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Strategic roadmapping of robotics technologies for the power industry: A multicriteria technology assessment

Tugrul U. Daim[a,*], Byung-Sung Yoon[a], John Lindenberg[b], Robert Grizzi[b], Judith Estep[c], Terry Oliver[c]

[a] Portland State University, Portland, OR, USA
[b] Electric Power Research Institute, Charlotte, NC, USA
[c] Bonneville Power Administration, Portland, OR, USA

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ABSTRACT

This paper presents an application of a strategic technology management tool in the power sector. Technology Development Envelope is an extension of hierarchical decision modeling and Analytical Hierarchy Process into the future. The process yields multiple paths for technology development enabling organizations to build roadmaps depicting their strategies. The focus of this paper is robotics technologies and their applications in the power sector. As robotics technologies advance, they replace humans in very critical areas such as maintenance of transmission lines or hydro dams as well as operations in nuclear power plants. A decision model was developed and quantified through this study. It is validated with a case study from Electric Power Research Institute (EPRI) reflecting their priorities. The model establishes a framework that any other organization can adopt and use to evaluate any emerging robotics technologies.

1. Introduction

Electricity is a fundamental public commodity for the welfare of the general public, and for sustaining the economy. Therefore, electric power utilities as important infrastructures should be operated stably without any failure in supply of electricity. For example, the Northeast blackout of 2003, which was an unexpected power outage throughout Midwestern and Northeastern United States and some Canadian regions caused countless amount of financial and social loss (*U.S.-Canada Power System Outage Task Force,* 2006). Therefore, for stable operation, it is necessary to input huge amount of resources and investment throughout power generation, transmission, and distribution facilities. Particularly, constant inspection and maintenance of the facilities requires highly skilled manpower and advanced technologies.

However, in spite of endless efforts, the electric power industry is facing serious challenges from social, economic, and environmental problems. In general, the working environment of electric power facilities includes hazardous conditions such as high voltage, high temperature, high density of electromagnetic field, and radiation. Therefore, alternative technologies that are available to carry out various tasks under these hazardous conditions, instead of human workforce, are indispensable (Park et al., 2012; Parker and Draper, 1998). In addition, the operation of electric power facilities is facing an ever-intensifying shortage of manpower due to aging population and the retirement of skilled people. According to Allen, electric power industries are aware the seriousness of an aging population and the shortage manpower due to job changes or the retirement of skilled professionals (Allan, 2012; Liu and Wayno, 2008). Furthermore, the strengthening of human safety related regulations encourages greater efforts for the prevention of industrial accidents, and for reinforcing safety technologies in electric power companies. Robotics technologies have been regarded as one of promising alternative technologies.

In this regard, a large amount of research and practical applications relevant to robotics technologies have been introduced in academia and the industrial world with a full-fledged distribution of industrial robotics. In practice, a number of robotic systems have been tested and applied for inspection and maintenance in nuclear power plants (Iqbal et al., 2012; Kim et al., 2010; Marinceu et al., 2012; Roman, 1993) and high voltage power transmission lines (Allan, 2012; de Oliveira and Lages, 2010; Elizondo et al., 2010; Lages and de Oliveira, 2012; Montambault and Pouliot, 2014; Montambault et al., 2012; Siebert et al., 2014; Wu et al., 2010). However, despite a variety of attempts, a lot of these efforts have not evolved beyond the R & D stages or have only been applied in limited areas in electric utilities (Allan, 2012). There are several reasons behind the slow dissemination of robotics technologies in the operation and maintenance of electric utilities. One

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* Corresponding author.
E-mail address: tugrul.u.daim@pdx.edu (T.U. Daim).

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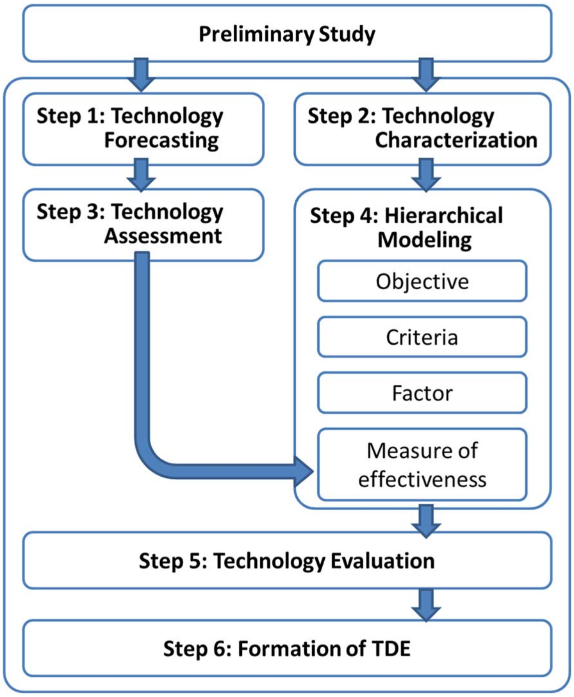

Fig. 1. Procedure of TDE formation.
(Source: Gerdsri, 2007).

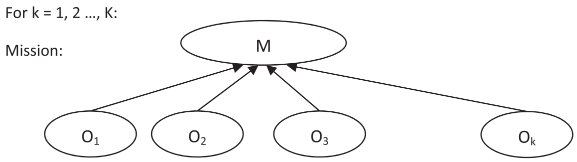

Fig. 2. HDM Structure.

of the reasons is that although the efforts and funding have been dispersed through all relative sectors, the key results of them have not been shared well with other sectors (*Program on Technology Innovation: EPRI State of Robotics—Assessment and Proposed Strategic Program*, 2013), which has lowered the efficiency of the funding.

This paper presents an analysis of available robotics technologies from the perspective of the power sector. The first stage of the analysis included identification of experts in the field through the integration of bibliometrics and social network analysis. The second stage utilized an approach based on hierarchical decision modeling to score technologies in multiple perspectives into the future. The results indicated that the concrete crawler robot is expected to have the highest benefit through 2020 while the snake robot will increase rapidly between 2015 and 2018. The transmission line robot technology will have gradual advancement, which will reach the highest benefit in 2022.

2. Literature review

In order to strengthen the technology management capability in organizations, technology assessment and forecasting is important in estimating potential technological changes. Tran and Daim (2008) and Daim and Kocaoglu (2008) provided a review of methods available for these purposes. Their results showed that choice of tool was dependent on the objective of technology acquisition as well as the type of the organization. Few tools support the technology assessment and forecasting of emerging technologies because most of the tools refer to historical data (Daim et al., 2006). In this case, qualitative methods such as Delphi and scenarios provide insights of future emerging technologies rather than other methods based on historical data.

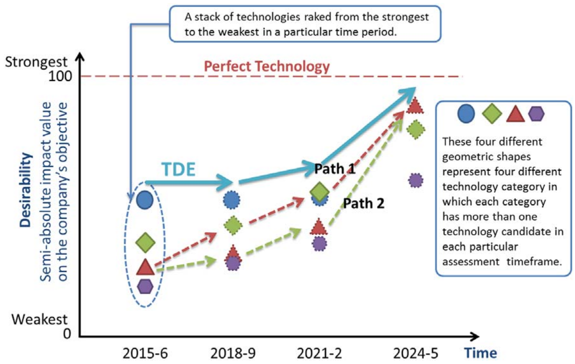

Fig. 3. TDE diagram.
(Source: Gerdsri, 2007).

Additionally, bibliometrics and patent analysis are useful for emerging technologies (Gerdsri et al., 2010b; Kajikawa et al., 2008b; Sasaki et al., 2010). With these various methods for technology management and planning, a lot of organizations strive against fierce competition of technological advancement (Daim et al., 2011).

In particular, technology roadmapping as a technology planning process supports developments of technological alternatives fulfilling product requirements or organizational objectives by identifying, selecting, and developing technology alternatives (Phaal et al., 2004). Nevertheless, according to Gerdsri (Gerdsri, 2007), although it is important to reflect various insights of either internal or external stakeholders in decision makings for technology forecasting and evaluation, few methods are capable of linking them. Also, while technology roadmaps are actively applied to establishing strategic plans among a variety of industries and organizations, it is somewhat difficult to update and revise technology roadmaps periodically due to the procedural nature of the methods (Daim et al., 2011; Gerdsri, 2007; Gerdsri and Kocaoglu, 2003).

3. Technology roadmapping

As reported by Phaal et al. (Phaal et al., 2011), technology roadmapping is a process that emerged from the industry and it is only natural that it is applied in the industry. The process has been improved by many researchers since its introduction (Amer et al., 2016; Gerdsri et al., 2009, 2010a; Phaal and Muller, 2009; Thorn et al., 2011). The new approaches demonstrated the integration of technology roadmapping with other tools to improve the value for the organizations. These tools included quantitative tools targeting to quantify the linkages or scenarios to explore possible alternative futures.

