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The role of single valued neutrosophic sets and rough sets in smart city: Imperfect and incomplete information systems

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ABSTRACT

During the recent years the smart cities knows a great extension as a modern shape of sustainable expansion. It's a urban area that utilize various devices connected with internet and integrates them with ICTs to promote goodness and execution of services for the best interaction among citizens and city's government. The basic for smart cities is distributed and independent information infrastructure. Using information effectively is going to be a main factor for success in the smart cities. The sources of information's (models, experts, and sensors) must be reason, perfect and complete. The generated information from independent and distributed sources can be imprecise, uncertain, and/or incomplete in real life. Any deficiency in gathered information will have a negative effect on the performance of services and decision making process within smart cities. So, we need a general framework to represent all types of imperfect and incomplete information. Since the classical methods fails to deal with vague, inconsistent and incomplete information, the fuzzy set was introduced to solve this drawback. The fuzzy set was not the perfect method for dealing with these drawbacks because it considers only truthiness and fails to deal with indeterminacy. The efficient mathematical tool for dealing with uncertain, vague and inconsistent objects is rough sets theory which introduced by Pawlak. The theory of neutrosophic rough sets is powerful for dealing with incompleteness and neutrosophic set deals with indeterminate and inconsistent data efficiently through considering truthiness, indeterminacy and falsity degrees. So, in this research we will propose a general framework for dealing with imperfect and incomplete information through using single valued neutrosophic and rough set theories. The combination of two sets will deal with all aspects of vagueness, inconsistency and incompleteness of data and information, and then will enhance the quality of introduced services and decisions from smart cities to their citizens. As experimentation, we applied the proposed framework for modeling imperfect and incomplete data in healthcare field.

1. Introduction

1.1. Research motivation

The challenges which faced traditional cities, forced cities to reconsider their strategies to innovate and preserve service levels. These levels includes: outsourcing services, online service delivery, minimizing demand on services and releasing data for allowing new services to improve and make citizens informed to make reasonable decisions, e.g. introducing real-time information on traffic to help citizens in designing journeys. To make citizen able to react quickly to existing and new challenges, the concept of smart cities has been appeared.

The major difference between traditional and smart cities is the near interaction between citizens and service suppliers. This shift between deliveries of services appears in Figs. 1 and 2. In traditional cities the interaction between city's citizens and provided services is not attractive as appears in Fig. 1. The citizen in traditional city is not a collaborative member of the society. For example, the citizens cannot provide a feedback on services quality as the state of education, public roads, etc. Only the private services are the sector which citizen can give feedback on it. Citizen in traditional cities isn't centric.

In smart cities as appears in Fig. 2, the citizens are centric and participative members of city, the public and private sectors are grouped and citizens can provide feedbacks easily on the two sectors. A smart strategic innovative unit exists in smart cities to keep service levels as we described previously. The city hall act and react with this strategic unit via the mayor of city.

The major aspects of smart cities, which are basically information driven:

(1) Digital infrastructure, integrated with a secure and open data, for enabling citizens to access the information they need any time.

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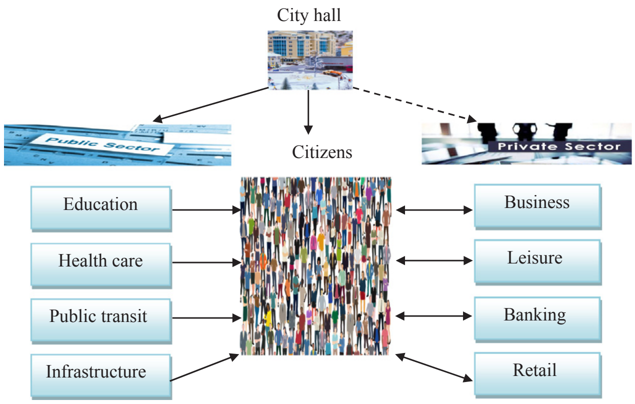

Fig. 1. Services and citizens in traditional cities.

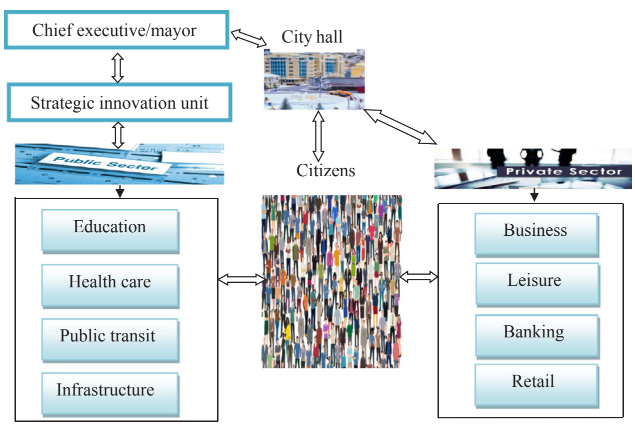

Fig. 2. Services and citizens in smart cities.

(2) Keeping citizen centric to deliver required services.
(3) A smart physical infrastructure (Internet of Things) for managing service delivery and making a strategic investment of city.
(4) Openness for learning from others and experiences.
(5) Translucence of performance and outcomes.

The most significant factors for constructing a smart city are: management organization, technology, governance, policy, people and communities, economy, built infrastructure and natural environment as appears in Fig. 3 [1].

