5-0.1|+|0.7-0.2|+|0.91-0.5|+|0.1-0.5|+|0.2-0.5|)$$

Thus, $dist\text{-}ham(BS, WS) = 7.71$

The distance of each solution from BS and WS is presented in Table 9. Based on the proximity of each solution to the best one, the solution can be considered optimal.

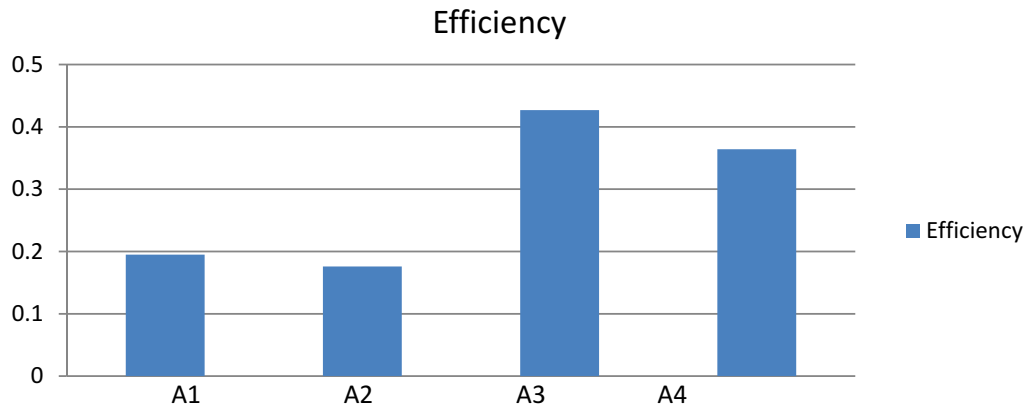
After arranging in descending order of efficiency, the sequence of alternatives is A3, A4, A1, and A2. Hence, the rank of A3 is 1, A4 is 2, A1 is 3, and A2 is 4. Figure 4(a) depicts the alternatives in terms of their efficiency. Figure 4(b) presents the distance of the alternatives from the best one (i.e. the efficiency of the best alternative minus that of the current alternative). Figure 4(c) presents the distance of the

Table 8. Example UDM.

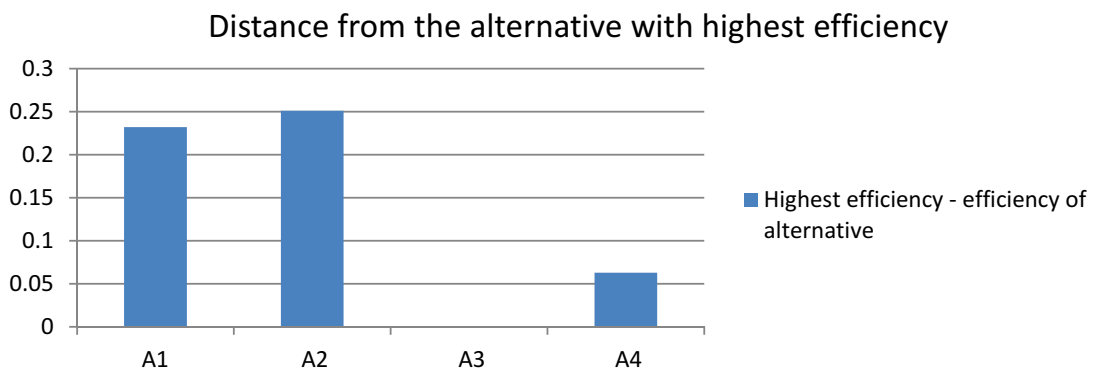
Cost → Alternative products ↓	C1 (performance)	C2 (cost)	C3 (service after delivery)
A1	<0.3, 0.5,0.2; 0.91,0.1, 0.2>	<0.5, 0.2,0.3; 1.0, 0>	<0.1, 0.8,0.1; 0.72,0.4, 0.4>
A2	<0.4, 0.1,0.5; 0.5,0.5, 0.5>	<0.4, 0.2,0.4; 0.91,0.21, 0.15>	<0.2, 0.1,0.7; 0.5,0.5, 0.5>
A3	<0.4, 0.3,0.3; 0.71,0.5, 0.4>	<0.3, 0.1,0.6; 0.5,0.5, 0.5>	<0.3, 0.1,0.6; 1.0,0, 0>
A4	<0.2, 0.1,0.7; 0.61,0.2, 0.4>	<0.1, 0.1,0.8; 0.61,0.2, 0.25>	<0.2, 0.7,0.2; 1.0, 0 >

Table 9. Proximity of a solution from BS and WS.

