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A novel approach to augment technology roadmapping through systematic innovation intelligence: a case of UAV technologies

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Abstract

Technology roadmapping has been employed for years as an important tool for managing technology and innovation. The latest discussions in technology roadmapping go beyond the T-plan, which is the most popular roadmapping process based on a few workshops of experts. Developing data-driven approaches to modernize this roadmapping process is an active area of research. In parallel with these efforts, we explore a new unified approach in this study by integrating an innovation intelligence process into roadmapping. This systematic innovation intelligence process incorporates relevant patent and publication data, and its methodology is based on topic modeling and type-2 fuzzy sets. Through this unified approach, we provide an augmented technology roadmapping schema that involves technology trendiness infographics. This study illustrates how this approach is executed by providing a case study on unmanned aerial vehicle (UAV) technologies.

Keywords: Innovation intelligence, technology roadmapping, UAV technologies.

1. Introduction

It is becoming apparent that technology management is no longer just a preference, but rather a necessity. The strategic plans of players at any scale incorporate acquisition and exploitation strategies for emerging and available technologies. These strategic management activities are frequently guided by a systematic approach commonly known as “technology roadmaps”.

Technology roadmapping is a long-term planning tool that links technology to businesses, according to Petrick and Echols (2004). The pioneering work on technology roadmapping was undertaken by Willyard and McClees (1987) at Motorola.

There are different types of technology roadmaps shaped by their purpose of use, according to Milshina and Vishnevsky (2019), and this is because of the absence of a standard process for their elaboration. Furthermore, a recent study by Park et al. (2020) revealed the development of seven distinctive “schools of thought”, which may result in multiple approaches to technology roadmapping (Zhang et al., 2021).

Eight different graphical formats have been identified for technology roadmaps; multiple layers, bars, tables, graphs, pictorial representations, flow charts, single-layer, and text (Jin et al., 2015). The most common version is a roadmap including multiple layers and a network of element relations on a yearly-based timeline. of The European Industrial Research Management Association (EIRMA) Working Group #52 has introduced a generic framework for technology roadmap (EIRMA, 1997). Figure 1 provides an illustrative view of this roadmap.

In practice, effective workshops and systematic implementation procedures are required to obtain a useful technology roadmap. It is true that this process may progress in different ways depending on the topic being worked on and other factors related to the implementers. However, a generic process, frequently highlighted in the literature is the “T-plan” process by Phaal et al. (2004) at the Cambridge University Institute for Manufacturing.

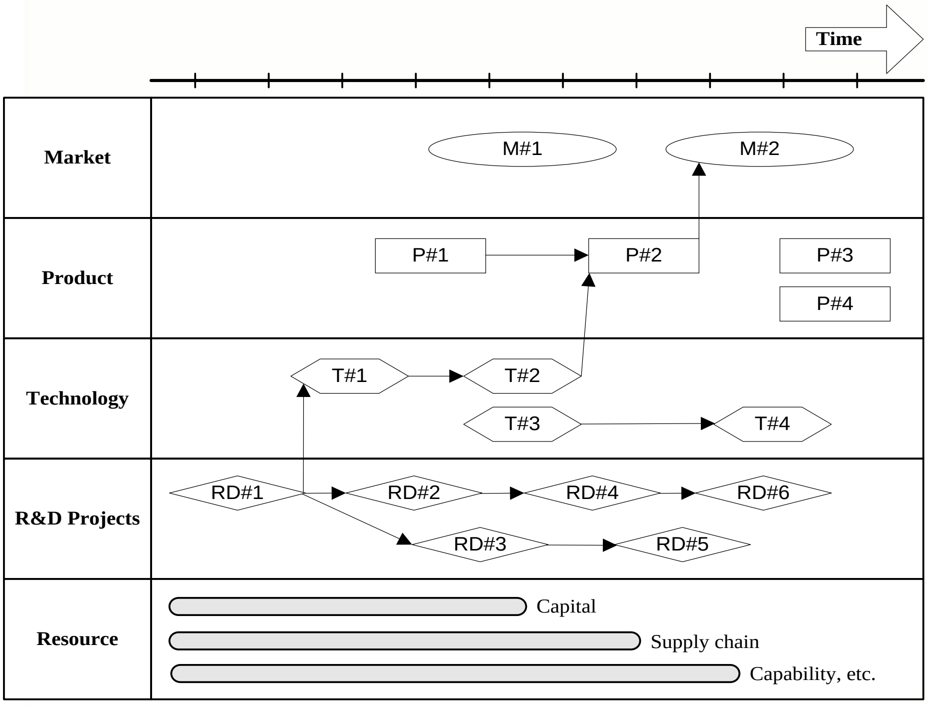


Fig. 1. An illustration of a typical product-technology roadmap.