The factors as appears in Fig. 3, have a two-way influence in smart city. This influence may be either inner or outer. The outer factors as appears in Fig. 3 are governance, people and communities, natural environment, infrastructure and economy. The inner factors are organization management, policy and technology. But technology is a meta-factor since it impacts on each other factors in smart city.

The development of Internet of Things (IoT), Information and Communication Technology (ICT) promoted the concept of smart city. The application areas of smart cities are peoples, houses, waste management, parking, traffic, grid, health and industry [2,3]. Some technological companies adopted the concept of smart cities according to their opinions. The smart city definition according to IBM companies is as follows “the city that uses all available information in efficient and effective ways to recognize and monitoring its operations and enhances the utilization process of restricted resources” [4]. Cisco company also defined smart cities as follows “cities that take the benefits of information and communications technology to raise efficiency, minimize cost and promote life's quality” [5]. So the intelligence rate of smart cities and their capabilities to enhance citizen's life depends mainly on available information sources. We also can say that the basic infrastructure for building smart cities is available data and information to city system.

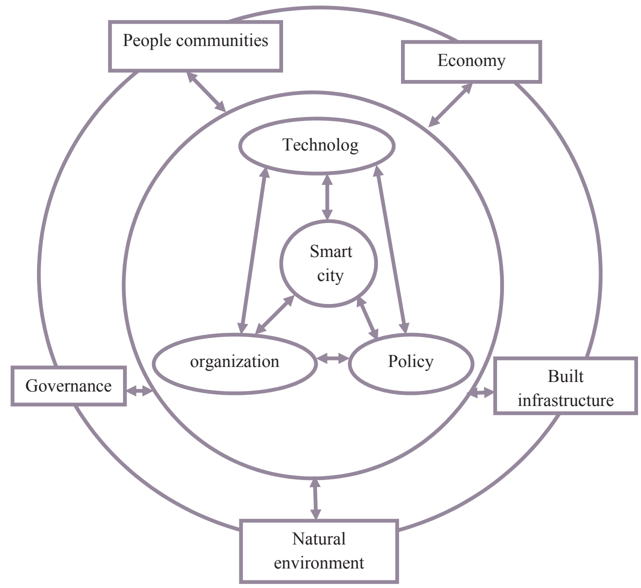

Fig. 3. Factors for building a smart city [1].

The sources of information must be valid and reliable to help smart cities, but in real life these information are imprecise, uncertain and/or incomplete and this already decrease efficiency of smart cities. The classical methods and probabilities fails to deal with vague, uncertain and incomplete information. The fuzzy set was introduced to deal with vague and uncertain information [6]. But the fuzzy set was not the ideal method, because it considered only truth membership and failed to deal with indeterminacy which exists usually in real life. Atanassov introduced intuitionistic fuzzy sets as a prolongation of fuzzy set [7]. The fuzzy and intuitionistic fuzzy sets fails to treat all types of uncertainties such as indeterminacy and inconsistency which exist usually in natural decision making process. For example, when decision maker gives his/her judgment about anything, he/she may say that, this statement is 50% true, 60% false and 20% I am not sure [8]. From this concept, Smarandache proposed the neutrosophic logic, probability and sets [9–11]. To facilitate the practical side of neutrosophic sets, a single-valued neutrosophic set (SVNS) was presented [8]. The concept of rough set (RS) introduced by Pawlak in [12], as a mathematical tool for processing incomplete information. Broumi et al. [13] combined the neutrosophic set with rough set and produced a neutrosophic rough set for enhancing performance of rough set.

1.2. Research contributions

Information systems have become prevailing in urban society, they have introduced chances to take information anytime and anywhere. Perception of city systems (water, transportation, material cycling, etc.) depends on available data and information. So the back stone of any successful urban area is basically the available and accessible data and information. In reality the information is always vague, inconsistent and/or incomplete and this affects the quality of introduced services and on decision making process. Due to the importance role of information in smart cities, we handle in this research the problems of imperfect, vague and incomplete information in smart cities through using single valued neutrosophic set with rough set. Our proposed model treats all aspects of imprecision and incompleteness of information and then increase efficiency and quality of used information. Accurate and reliable information increases the efficiency of the provided services. Increasing the quality of introduced services to the smart city's citizens will also increase satisfaction rates. Also perfect and complete information makes decision making process more reasonable and accurate.

When applying proposed model to any system of smart cities it will reduce cost, time and increase decision accuracy. For example, when a group of citizens plans to carry out a journey and obtained information about the traffic state, if the available information was precise, consistent and complete, then the citizen will select the suitable time for making journey and this will also reduce cost via avoiding making journey in a bad traffic state and forcing citizens to return home. The previous example can be on any field in smart city as healthcare, education, etc.

The structure of this research is as follows. A literature review on the smart cities concepts, dimensions and applications presented in Section 2. The main concepts of neutrosophic sets and its operations, rough set and incomplete information systems illustrated in Section 3. The problems of imperfect and incomplete information over the smart cities described in Section 4. The proposed framework for dealing with imperfect and imprecise information presented in Section 5. The conclusions and future trends presented in Section 6.

2. Literature review

The concept of smart cities has been proposed by several researchers in recent years. So, we aim in this section to illustrate the definitions, applications and benefits of smart cities.