The approach is used in areas including energy (Amer and Daim, 2010; Daim et al., 2012a, 2012b, 2012c), business modeling (Abe et al., 2009), dual technology (Geum et al., 2013), services (Daim and Oliver, 2008; Geum et al., 2011; Martin and Daim, 2012), policy making (Yasunaga et al., 2009), customized roadmaps (Lee and Park, 2005), sustainable products (Petrick and Echols, 2004), disruptive technologies (Rinne, 2004), silicon industry (Walsh et al., 2005), foresight (Saritas and Oner, 2004), parts and materials industry (Lee et al., 2007), wood pellets (Lamb et al., 2012).

Many integrated other used approaches making roadmapping more effective including integration of science and technology indicators (Kajikawa et al., 2008a), evaluating disruptive threats and opportunities (Galvin, 2004; Kostoff et al., 2004; Vojak and Chambers, 2004), using data mining (Geum et al., 2015), integrating services and devices for smart cities (Lee et al., 2013), evaluation of success in the renewable energy sector (Jeffrey et al., 2013), transition management (McDowall, 2012), technology convergence (Yasunaga et al., 2009), communications theory (Lee et al., 2012), scenarios (Hansen et al., 2016), corporate foresight (Vishnevskiy et al., 2015), smart specialization

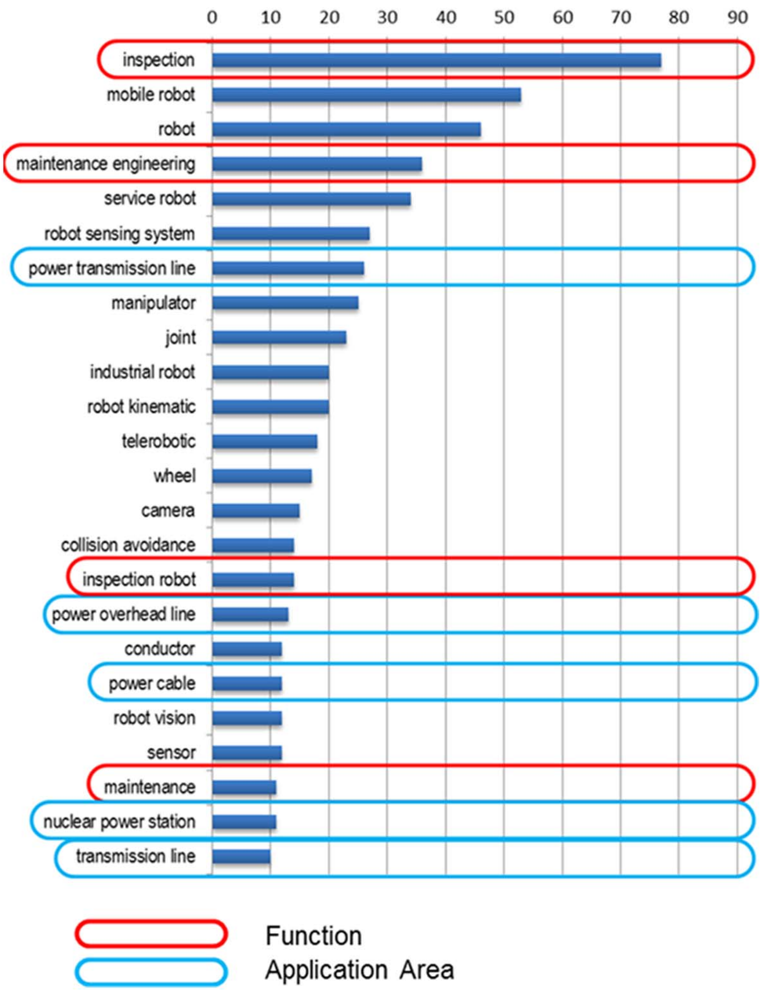

Fig. 4. Frequency of Each Keyword.

(Paliokaitė et al., 2016), process integration (Toro-Jarrín et al., 2016; Vishnevskiy et al., 2016), case studies (Amadi-Echendu et al., 2011; Battistella et al., 2015), patent analysis (Jeong et al., 2015), scenarios applied for rail automation (Hansen et al., 2016).

On the other hand, TDE is available to provide an opportunity to link internal technology developers with external experts to complement the weakness of typical technology roadmapping techniques (Daim et al., 2011; Gerdsri, 2007; Gerdsri and Kocaoglu, 2003). Originally, this methodology was developed for managers of technology development parts in organizations to identify and select the proper emerging technology alternatives (Gerdsri and Kocaoglu, 2003). In order to determine appropriate emerging technologies, the value of

Table 1
List of journals for expert identification.

Robotics technology	Electrical Engineering
The International Journal of Robotics Research	IEEE Transactions on Smart Grid
IEEE Transactions on Robotics	IEEE Transactions on Power Systems
IEEE Robotics & Automation Magazine	IEEE Transactions on Energy Conversion
Journal of Field Robotics	Automatica
Robotics and Computer-Integrated Manufacturing	IEEE Transactions on Power Delivery

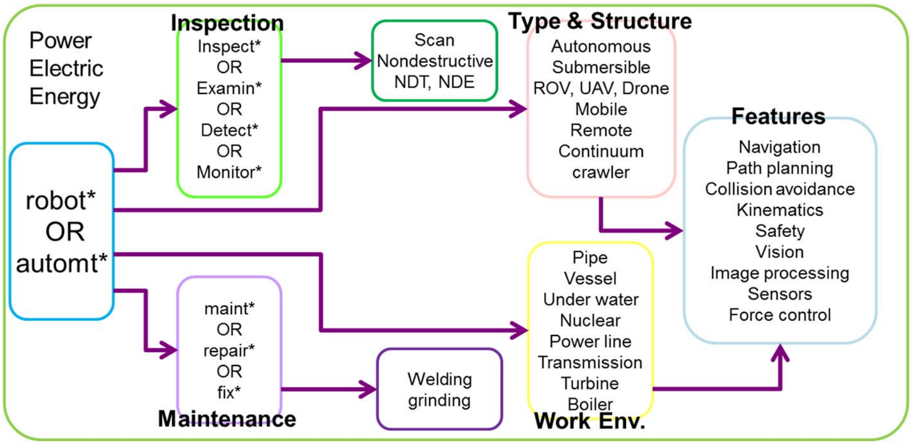

Fig. 5. The technology system tree of robotic technologies in the electric power sector.

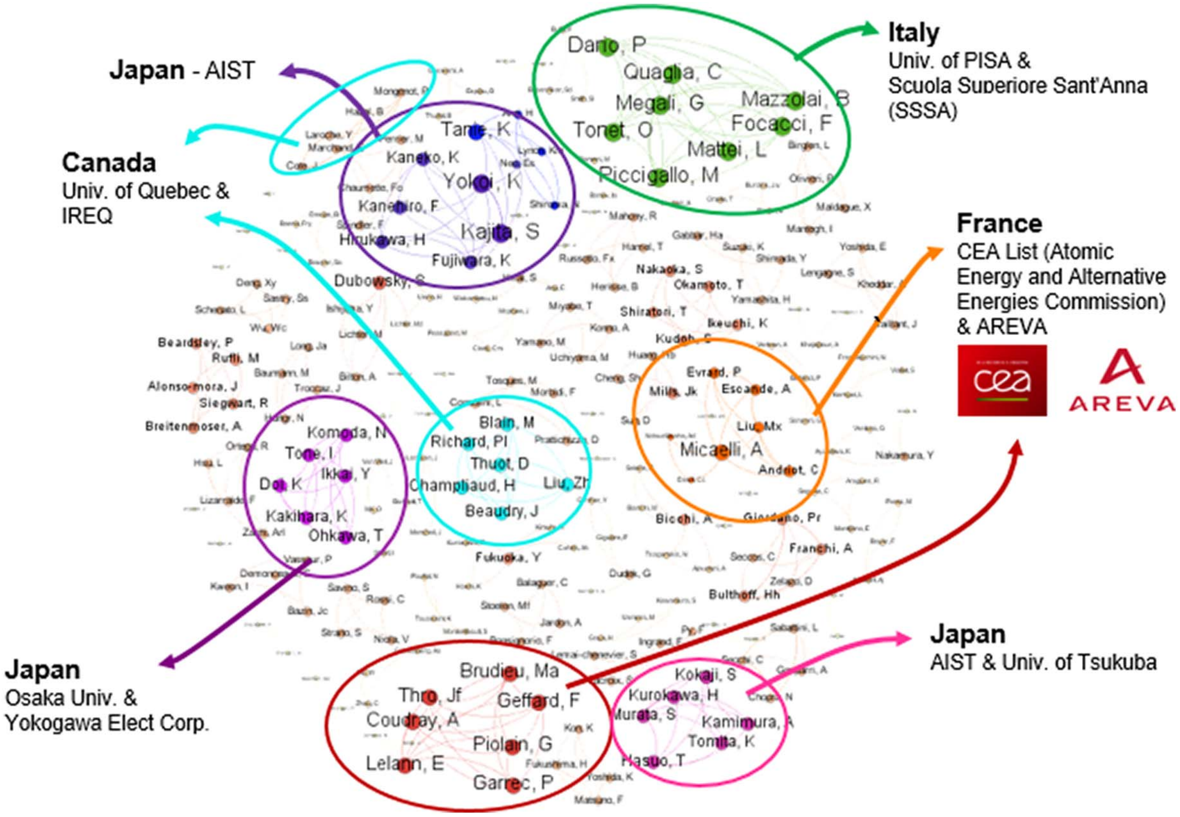

Fig. 6. An example of expert group identification.

technologies is evaluated by expert panels, and the technology development path is formed by connecting technology values from one generation to the next. Consequently, the best path can be determined by selecting technologies which have the highest value over the time periods. With the best path, organizations establish the optimum strategy for technology development (Daim et al., 2011). Since its introduction, TDE has been applied to various cases from cooling technology for the computer industry (Daim et al., 2011; Fenwick et al., 2009; Gerdsri, 2005; Kockan et al., 2010) and internet security technologies to powertrain technology for automotive industry.