The T-plan process is also known as the "fast-start" workshop technique. It is a procedure specialized in product-technology roadmapping. Its more general variant, addressing strategic issues as well, is called the "S-plan". Groups of cross-functional stakeholders conduct serial workshops for technology roadmapping. Although the number of the workshops depends on the layers of the planned roadmap, there are generally four serial workshops to address market, product, technology, and charting, respectively. Further details on running a fast-start workshop can be found in Phaal et al (2013).

A group of experts in the area of interest (which might involve 8-12 experts) drive these workshops in practice. The main challenge is finding these experts, particularly at the corporate level. A significant amount of work has been carried out in this area, and an up-to-date overview of themes and methods used for technology roadmapping is presented in de Oliveira Valerio et al. (2020). A concise list of successful implementations and application areas of technology roadmapping is provided in Zhang et al. (2021). A bibliometric literature review clustering the emerging research streams of technology roadmapping can also be found in Vinayavekhin et al. (2021). Quantitative tools and techniques have been integrated into roadmapping workshops to quantify the process, and different technology management activities and decision modeling approaches have also been incorporated. In recent years, according to de Oliveira Valerio et al. (2020), there has been an increased interest in exploring data-driven approaches to modernize technology roadmapping.

High technology is favoring planning in the recent trend of technology roadmapping. Recent studies in the literature aim to develop new perspectives through data-driven approaches. Data-driven market and technology intelligence can contribute to discovering technological opportunities. Scientific publications and patents have been the major data sources of these data-driven approaches. Advances in data analytics handling these patent and publication data can enhance these expert-centric workshops as well. Correspondingly, in a recent study by Son et al. (2020), technology roadmapping in the big data era has been discussed, and fuzzy cognitive maps and text mining have been employed. In another study by Son and Lee (2019), type-1 fuzzy set theory has been employed to analyze the element relations in technology roadmapping. Barip and Altun (2022) have also provided a type-2 fuzzy systems-based approach to analyze the element relations. The reader is directed to the overviews of de Oliveira Valerio et al. (2020) and Winkowski (2020) for further reading.

Patents and scientific publications have been the main data sources for monitoring technology development and evaluating the competitive environment (Trappey et al., 2011). As discussed by Wang and Chen (2019), mapping the relationship between scientific and technological knowledge can facilitate the discovery of technological innovation opportunities. Recent trends confirm that incorporating the experience of the technology intelligence literature (which is highly data-driven and uses advanced data analytics and algorithms to analyze patent and publication data) into the technology roadmapping has a complementary effect. There is still a great deal of work to be done in this area. In this respect, this study proposes a novel approach to augment technology roadmapping by integrating an "innovation intelligence" process, which is also considered to have a complementary effect.

This innovation intelligence process incorporates relevant patent and publication data, and its methodology is based on topic modeling and type-2 fuzzy sets. The augmented technology roadmapping proposed in this study enables assessment of the innovation potentials resulting from this integration and visualizes this assessment through infographics. This is where the novelty of this work lies. The study illustrates how this augmented technology roadmapping is executed by providing a case study on Unmanned Aerial Vehicle (UAV) technologies.

The remainder of this study is organized as follows: Section 2 introduces the methodology, an illustrative implementation addressing UAV technologies is presented in Section 3, and concluding remarks are provided in the last section.

2. Methodology

This study presents an augmented technology roadmapping approach aimed at improving the roadmapping process through data-driven innovation intelligence. This approach is based on a methodology involving four main phases, which are described in the following subsections with further details:

(1) Keyword generation for the main topic
(2) Topic modeling to determine the elements
(3) Assessing the trendiness of the elements by using the quick innovation intelligence process
(4) Network visualization.