2.1. Smart cities definitions

There exist several researchers that explored diverse definitions of smart cities. According to Hall's opinion, the smart city is "a city that observes and combines conditions of its entire stringent infrastructures, optimizes its resources efficiently, controls all aspects of security and then maximizing quality of introduced services" [14]. Giffinger et al. [15] defined smart cities as "Modern cities based on search and intelligent solutions implemented in a forward-looking path for enhancing the quality of citizen's service". Eger defined smart city as "a city which makes a sentient decision to prevail technology as a catalyst to solve its problems and achieve needs" [16]. Harrison et al. [17] defines smart cities as "a connection between physical, social, business and IT infrastructure to strength the intelligence for the entire city". Chen defined smart city as "Optimization process of transportation, electrical, and other logistical processes to support and improve the quality of life through taking the benefits of communications and sensor capabilities" [18]. The defined smart city as "a creative area which attracts knowledge workers for livening and working inside it, to invest in citizen's life quality" [19]. Harrison and Donnelly defined smart city as "a modern policy for urban designing" [20]. According to Nam and Pardo [21] the smart city is "an essential integration between human, technological and institutional ingredients". Cretu defined smart cities as "cities that integrates smart devices, networks of sensors, real-time data, and ICT to all parts of human life" [22]. Guan defined smart city as "a city which designed to introduce conditions for happy and healthy society under the defying conditions which comes via economic, environmental, and social directions" [23]. Lazaroiuand Roscia defined smart city as "a technological, connected, sustainable, convenient, charming and secure city" [24]. Lombardi et al. [25] defined smart city as "a city that apply information and communications technology (ICT) to various issues such as environmental, social, educational and human capital". Bakıcı et al. [26] defined smart city as "advanced and urban areas that uses technologies and information to connect city elements for creating a sustainable, competitive and innovative environment and then increase quality of citizen's life". Marsal-Llacuna defined smart city as "a city that enhances urban representation via using data, information and information technologies (IT) to introduce efficient services to its citizens, control and enhance city's infrastructure, maximize collaboration among various economic actors, and to create innovative models of business" [27]. Caragliu et al. [2] defined smart city as "the city that invest in humans, with economically stable conditions, high life quality of their citizens and intelligent management of their resources. In their research they present the combination of complex information systems applications to operate urban infrastructure such as houses, electric, water sources, public security and transportation". The researchers in [28–30] clarified the smart city as "city that utilizes information and communications technology, human and environmental resources to warranty the economic expansion for ensuring human life's quality". Vanolo defined smart city as a city that uses the sophisticated technologies [31]. The authors in [32–34] clarified the smart city as "city that utilizes networks to enhance political and economic efficiency to warranty the urban expansion". Ojo et al. [35] defined smart city as an urban invention including policy, technological and organizational invention. Chourabi et al. [1] defined the smart city as "a big essential system aggregating many subsystems in an intelligent way". Schaffers et al. [21] described the smart city as "a multi-dimensional concept: it's an urban strategy based on ways of enhancing citizen's lives through using modern technologies".

Two basic definitions of smart cities have been concluded from the current literature: The first definition defines smart city as "the city that utilize the ICTs for conventional infrastructures to enhance the active involvement between human and government" [27,36]. The second definition of smart city is "the city with intelligent infrastructures, technologies and innovative methods for enhancing competitive advantages of city" [4,28]. So, we can describe the basic of smart city as "an urban city that utilize intelligent information infrastructures (includes perfect and complete data) to guarantee the sustainability and competitive advantage of city's environment to enhance the fineness of citizens' lives".

2.2. Dimensions and applications of smart cities

Four components of smart cities identified by Giffinger et al. [15] which are education, industry, technical infrastructure and participation. These components are expanded by the Vienna University of Technology to six major components which are as follows: a smart environment, smart mobility, smart people, smart living, smart governance and smart economy. The previous components are the inclusion of citizen's life's quality [28]. Raising life's quality represents the major component according to Shapiro [37]. Nam and Pardo [21] defined the major components of smart cities, which are technology, people, and the institutions. Thuzar defined the major dimensions of smart cities which are life's quality, economic sustainability, and resources management process, rapprochement of social, economic and environmental objectives [38]. According Eger's opinion, the major dimensions of smart city are technology, economic expansion, job growth and increasing quality of citizen's life [16]. Barrionuevo et al. [39] considered the economic factors, human, social, environmental, and institutions as the major components of smart cities. The human capital, infrastructural capital, social and entrepreneurial capital were the key dimensions of smart cities according to Kourtit, and Nijkamp [40]. Organization's management, technology, government, people, economy, built infrastructure and natural environment are the major dimension according to Chourabi et al. [1].

For enhancing quality of citizens' life, all smart cities implementations initiated in 2005 through various models. Application areas of smart cities are smart health, people, traffic, waste management, parking, government and industry. Cisco was the first company which proposed a smart city's model applied in Dubai [41]. The smart city's model in Dubai contained the electronic government, smart media city, healthcare city and a village of knowledge. Another smart city's model proposed by IBM Company and was applied in New York [42]. The application areas of IBM model includes: a smart management network of transportation, smart building and smart management of water resources. A smart city model in Germany was proposed by Siemens [43] and another pattern of smart city applied in Montreal [44]. All smart cities patterns that have been proposed include the same smart components such as economy, mobility, government, environment and people [45]. The sustainability of the various urban tasks must depend primarily on perfect and complete information infrastructure. The origin of information in smart cities comes from various sources and the most part of this information may be uncertain, imprecise and/or incomplete. To handle the imperfections of data, several theories have been proposed such as probability theory [46,47] for handling incomplete data, the possibility theory [48,49] for handling imprecise data, the fuzzy set logic [50,51] for handling ambiguity and imprecise data, the bipolar logic [52] and rough sets [53]. The most widely used theory is Dempster [54,55], Shafer [56] theory. It's a powerful tool for representing all forms of data's imperfection [57]. The probability theory is the ancient tool for handling incomplete data and failed to recognize uncertainty [58,59]. For handling imprecision and vagueness, the fuzzy sets theory was proposed [60]. However, the neutrosophic theory is a strong tool for handling all types of imperfection [61].

