Computers & Industrial Engineering 65 (2013) 624–633

Contents lists available at SciVerse ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Technology evaluation through the use of interval type-2 fuzzy sets and systems

Türkay Dereli, Koray Altun *

Department of Industrial Engineering, Gaziantep University, 27310 Gaziantep, Turkey

ARTICLE INFO

Article history:
Received 19 May 2012
Received in revised form 23 January 2013
Accepted 14 May 2013
Available online 23 May 2013

Keywords:
Technology evaluation
Type-2 fuzzy logic
Scientometrics
Technometrics

ABSTRACT

Even though fuzzy logic is one of the most common methodologies for matching different kind of data sources, there is no study which uses this methodology for matching publication and patent data within a technology evaluation framework according to the authors' best knowledge. In order to fill this gap and to demonstrate the usefulness of fuzzy logic in technology evaluation, this study proposes a novel technology evaluation framework based on an advanced/improved version of fuzzy logic, namely; interval type-2 fuzzy sets and systems (IT2FSSs). This framework uses patent data obtained from the European Patent Office (EPO) and publication data obtained from Web of Science/Knowledge (WoS/K) to evaluate technology groups with respect to their trendiness. Since it has been decided to target technology groups, patent and publication data sources are matched through the use IT2FSSs. The proposed framework enables us to make a strategic evaluation which directs considerations to use-inspired basic researches, hence achieving science-based technological improvements which are more beneficial for society. A European Classification System (ECLA) class – H01-Basic Electric Elements – is evaluated by means of the proposed framework in order to demonstrate how it works. The influence of the use of IT2FSSs is investigated by comparison with the results of its type-1 counterpart. This method shows that the use of type-2 fuzzy sets, i.e. handling more uncertainty, improves technology evaluation outcomes.

1. Introduction

Scientific and technological findings are generally transformed into publications, patents or industrial applications in due course. This transformation process is quite essential in order to introduce, protect and commercialize those findings. For this reason, publications and patents are the most reliable indicators which are able to reflect the status of *science* and *technology*, respectively. Although *technology* is not the binding goal for developing *science* as in *pure applied researches*, just as *science* is not the necessary prerequisite for developing *technology* as in *pure basic researches*, these can produce high benefits for society when they are matched (Dvorkin, 2010). Therefore, investments and incentives for R&D activities should be inspired not only by the goal of fundamental understanding but also on occasion by the goal of use while policy making (Stine, 2009).

Scientometrics and Technometrics are well established methods in the evaluation of science and technology. Publications and patents – as by products of the exploitation and exploration of science and technology – provide a great deal of insight into actual practices leading to technological innovation (Porter & Cunningham, 2005). Any attempt to match existing metrics to the evaluation scheme would almost inevitably encounter gaps, challenges, and unanswered questions (Geisler, 2002). Therefore, while performing strategic technology evaluation, data derived from patents and publications should be used together as matching each other in order to direct the considerations to *use-inspired basic researches* (also called *Pasteur's quadrant*) and hence to achieve science based technological improvements. These are more beneficial for society.

Matching different kinds of data sources and inferring something which is dependent upon these data sources requires a proper data-fusion methodology. Fuzzy logic is an effective and the most common data-fusion methodology by which logical inferences can be derived on the basis of matching different kinds of data sources. Fuzzy logic has found so many applications in variety of fields since it was introduced by Lotfi A. Zadeh in 1965 through his first paper in the field. Over these approximately 50 years, interest in fuzzy logic has grown exponentially, bringing some new theoretical advances such as *type-2 fuzzy sets and systems* (Zadeh, 1975) and *fuzzy functions* (Celikyılmaz & Türksen, 2009). Nevertheless, fuzzy logic has not found any application for matching patent and publication data sources within a framework for technology evaluation. In order to fill this gap and to demonstrate the usefulness of fuzzy logic in such evaluation, this study proposes a novel technology evaluation framework based on an advanced/improved version of fuzzy logic: namely, interval type-2 fuzzy sets and systems (IT2FSSs).

* Corresponding author. Tel.: +90 342 317 2621; fax: +90 342 360 4383.
E-mail address: kaltun@gantep.edu.tr (K. Altun).

0360-8352/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.cie.2013.05.012

The reminder of this study is organized as follows: Section 2 presents a literature review on technology evaluation. Section 3 presents basic concepts, operators of type-2 fuzzy sets and structure of type-2 FISs. In Section 4, the proposed technology evaluation framework based on IT2FSSs is presented. In Section 5, an application is given to show how the framework operates and a comparison is performed by handling the same problem with a type-1 counterpart. Finally, concluding remarks and future work proposals are presented.

2. Literature review

2.1. Scientometrics

(sometimes called as *Bibliometrics*) is a research method – focused and frequency based quantitative exploration of publications. This research method aims to describe patterns within a part of scientific literature and hence to obtain a better understanding of what is actually taking place in the literature. This deeper understanding can better inform those charged with making difficult choices about allocating resources, generally in the context of peer review (Pendlebury, 2008).

2.2. Technometrics

takes place instead of *Scientometrics* when patent data are explored. Once a specific technological thrust has been identified, Scientometrics and Technometrics can be used to determine its position in its life cycle (Martino, 2003). For this reason, many researchers have used data derived from publications and patents in order to evaluate science and technology (Arman, Hodgson, & Gindy, 2009).

Some previous studies on technology evaluation have ignored the scientific publications while evaluating. For instance, Lee, Cho, Seol, and Park (2012); Lee, Lee, and Yoon (2012) used data derived from patents for modeling trends and patterns of innovation in the energy sector. In another study, Yu and Lo (2009) developed a type-1 fuzzy inference system (FIS) for technological strategy planning by the help of using only patent data as an input of the system. Huang and Li (2010) proposed a framework based on time series analysis, patent analysis and patent international-patent-classification (IPC) analysis in order to evaluate technology trends.

There is nevertheless a need to consider the linkages between the conceptual background of scientific generation and progress – and the measurement of its process and outcomes (Geisler, 2005). However, only a limited number of studies address matching data derived from patents and publications in the literature.

Some of these studies matched these different data sources without using a concise data-fusion methodology. For example, Bengisu and Nekhili (2006) used the data derived from patents and publications to quantify and test expert views on selected technologies comparing the number of patents and publications related to the same technologies for a given year. Quintella et al. (2011) also benefited from patents and publications while presenting a contextualized overview of CO_2 capture technology, with critical evaluation of state-of-the-art and technological development. Bengisu and Nekhili (2006) and Quintella et al. (2011) considered the correlations between patent and publication growth curves of corresponding technologies in order to infer about technologies rather than using a concise data-fusion methodology. Zhang et al. (2011) proposed a process integrating expert knowledge and bibliometric methods, including terms frequency analysis and association analysis, in order to engage the challenge of technology roadmapping. Their terms frequency analysis uses technology core terms and IPCs retrieved from publications and patent documents. They considered the data obtained from patents and publications as a whole. They analyzed this data through text-mining. Their approach may not be thought as a data-fusion process because collecting data from different sources without processing them in a logical way may not be considered to be a fusion process.