2.1 Keyword generation for the main topic

To retrieve related data from the publication and patent database, a concise list of keywords is needed. It is common for different terms to be used to describe the same topic. For example, "autonomous driving" and "autonomous vehicle" may both be used. To obtain a list of the most relevant keywords for any given topic, keyword suggestion tools of search engine optimization (SEO) can be used, resulting in reliable keyword lists.

2.2 Topic modeling to determine the elements

Topic modeling is an unsupervised machine learning method used to extract meaningful information from large amounts of text sources. It automatically clusters similar expressions into phrases that best characterize the document set. In topic modeling, abstract topics are generated by clustering words that frequently appear together in the text, and related texts are assigned to one or more clusters based on the words they contain. Comprehensive reviews on topic modeling can be found in Vayansky and Kumar (2020) and Kherwa and Bansal (2018). There are many topic modeling methods in the literature, and determining which method best suits the case under consideration is not an easy task. Vayansky and Kumar (2020) also provide a very practical decision tree on this matter. Among the topic modeling methods, the most widely used one is the "LDA - Latent Dirichlet Allocation". The use of LDA is recommended for cases where the number of words in the documents being studied is more than 50 and complex topic relations are not expected. This study proposes the use of the LDA method (see Jelodar et al., 2019).

Having completed the keyword generation phase, we can now obtain the relevant patent and publication data. By processing this data set using topic modeling techniques (e.g., LDA - Latent Dirichlet Allocation), we can determine the elements of the product and technology layers. This phase is crucial when experts are unable to list the elements based on their knowledge and experience. It allows for more reliable keyword lists to be defined for each element of the product and technology layers.

2.3 Assessing trendiness of the elements

In this phase, the corresponding patent and publication data are retrieved from the databases such as WoS - Web of Science for the publications and WIPO IP Portal for the patents. An innovation intelligence process based on interval type-2 fuzzy system computes the trendiness of each element by processing these obtained patent and publication data. This trendiness evaluation process is based on a methodology proposed by Dereli and Altun (2013), and an overview of this framework is provided in Figure 2.

This framework uses patent data retrieved from online patent office databases and publication data retrieved from the Web of Science/Knowledge (WoS/K).

The keywords generated in previous phases connect the patents and their related publications. The hotness of the growth rate of technologies is the main input parameter of this framework. Type-2 fuzzy sets are used to handle the uncertainty of this fuzzy term "hotness" in this framework. The k-means clustering developed by MacQueen (1967) finds centroids of the clusters: low, medium, and high. These centroids and the values limiting these clusters are needed to define triangular membership functions. A fuzzy rule base maps the relationship between patent and publication data, and the inference process incorporating the Karnik-Mendel algorithm (Mendel and Wu, 2010) determines the trendiness degrees. For further details, see Dereli and Altun (2013).

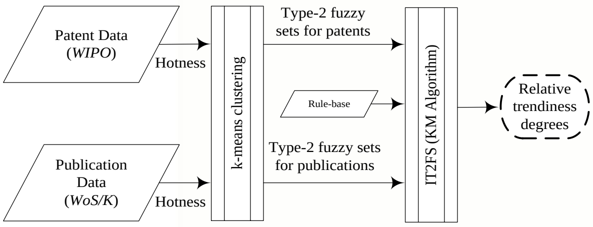


Fig. 2. The framework fusing the patent and publication data.

2.4 Network visualization through bubbles

The ultimate goal of this approach is to obtain an augmented technology roadmap, as illustrated in Figure 3, to assist decision-makers through network visualization. This augmented technology roadmap includes bubble diagrams, where each bubble represents a node of the elements' network. These bubbles are based on patent and publication data corresponding to these elements, and their radius of is proportional to the relative volumes of the patent and publication data. Their colors, on the other hand, are based on the trendiness degrees computed in the previous phase.