3.1. Bibliometrics and social network analysis

Mapping the bibliometric and patent data has been used in forecasting technologies as well as identification of key scientists, organizations or technologies (Avila-robinson and Miyazaki, 2011; Boyack et al., 2014; Cunningham and Kwakkel, 2014; Fujita et al., 2014; Guo et al., 2015; Igarashi and Okada, 2015; Ittipanuvat et al., 2014; Karvonen and Kässi, 2013; Newman et al., 2014; No et al., 2015; Roepke and Moehrle, 2014; Sakata et al., 2013; vom Stein et al., 2015). Newman et al. (Newman et al., 2014) provided a good overview of such methods. Others used these methods in innovative ways to decode the

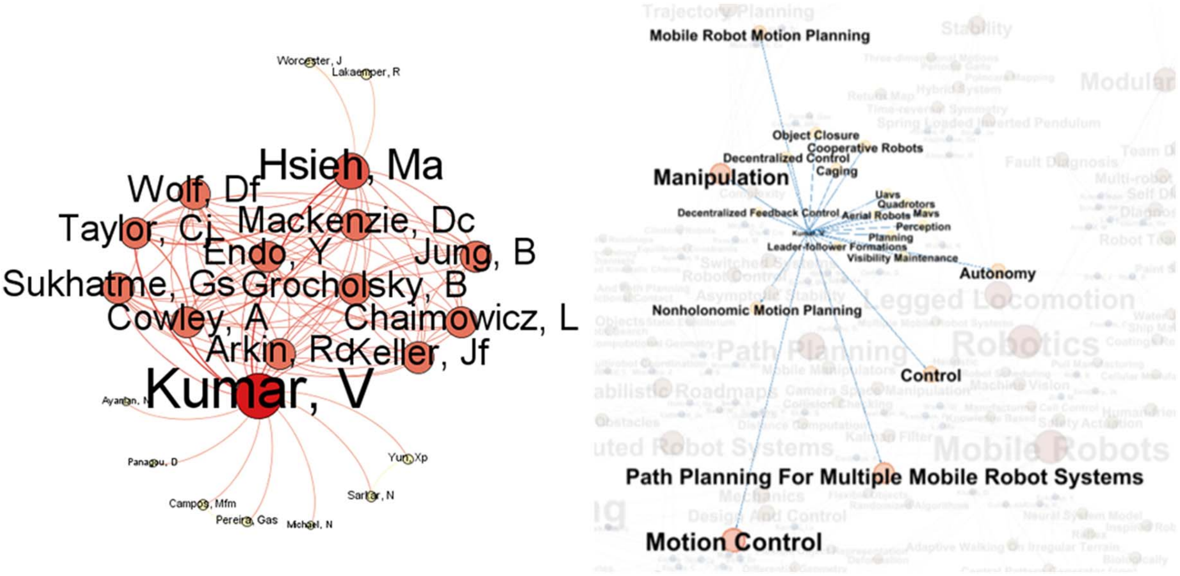

Fig. 7. Co-authorship and related-keyword network diagrams of an expert.

Table 2
Information of four identified technology alternatives.

No.	Robot or Application	Main Function	Working Environment	Motion Pattern	Propulsion	Requirement
1	Submersible Mini-Robot	Visual **inspection** of submerged components in nuclear reactor vessels and spent fuel pools	Underwater	Underwater navigating	Water Jet	- Appendage-free appearance - Ability to navigate through intricate and tight geometries - Ability to conduct inspection-type passes over surfaces - Enough payload for two camera - - Wireless optical communication
2	Concrete Crawler for Robotic Inspection	**Inspection** of concrete structure	On the concrete surface	Climbing & Crawling	Caterpillar track	- Ability to climb the surface of large power industry structures - Including Simultaneous Localization and Mapping (SLAM) - Including Nondestructive Evaluation (NDE) systems - Ability to conduct automated, high-precision inspections - Ability to capture computer-encoded data and images for maintenance decision-making
3	Snake Robot for Heat Recovery Steam Generator Inspection	Inspection of heat recovery steam generator (HRSG) tubing	Tight space surrounded by bundle of tubes	Snake motion	Body	- Ability to navigate a variety of terrains
4	Transmission Line Robot	Transmission line inspection - To improve inspection and monitoring capabilities and worker safety relative to hovering helicopters at cost savings of at least 30%.	General atmosphere	Crawling over conductor shield wires	Wheels on a wire	- High-definition cameras and LiDAR sensors - Electromagnetic interference detectors - Data collection for monitoring vibration, lightning strikes, wind-related damage, and corrosive condition

Table 3
Description of each criterion in the validated HDM.

Perspectives	Criterion	Description	Measurement Unit
Functionality	Multi-Functions	A robotic system consists of multiple functions enabling the system to conduct diverse tasks given. In order to complete the tasks successfully, a reasonable number of functions need to be combined.	ea
	Multi-Environments	A robotic system for the electric power industry needs to conduct diverse tasks given under one or more environments (e.g. high temperature, high radiation, over high-voltage transmission lines, or underwater). The capability of working under multiple environments increases the versatility of the system. However, because of design constraints, the number of applicable environments needs to be identified.	ea
	Multi-Applications	A robotic system is designed for one or multiple applications or tasks such as inspection, monitoring, maintenance, and cleaning. The number of applications the system should carry out needs to be identified.	ea
Design	Heavy-Duty	A robotic system should carry out tasks given without any failure during its operation. In particular, a trouble-free design is desirable for the robotic systems in the electric power industry because of its severe environments. The reliability in operation for a robotic system is quantified as mean time before failure (MTBF). It is defined as total operation time over the number of failure.	MTBF (yr)
	Motion Flexibility	A robotic system must carry out its tasks through multiple motions such as moving and handling. Therefore, the motion flexibility of the system is quantified as the degree of freedom (dof).	Dof
	Size	The size of a robotic system should be within acceptable dimensions or appropriate volume to be used, carried, applied, and operated effectively. This is quantified by 5-point scale (1: Gigantic, 2: Large, 3: Small, 4: Miniature, 5: Microscopic)	5-point Scale
	Contamination Proof	A robotic system for the electric power industry should be highly protected from the negative impacts of hazardous materials or environmental causes during its operation. Therefore, the long-hour operation without any failures under the severe environments is desirable for the robotic system.	h
	Nondestructive	In carrying out inspection or monitoring tasks given, a robotic system must do the jobs without negative impact/damages or residues to the surroundings or working objects. Therefore, the capability of carrying out tasks without any negative impact on working objects is desirable for the system. The capability is quantified as the depth from the surface of working objects to the position where the system can measure under the surface of a concrete structure	mm
Technological	Positioning	A robotic system should be capable of identifying its location and position while performing its job, or to be located easily at certain location. Therefore, the high accuracy of positioning is desirable. The measure of positioning accuracy is quantified as the maximum radius of errors in positioning.	M
	Precision	A robotic system should be capable of identify the location of its end-effector in order to assure high performance and accurate results. Therefore, the precise operation is desirable. The measure of precision is quantified as the percent accuracy in operating its end-effector.	%
	Assessment Time	In inspecting or monitoring the status of working objects, the speed of issue evaluation leads to reduction of time or efforts.	h
User Experience	Easy to Use	Simple, effortless, trouble-free, straightforward, and direct use are desirable for operating a robotic system. The level of ease of use is quantified by a 6-point scale related to training. For example, while 1 point means that a longer training period is required for operation, 6 points means that no training is required.	6-point Scale
	Upgradability	The potential for more improvement to accommodate future needs is sometimes required. The level of upgradability is quantified as the percent improvement. For example, > 100% of upgradability means that the system is capable of improving its performance over twice by upgrade.	%
	Maintainability	Mean Time To Repair (MTTR) is defined as the time needed to repair a failed hardware module. A short MTTR of a module means that the maintainability of it is better than one that needs a longer MTTR.	MTTR (h)
	Working Speed	In carrying out tasks given, the working speed of a robotic system enables the reduction of time and effort. It is quantified by the average hours of total working time on the system	h
Electronics	Remote Operation	A robotic system needs to be operated and controlled remotely from an acceptable distance of operation.	Miles
	Visual Capability	In order to achieve visual information around a robotic system, the visual capability of imaging system (e.g. still cameras or video cameras) is required. The capability is quantified by the resolution of the image achievable from the imaging system.	Resolution
	Dual Communication	Two-way and high-rate of data transmission for easy operation and real-time control or assessment is desirable between a robot and operator/controller. The communication capability is quantified by the sampling rate of its communication system (Mega sample per second, MSPS).	MSPS
	Data Processing	The data processing speed of a robotic system is critical for reducing working time in carrying out tasks given. This capability depends on the performance of the data processing system such as processors and communication bus.	Mb/s
	Interface Proof	Some robotic systems need to carry out tasks given under high radiation environment. Therefore, the systems are capable of operating without any failure under a certain amount of radiation does. The capability of interface proof against radiation is quantified by the level of radiation which the robotic system can conduct tasks normally under over 3 h.	Sv/h