However, some of studies in the literature utilized a data-fusion methodology while matching patent and publication data sources. For example, Daim, Rueada, Martin, and Gerdsri (2006) forecast some emerging technology areas through integrating the use of bibliometrics and patent analysis into scenario planning, growth curves and analogies. A system dynamics approach was used as a data-fusion methodology. Although traditional system dynamics models were used for calibration and validation, the proposed approach is a useful decision making tool as a result of the integration. In another study, Arman et al. (2009) developed a methodology which tries to combine three different rankings obtained from publications, patents and experts' opinions in order to obtain a unique ranking. This methodology was based on the consensus indicated by these three different evaluation results. If a candidate technology appears to be in the top three in patents, publications and expert opinion, it is considered as a technology with which all approaches agreed. If the technology appears to be in the top three in any two evaluation results, then it is considered as a technology which two approaches agree upon. Although this data-fusion methodology is clear and easy-to-use, it has some deficiency when the importance of the evaluations shows discrepancy and in determining the limit for top technologies.

As it is discussed in the first section of this paper, fuzzy logic is an effective and one of the most common data-fusion methodologies from which logical inferences can be derived on the basis of matching different kinds of data sources. In our preliminary studies, Dereli and Altun (2013) and Dereli, Durmusoglu, Altun, and Bozyer (2010), patent data and publication data have also been matched by using a type-1 fuzzy inference system in order to evaluate trendiness of candidate technologies. While producing membership functions (MFs), Dereli and Altun (2013) have used a linguistic term indicating uncertainty, calling this "hotness". The perception of hotness can change from expert to expert, although it is commonly thought of as the number of appearances in the last three years compared to the percentage of those which appeared in the last 10 years. This uncertainty has been camouflaged through averaging in Dereli and Altun (2013) by determining the membership functions as type-1 fuzzy sets. Celikyılmaz and Türksen (2009) state that membership functions of type-1 fuzzy sets are "crisp" sets and do not provide sufficient support for many kinds of uncertainty which appear in the subjectively expressed knowledge of experts. The uncertainty that we have faced in Dereli and Altun (2013) actually requires the use of type-2 fuzzy sets and systems (T2FSSs) since handling more uncertainty can be possible by using fuzzy-MFs, i.e., "*membership of membership*". In this study, we extend our previous approach in order to handle more uncertainty in terms of different hotness ratios through modeling the uncertainty in the problem by using T2FSSs. However, we employ interval valued type-2 fuzzy sets since full kinds of type-2 fuzzy sets are computationally complex.

3. Type-2 fuzzy sets

3.1. Why type-2 fuzzy sets should be used

Levels of uncertainty increase from "*number*", to "*word*" and to "*perception*", respectively (John & Coupland, 2009). Traditional mathematical modeling techniques are expected to tackle the problems that contain crisp data, i.e., *numbers*. However, we are living in a world full of uncertainty and we make decisions in uncertain environments. For this reason, traditional mathematical modeling techniques are insufficient to handle this uncertainty. Therefore, fuzzy sets and systems have been used in a wide range of fields since Zadeh (1965), Zadeh (1975) introduced *type-1 fuzzy sets* to model *words* and *type-2 fuzzy sets* to model *perceptions*.

Türksen (2002) argued that type-1 representation does not provide a good approximation to meaning in representation of words and doesn't allow computing-with-words (CWWs) within a richer platform, since it discards the spread of membership values by using averaging or curve fitting techniques and hence, camouflages the uncertainty in the definition of the MFs. Industrial applications of T2FSSs also show that handling more uncertainty and hence producing more accurate and robust results can be achievable with the use of T2FSSs (Dereli, Baykasoglu, Altun, Durmusoglu, & Türksen, 2011). Handling more uncertainty means making less assumption and making less assumption provides more realistic solutions to the real life problems. Because of these advantages, type-2 fuzzy sets have potential to go beyond type-1 fuzzy sets, and therefore an evolution from CWW to computing-with-perceptions (CWPs) has started but it still appears to be in its infancy according to a recent review study (Dereli et al., 2011).

3.2. Basic concept

$\tilde{A}$ denotes a type-2 fuzzy set on a universe of discourse X. It is characterized by a set of pairs $\{x, \mu_{\tilde{A}}(x)\}$, where $x \in X$ and $\mu_{\tilde{A}}(x)$ is the membership degree defined in $[0,1]$ interval

$$\tilde{A} = \int_{x\in X} \mu_{\tilde{A}}(x)x = \int_{x\in X}\left[\int_{u\in J_x} f_x(u)/u\right]\Big/ x, \quad J_x \subseteq [0,1] \tag{1}$$

Secondary MF is denoted as $f_x(u)$ and u is the argument of this function. J_x is the primary membership of x. $\int$ represents that the function is defined for continuous universe of discourse. $\sum$ takes place instead of $\int$ for discrete universe of discourse.

Fig. 1 shows a type-2 MF. Type-2 MFs are three-dimensional because of secondary membership degrees. Secondary MFs provide new design degrees of freedom for handling more uncertainties. However, full type-2 fuzzy sets are computationally complex when the number of variables is large. Therefore, interval type-2 fuzzy sets (IT2FSs) are generally preferred by researchers (Celikyılmaz & Türksen, 2009; Karnik, Mendel, & Liang, 1999; Kazemzadeh, Lee, & Narayanan, 2008; Mendel, John, & Liu, 2006). IT2FSs have bounded from above and below inferior MF, i.e., lower MF (LMF), and superior MF, i.e., upper MF (UMF), respectively. The area between LMF and UMF is called as footprint of uncertainty (FOU). An IT2FS is denoted by

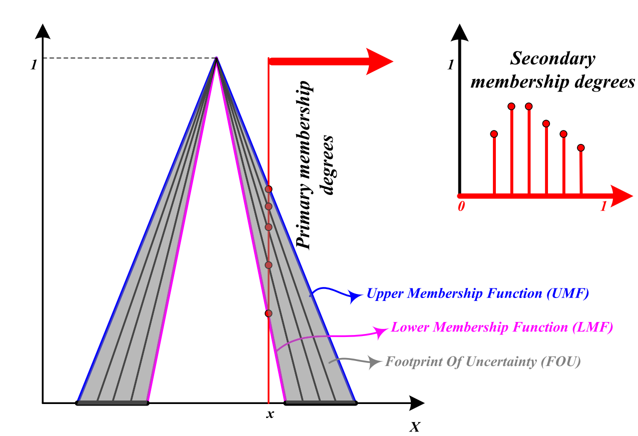


Fig. 1. Example of a type-2 membership function.

$$\tilde{A} = \int_{x\in X}\left[\int_{u\in[\underline{J}_x, \bar{J}_x]} 1/u\right]\Big/ x, \quad [\underline{J}_x, \bar{J}_x] \subseteq [0,1] \tag{2}$$

3.3. Operators of type-2 fuzzy sets

T-conorm and t-norm operations between type-1 fuzzy sets are utilized in order to perform operations as union and intersection on type-2 fuzzy sets since membership degrees of type-2 fuzzy sets are type-1 fuzzy sets (Zarandi, Rezaee, Türksen, & Neshat, 2009). Therefore following definitions are given (adapted from Karnik & Mendel, 1999):

I. The *union* of two type-2 fuzzy sets, $\tilde{A}$ and $\tilde{B}$, is given

$$\tilde{A}\cup\tilde{B} = \int_{x\in X} \mu_{\tilde{A}}(x) \cup \mu_{\tilde{B}}(x) = \int_{x\in X}\left[\int_{u\in\left[\underline{J}_{x(\tilde{A})} \vee \underline{J}_{x(\tilde{B})},\, \bar{J}_{x(\tilde{A})} \vee \bar{J}_{x(\tilde{B})}\right]} 1/u\right]\Big/ x \tag{3}$$