3. Preliminaries

Brief definitions of neutrosophic set, rough set and incomplete information systems presented in this section.

3.1. Neutrosophic set definitions

Definition 1 (*[8]*). A neutrosophic set (NS) N in X is specified by a truth $T_N(x)$, indeterminacy $I_N(x)$ and a falsity $F_N(x)$ membership functions. Where X be a set of points and $x \in X$, $T_N(x)$, $I_N(x)$ and $F_N(x)$ are subsets of $]^-0, 1^+[$: $T_N(x){:}X \to]^-0, 1^+[$, $I_N(x){:}X \to]^-0, 1^+[$ and $F_N(x){:}X \to]^-0, 1^+[$. There are no constraints on the sum of $T_N(x)$, $I_N(x)$ and $F_N(x)$, so $0^- \le \sup T_N(x) + \sup I_N(x) + \sup F_N(x) \le 3^+$.Neutrosophic is built on a philosophical concept which makes it difficult to process during engineering applications or to apply to real applications. For it, Wang et al. [8], defined the SVNS, which is a particular case of NS.

Definition 2. A single valued neutrosophic set (SVNS) N over X, takes the form $N = \{\langle x, T_N(x), I_N(x), F_N(x) \rangle{:}x \in X\}$, where $T_N(x){:}X \to [0, 1]$, $I_N(x){:}X \to [0, 1]$ and $F_N(x){:}X \to [0, 1]$ with $0 \le T_N(x) + I_N(x) + F_N(x) \le 3$ for all $x \in X$. For simplification, a SVN number is exemplified by $N = (a_1, a_2, a_3)$, where $a_1, a_2, a_3 \in [0, 1]$ and $a_1 + a_2 + a_3 \le 3$.

Definition 3. The single valued triangular neutrosophic number $\tilde{n} = \langle (n_1,n_2,n_3);_{\tilde{n}} ,_{\tilde{n}} ,_{\tilde{n}} \rangle$ is a neutrosophic set whose truth, indeterminacy and falsity membership functions are as follows:

$$T_{\tilde{n}}(x) = \begin{cases} \alpha_{\tilde{n}}\left(\frac{x-n_1}{n_2-n_1}\right) & (n_1 \leqslant x \leqslant n_2) \\ \alpha_{\tilde{n}} & (x = n_2) \\ \alpha_{\tilde{n}}\left(\frac{n_3-x}{n_3-n_2}\right) & (n_2 < x \leqslant n_3) \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

$$I_{\tilde{n}}(x) = \begin{cases} \frac{(n_2-x+\beta_{\tilde{n}}(x-n_1))}{(n_2-n_1)} & (n_1 \leqslant x \leqslant n_2) \\ \theta_{\tilde{n}} & (x = n_2) \\ \frac{(x-n_2+\beta_{\tilde{n}}(n_3-x))}{(n_3-n_2)} & (n_2 < x \leqslant n_3) \\ 1 & \text{otherwise,} \end{cases} \tag{2}$$

$$F_{\tilde{n}}(x) = \begin{cases} \frac{(n_2-x+\theta_{\tilde{n}}(x-n_1))}{(n_2-n_1)} & (n_1 \leqslant x \leqslant n_2) \\ \beta_{\tilde{n}} & (x = n_2) \\ \frac{(x-n_2+\theta_{\tilde{n}}(n_3-x))}{(n_3-n_2)} & (n_2 < x \leqslant n_3) \\ 1 & \text{otherwise.} \end{cases} \tag{3}$$

where $\alpha_{\tilde{n}}, \theta_{\tilde{n}}$ and $\beta_{\tilde{n}} \in [0,1]$, exemplify the upper degree of truth, lower degrees of indeterminacy and falsity respectively.

Definition 4 (*Neutrosophic rough set*). Let N_r be a non-empty set and the equivalence relation on N_r is R. Let N be neutrosophic set in N_r with truth-function T_N, indeterminacy I_N and falsity F_N functions. The lower and the upper approximations of N in the approximation (N_r, R) denoted by $\underline{A}(N)$ and $\overline{A}\ (N)$ and called a rough neutrosophic set in (N_r, R) [13].

3.2. Incomplete information systems

Any information system represented by a pair of sets and takes the following form $I_S = (O,T)$, where O is a universe of discourse contains a finite set of objects and T is a finite set of attributes such that $a{:}\ O \to V_a$ for any $a \in T$, where V_a is the value of attribute. In some cases the attributes values are doesn't exist (missing) and here we will represent missing values by "$*$". Then a system $I_S = (O,T)$ with missing values is named an incomplete information system [62,63].