technology evolution (Roepke and Moehrle, 2014), for detecting research fronts (Fujita et al., 2014), to understand technology emergence (Ávila-Robinson and Miyazaki, 2013; Boyack et al., 2014; Karvonen and Kässi, 2013) and social linkages (Igarashi and Okada, 2015; Ittipanuvat et al., 2014), to identify tipping points in science (Cunningham and Kwakkel, 2014) or knowledge networks (No et al., 2015; Sakata et al., 2013), to measure technological distance (vom Stein et al., 2015) or future national technological competitiveness (Guo et al., 2015). However, a few managed to integrate it with roadmapping approaches (Li et al., 2015). Daim et al. (2016) edited a recent book presenting varying approaches to analyze this kind of data to create technology intelligence.

4. Research methodology

In this section, the procedure of the TDE approach is provided briefly. As shown Fig. 1, the process of developing the TDE consists of six steps: technology forecasting, technology characterization, technology assessment, hierarchical modeling, technology evaluation, and the formation of a TDE.

In order to identify the trend of a specific technological field, a technology forecasting model will be developed by using experts' opinions. At this time, it is important to identify experts taking into consideration their experiences and expertise in balance. Accordingly, based on the literature analysis in relevant technologies to a target research, expert panels are formed in technology development and technology implementation areas. After a Delphi study based on

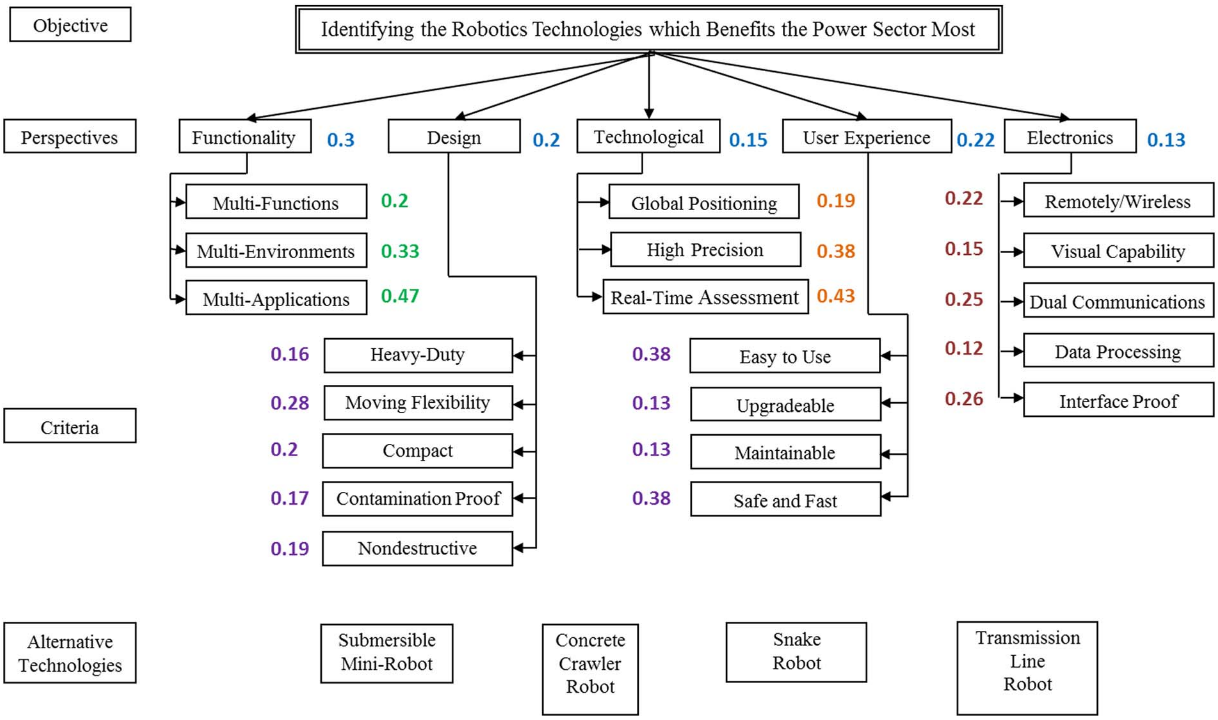

Fig. 8. The validated HDM and relative weights judged by experts.

technology focusing on experts' opinion and state-of-the-art literature, emerging technologies relevant to the target research are selected as technology alternatives.

The next step is to characterize the identified technologies to satisfying the research objective. In this step, the experts who have experiences and expertise in the technology implementation area define the significant criteria and technological factors associated with each criterion. Then, the identified emerging technologies are assessed based on the measures of effectiveness by the experts. The experts are assigned to specific criteria, considering their expertise, to provide their estimates on the technological metrics indicating the future development progress of emerging technologies defined at the first step.

Simultaneously, the evaluation model is constructed in a hierarchical structure, a so-called hierarchical decision model (HDM) (Daim, 2015), with four levels: objective, perspectives, technological criteria, and technology alternatives. HDM, developed by Kocaoglu (1983), is based on similar concept as Analytical Hierarchy Process (AHP) (Saaty, 1980), but uses different numerical comparison scales

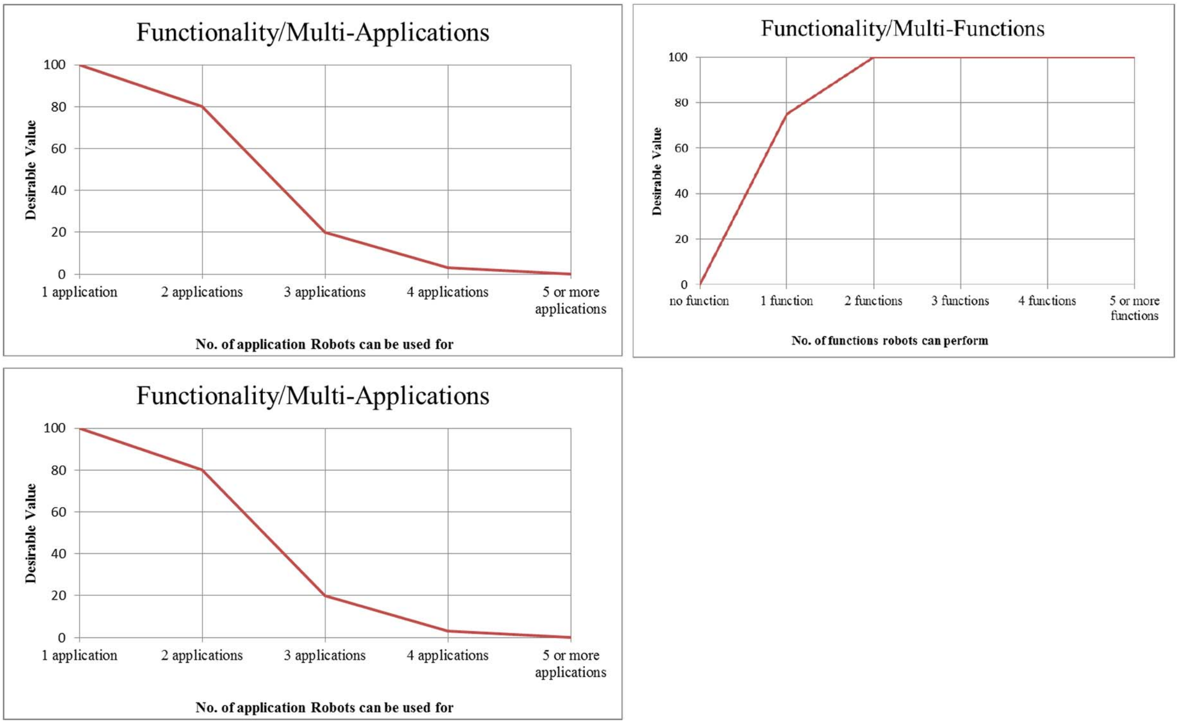

Fig. 9. Desirability curves for functionality criteria.