II. The *intersection* of two type-2 fuzzy sets, $\tilde{A}$ and $\tilde{B}$, is given

$$\tilde{A}\cap\tilde{B} = \int_{x\in X} \mu_{\tilde{A}}(x) \cap \mu_{\tilde{B}}(x) = \int_{x\in X}\left[\int_{u\in\left[\underline{J}_{x(\tilde{A})} \wedge \underline{J}_{x(\tilde{B})},\, \bar{J}_{x(\tilde{A})} \wedge \bar{J}_{x(\tilde{B})}\right]} 1/u\right]\Big/ x \tag{4}$$

III. The *complement* of type-2 fuzzy set, $\tilde{A}$, $\bar{\tilde{A}}$ is given

$$\bar{\tilde{A}} \iff \mu_{\bar{\tilde{A}}}(x) = \neg\mu_{\tilde{A}}(x) = \int_{x\in X}\left[\int_{u\in[1-\bar{J}_x, 1-\underline{J}_x]} 1/u\right]\Big/ x \tag{5}$$

3.4. Type-2 fuzzy inference system

Fig. 2 shows the schematic diagram of type-2 FIS. It is similar to type-1 FIS. The only difference is having an additional process, namely; *type-reduction*. Type-2 FISs have type-2 antecedent and/or consequent sets. When an input applied to a type-2 FIS, inference engine computes type-2 output set corresponding to each rule. *Defuzzifier* requires a type-1 fuzzy set to produce crisp output but the output sets of the inference engine are type-2 fuzzy sets. Therefore, *type-reduction* process which aims to transform type-2 fuzzy sets into type-1 fuzzy sets takes place between *defuzzifier* process and *inference* process.

4. Designing a type-2 FIS for technology evaluation

This section proposes a novel framework for technology evaluation that is based on IT2FSSs. Fig. 3 shows general structure of the technology evaluation framework. Following subsections of this section present in details about which data sources are used, how they are derived and processed, and how this structure works, step by step.

4.1. Input processing

Patent counts and *publication counts* are the uncontaminated input sources of this technology evaluation framework. The patent count data is retrieved from the online database of European Patent Office (EPO). European Classification System (ECLA) is used by EPO for carrying out searches of patent applications. ECLA, in

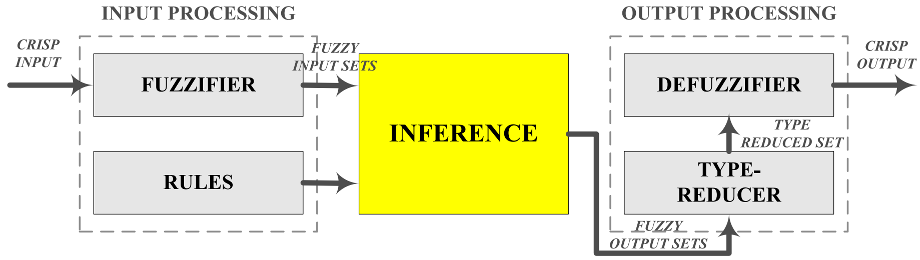


Fig. 2. Structure of type-2 fuzzy inference system.

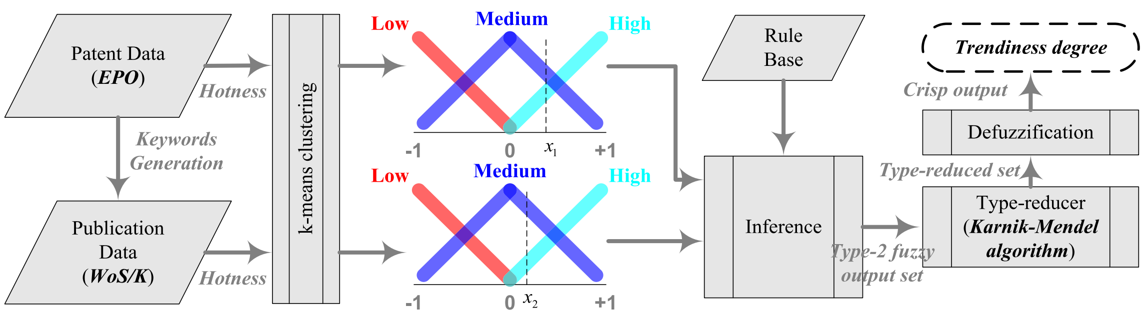


Fig. 3. Technology evaluation framework based on type-2 FIS.

which the entire range of technologies is divided into sections, classes, sub-classes, and groups according to their scope, is used to collect patent data in the corresponding technology groups. For retrieving publication count data, the framework uses online database of Web of Science/Knowledge (WoS/K).

It should be noted here that the transition from resource-based products to knowledge-based products is forcing the new-product-development (NPD) process to be more innovative, and making technological innovation process ever more challenging (Leon, 2009). Preference of customers of today is dissimilar than they had in a few decades ago. *Innovativeness* is getting an important issue beside price and quality when making buying decisions. This change leads to shorten product life cycles. Shortened product life cycles compel companies to be innovative. It can be said that sustainable success on innovation is possible with having culture for innovation. Technology is the core of a technological innovation. Therefore, while evaluating technologies by considering the sustainability, assessment of the corresponding technology classes/subclasses can be more appropriate approach rather than assessment of a specific technology as unit of analysis. The recent literature therefore seems to have taken assessment this direction, whereby classes/subclasses are taken as units of analysis (see Fleming, 2001; Lee, Cho, et al., 2012; Lee, Lee, et al., 2012). For this reason, ECLA classes/subclasses are the core of this technology evaluation framework. For each candidate technology, an ECLA class or subclass is specified. Afterwards, some keywords are needed to be generated to make a connection between patents and their related publications. The selection of keywords is a critical issue because it can greatly influence the results (Bengisu & Nekhili, 2006). Robust selection of the keywords can be accomplished with the help of experts of relevant technology class. For another way, given definitions for the corresponding classes by ECLA can also be very helpful to generate keywords. The generated keywords can be validated through controlling with probability plot of patents and publications trends.

4.2. Generation of fuzzy sets

Taking the amounts of patents and publications into account while generating input fuzzy sets could yield bias since the grade of importance of amount can change from one technology class to another technology class. Use of "*hotness*" values instead of amounts is more appropriate to evaluate trendiness of technologies since it is related with growth rate of technologies that is more suitable for trendiness evaluation. Arman et al. (2009) determine *hotness* values by calculating the number of patents appearing in the last three years as a percentage of those that appeared in the last ten years. In this framework, we measure the *hotness* values in order to evaluate candidate technologies with respect to their trendiness. However, perception of the term, *hotness,* can vary from person to person. Therefore, the term *hotness* is also fuzzy. This framework uses type-2 fuzzy sets in order to handle this uncertainty.

4.3. Design of membership functions

Both patent data and publication data are classified into three clusters as *low*, *medium* and *high.* In this step, in order to find centroids of the clusters, we use a well known technique, namely; *k-means clustering* developed by MacQueen (1967). In the first step of this technique, initial guesses are made for the means of *low*, *medium* and *high*. These points represent initial group centroids. In the next step, every datum of patents and publications are assigned to the cluster that has the closest centroids. These two steps alternate until there are no changes in any mean. The proposed version for clustering patents and publications data into three clusters can be viewed as a greedy algorithm for partitioning the samples into three clusters in order to minimize the sum of the squared distances to the cluster centers. The values limiting these clusters are used to define fuzzy membership functions for a certain patent and publication data. In the design of input fuzzy sets, we use triangular membership functions, these are have been frequently used because of their striking simplicity (Pedrycz, 1994). Having found the centroids of the clusters, in order to find left and right end points, standard deviations of the patent data and publication data can be used.