Let $I_S = (O,T)$ be an incomplete information system, $A \subseteq T$, a similarity relation on O is defined as follows [63]:

$$S_M(A) = \{(x,y) \in O \times O |\ \forall\ a \in A, a(x) = a(y)\ or\ a(x) = *\ or\ a(y) = *\}. \tag{4}$$

The set of all objects which is similar to x with respect to A, be as follows:

$$S_A(x) = \{y \in O | (x,y) \in S_M(A)\} \tag{5}$$

For $X \subseteq O, A \subseteq T$, the lower and upper approximations of X defined as follows:

$$\underline{A}(X) = \{x \in O | S_A(x) \subseteq X\} \tag{6}$$

$$\overline{A}(X) = \{x \in O | S_A(x) \cap X \neq \varnothing\} \tag{7}$$

where $\underline{A}(X)$ is the set of objects which belong to X, and $\overline{A}(X)$ is the set of objects that possibly belong to X. The impossibility of belonging objects to X denoted by $\sim \overline{A}(X)$.

4. Handling imperfect information in smart city

Understanding the correlation among data and applications of smart city will aid in decision making process and optimize different functions of smart city via using right data in required applications. A simple diagram which illustrate the values of such studies presented in [64] as appear in Fig. 4.

The sustainability of the various urban tasks depends primarily on perfect and complete information infrastructure. The sources of information in smart cities come from various sources as in Fig. 5. Always the most part of this information may be uncertain, imprecise and/or incomplete.

To handle the imperfections of data several theories have been proposed as summarized in Table 1.

This imperfection of information which appeared in smart cities has various shapes such as:

- Uncertainty: It means the shortage of knowledge (e.g. 'I believe that the percent of pollution in the Earth's ocean surface equal to 80%').
- Imprecision: It means the non-specification (e.g. 'I believe that the percent of pollution in the Earth's ocean surface between 80% and 85%').
- Vagueness: It means the ambiguity (e.g. 'I believe there are great amounts of pollution in the Earth's ocean surface').
- Incompleteness: It means the not found or missing of information.

It's a hard process to make accurate decisions when dealing with imperfect information. This due to the strong relation between data/information and final decision, and then imperfect data will lead to imperfect decisions. All kinds of imperfections affect the quality of urban services. So, it is significant to handle imperfection to guarantee liability and increase quality of services and then increasing smart cities efficiency.

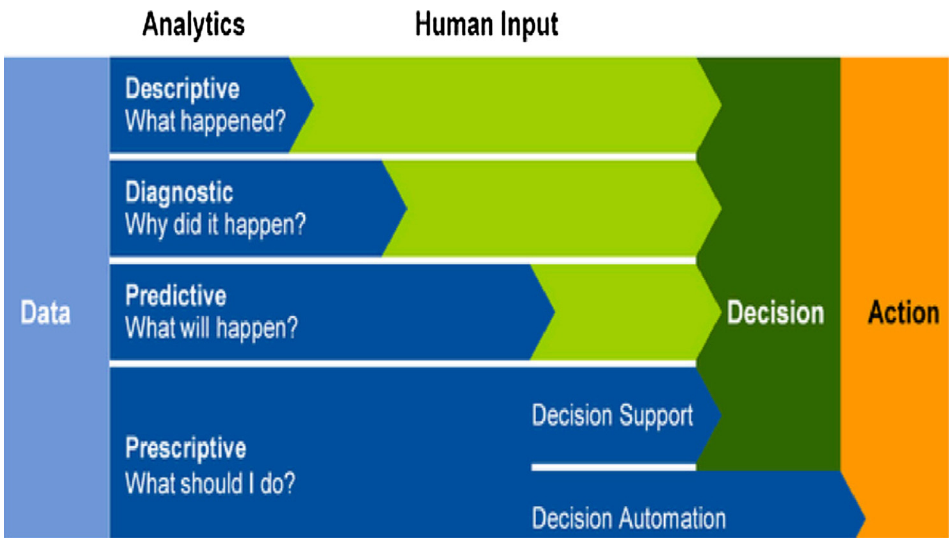

Fig. 4. The correlation between data and decision making process according to Gartner [64].

Fig. 5. Sources of information in smart cities.

5. The proposed method for dealing with imperfect information

To enhance the efficiency of smart cities, we proposed an algorithm for handling all kinds of information's imperfection in this section.

5.1. The steps of proposed algorithm

Step 1: For each data (D_i), determine its source (s_j) and the frame which specific data belong to it (e.g. health, social, transport, economy, …).

/∗Dealing with uncertain, imprecise and vague data using single valued neutrosophic set∗/

Table 1
Theories for dealing with imperfection of information.

Theory	Application regions	Origin
Theory of probability	Incomplete data	[46,47]
Theory of fuzzy logic	Data's imprecision and ambiguity	[50,51]
Theory of possibility	Uncertainty of data and imprecision	[48,49]
Bipolar fuzzy sets	Missing information	[52]
Theory of rough sets	Vagueness	[53]
Theory of belief functions	Imprecision, uncertainty, incompleteness, ignorance and conflict	[65]

Step 2: Determine the certainty degree (C_d) of the specified data, where $C_d \in [0,1]$ and calculates either as follows:

• For each (D_i) obtained from any (s_j);

– Represent these data using a neutrosophic set, according to Definition 3 calculates the truth-membership T_D, indeterminacy-membership I_D and falsity-membership F_D.

– If $T_D > I_D, T_D > F_D$ then,

$C_d \in$ Acceptance region (A_r) and this data is valid and perfect for using.

Else

If $F_D > T_D, F_D > I_D$ then,

$C_d \in$ Rejection region (R_r) and this data is not valid and imperfect for using.