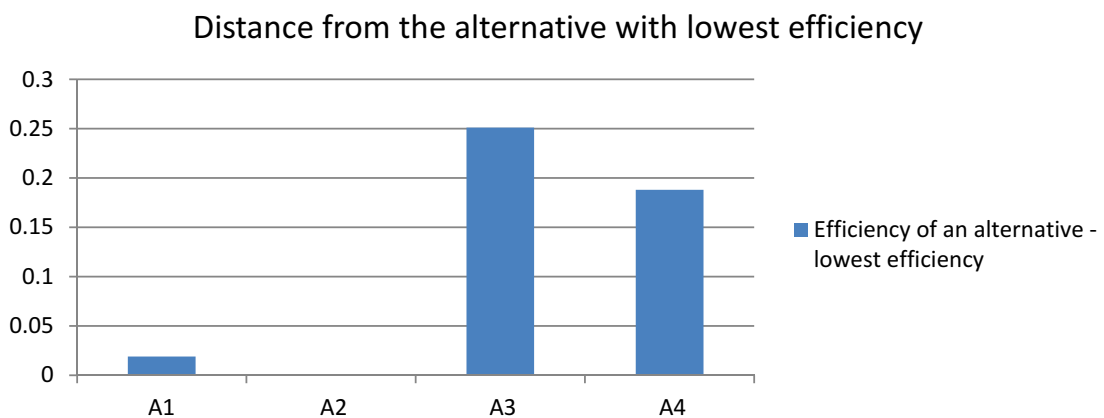
Alternative Products	Solution	Distance from BS	Distance from WS	Efficiency
A1	{0.3, 0.5,0.2; 0.91,0.1, 0.2,,, 0.5, 0.2,0.3; 1,0, 0,,, 0.1, 0.8,0.1; 0.72,0.4, 0.4}	4.82	3.23	0.195
A2	{0.4, 0.1,0.5; 0.5,0.5, 0.5,,, 0.4, 0.2,0.4; 0.91,0.21, 0.15,,, 0.2, 0.1,0.7; 0.5,0.5, 0.5}	5.36	3.43	0.176
A3	{0.4, 0.3,0.3; 0.71,0.5, 0.4,,, 0.3, 0.1,0.6; 0.5,0.5, 0.5,,, 0.3, 0.1,0.6; 1,0,0, 0}	2.7	5.01	0.427
A4	{0.2, 0.1,0.7; 0.61,0.2, 0.4,,, 0.1, 0.1,0.8; 0.61,0.2, 0.25,,, 0.2, 0.7,0.2; 1,0, 0}	3.16	4.55	0.364



a: Efficiencies of alternatives A1, A2, A3, and A4



b: Distance from the alternative with the highest efficiency



c: Distance from the alternative with the lowest efficiency

Figure 4. Efficiencies of alternatives A1, A2, A3, and A4.

alternatives from the lowest one (i.e. the efficiency of an alternative minus that of the worst alternative).

From the above, A3 appears to be the optimal solution, with the lowest distance from the best and highest distance from the worst solutions.

6. Conclusion

In this study, we investigate the problem of generating company rank based on its products vis-à-vis its competitors to demonstrate its standing in the market and the eye of its current customers, as well as the potential ones. Thus, we propose an AI alternative scheme for this task. Currently, the common process followed by companies is to conduct market surveys through questionnaires and by analysing the results. However, the responses provided in the questionnaires may not present the actual feedback of the respondents. This is because the responders may feel that filling in questionnaires is a non-value adding activity for them. Thus, this paper proposes that the questionnaires can alternatively be filled in using feedback obtained from IoT sensors integrated with the products and from the social media contents created by customers and non-customers who commented on a product of a company. This task does not involve manual filling in the questionnaires and, thus, likely gains a larger pool of feedback. We used the service of SIoT and company objects to manage the entire process.

Each response is evaluated based on its reliability – responses of a responder are taken seriously as long as that he seems reliable and knowledgeable enough to provide such feedback. Further, each response is associated with a certain degree of truth, falsity, and indeterminacy. We modelled every response to every question in the questionnaire in the form of a neutrosophic set with six components: The first three relate to efficiency, neutrality, and inefficiency of the product. Meanwhile, the other three relate to the degree of truthiness, indeterminacy, and falsity associated with the response and is based on qualification, the experience from previous use of the same or alternative products, and age of the responder. These were combined using a fuzzy controller FUZZ-MARK to obtain the final product rank.

The major contributions of this study are (1) an innovative method of collecting customer feedback using IoT as well as from social media, (2) incorporating the reliability and knowledge of the responder in the feedback, and (3) the use of neutrosophic set theory to represent and analyse the feedback to finally compute the given company's product rank against its competitors. Before deciding on the optimal solution, the distance between best and worst cases were computed. Hence, the overall or effective efficiency of a solution with respect to the solution space available can be known. The conventional process of collecting and

analysing feedback has been made intelligent and interesting through social IoT and social media-based sentiment analysis.

The study was of course focused on a particular example case, which is that of a car company. The questionnaire for other companies, and the aspects that they might be interested in about their products and/or services, may remarkably vary. Thus, predicting whether this scheme can be generalised across products and/or services is difficult. To address this limitation and check for generalisability of the results, the scheme across companies should be checked. Thus, as part of future work, we propose conducting case studies that determine the ranks of various companies. This would also include comparison of ranking based on analysis of questionnaires filled in physically by respondents and those filled in through Neutro-KYR. The future study involves managers from companies to evaluate the analysis, based on their practical experiences. Hence, the performance of the scheme can be estimated. If found successful, the scheme would be able to assist in the managerial decision of a company regarding its strategy for any given product in its portfolio.

Notes

1. www.teamenterprises.co.uk/wp-content/uploads/2014/10/collecting-customer-feedback.pdf
2. <https://www.forbes.com/sites/insights-hitachi/2017/12/18/5-areas-where-the-iot-is-having-the-most-business-impact/#6e3c664f4396>
3. <http://mathforum.org/library/drmath/view/68272.html>
4. <http://www.capgemini.com/application-services>
5. https://economictimes.indiatimes.com/tech/internet/right-time-to-build-iot-in-india-bharti-airtel/article-show/71228047.cms?utm_source=contentofinterest&utm_medium=text&utm_campaign=cppst
6. www.inc.com
7. <https://about.crunchbase.com/blog/crunchbase-rank-trend-score/>
8. www.teamenterprises.co.uk/wp-content/uploads/2014/10/collecting-customer-feedback.pdf
9. <https://www.hrw.org/reports/2001/ustat/ustat0301-01.htm>

Disclosure statement

No potential conflict of interest was reported by the authors.

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