4.4. Generation of rule-base

After developing the fuzzy sets for each input and output variables, a rule-base is needed to be generated. The framework proposed in this study uses *type-2 FIS* while matching patents and publications as a data-fusion methodology. Therefore, having past experience is not necessary to generate a rule-base. However, it should be known that which data source is more reliable. The rule-base should be generated in accordance with the importance degree of patent and publication data.

Table 1
Patent classes of corresponding candidate technologies.

Candidate	ECLA class	Related technologies
C1	H01B	Cables; Conductors; Insulators; Selection of materials for their conductive, insulating or dielectric properties
C2	H01C	Resistors
C3	H01F	Magnets; Inductances; Transformers; Selection of materials for their magnetic properties
C4	H01G	Capacitors; Capacitors, rectifiers, detectors, switching devices or light-sensitive devices, of the electrolytic type
C5	H01H	Electric switches; Relays; Selectors; Emergency protective devices
C6	H01J	Electric discharge tubes or discharge lamps
C7	H01K	Electric incandescent lamps
C8	H01L	Semiconductor devices; Electric solid state devices not otherwise provided for
C9	H01M	Processes or means, e.g. batteries, for the direct conversion of chemical into electrical energy
C10	H01P	Waveguides; Resonators, lines, or other devices of the waveguide type
C11	H01Q	Aerials
C12	H01R	Line connectors; Current collectors
C13	H01S	Devices using stimulated emission
C14	H01T	Spark gaps; Overvoltage arresters using spark gaps; Sparking plugs; Corona devices; Generating ions to be introduced into non-enclosed gases

4.5. Inference process

Having performed input processing step, inference process is performed as follows:

Consider a rule-base that includes N rules as:

Rule (n): If x_1 is $\widetilde{X}_1^n$ and x_2 is $\widetilde{X}_2^n$ then y is Y^n $n = 1, 2, \ldots, N$.

where $\widetilde{X}_1^n$ are interval type-2 fuzzy sets which are generated from patent data and $\widetilde{X}_2^n$ are interval type-2 fuzzy sets which are generated from publication data. x_1 and x_2 are the calculated patent and publication hotness values of candidate technologies respectively. Y^n amounts are intervals $(= [\underline{y}^n, \bar{y}^n])$ which represents the trendiness in a gradual manner.

Compute the membership of x_1 on each $\widetilde{X}_1^n$, $\left[\mu_{\underline{X}_1^n}(x_1), \mu_{\overline{X}_1^n}(x_1)\right]$, $n = 1, 2, \ldots, N$.

Compute the membership of x_2 on each $\widetilde{X}_2^n$, $\left[\mu_{\underline{X}_2^n}(x_2), \mu_{\overline{X}_2^n}(x_2)\right]$, $n = 1, 2, \ldots, N$.

Compute the firing interval of the nth rule, $F^n(x_1, x_2)$, through

$$F^n(x_1,x_2) = \left[\mu_{\underline{X}_1^n}(x_1) \times \mu_{\underline{X}_1^n}(x_1),\ \mu_{\overline{X}_1^n}(x_1) \times \mu_{\overline{X}_2^n}(x_2)\right] \equiv [\underline{f}^n, \bar{f}^n], \quad n = 1, 2, \ldots, N \tag{6}$$

4.6. Type-reduction process

Type-reduction process aims to convert type-2 fuzzy sets into type-1 fuzzy sets for preparation to defuzzification process. Center of sets ($Y_{\cos}$) type reducer, that is one of the most commonly

Table 2
Annual quantities of corresponding patents.

	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000	1999
H01B	701	686	538	595	558	499	499	458	348	313	300
H01C	94	98	96	81	87	100	87	91	81	61	78
H01F	8167	7656	7426	7222	8145	7789	8147	9082	8062	7440	7356
H01G	4467	4563	4453	4664	4968	4570	4452	4653	3952	3626	2921
H01H	11232	11484	11160	10673	10653	10431	10024	10704	10245	9777	9387
H01J	12479	14033	16496	18528	19311	17614	17222	17531	15388	15097	13438
H01K	604	649	675	895	832	785	800	730	725	626	484
H01L	98112	100000	100000	100000	100000	100000	99209	99696	87813	76647	62951
H01M	25997	25808	25000	23751	22977	21423	20031	18981	15500	12979	10574
H01P	2382	2300	2427	2602	2963	3275	3452	3717	3131	2823	2360
H01Q	8188	8311	8923	9074	9004	8331	7949	8266	7768	6336	5396
H01R	18878	19525	19601	18661	19427	17904	17831	17352	17783	16451	14159
H01S	5909	6072	6661	6896	8193	8546	9412	9747	7972	6544	5808
H01T	1225	1098	1188	1150	1235	1171	1118	1120	1045	966	982

Table 3
Calculated *"hotness"* values of related patents and publications.

	Patents			Publications		
	*hotness*1	*hotness*2	*hotness*3	*hotness*1	*hotness*2	*hotness*3
H01B	0.25241128	0.35031847	0.45859872	0.27841205	0.38002160	0.46729204
H01C	0.20125786	0.30188679	0.38679245	0.31037362	0.40222190	0.48144636
H01F	0.18294177	0.26879942	0.35229847	0.30072004	0.39975112	0.48421295
H01G	0.19095349	0.28511916	0.38374674	0.22750239	0.33111672	0.42182419
H01H	0.19621663	0.29261466	0.38480608	0.38273707	0.47931690	0.55305254
H01J	0.14966946	0.24279512	0.34739213	0.29233578	0.39251002	0.47649936
H01K	0.16053811	0.24702114	0.36169122	0.31525037	0.41957511	0.50569044
H01L	0.19338792	0.29100337	0.38861881	0.24807718	0.35232506	0.43877492
H01M	0.23228754	0.34438461	0.45088130	0.31208353	0.44226874	0.55840285
H01P	0.14895647	0.22617078	0.30895266	0.23797623	0.34567709	0.44185813
H01Q	0.18846092	0.29038448	0.39403285	0.31735356	0.43989074	0.53755386
H01R	0.19437470	0.29358411	0.38803575	0.30524811	0.40579946	0.48691035
H01S	0.14653865	0.22800880	0.31235322	0.23519941	0.34182805	0.43456460
H01T	0.18889250	0.28549357	0.37900471	0.24693790	0.35314775	0.43768736

preferred type-reducers, is used to perform the type-reduction process. $Y_{\cos}$ is expressed as

$$Y_{\cos}(x) = \cup_{\substack{f^n \in F^n(x) \\ y^n \in Y^n}} \frac{\sum_{n=1}^{N} f^n y^n}{\sum_{n=1}^{N} f^n} = [y_l, y_r] \tag{7}$$

y_l and y_r are the end points of the interval set. They are expressed as Eqs. (8) and (9) respectively

$$y_l = \frac{\sum_{n=1}^{L} \bar{f}^n \underline{y}^n + \sum_{n=L+1}^{N} \underline{f}^n \underline{y}^n}{\sum_{n=1}^{L} \bar{f}^n + \sum_{n=L+1}^{N} \underline{f}^n} \tag{8}$$

$$y_r = \frac{\sum_{n=1}^{R} \underline{f}^n \bar{y}^n + \sum_{n=R+1}^{N} \bar{f}^n \bar{y}^n}{\sum_{n=1}^{R} \underline{f}^n + \sum_{n=R+1}^{N} \bar{f}^n} \tag{9}$$

where switch points L and R are specified by $\underline{y}^L \leqslant y_l \leqslant \underline{y}^{L+1}$ and $\bar{y}^R \leqslant y_r \leqslant \bar{y}^{R+1}$.