3. A case of UAV technologies

3.1 Keyword generation for UAV technologies

To retrieve related data on UAV technologies, a keyword list was created using an SEO keyword research tool called "Semrush". This type of tool checks keywords that have the most traffic in website rankings on Google and finds the most relevant keywords for the niche. When the keyword "unmanned aerial vehicle" is searched in this tool, relevant keywords are obtained. The following query uses these keywords to retrieve relevant data.

"Unmanned Aerial Vehicle" related keywords:

TS = "unmanned aerial vehicle" OR "unmanned airborne vehicle" OR "aerial drone system" OR "unmanned aircraft system" OR "uav aircraft" OR "uas vehicle"

3.2 Topic modeling to determine the elements

Having completed the previous phase, topic modeling is conducted to identify the elements of product and technology layers. The query "unmanned aerial vehicle" created in the first phase can be used to retrieve the dataset for topic modeling. However, technology roadmapping for UAV technologies has been addressed in the literature. One recent study in the literature is that of Son et al. (2020), where they conducted topic modeling (using LDA) for UAV technologies by considering 3,236 textual documents. In this phase, this study employs the results of Son et al. (2020). The following queries are used to retrieve relevant data.

Elements of the "product" layer and their queries:

P1-Internet service: TS = "broadband" OR "mobile" OR "cloud" OR "server" OR "wireless" OR "density" OR "database"

P2-Entertainment: TS = "heritage" OR "program" OR "entertainment" OR "recording" OR "highlight" OR "gathering" OR "library" OR "briefing" OR "soccer" OR "tourism" OR "storage" OR "voyage" OR "racing" OR "motion" OR "climbing"

P3-Warfare and weapons: TS = "agent" OR "capture" OR "captain" OR "gear" OR "veteran" OR "cruise" OR "war" OR "kill" OR "power" OR "military" OR "repression" OR "force" OR "fuel" OR "imprisonment" OR "murder" OR "secret" OR "squadron" OR "artillery"

P4-Disaster and safety: TS = "police" OR "storm" OR "evacuation" OR "die" OR "coast" OR "surge" OR "travel" OR "hurricane" OR "flood" OR "hazard" OR "cold" OR "instability" OR "violate" OR "vulnerability" OR "warrant" OR "prevention" OR "hazard" OR "criminal"

P5-Agricultural support: TS = "farming" OR "zoning" OR "mark" OR "crop" OR "imagery" OR "deforestation" OR "forest" OR "screen" OR "verification" OR "pollution" OR "chemical" OR "livestock" OR "tracking" OR "seed" OR "conservation"