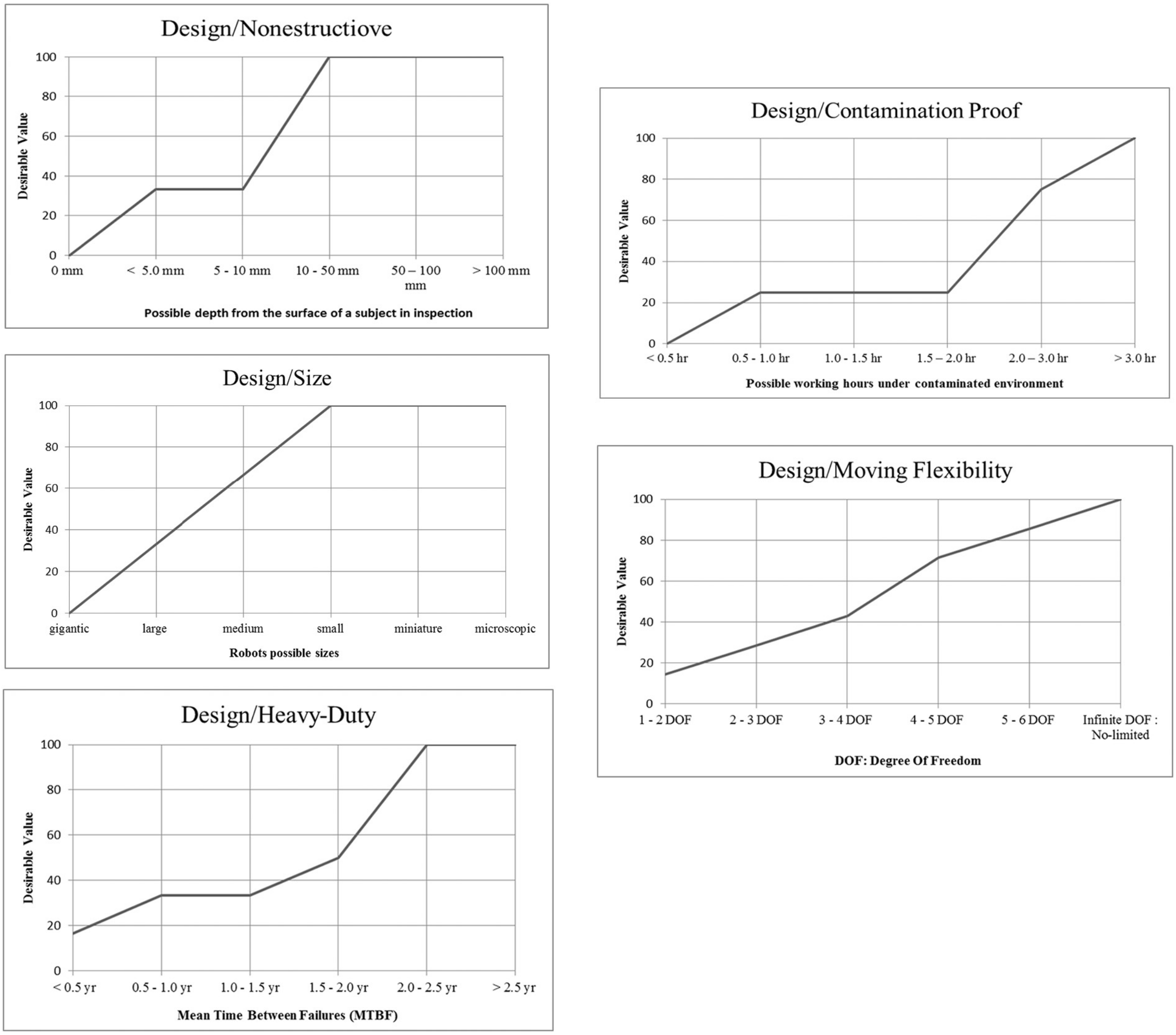

Fig. 10. Desirability curves for design criteria.

and judgmental quantification techniques. HDM has several built-in advantages including simplicity of structure, ease of use, and flexibility. It can be applied to assist complex decision-making when a relatively large number of quantifiable or intangible criteria are involved. The method allows calculating priorities and weights in a hierarchical structure in order to identify the most important elements (Saaty, 1980).

The quantification process utilizes the Pair-wise Comparison Method (PCM), where experts are asked to allocate weights for the elements. By using the constant-sum method, a total of 100 points will be assigned between any two elements at the same level. The following figure depicts a simple application of evaluating multiple objectives' contributions to a mission. Under Mission (M), quantifying expert judgment of relevant technology fields to obtain the value (O_k). For each objective O_k (k = 1, 2 …, K), using pair-wise comparison to determine the relative value of O_k in terms of their desirability for M.

Judgmental value of the best O_k for M is based on a scale of 0–100, and then normalized to be within the range of 0–1.

During the above processes, inconsistency values for the constant sum method are calculated as follows (Kocaoglu, 1983): For n elements, the constant sum calculations will result in a total of n! orientations with vector values represented by $r_1, r_2 \ldots r_n$ for each. If the expert is totally consistent, the relative values will be the same for each orientation. Otherwise, if inconsistency exists it will result in differences in the relative values in different orientations. According to prior research, if the inconsistency level is < 10% or 0.1, the related judgmental data should be acceptable (Iskin and Daim, 2016; Wang et al., 2010). According to Abbas (2016), the acceptable inconsistency sought should be higher when the number of alternatives increase.

Let r_{ij} = relative value of the ith element in the jth orientation for an expert

$\bar{r}_i$ = mean relative value of the ith element for that expert: $\bar{r}_i = (1/n!) \sum_{j=1}^{n!} r_{ij}$

Variance in the relative value of the ith element:

$$(1/n!) \sum_{j=1}^{n!} (\bar{r}_i - r_{ij})^2 \qquad i = 1, 2 \ldots n$$

Inconsistency of the expert in providing relative values for the n elements is defined as:

$$\text{Inconsistency} = \sqrt{(1/n) \sum_{i=1}^{n} (1/n!) \sum_{j=1}^{n!} (\bar{r}_i - r_{ij})^2}$$

HDM has been applied in various areas including regional energy efficiency planning (Iskin and Daim, 2016), adoption of energy efficiency devices (van Blommestein and Daim, 2013), evaluation of energy storage technologies (Daim et al., 2012a, 2012b, 2012c), remote health monitoring (Basoglu et al., 2012), communication breakdown in virtual teams (Daim et al., 2012a, 2012b, 2012c), planning for

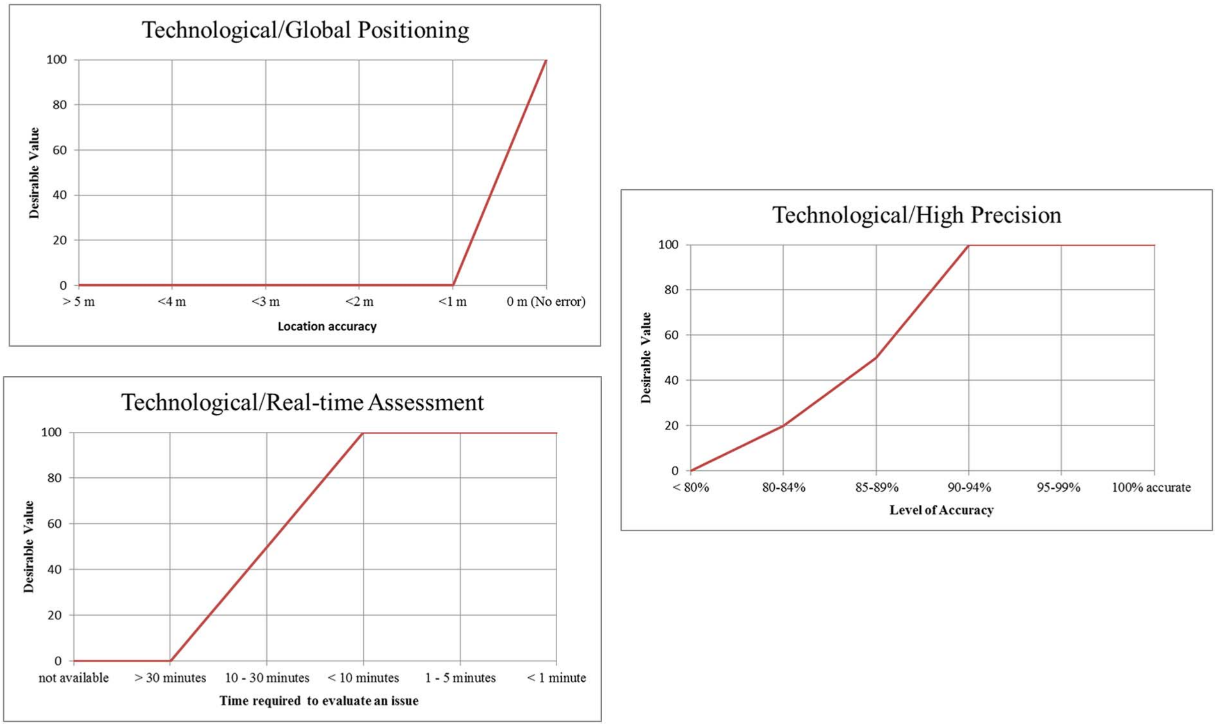

Fig. 11. Desirability curves for technological criteria.

developing countries (Amer and Daim, 2011), personnel management (Harrel and Daim, 2010; Keneddy and Daim, 2010), energy planning (Cowan et al., 2010).