Karnik–Mendel (KM) algorithm, which is one of the most common approaches in the literature, is employed in order to find switch points for each end points of the interval set. The steps of the algorithm are as follows (Mendel & Wu, 2010).

KM algorithm for computing y_l:

- ***Step1*** – $\underline{y}_n$ values are sorted in increasing order.
- ***Step2*** – The weights $F^n(x)$ are matched with their respective $\underline{y}_n$ values.
- ***Step3*** – f^n are initialized through $f^n = \frac{\underline{f}^n + \bar{f}^n}{2}$ and then y is computed as;

$$y = \frac{\sum_{n=1}^{N} \underline{y}^n f^n}{\sum_{n=1}^{N} f^n}$$

- ***Step4*** – Switch point $k(1 \leqslant k \leqslant N-1)$ is found as $\underline{y}^k \leqslant y \leqslant \underline{y}^{k+1}$.
- ***Step5*** – $f^n = \begin{cases} \bar{f}^n, n \leqslant k \\ \underline{f}^n, n > k \end{cases}$ are set and then y' is computed as;

$$y' = \frac{\sum_{n=1}^{N} \underline{y}^n f^n}{\sum_{n=1}^{N} f^n}$$

- ***Step6*** – Check if $y' = y$. If yes, stop and set $y_l = y$ and $L = k$. If no, go to *Step7*.
- ***Step7*** – Set $y = y'$ and go to *Step4*.

KM algorithm for computing y_r:

- ***Step1*** – $\bar{y}_n$ values are sorted in increasing order.
- ***Step2*** – The weights $F^n(x)$ are matched with their respective $\bar{y}_n$ values.
- ***Step3*** – f^n are initialized through $f^n = \frac{\underline{f}^n + \bar{f}^n}{2}$ and then y is computed as;

$$y = \frac{\sum_{n=1}^{N} \bar{y}^n f^n}{\sum_{n=1}^{N} f^n}$$

Table 4
Keywords generated from each ECLA patent class (Dereli et al., 2010).

	Keywords
H01B	Electric* and (cable* or conductor*) or power cable* or insulator* or conductive bod*
H01C	Resistor*
H01F	"magnet" Or "magnets" or inductance* or transformer* or magnetic film* or conduct* and coil* or armature
H01G	Detector* or capacitor* or rectifier* or switching and device*
H01H	Electric* and switch* or electric* and relay* or electric* and selector* or electric* and fuse* or current fuse*
H01J	Discharge* tube* or discharge* lamp* or X-ray tube* or cathode tube* or photoelectric tube* or vacuum tube* or cathode ray lamp* or transit time tube* or gas filled tube* or ion beam tube*
H01K	Incandescent* lamp*
H01L	Semiconductor* device* or solid* state* device* or "thermo* device*" or electrostrictive device* or magnetostrictive device*
H01M	"electrode and electrolytic*" Or "primary cell*" or "secondary cell*" or "fuel cell*" or "hybrid cell*" or electrochemical battery*
H01P	Waveguide* or resonator* or coupling device* or auxiliary device*
H01Q	Antenna* and (wave* or radiat* or electric* or reflect* or device* or circuit* or transmission* or refract* or difract* or optic*)
H01R	Line* connector* or current* and collector* or current* distributer* or rotary* and current collector*
H01S	Stimulated* and emission* or laser* and red or maser* or wave energy
H01T	Spark* and gap* or overvoltage* and arrester* or spark* and plug* or corona charge* or corona discharge* or spark gap and (oscilliat or rectif) or rotary spark* gap*

Table 6
Center values of the MFs.

	MFs	Patents	Publications
Hotness1	High	0.2423	0.3827
	Medium	0.1921	0.3040
	Low	0.1514	0.2391
Hotness2	High	0.3474	0.4538
	Medium	0.2867	0.4000
	Low	0.2360	0.3448
Hotness3	High	0.4547	0.5497
	Medium	0.3833	0.4837
	Low	0.3302	0.4349

Table 5
Annual quantities of corresponding publications.

	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000	1999
H01B	17 910	17 913	13 074	11 229	11 210	11 317	10 944	9539	8658	8677	8198
H01C	11 266	10 665	6490	5598	5921	6109	6034	5399	4186	4622	4370
H01F	34 302	33 606	22 363	19 073	19 009	18 151	19 089	16 429	14 744	15 436	13 616
H01G	60 132	62 654	55 922	48 956	50 293	49 831	50 160	44 158	38 497	39 656	39 454
H01H	15 359	17 228	8223	6278	6663	6311	6259	4852	4344	4950	4675
H01J	6990	6936	4772	4001	3974	4124	4217	3442	3069	3155	2957
H01K	422	409	275	227	240	195	210	184	151	188	135
H01L	37 171	36 466	30 944	25 661	26 547	27 296	27 556	26 837	19 125	19 802	19 426
H01M	14 548	15 192	12 406	11 067	10 807	9384	7511	5259	3702	3042	2377
H01P	12 774	13 317	11 808	10 545	11 214	10 356	10 352	8454	7108	7167	6542
H01Q	12 768	13 374	10 094	8045	8035	7076	6429	5224	4229	3806	3295
H01R	3826	3648	2462	1986	1880	2098	2020	1742	1608	1672	1543
H01S	2558	2555	2318	2016	2032	1921	1788	1782	1590	1607	1572
H01T	1471	1412	1240	987	1020	1023	1034	873	861	894	860

- ***Step4*** – Switch point $k(1 \leqslant k \leqslant N-1)$ is found as $\bar{y}^k \leqslant y \leqslant \bar{y}^{k+1}$.
- ***Step5*** – $f^n = \begin{cases} \underline{f}^n, n \leqslant k \\ \bar{f}^n, n > k \end{cases}$ are set and then y' is computed as;

$$Y' = \frac{\sum_{n=1}^{N} \bar{y}^n f^n}{\sum_{n=1}^{N} f^n}$$

- ***Step6*** – Check if $y' = y$. If yes, stop and set $y_r = y$ and $R = k$. If no, go to *Step7*.
- ***Step7*** – Set $y = y'$ and go to *Step4*.

4.7. Defuzzification process

Having performed KM algorithm, we reach to value of switch points of the interval set. Afterwards, defuzzified output is computed using

$$y = \frac{y_l + y_r}{2} \tag{10}$$

After defuzzification process, we obtain a crisp value for each candidate technology which shows the *trendiness* of corresponding technology through fusing patent data and publication data. These values are then used to rank the candidate technologies with respect to their trendiness.

5. Evaluation of H01-Basic Electric Elements class

An application of the proposed framework is given in this section. There are fourteen candidate technologies waiting for investment decision. Their technology classes are shown in Table 1. These technologies are evaluated with respect to their trendiness through the proposed technology evaluation framework.

Table 7
Rule-base.