Else

$C_d \in$ Boundary region (B_r) and we need to meet a group of experts who are specialized in data domain and ask them to make a verification of these data, and finally add these data either to (A_r) or (R_r) according to experts opinions.

End if

End if

End for

/∗ Dealing with uncertain, imprecise and vague data using rough set and neutrosophic set concept, then the certainty degree calculates as follows and the step 2 will be as follows∗/

• Or by using rough and neutrosophic set concept, Calculate the certainty degree (C_d) of the specified data, where $C_d \in [0,1]$ as follows:

– Determine the pair of threshold (α,β) according to decision theoretic rough set, and which usually set equal $\alpha = 0.5$ and $\beta = -0.5$.

– For each (D_i) obtained from any (s_j);

– Represent these data using a neutrosophic set, according to Definition 3 calculates the truth T_D, indeterminacy I_D and falsity F_D memberships.

– If $T_D - I_D - F_D > \alpha$ then,

$C_d \in$ Acceptance region (A_r) and this data is valid and perfect for using and the value of C_d will equals $T_D - I_D - F_D$.

Else

If $T_D - I_D - F_D < \beta$ then,

$C_d \in$ Rejection region (R_r) and this data is not valid and imperfect for using and also the value of $C_d = T_D - I_D - F_D$.

Else

If $\beta \leqslant T_D - I_D - F_D \leqslant \alpha$ *then*, $C_d \in$ boundary region (B_r) and we need to meet a group of experts who are specialized in data domain, and ask them to make a verification of these data, and finally add these data either to (A_r) or (R_r) according to experts opinions.

End if

End if

End for

/∗ Dealing with incomplete information system∗/

Step 3: For incomplete information systems as we illustrated in Section 3.2 do the following:

• For each incomplete values of attributes which denoted by $X^* = \{\langle x, T_{(x)}, I_{(x)}, F_{(x)} \rangle | x \in O\}$ and is a neutrosophic set on O do

– Calculate the similarity relations using Eq. (5).

– Calculate $\underline{A}(X)$ which is the set of objects that belong to X using Eq. (6).

– Calculate $\overline{A}(X)$ which is the set of objects that possibly belong to X using Eq. (7).

– Calculate $T_{(x)} = \frac{|S_A(x) \cap \underline{A}(X)|}{|S_A(x)|}$ (8), where || means the cardinality of set X.

– Calculate $F_{(x)} = \frac{|S_A(x) \cap \overline{A}(X)|}{|S_A(x)|}$ (9), and because the value of indeterminacy in neutrosophic set doesn't depend on the value of truth and falsity memberships then we make experts infers it according to their opinions.

Calculate the C_d of obtained data as in step 2 either by using first procedure or by using value of $\alpha = 0.5$ and $\beta = -0.5$.

– Classify the obtained data either to A_r or R_r and for boundary regions do as in step 2.

End for

Step 4: Store and/or retrieve only data which felled into acceptance region.

Step 5: Use these perfect and complete data in decision making process and apply it in all fields of smart cities for enhancing quality of service level.

The role of proposed algorithm in smart cities appears in Fig. 6.

The sources of data, information are everywhere around us, efficient analysis and utilization of this data is going to be a major factor of achieving success in smart cities. Large amounts of data and information that depict what happens in the city are obtainable and could be used to make and modify intelligent solutions within related areas. There are different data and information acquired from city managers, decision makers and/or other stakeholders. These data and information in real life situations are always vague, imprecise and/or incomplete, and then will negatively affect the quality of provided solutions, decisions and/or services. In order to deal with all aspects of data and information's imprecision the proposed algorithm was presented. In our proposed algorithm the certainty degree of required and obtained data is calculated. Also a classification process of data and information is made; the data / information may fall in acceptance (truth) region or rejection (falsity) region or boundary region. As appeared in detailed steps of proposed algorithm, if data/information existed in acceptance region then this data/information is precise and decision makers or city manager or any other stakeholders can safely use and apply it in various regions. If data/information existed in a rejection region, then it's not safe for using in any application. In case of existing data/information in boundary region, a group of experts in data/information's domain should consulates to ensure its correctness or falseness. So we can use only the precise and complete data/information in city's systems, and then build our smart city on a strong information infrastructure. In order to increase the quality of provided services and achieve citizen's satisfaction, the obtained data/information can apply in various applications.

These application areas are:

(1) Smart traffic,
(2) Smart home,
(3) Smart people,
(4) Smart health,
(5) Smart waste management,
(6) Smart parking,
(7) Smart grid,
(8) Smart industry and
(9) Smart police.