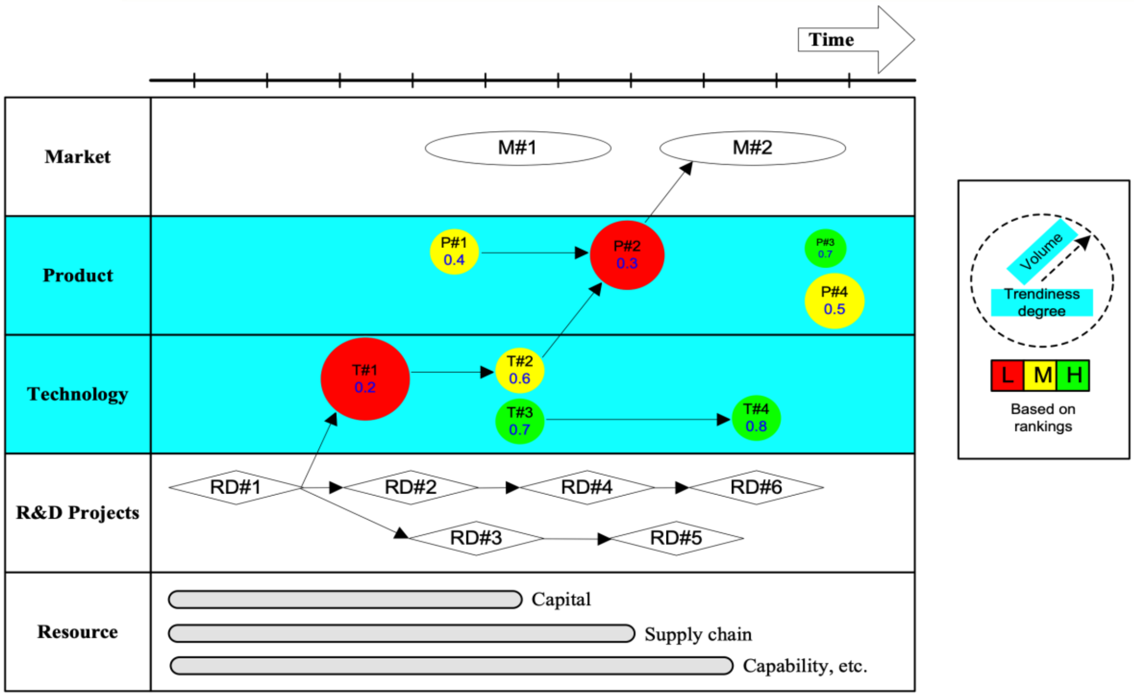


Fig. 3. Augmented technology roadmap through patent and publication data.

P6-Logistics: TS = "transport" OR "packaging" OR "docking" OR "delivery" OR "workplace" OR "shipping" OR "shopping" OR "precision" OR "neighborhood" OR "membership" OR "door" OR "subsidy" OR "unemployment"

Elements of the "technology" layer and their queries:
T1-Software technology: TS = "hunting" OR "observation" OR "biometric" OR "monitoring" OR "precedent" OR "treatment" OR "improve" OR "risk" OR "development" OR "assessment" OR "analytic" OR "framework" OR "storage" OR "warning" OR "response" OR "prevention"
T2-Detection avoidance: TS = "obstacle" OR "control" OR "landing" OR "sonar" OR "carrier" OR "collision" OR "avoidance" OR "robotics" OR "travel" OR "platform" OR "shadow" OR "cruise" OR "awareness" OR "scan" OR "image" OR "drop" OR "altitude" OR "velocity"
T3-Navigation technology: TS = "pilot" OR "radar" OR "processing" OR "monitoring" OR "access" OR "miss" OR "return" OR "reliability" OR "driving" OR "navigation" OR "telecommunication" OR "traffic" OR "gps" OR "control"
T4-Platform and power technology: TS = "imprisonment" OR "censorship" OR "injustice" OR "tyranny" OR "repression" OR "plutocracy" OR "genocide" OR "cruelty" OR "prosecutor" OR "campaigning" OR "coup" OR "impunity" OR "punishment" OR "reconnaissance"

3.3 Assessing trendiness of the elements

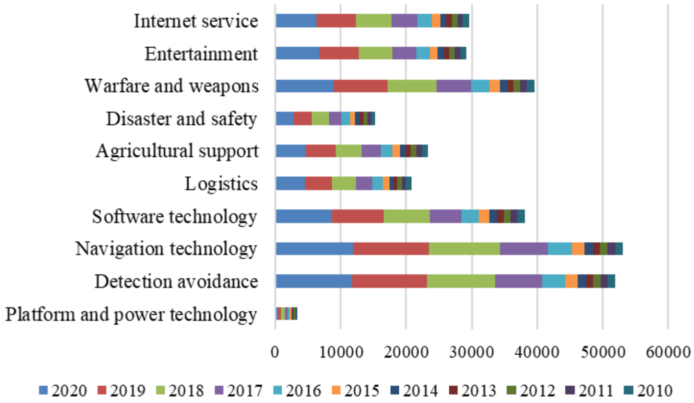
In this phase, data on the number of publications and patents from the last ten years are retrieved from the databases of WoS/K and WIPO IP Portal, respectively (see Table 1 and Table 2). The framework illustrated in Figure 2 is then executed to obtain the relative trendiness degree of each element considered.

According to this framework, hotness values are calculated and then clustered using the k-means clustering algorithm. Subsequently, fuzzy membership functions are determined for patents and publications, resulting in tags of "low", "medium", and "high" (see Table 3).

This framework uses the Karnik-Mendel (KM) algorithm (Mendel and Wu, 2010) for fuzzy inference. The input parameters of this fuzzy inference system are the average hotness values calculated for each roadmap element. A fuzzy rule base is used to map the relationship between patents and publications (see Dereli and Altun, 2013).