R1	If (Avrg *Hotness* of Patent is *Low*) and (Avrg *Hotness* of Publication is *Low*) then (Trendiness of Technology is [0.1,0.4])
R2	If (Avrg *Hotness* of Patent is *Low*) and (Avrg *Hotness* of Publication is *Medium*) then (Trendiness of Technology is [0.1,0.4])
R3	If (Avrg *Hotness* of Patent is *Low*) and (Avrg *Hotness* of Publication is *High*) then (Trendiness of Technology is [0.4,0.6])
R4	If (Avrg *Hotness* of Patent is *Medium*) and (Avrg *Hotness* of Publication is *Low*) then (Trendiness of Technology is [0.1,0.4])
R5	If (Avrg *Hotness* of Patent is *Medium*) and (Avrg *Hotness* of Publication is *Medium*) then (Trendiness of Technology is [0.4,0.6])
R6	If (Avrg *Hotness* of Patent is *Medium*) and (Avrg *Hotness* of Publication is *High*) then (Trendiness of Technology is [0.6,0.9])
R7	If (Avrg *Hotness* of Patent is *High*) and (Avrg *Hotness* of Publication is *Low*) then (Trendiness of Technology is [0.4,0.6])
R8	If (Avrg *Hotness* of Patent is *High*) and Avrg *Hotness* of Publication is *Medium*) then (Trendiness of Technology is [0.6,0.9])
R9	If (Avrg *Hotness* of Patent is *High*) and (Avrg *Hotness* of Publication is *High*) then (Trendiness of Technology is [0.6,0.9])

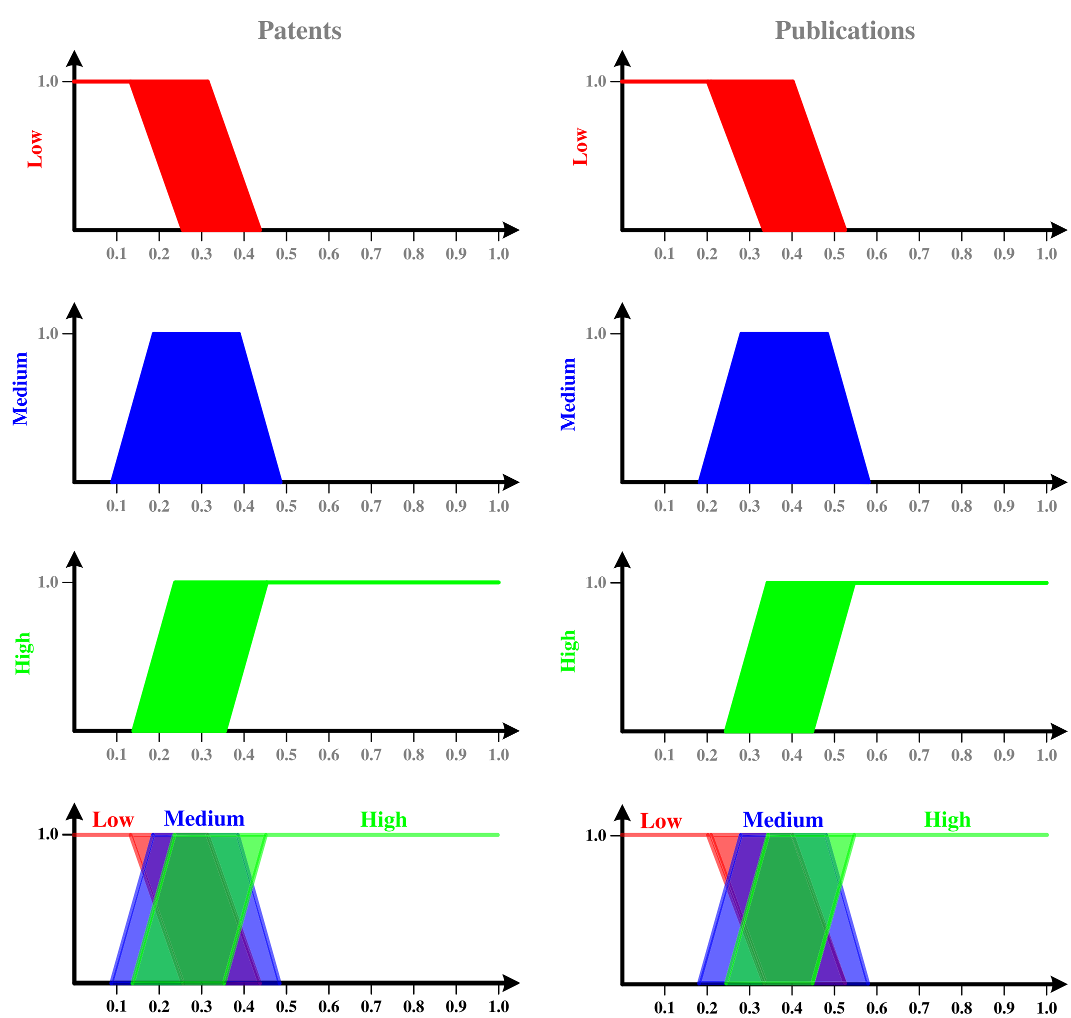


Fig. 4. Type-2 fuzzy input sets for patents and publications.

Initially, patents count data are retrieved from the database of EPO. Table 2 shows the corresponding data. As is discussed in the previous section of this study, the proposed technology evaluation framework uses *hotness* values rather than the amounts of the patents of the related technology classes. Therefore, after reaching the patent count data, they are processed to calculate *hotness* values. Three types of *hotness* values are used to generate type-2 fuzzy input sets for both patents and publications: *hotness*1 (*h*#1), *hotness*2 (*h*#2) and *hotness*3 (*h*#3). While calculating the first types of *hotness* values, i.e., *h*#1, total quantities of last two years are divided by total quantities of last ten years. The second types of *hotness* values, i.e., *h*#2, are calculated by dividing the last three years to last ten years. The total quantities of last four years are divided by total quantities of last ten years for calculating the third types of hotness values, i.e., *h*#3. The *hotness* values derived from corresponding patent classes are shown in Table 3.

Table 4 shows the keywords generated from each ECLA patent class in order to make a link between patents and publications. The keywords are obtained from one of our earlier studies (Dereli et al., 2010). They were determined by using the definitions of the each sub-class. Subsequently, the publications count data are obtained by using the database of WoS/K. *Hotness* values for publications are calculated by using the data of annual quantities of corresponding publications (Table 5).

Calculated hotness values are classified into three groups as *low*, *medium* and *high* for both patents and publications through using *k-means clustering* technique. Table 6 shows the center values of the MFs. Three input type-1 fuzzy sets are obtained for each *hotness* values. Through observing LMFs and UMFs for each linguistic variable, type-2 fuzzy input sets are obtained as shown in Fig. 4.

Beside the generation of input fuzzy sets, *input processing* phase also requires a rule-base for ending the process and starting to subsequent process, i.e., *inference*. The proposed technology evaluation framework uses FIS in order to match two different data sources, i.e., patents and publications. Therefore, generation of a rule-base with respect to earlier experiences and/or opinions of corresponding experts cannot be a feasible and appropriate approach. One way, can be observing similarity of patents and publications trends through probability plot. If the trends are the same, a rule-base that has homogenous consequence distribution can be generated. In other conditions, a rule-base that influences the consequences to more reliable data source should be generated.

Verbeek et al. (2002) paid attention to that some technology fields are highly science oriented while others are not. There are not equal likelihoods for different patent classes to link to science that is published in peer reviewed journals (Boyack & Klavans, 2008). Therefore, *science orientation* of corresponding patent classes also need to be taken into account while generating a rule-base since reliability of publications and patents can change with respect to different patent classes. See Boyack and Klavans (2008) in order to review a map of IPC patent subclasses that includes the distribution of patent classes with high *science orientation* and low *science orientation*. *H01*-Basic Electric Elements class is one of the highest science oriented patent classes. Therefore, by taking into account this property provided by *H01*-Basic Electric Elements class, we generate a rule-base that has homogenous consequence distribution as shown in Table 7.