With HDM the relative importance of each perspective and the relative impact of each criterion are determined by using the pairwise comparison method. And also, the desirability curve of each technology is developed for quantifying the impact of each technology referring to the objective. The quantified values of desirability curves are used for the calculation of technology values, which indicates how well technological alternatives satisfy the objective, with prioritized perspectives and technological criteria. From the calculation, the technology value of each technology alternative is mapped graphically over the time periods. Finally, the TDE is formed by linking technologies that have the highest technology value in each time period. Fig. 3 shows the graphical explanation of the TDE concept.

The TDE can be used for two ways. First, if the organization has the most advanced capability and technology leadership in its field, the TDE is used as the technology roadmap. On the other hand, if the organization is chasing technology leaderships, the TDE is an index for benchmarking.

5. Application of the model

As mentioned in the Introduction section, the objective of this study is to evaluate the current robotics technologies and to identify the future development strategy in the electric power industry using the TDE approach. This section, along with the abovementioned procedure, demonstrates how technology alternatives are evaluated and how the future development strategies are identified.

5.1. Preliminary study

Before the full-fledged study, an in-depth preliminary study was conducted in order to obtain background knowledge of robotic technology in the electric power industry. A number of academic papers and practical reports were collected. For example, one report from EPRI provides the information of the state-of-the-art robotic technologies that the organization has been developing for various applications in power facilities. In addition, real-world information was obtained through a number of meetings with several experts in the electric power industry. In particular, the experts noted that a lot of the research that was directly related to this study was presented at a biannual conference, the 2010 International Conference of Applied Robotics in Power Industry (CARPI). Consequently, during this preliminary study, fundamental references were accumulated for identifying technological trends and experts in the electric power industry.

5.2. Expert identification

First of all in order to identify experts for collecting technology insights, main keywords were extracted through an investigation of keyword frequency from the bibliometric data of one hundred eleven papers presented at the first (2010) and the second (2012) CARPI. The bibliometric data includes title, authors, affiliations of authors, keywords of each paper. This data was converted into a proper format for pre-processing. In the pre-processing step, the co-occurrence of keywords was investigated for analyzing the interrelation between each keyword using a social network analysis technique. This analysis allows researchers to know which keywords are frequently used with other keywords within the body of robotics technology research. In addition, the information that results from the co-occurrence analysis shows the interrelations between keywords. To visualize the interrelation, the result of the co-occurrence analysis should be converted to the social network structure. With the social network analysis, the frequency of each keyword is calculated. Fig. 4 depicts the frequency rank of each keyword.

These main keywords are classified into the function and the application areas. In terms of the functional class, two keywords, 'inspection' and 'maintenance,' are frequently used in the conference. This shows that the main functions of robotic technologies in the electric power sector are focused on inspection and maintenance of facilities. Researchers who participated in the conference actively researched 'power transmission line' and 'nuclear power station' as main application areas of robotic technology in the electric power sector. Moreover,

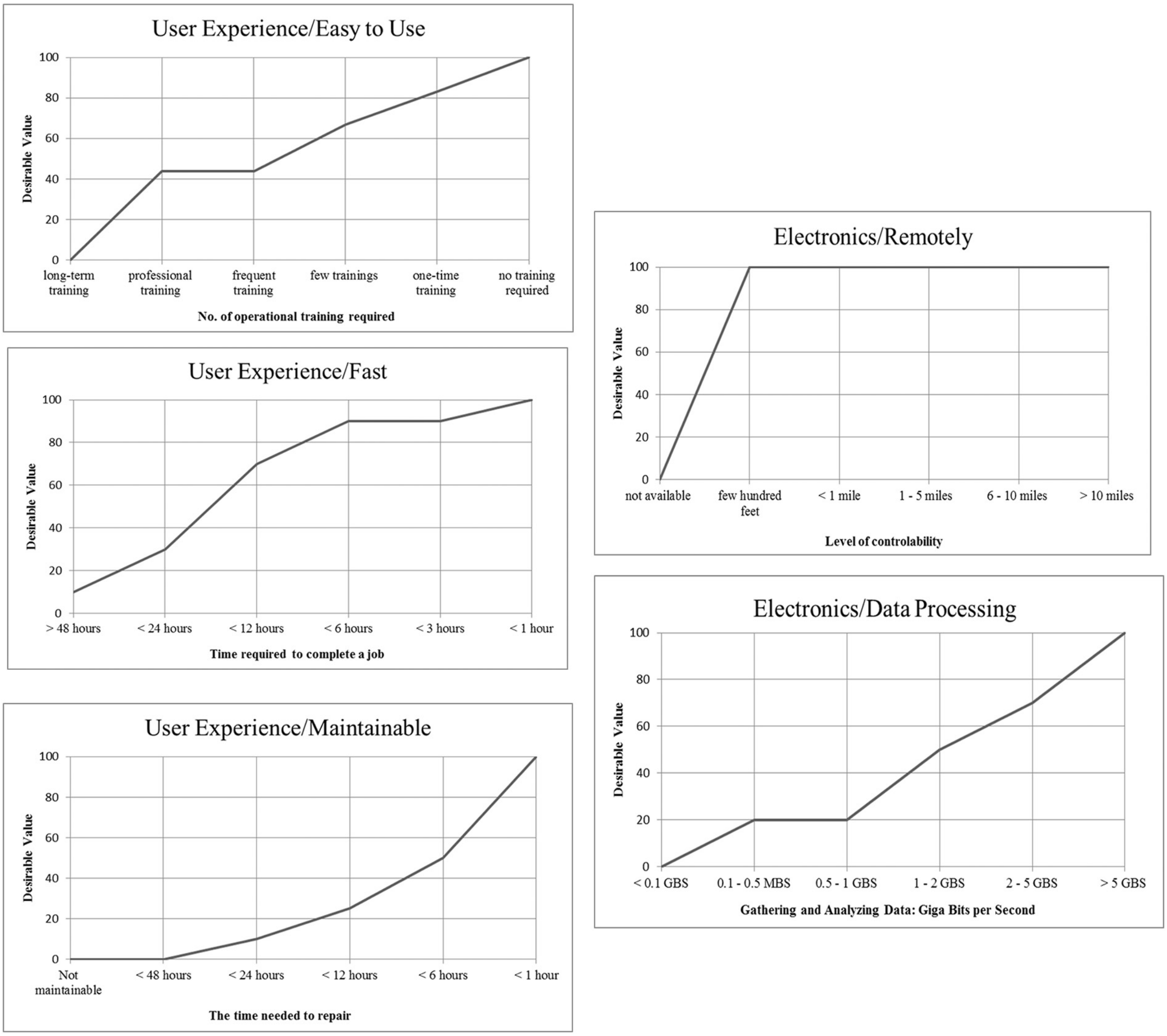

Fig. 12. Desirability curves for user experience and electronics.

'sensor,' 'vision,' 'telerobotics' and 'mobile robot' are popular terms for features of robotic technologies in this sector. With these keywords, the technology system tree of robotic technologies in this sector is configured like Fig. 5.

Before identifying experts by literature search with the above defined keywords, the range of literature search also should be defined because there are huge numbers of journals and conferences related to robotic technology and electric engineering. In establishing the range, high quality journals and conferences should be selected as the source of literature search. One of criteria to ensure the quality of each journal is the impact factor of each journal, which is calculated based on the citations in the Web of Science (Björk et al., 2010). Therefore, in this study, the Journal Citation Reports® (JCR) database provided by the Web of Science is referred to for selecting journals in establishing the literature searching range. Similarly, Google also provides a similar service, Google Scholar Metrics (https://scholar.google.com/citations?view_op=top_venues&hl=en&vq=eng_robotics) with JCR based on h-index. Referring to these two journal ranking services, five robotics technology and five electrical engineering journals are selected for the literature source to identify potential experts. Table 1 summarizes the list of journals referred for the expert identification.

In addition, five conferences relevant to robotics and the electrical power industry also are used for the literature selection like below:

- International Conference on Robotics and Automation (ICRA)
- IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
- IEEE PES Innovative Smart Grid Technologies Conference (ISGT)
- IEEE Power Tech (Power Tech)
- IEEE PES General Meeting

From the abovementioned literature and keywords, the bibliometric information was collected from the academic publications that were published after 1990.

With the collected bibliometric data, co-authorship, and author-keywords, data is extracted by using preprocessing tools designed for the bibliometric analysis of academic literature, Science of Science (Sci2) (Sci2 Team, 2009). The preprocessed data is transferred to social network analysis (SNA) and visualization tools Gephi (Bastian et al., 2009) for post-processing. The results of this analysis include following items:

- Number of publication: the total number of publications by an author (or expert)
- Times cited count: the total number of times the published papers of an author were cited by other papers
- Degree: the number of other authors who worked with an author

Table 4
Calculation of technology values for technology alternatives.