The framework uses these average hotness values and their firing intervals to infer the trendiness degree of each element by executing the following inference procedure:

Table 1. Patent data for the identified elements (retrieved from WIPO IP Portal)



	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011
Platform and power technology	443	479	507	465	353	221	224	142	194	192
Detection avoidance	11718	11494	10423	7064	3567	1898	1327	1045	1135	1075
Navigation technology	11850	11661	10843	7225	3674	1922	1365	1070	1143	1094
Software technology	8652	7860	7091	4870	2671	1552	1212	1001	1050	1018
Logistics	4549	4142	3567	2572	1568	968	705	599	659	670
Agricultural support	4709	4543	3973	2894	1823	1134	885	751	854	814
Disaster and safety	2808	2814	2570	1967	1241	810	671	557	569	574
Warfare and weapons	8941	8157	7586	5224	2809	1569	1150	968	1039	986
Entertainment	6751	6024	5128	3682	2030	1229	920	794	854	819
Internet service	6243	6022	5427	3970	2259	1287	955	773	864	843

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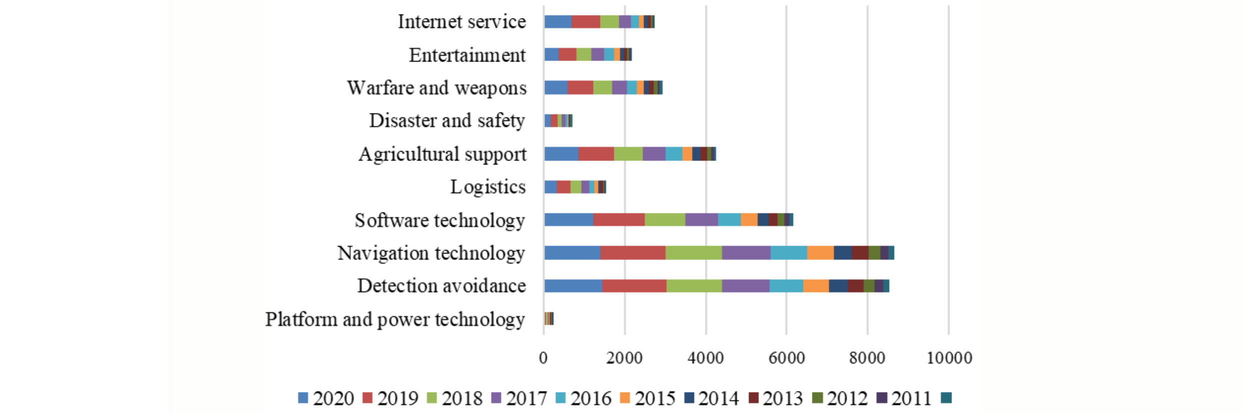
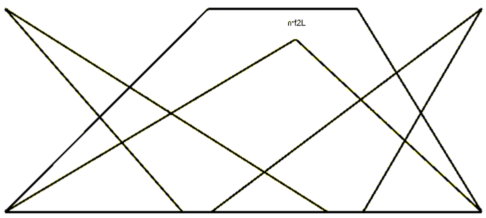
Table 2. Publication data for the identified elements (retrieved from WoS/K)



	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011
Platform and power technology	24	34	36	23	10	14	15	18	26	14
Detection avoidance	1439	1602	1361	1177	838	620	459	394	280	205
Navigation technology	1395	1622	1387	1191	916	654	449	404	293	194
Software technology	1234	1252	1023	801	561	416	271	212	161	124
Logistics	324	335	264	201	137	84	61	54	31	19
Agricultural support	863	871	711	567	415	247	202	148	114	62
Disaster and safety	186	151	111	86	53	38	28	17	15	7
Warfare and weapons	589	627	478	368	239	161	133	133	84	59
Entertainment	381	434	364	320	231	159	91	75	61	41
Internet service	679	724	450	292	195	132	103	77	44	25