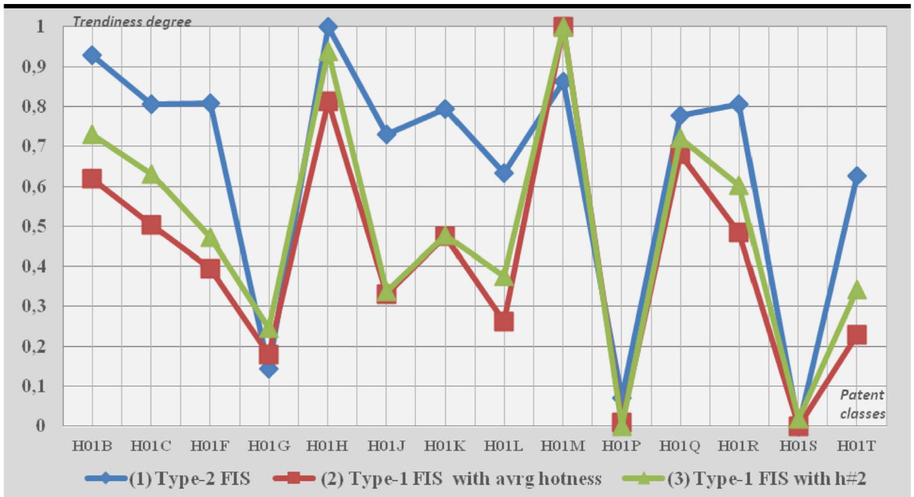
Inference process is ready to produce type-2 fuzzy output sets after finishing the *input processing*. Average *hotness* values of each technology class are the inputs of the inference system. The firing intervals of the nine rules are calculated for each candidate technology. In the type-reduction process, KM algorithm is executed to find the switch points for each end points of the interval set of each candidate technology. After finding the end points, *defuzzification* process is executed. For each candidate technology, type-2 FIS provides a crisp output which represents the trendiness degree that is obtained by matching the data of corresponding patents and publications.

In order to analyze the effect of employing type-2 FIS on the evaluation, the candidate technologies are also evaluated with two different type-1 FISs. While former uses average of the calculated *hotness* values, latter uses only *h*#2 values. Type-1 FIS with average *hotness* camouflages the uncertainty in the definition of the type-2 fuzzy input sets through discarding the spread of membership values by averaging. Type-1 FIS with *h*#2 does not take into account the uncertainty in the definition of the membership functions. Therefore, type-1 FIS with average *hotness* can be considered as a inter phase between the type-1 FIS and the type-2 FIS with respect to handled uncertainties. Table 8 shows the evaluation results for each FIS. The evaluation results are standardized to make range from start (0) to end (1) in order to observe clearly how handling more uncertainty effects the evaluation results.

Fig. 5 shows distribution of standardized values of evaluation results and rankings of the technology classes with respect to their trendiness degrees. When the results are reviewed in terms of trendiness degrees, it is observed that the results of type-2 FIS are generally the highest value whereas the results of type-1 FIS with average *hotness* are generally the lowest value for technology classes except for H01G and H01M. When the results are reviewed in terms of rankings, it is seen that the evaluation results do not affect the ranks of H01K and H01G technology classes. Handling more uncertainties affects the rankings of H01H, H01R, H01F, H01J and H01P technology classes positively. In contrast to this, handling more uncertainties creates a negative effect for H01C, H01L, H01T and H01S technology classes. However, there is not a monotonic relation between uncertainties and technology classes for rankings of H01B and H01Q technology classes.

Table 8
Evaluation results of type-2 FIS, type-1 FIS with average *hotness* and type-1 FIS with *h*#2, and their standardized values.

Patent classes	Type-2 FIS	Standardized to [0,1]	Type-1 FIS with avrg *hotness*	Standardized to [0,1]	Type-1 FIS with *h*#2	Standardized to [0,1]
H01B	0.6233	0.9281	0.5880	0.6201	0.5520	0.7307
H01C	0.6163	0.8056	0.5460	0.5027	0.5180	0.6301
H01F	0.6165	0.8091	0.5070	0.3938	0.4650	0.4733
H01G	0.5785	0.1436	0.4300	0.1787	0.3880	0.2455
H01H	0.6274	1	0.6570	0.8128	0.6220	0.9378
H01J	0.6120	0.7302	0.4840	0.3296	0.4190	0.3372
H01K	0.6156	0.7933	0.5360	0.4748	0.4660	0.4763
H01L	0.6064	0.6322	0.4600	0.2625	0.4320	0.3757
H01M	0.6196	0.8633	0.7240	1	0.6430	1
H01P	0.5743	0.0700	0.3690	0.0083	0.3050	0
H01Q	0.6147	0.7775	0.6100	0.6815	0.5490	0.7218
H01R	0.6163	0.8056	0.5390	0.4832	0.5090	0.6035
H01S	0.5703	0	0.3660	0	0.3110	0.0177
H01T	0.6061	0.6269	0.4480	0.2290	0.4210	0.3431



FIS \ *Rank*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*
(1)	H01H	H01B	H01M	H01F	H01R	H01C	H01K	H01Q	H01J	H01L	H01T	H01G	H01P	H01S
(2)	H01M	H01H	H01Q	H01B	H01C	H01R	H01K	H01F	H01J	H01L	H01T	H01G	H01P	H01S
(3)	H01M	H01H	H01B	H01Q	H01C	H01R	H01K	H01F	H01L	H01T	H01J	H01G	H01S	H01P

Fig. 5. Evaluation results of the FISs and rankings of the technology classes.

It has been observed that handling more uncertainties can affect the evaluation results of candidate technologies and prioritizing of them by the help of this comparison. The use of IT2FSSs enables us to handle more uncertainties. Handling more uncertainties provides more realistic solutions to problems because of decreasing assumptions made while modeling. The use of IT2FSSs provides a richer platform in the definition of the MFs. While Dereli and Altun (2013) camouflage the uncertainty in the definition of the MFs by averaging, the use of IT2FSSs enables us to computing with perceptions that shows discrepancy in the definition of MFs and hence to handle more uncertainties. Therefore, it is believed that the evaluation results of IT2FSSs are more accurate and robust when compared with type-1 counterpart presented in Dereli and Altun (2013).

6. Concluding remarks and future work

Evaluation and consideration of "*trendiness*" of candidate technologies is one of the most important prerequisites in order (i) to make rational investment decisions (ii) to draw strategic roadmaps and (iii) to direct investments and incentives to the most rewarding technologies. This study presents a novel framework in order to evaluate candidate technologies according to their "*trendiness*". This framework makes use of an interval type-2 fuzzy inference system which matches relevant publication and patent data to infer about the *trendiness* of candidate technologies. We employed interval valued type-2 fuzzy sets since full types of type-2 fuzzy sets are computationally complex.

In order to demonstrate how it works, an ECLA class – H01-Basic Electric Elements – is evaluated by way of the proposed framework. How the results change upon the uncertainties handled in the problem in consideration is investigated by comparison with the results of the type-1 counterpart of the proposed framework. Because of the utilization of interval valued type-2 fuzzy sets actually handles the uncertainties (e.g. the description of the hotness values corresponding to patents and publication, etc.) and provides for making fewer assumptions on technology evaluations, the results are believed to be more realistic than those of the type-1 counterparts.