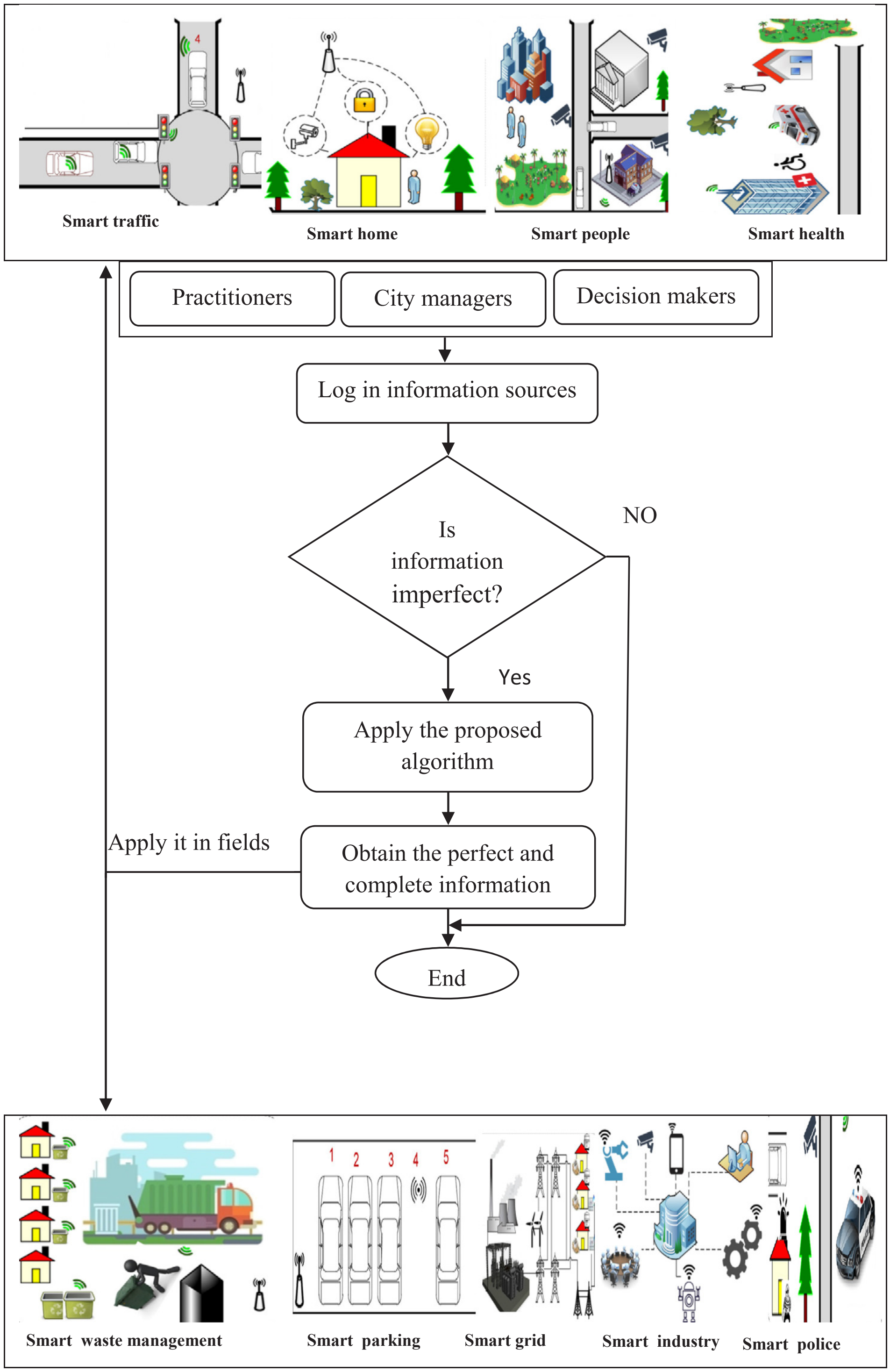

Fig. 6. Application areas of proposed algorithm in smart cities.

So, we can say that smart Cities are "cities with a precise, complete and intelligent information system, which is properly managed to increase efficiency, reduce cost, promote quality of services and then achieving citizen satisfaction".

5.2. Case study for dealing with imperfections of information's in healthcare field

We present a simple case for handling imperfect data in the platform of crowd-sourcing which given on healthcare field in this section.

The crowd-sourcing means the volunteer process of a set of peoples to disband some problems through the internet. It's already identified in [66]. In this platform, we assume that there are only the experts. So, the applicants inquire the questions and the experts in healthcare's field must be answered by one or more answers. If they inquired experts about a set of patients the following question, ' Do these patients have Alzheimer's symptoms? 'Through listing a set of symptoms for each patient as in Table 2.

In the previous table some patients have complete information and then we only need to check the validation of decision that expert should

Table 2
The patients and symptoms that they are suffer from.

Patients	Forgetfulness	Depression	Anger	Non-discrimination
p_1	have	have	Have	have
p_2	have	*	Have	have
p_3	*	*	Have	Have
p_4	have	*	Have	Have
p_5	*	*	Have	Have
p_6	have	have	Have	*

take depending on the accuracy of given information. The other patient doesn't have a complete information system, and the decision in this case is a very hard process. So we will apply the proposed algorithm for handling all types of imperfections of information and taking the right decision, which will change the path of treatment for patients and then increase the healthcare quality.

Step 1: The source of previous information (s_j) is a crowd-sourcing platform and frame which specific data belong to it is the health.

Step 2: Determine the degree of certainty C_d for first patient data:

- *Represent first patient data (D_1) using a neutrosophic set, according to Definition 3 and calculates the truth T_D, indeterminacy I_D and falsity F_D memberships.*
  $\langle p_1 : (T_D, I_D, I_D)\rangle = \langle p_1 : (1,0,0)\rangle$
  – since $T_D > I_D, T_D > F_D$ then,
  $C_d \in$ Acceptance region (A_r) and first patient already suffers from Alzheimer's symptoms.
- *Or by using rough sets concept with neutrosophic set:*
  – Let $\alpha = 0.5$ and $\beta = -0.5$. then
  – Since $T_D - I_D - F_D = 1$,$> \alpha$ then,
  $C_d \in$ Acceptance region (A_r) and this data is valid, first patient already suffers from Alzheimer's symptoms with $C_d = 1$.