Table 3. Fuzzy membership functions for the patent and publication data

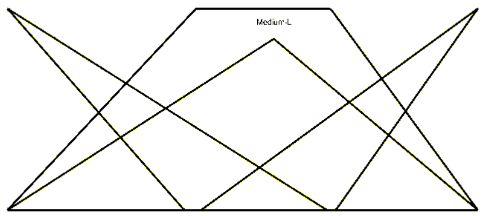
Fuzzy MFs for the *patent* data



Limits of the MFs
Low-U: [0 0 0.6768 1]
Low-L: [0 0 0.3725 1]
Medium-U: [0 0.4262 0.7387 1 1]
Medium-L: [0 0.6098 1 0.85]
High-U: [0.4326 1 1 1]
High-L: [0.7514 1 1 1]

Input values (avrg hotness)
Platform and power technology: 0,4185
Detection avoidance: 0,6257
Navigation technology: 0,6246
Software technology: 0,5995
Logistics: 0,5749
Agricultural support: 0,5523
Disaster and safety: 0,5260
Warfare and weapons: 0,6040
Entertainment: 0,5976
Internet service: 0,5812

Fuzzy MFs for the *publication* data



Limits of the MFs
Low-U: [0 0 0.6796 1]
Low-L: [0 0 0.3761 1]
Medium-U: [0 0.401 0.6868 1 1]
Medium-L: [0 0.5662 1 0.85]
High-U: [0.4114 1 1 1]
High-L: [0.698 1 1 1]

Input values (avrg hotness)
Platform and power technology: 0,3848
Detection avoidance: 0,5090
Navigation technology: 0,5010
Software technology: 0,5580
Logistics: 0,5914
Agricultural support: 0,5626
Disaster and safety: 0,6298
Warfare and weapons: 0,5646
Entertainment: 0,5326
Internet service: 0,6544

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

where $\tilde{X}_1^n$ are the MFs which are generated from patent data and $\tilde{X}_2^n$ are the MFs which are generated from publication data. x_1 and x_2 are the average hotness values of the elements, respectively. Y^n values are intervals ($=[\underline{y}^n, \bar{y}^n]$) representing the trendiness degree.

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

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

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

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

These type-2 fuzzy sets transform into their type-1 counterparts in the type-reduction process. This framework prefers to use the center of sets ($Y_{\cos}$) type reducer expressed as the following equation:

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

where y_l and y_r are the endpoints of the interval set. These points are expressed in the following equations, respectively.

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

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

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

The KM algorithm (see Mendel and Wu, 2010) is executed for computing y_l and y_r. The following equation provides the defuzzified outputs corresponding to the trendiness degrees:

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

After execution of this fuzzy inference process, the trendiness degrees of each corresponding roadmap element are quantified (see Table 4 for the quantified trendiness degrees).

Table 4. Relative trendiness degrees of the elements and volume of the patents

	Bubble Color (Red, Yellow, Green)			Bubble Size (Small, Moderate, Big)		
	Relative trendiness degrees	Ranking	Bubble color	Number of the last three years' patent (Volume)	Standardize the volume to [1, 4] interval	Bubble size
Platform and power technology	0.426	9	Red	1429	1.00	Small
Detection avoidance	0.5118	5	Yellow	33635	3.93	Big
Navigation technology	0.5099	7	Red	34354	4.00	Big
Software technology	0.5159	4	Yellow	23603	3.02	Big
Logistics	0.5178	3	Green	12258	1.98	Small
Agricultural support	0.5072	8	Red	13225	2.07	Moderate
Disaster and safety	0.5159	4	Yellow	8192	1.61	Small
Warfare and weapons	0.5181	2	Green	24684	3.11	Big
Entertainment	0.5105	6	Yellow	17903	2.50	Moderate
Internet service	0.5337	1	Green	17692	2.48	Moderate