The main contribution of this study is the demonstration of usefulness of fuzzy logic in technology evaluation by presenting a unique framework. In addition to the theoretical contribution described above, this study has also provided new insights for making business policy. As is discussed in the second section of this paper, this study is an extension of a part of one of our preliminary studies (Dereli & Altun, 2013) which proposes a novel approach for the assessment of candidate technologies with respect to their innovation potentials. While evaluating innovation potentials of candidate technologies, we proposed a process that also includes an evaluation phase considering trendiness of the candidate technologies. The technology evaluation framework proposed in this study therefore improves the innovation potential evaluation process described in Dereli and Altun (2013) and hence, improves the business policy making by matching patents and publications data in a more concrete way. Thus, the focus and attention of business policy makers as well as investors can be directed into science-oriented and trendy technologies. The effective consideration of *science orientation* degree of candidate technologies in the technology evaluation process can enhance decisions (e.g. on investment and incentives) by directing considerations into the technological innovations, which are more value-added and not easy to imitate because of the inclusion of more tacit knowledge, etc.

This study has used *hotness* indices for evaluation of trendiness. Utilization of the hotness indices has some limitations in the case of the range between the quantities of patent and the publication of candidate technologies is considerably higher. In order to overcome this obstacle, future research can potentially address the use of more precise and reliable indices for trendiness detection. When the advancements on fuzzy logic become applicable easily, future work can address the use of full type-2 fuzzy logic and fuzzy functions within a technology evaluation framework in order to handle existing uncertainties more comprehensively.

Acknowledgments

The authors would like to thank the anonymous reviewers for their valuable comments, suggestions and corrections, which greatly improved the quality of the paper. The authors would also like to acknowledge the financial support provided by Scientific Research Projects Governing Unit (BAPYB) of Gaziantep University and The Scientific and Technological Research Council of Turkey (TUBITAK).

References

Arman, H., Hodgson, A., & Gindy, N. (2009). Technologies watch exercise: Foresight approach enhanced with scientific publications and patents analysis. *International Journal of Technology Intelligence and Planning, 5*, 305–321.

Bengisu, M., & Nekhili, R. (2006). Forecasting emerging technologies with the aid of science and technology databases. *Technological Forecasting and Social Change, 73*, 835–844.

Boyack, K. W., & Klavans, R. (2008). Measuring science–technology interaction using rare inventor–author names. *Journal of Informetrics, 2*, 173–182.

Celikyılmaz, A., & Türksen, I. B. ((2009). *Modeling uncertainty with fuzzy logic*. In *Studies in fuzziness and soft computing*. Springer Book Series.

Daim, T. U., Rueada, G., Martin, H., & Gerdsri, P. (2006). Forecasting emerging technologies: Use of bibliometrics and patent analysis. *Technological Forecasting & Social Change, 73*, 981–1012.

Dereli, T., & Altun, K. (2013). A novel approach for assessment of candidate technologies with respect to their innovation potentials: Quick innovation intelligence process. *Expert Systems with Applications, 40*(3), 881–891.

Dereli, T., Baykasoglu, A., Altun, K., Durmusoglu, A., & Türksen, I. B. (2011). Industrial applications of type-2 fuzzy sets and systems: A concise review. *Computers in Industry, 62*, 125–137.

Dereli, T., Durmusoglu, A., Altun, K., Bozyer, Z. (2010). Predicting the future of technology by using data fusion methodologies: Techpredict v1.0. In *Proc. of the 7th international symposium on intelligent manufacturing systems (IMS 2010)* (pp. 215–223).

Dvorkin, E.N. (2010). Argentina: the development of science based technology. In *Engineering 2010 – Argentina – ISTIC – UNESCO workshop, science, engineering and productive enterprise*.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science, 47*(1), 117–132.

Geisler, E. (2002). The metrics of technology evaluation: Where we stand and where we should go from here. *International Journal of Technology Management, 24*(4), 341–374.

Geisler, E. (2005). The measurement of scientific activity: Research directions in linking philosophy of science and metrics of science and technology outputs. *Scientometrics, 62*(2), 269–284.

Huang, L., Li, Y. (2010). Evaluation frame of technological developing trend based on patent information. In *Proceedings of 12th international conference on computer modelling and, simulation* (pp. 299–304).

John, R., & Coupland, S. (2009). Type-2 fuzzy logic and the modelling of uncertainty in applications. *Human-Centric Information Processing*, 185–201.

Karnik, N. N., & Mendel, J. M. (1999). Applications of type-2 fuzzy logic systems to forecasting of time-series. *Information Sciences, 120*, 89–111.

Karnik, N. N., Mendel, J. M., & Liang, Q. (1999). Type-2 fuzzy logic systems. *IEEE Transactions on Fuzzy Systems, 7*(6), 643–658.

Kazemzadeh, A., Lee, S., & Narayanan, S. S. (2008). An interval type-2 fuzzy logic system to translate between emotion-related vocabularies. *Interspeech*, 2747–2750.

Lee, C., Cho, Y., Seol, H., & Park, Y. (2012). A stochastic patent citation analysis approach to assessing future technological impacts. *Technological Forecasting and Social Change, 79*(1), 16–29.

Lee, S., Lee, H., & Yoon, B. (2012). Modeling and analyzing technology innovation in the energy sector: Patent-based HMM approach. *Computers & Industrial Engineering, 63*(3), 564–577.

Leon, N. (2009). The future of computer-aided-innovation. *Computers in Industry, 60*, 539–550.

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of 5th berkeley symposium on mathematical statistics and probability* (Vol. 1, pp. 281–297). Berkeley: University of California Press.

Martino, J. P. (2003). A review of selected recent advances in technological forecasting. *Technological Forecasting & Social Change, 70*, 719–733.

Mendel, J. M., John, R. I., & Liu, F. (2006). Interval type-2 fuzzy logic systems made simple. *IEEE Transactions on Fuzzy Systems, 14*(6), 808–821.

Mendel, J. M., & Wu, D. (2010). *Perceptual computing: Aiding people in making subjective judgments*. IEEE Press Series on Computational Intelligence.

Pedrycz, W. (1994). Why triangular membership functions? *Fuzzy Sets and Systems, 64*, 21–30.

Pendlebury, D.A. (2008). *Using bibliometrics in evaluating research*. White paper, Thomson Reuters.

Porter, A. L., & Cunningham, S. W. (2005). *Tech mining: Exploiting new technologies for competitive advantage*. New Jersey: Wiley.

Quintella, C. M., Hatimondi, S. A., Musse, A. P. S., Miyazaki, S. F., Cerqueira, G. S., & Moreira, A. A. (2011). CO_2 capture technologies: An overview with technology assessment based on patents and articles. *Energy Procedia, 4*, 2050–2057.

Stine, D.D. (2009). *Science and technology policymaking: A primer*. Congressional Research Service.

Türksen, I. B. (2002). Type-2 representation and reasoning for CWW. *Fuzzy Sets and Systems, 127*, 17–36.

Verbeek, A., Debackere, K., Luwel, M., Andries, P., Zimmermann, E., & Deleus, F. (2002). Linking science to technology: Using bibliographic references in patents to build linkage schemes. *Scientometrics, 54*(3), 399–420.

Yu, W. D., & Lo, S. S. (2009). Patent analysis-based fuzzy inference system for technological strategy planning. *Automation in Construction, 18*(6), 770–776.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*, 338–353.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning-1. *Information Sciences, 8*, 199–249.

Zarandi, M. H. F., Rezaee, B., Türksen, I. B., & Neshat, E. (2009). A type-2 fuzzy rule-based expert system model for stock price analysis. *Expert Systems with Applications, 36*, 139–154.

Zhang, Y., Zhu, D., Wang, X., Guo, Y., Chen, H., Liu, C., et al. (2011). Composing technology roadmapping according to bibliometrics: Hybrid model and empirical study. In *Proc. of CSIT: International conference on computer communication and management* (Vol. 5, pp. 405–410).