Step 3: For all patients and other with incomplete information about Alzheimer's symptoms do

- *For each patient in Table 2 and with incomplete values of attributes A which denoted by $X^* = \{\langle x, T_{(x)}, I_{(x)}, F_{(x)}\rangle | x \in O\}$ and is a neutrosophic set on O do*
  – Calculate the similarity relations using Eq. (5).
  Let $A = T, O|S_M(A) = \{S_A(p_1), S_A(p_2), S_A(p_3), S_A(p_4), S_A(p_5), S_A(p_6)\}$, where $O = \{p_1, p_2, p_3, p_4, p_5, p_6\}$, $T = \{\text{Forgetfulness}, \text{Depression}, \text{Anger}, \text{Non discrimination}\}$, $S_A(p_1) = \{p_1\}$, $S_A(p_2) = \{p_2, p_6\}$, $S_A(p_3) = \{p_3\}$, $S_A(p_4) = \{p_4, p_5\}$, $S_A(p_5) = \{p_4, p_5, p_6\}$, $S_A(p_6) = \{p_2, p_5, p_6\}$
  – Calculate $\underline{A}(X)$ which is the set of objects that belong to X using Eq. (6).
  – Calculate $\overline{A}(X)$ which is the set of objects that possibly belong to X using Eq. (7).
  – In case of incomplete information the expert decision may be as follows: The patient extremely have the disease, or may be have the disease, or not have the disease and this depend on given information.
  – The values of calculated $\underline{A}(X), \overline{A}(X)$ represented in Table 3.
  – Calculate $T_{(x)} = \frac{|S_A(x) \cap \underline{A}(X)|}{|S_A(x)|}$, where || means the cardinality of set X.
  – Calculate $F_{(x)} = \frac{|S_A(x) \cap \overline{A}(X)|}{|S_A(x)|}$, and because the value of indeterminacy in neutrosophic set doesn't depend on the value of truth and falsity memberships then we make experts infers it according to their opinions. The values of T, I, F for attributes data of patients presented in Table 4.
  – Calculate the C_d of obtained data as in step 2 either by using first procedure or by using value of $\alpha = 0.5$ and $\beta = -0.5$.
  – For p_1, $TA_{p_i} - IA_{p_i} - FA_{p_i} = 1 > \alpha$, then $C_d = 1$, then p_1 belong to acceptance region and patient already have the disease by depending on a perfect information.
  – As similar for p_1, the C_d for p_2 = 0.4 <α, then p_2 belong to boundary region and patient may have the disease, and then in this case the expert will ask applicants another questions to obtain final decision.
  – The C_d for p_3 = −1 <β, then p_3 belong to negative region and patient doesn't have the disease.
  – -The C_d for $p_4 = -0.5$, $\beta \leqslant -0.5 \leqslant \alpha$, then p_4 belong to boundary region and patient may have the disease, and then in this case the expert will ask applicants another questions to obtain final decision.
  – The C_d for $p_5 = -0.3$, $\beta \leqslant -0.3 \leqslant \alpha$, then p_5 belong to boundary region and patient may have the disease, and then in this case the expert will ask applicants another questions to obtain final decision.
  – The C_d for $p_6 = 0.23$, $\beta \leqslant 0.23 \leqslant \alpha$, then p_6 belong to boundary region and patient may have the disease, and then in this case the expert will ask applicants another questions to obtain final decision.

Table 3
The approximation values of set.

Initial decision	$\underline{A}(X)$	$\overline{A}(X)$
Have disease	$\{p_1, p_2\}$	$\{p_1, p_2, p_4, p_5, p_6\}$
May have disease	$\varnothing$	$\{p_4, p_5, p_6\}$
Not have disease	$\{p_3\}$	$\{p_3\}$

Table 4
The membership degrees.

p_i	$TA_{(p_i)}$	$IA_{(p_i)}$	$FA_{(p_i)}$
p_1	1	0	0
p_2	0.5	0.1	0
p_3	0	0	1
p_4	0	0.5	0
p_5	0	0.3	0
p_6	1/3	0.1	0

From the previous results the perfect decision is that, the first patient exactly has Alzheimer, and third patient exactly doesn't have Alzheimer. All other patients belong to boundary region and experts will ask more detailed questions and repeating the previous steps to determine the exact diagnoses of disease.

Then by using the proposed algorithm we becomes able to classify the imperfection of information and dealing with it, and then help us in making a reliable and confidence decision. Also, it will increase service's quality of smart cities due to using only the perfect information for storing and retrieval processes.

6. Conclusions and future directions

The main confrontation of smart cities is the analysis and modeling of imperfect information. In this research, we focus on modeling all kinds of data's imperfection in smart cities. We allow users to clear their level of certainty about the given information, by modeling the imperfect data using the concepts of neutrosophic and rough set theory. The modeled data by using the proposed algorithm will apply in smart cities fields such as health, waste management, industry, etc. By using perfect and complete information in smart cities, the quality of obtained services will increase, enhance the decision making process, reduce cost and time which may take via making a wrong decision, due to imperfect information. We will stratify the proposed algorithm in various fields such as industry and waste management in the near future, for serving smart cities.

Limitation of proposed research

More involvements from more companies will make our research better.

Competing interests

The authors announce that there is no discrepancy of interests concerning the publication of this research.

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