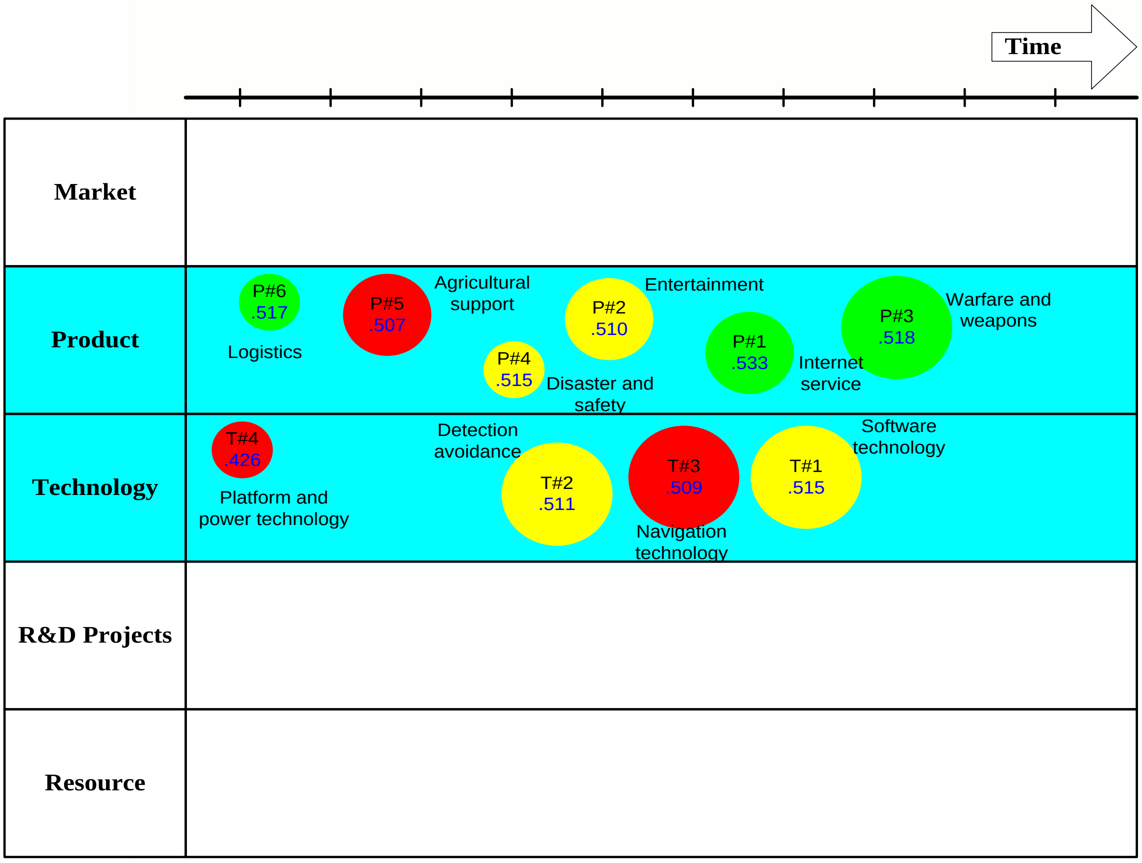


Fig. 4. An illustration of the augmented technology roadmap for UAV technologies (Product and Technology layer)

3.4 Network visualization through bubbles

After computing the trendiness degrees, a ranking is performed to classify the elements into three groups (colored with red, yellow, and green, in descending order, so that the trendiest elements have a green bubble in the technology roadmap). While the color of the bubbles is based on the trendiness evaluations, the size of the bubbles is based on the volume of patent data. To specify the radius/size of the element bubbles, the numbers of the last three years' patent data are considered. After retrieving this patent data, it is standardized to [1, 4] intervals. Corresponding elements are then classified into three bubble-size groups as small, moderate, and big according to their standardized volume values ([1, 1.99] – small, [2, 2.99] – moderate, [3, 4] – big).

Figure 4 depicts the augmented technology roadmap for unmanned aerial vehicle technologies, which is based on patent and publication data. The ultimate goal of these phases is to enhance the technology roadmap by utilizing these bubbles, where the color depends on the trendiness degree and the size depends on the volume.

4. Concluding remarks

This study presents an augmented technology roadmapping process that incorporates an innovation intelligence process driven by patent and publication data. This process involves four main phases: keyword generation, topic modeling, trendiness determination using type-2 fuzzy sets, and visualization of element relations through bubbles.

This process can help users understand the element relations that affect the strategic decisions. The case of unmanned aerial vehicle technologies is used to demonstrate the execution of this process. This study provides a new perspective on technology roadmapping, and future research can use these data-driven elements and layers for network analysis to support decision-making based on this augmented technology roadmap.

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