Perspectives	Criteria	Global Weight	Robotic Systems					
			Submersible Mini-Robot			Transmission Line Robot		
			Tech Metrics	Desirability Values	Tech Values	Tech Metrics	Desirability Values	Tech Values
Functionality	Multi-Functions	0.06	2 (Locomotive-Ability, Imaging)	100	6.00	3 (Locomotive-Ability, Imaging, Sensing)	100	6.00
	Multi-Environments	0.10	1 (Underwater)	100	9.90	1 (On the Transmission Line)	100	9.90
	Multi-Applications	0.14	2 (Inspection, Monitoring)	80	11.28	2 (Inspection, Monitoring)	80	11.28
Design	Heavy-Duty	0.03	–	17	0.54	4 (MTBF 2.0–2.5 yr)	100	3.20
	Moving Flexibility	0.06	3 (4-5 DOF)	71	3.98	2 (3-4 DOF)	43	2.41
	Compact	0.04	3 (Small)	100	4.00	2 (Medium)	67	2.68
	Contamination Proof	0.03	0 (< 0.5 h)	0	0.00	5 (> 3.0 h)	100	3.40
	Nondestructive	0.04	0 (No Function)	0	0.00	0 (No Function)	0	0.00
Technological	Global Positioning	0.03	– (Unavailable)	0	0.00	4 (0-2.5 m)	0	0.00
	High Precision	0.06	4 (95-99%)	100	5.70	4 (95-99%)	100	5.70
	Real-Time Assessment	0.06	0 (Unavailable)	0	0.00	5 (Spontaneous)	100	6.45
User Experience	Easy to Use	0.08	4 (One-Time training)	83	6.94	3 (Less Training Required)	67	5.60
	Upgradeable	0.03	0 (Impossible)	100	2.86		100	2.86
	Maintainable	0.03	4 (< 6 h)	50	1.43	3 (< 12 h)	25	0.72
	Fast	0.08	– (Unavailable)	10	0.84	– (Unavailable)	10	0.84
Electronics	Remotely/Wireless	0.03	1 (< x00 ft.)	100	2.86	5 (> 10 miles)	100	2.86
	Visual Capability	0.02	0 (VGA)	5	0.10	0 (VGA)	5	0.10
	Dual Communications	0.03	0 (< 1 MSPS)	0	0.00	1 (1 to 40 MSPS)	50	1.63
	Data Processing	0.02	–	0	0.00	2 (500 Mb/s to 1 Gb/s)	20	0.31
	Interface Proof	0.03	0 (< 2.7 μSv/h avg.)	0	0.00	–	0	0.00
Tech Level					56.42			65.92

Perspectives	Criteria	Global Weight	Robotic Systems					
			Concrete Crawler Robot			Snake Robot		
			Tech Metrics	Desirability Values	Tech Values	Tech Metrics	Desirability Values	Tech Values
Functionality	Multi-Functions	0.06	4 (Locomotive-Ability, Crawling, Sensing, Imaging)	100	6.00	2 (Locomotive-Ability, Imaging)	100	6.00
	Multi-Environments	0.10	1 (High Reach Areas)	100	9.90	4 (Underground, Tight Or Narrow Pipes, High Reach Areas, Variety Of Terrains)	0	0.00
	Multi-Applications	0.14	3 (Inspection, Monitoring, Maintenance)	20	2.82	2 (Inspection, Monitoring)	80	11.28
Design	Heavy-Duty	0.03	3 (MTBF 1.5-2.0 yr)	50	1.60	3 (MTBF 1.5–2.0 yr)	50	1.60
	Moving Flexibility	0.06	1 (2-3 DOF)	29	1.62	5 (Infinite DOF)	100	5.60
	Compact	0.04	2 (Medium)	67	2.68	3 (Small)	100	4.00
	Contamination Proof	0.03	5 (> 3.0 h)	100	3.40	1 (0.5–1.0 h)	25	0.85
	Nondestructive	0.04	?	0	0.00	0 (No function)	0	0.00
Technological	Global Positioning	0.03	?	0	0.00	?	0	0.00
	High Precision	0.06	4 (95-99%)	100	5.70	?	0	0.00
	Real-Time Assessment	0.06	5 (Spontaneous)	100	6.45	5 (Spontaneous)	100	6.45
User Experience	Easy to Use	0.08	3 (few training required)	67	5.60	4 (one-time training)	83	6.94
	Upgradeable	0.03	5 (0–25%)	0	0.00	?	100	2.86
	Maintainable	0.03	3 (< 12 h)	25	0.72	4 (< 6 h)	50	1.43
	Fast	0.08	– (Unavailable)	10	0.84	– (Unavailable)	10	0.84
Electronics	Remotely/Wireless	0.03	2 (< 1 mile)	100	2.86	2 (< 1 mile)	100	2.86
	Visual Capability	0.02	–	5	0.10	0 (Analog NTSC)	5	0.10
	Dual Communications	0.03	1 (1 to 40 MSPS)	50	1.63	0 (< 1 MSPS)	0	0.00
	Data Processing	0.02	2 (500 Mb/s to 1 Gb/s)	20	0.31	0 (< 100 Mb/s)	0	0.00
	Interface Proof	0.03	0 (< 2.7 μSv/h avg.)	0	0.00	0 (< 2.7 μSv/h avg.)	0	0.00
Tech Level					52.22			50.80

Table 5
Data collection form of future technology estimation.

Perspectives	Criterion	Measurement Unit	Time Period				Note
			2015–2016	2017–2018	2019–2020	2021–2022	
Functionality	Multi-Functions	ea					
	Multi-Environments	ea					
	Multi-Applications	ea					
Design	Heavy-Duty	MTBF (yr)					
	Motion Flexibility	dof					
	Size	5-point Scale					
	Contamination Proof	h					
	Nondestructive	mm					
Technological	Positioning	m					
	Precision	%					
	Assessment Time	h					
User Experience	Easy to Use	6-point Scale					
	Upgradability	%					
	Maintainability	MTTR (h)					
	Working Speed	h					
Electronics	Remote Operation	miles					
	Visual Capability	Resolution					
	Dual Communication	MSPS					
	Data Processing	Mb/s					
	Interface Proof	Sv/h					

Table 6
Survey result about transmission line robot.

			Expert Estimation				Tech Value			
Perspectives	Criterion	Measurement Unit	Time Period				Time Period			
			2015–2016	2017–2018	2019–2020	2021–2022	2015–2016	2017–2018	2019–2020	2021–2022
Functionality	Multi-Functions	ea	4	5	8	10	6.00	6.00	6.00	6.00
	Multi-Environments	ea	1	1	1	1	9.90	9.90	9.90	9.90
	Multi-Applications	ea	1	2	3	4	0.42	2.82	7.05	11.28
Design	Heavy-Duty	MTBF (yr)	2	2	2.5	2.5	1.60	3.20	3.20	3.20
	Motion Flexibility	dof	3	4	5	6	2.41	3.98	4.82	5.60
	Size	5-point Scale	2	2	3	3	2.68	2.68	4.00	4.00
	Contamination Proof	h	0	0	0	0	0.00	0.00	0.00	0.00
	Nondestructive	mm	0	0	0	0	0.00	0.00	0.00	0.00
Technological	Positioning	m	0.5	0.5	0.25	0.1	0.00	2.85	2.85	2.85
	Precision	%	95%	95	98	99	5.70	5.70	5.70	5.70
	Assessment Time	h	0	0	0	0	6.45	6.45	6.45	6.45
User Experience	Easy to Use	6-point Scale	3	4	4	5	5.60	6.94	6.94	8.36
	Upgradability	%	0	25	50	50	0.00	0.14	0.57	0.57
	Maintainability	MTTR (h)	8	8	4	4	0.72	0.72	1.43	1.43
	Working Speed	h	0	0	0	0	8.36	8.36	8.36	8.36
Electronics	Remote Operation	miles	> 10	> 10	> 10	> 10	2.86	2.86	2.86	2.86
	Visual Capability	Resolution	HD	4 k	4 k	4 k	1.95	1.95	1.95	1.95
	Dual Communication	MSPS	40	40	40	80	3.25	3.25	2.60	2.60
	Data Processing	Mb/s	500	500	1000	2000	0.31	0.31	0.78	1.09
	Interface Proof	Sv/h	< 2.7 μSv/h	< 2.7 μSv/h	< 2.7 μSv/h	< 2.7 μSv/h	0.00	0.00	0.00	0.00
							58.21	68.10	75.46	82.20

- Betweenness centrality: the capacity of an author to connect other authors within the network (Acedo et al., 2006; Liu et al., 2005)
- Eigenvector centrality: the capacity of an author to influence other authors within a local network (Abbasi et al., 2011; de Stefano et al., 2011)

Fig. 2 shows an example how expert groups are identified by analyzing the co-authorship network. This network includes seven independent co-authorship groups in academic research relevant to robotic maintenance systems. The size of a circle indicates the number of connections with other authors, while the width of line between two authors presents the frequency of publications. Therefore, an author who has a relatively bigger circle may have a stronger influence than others. From this analysis, we identified experts who actively published their research within each co-authorship group. (See Fig. 6.)

Consequently, high ranked authors in each abovementioned item are identified as experts who, as an expert panel (EP1), would do the technology assessment and the technology evaluation through this study. Bibliometric and social networking analysis as shown in Fig. 7 were used to identify the most critical authors in the related technologies. Meanwhile, another expert panel, EP2, was formed for the technology characterization and the HDM establishment with experts who have had experiences of leading or managing practical projects that adopted robotic systems for facilities of electric power systems. In the case of EP2, the experts were identified based on their expertise in a perspective area related to robotics. However in EP1, the main

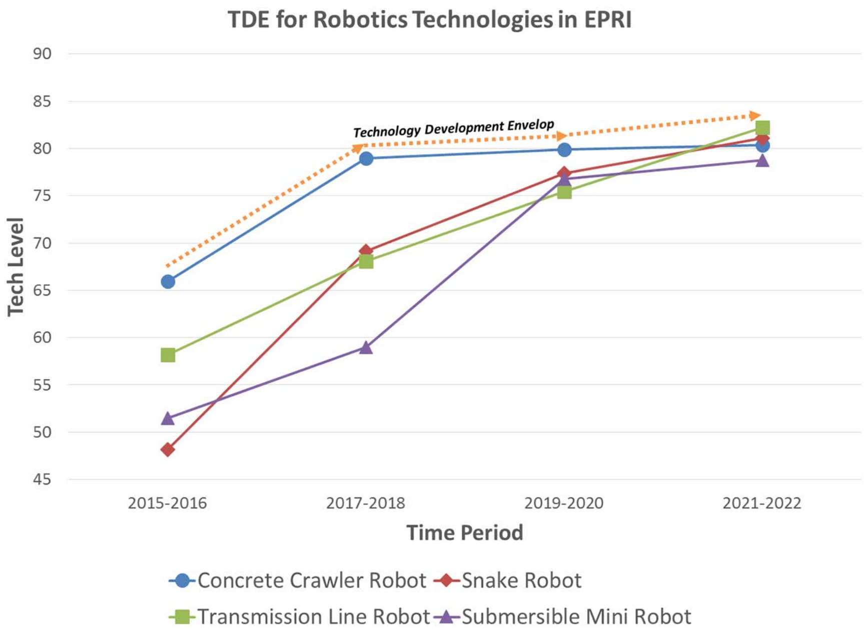

Fig. 13. TDE of robotics technologies in the power industry.

Table 7
Future scenarios.

	Functionality	Design	Technology	UX	Electronics
Base Case	**0.30**	**0.20**	**0.15**	**0.22**	**0.13**
Case A	**0.60**	0.10	0.10	0.10	0.10
Case B	0.10	**0.60**	0.10	0.10	0.10
Case C	0.10	0.10	**0.60**	0.10	0.10
Case D	0.10	0.10	0.10	**0.60**	0.10
Case E	0.10	0.10	0.10	0.10	**0.60**

qualification was their knowledge of technologies.

5.3. *Identification of technology alternatives*

From discussions with an expert panel based on the above-mentioned EPRI report (*Program on Technology Innovation: EPRI State of Robotics—Assessment and Proposed Strategic Program*, 2013), four robotic systems were identified as technology alternatives: the submersible mini-robot, the concrete crawler for robotic inspection, the transmission line robot and the snake robot for heat recovery steam generator inspection. Table 2 shows the information for each identified technology alternatives.

5.4. *Hierarchical decision model*

In order to build a HDM for the evaluation of robotics technologies, the objective of the evaluation model was defined as “identifying the robotics technologies that benefit the power sector most.” For fulfilling the evaluation objective, the evaluation model was built with six perspectives: functionality, design, economic, technology, user experience, and electronics. Each perspective was comprised of two to six criteria. The perspectives and criteria of the model were validated by the experts assigned as EP1 and EP2. As a result, the economic perspective and two criteria, “appendage free/less” under the design perspective and “power harvesting” under the electronics perspective, were eliminated from the

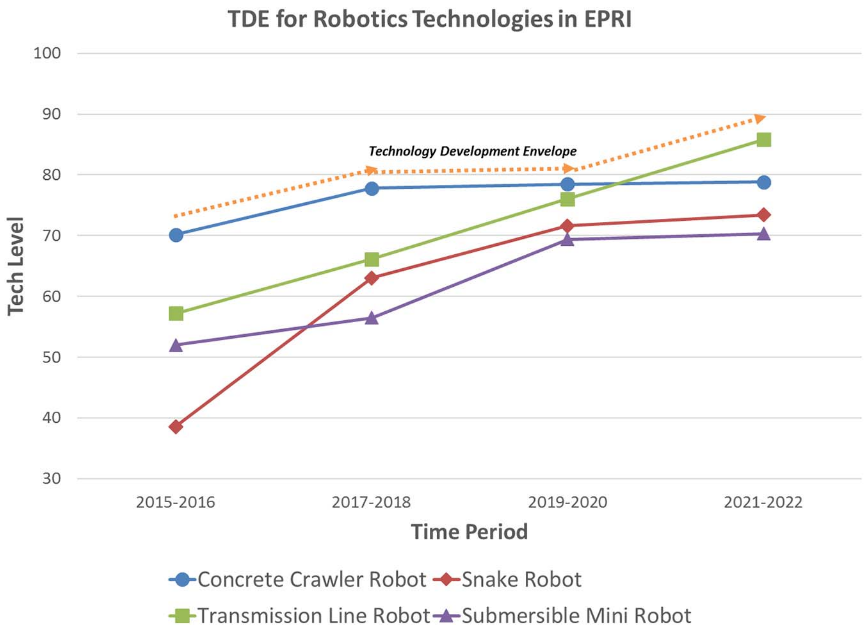

Fig. 14. TDE Plot for functionality-focused strategy.

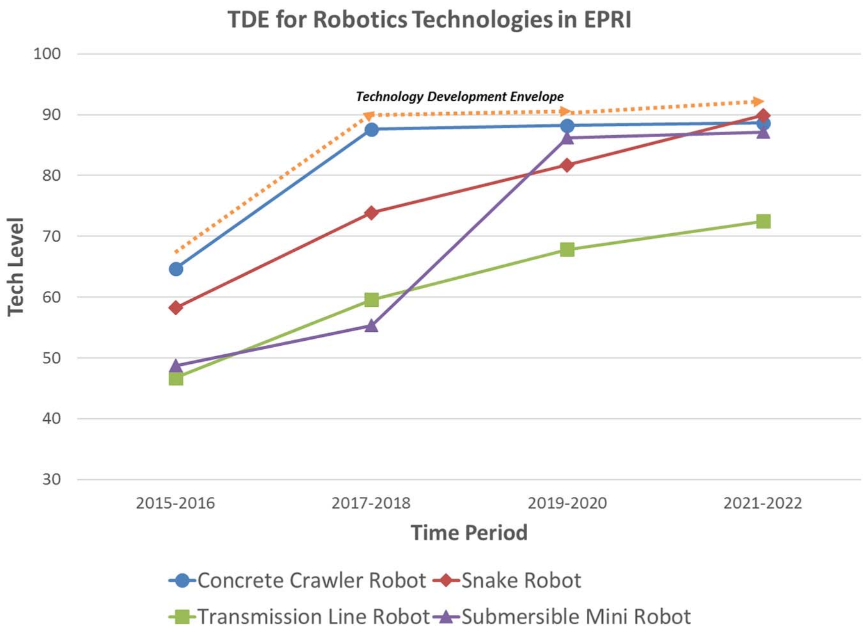

Fig. 15. TDE Plot for design-focused strategy.

model. Table 3 summarizes the description of each criterion in the five perspectives of the validated HDM.

Experts were asked to determine their comparative judgements on the perspectives and criteria of the validated model by the pairwise comparison method. Exhibit 10 depicts the validated HDM. The number beside each perspective in Exhibit 10 is the relative priority (w_k) with respect to the evaluation objective. Similarly, the relative impact ($f_{j_k,}k$) of each criterion, j_k, with respect to each perspective (k) was evaluated and presented beside each criterion in Fig. 8. For reference, the sum of relative priorities and the sum of relative impacts in a perspective are equal to 1.

5.5. Development of desirability curves

In order to represent the organization's preference on the technological metrics (t_{n,j_k},k), EP2 (experts) created desirability curves to assess the performance and physical characteristics of a technology (n) for each criterion. The desirability values enable the calculation of the technology value of an alternative technology by normalizing the different units of the metrics in HDM. Interview sessions were held with the experts to develop the curves using the following steps as suggested by Gerdsri (2010) and Daim et al. (2011):

Step 1. Trace the best and worst limits of desirable values that each criterion can take on.

Step 2. Verify the availability of assigning desirability values to intermediate metrics between the two limits.

Step 3. Assign 0 point to the worst and 100 points to the best desirable value of metrics under each criterion.

Step 4. Calculate the relative desirability, $V(t_{n,j_k},\ k)$, of each intermediate metric between the two limits.

Figs. 9 through 12 shows all desirability curves developed by EP2.

5.6. Technology value calculation

As mentioned above, the technology value, TV_n of each alternative technology is calculated to evaluate its current status with the Eq. (1)

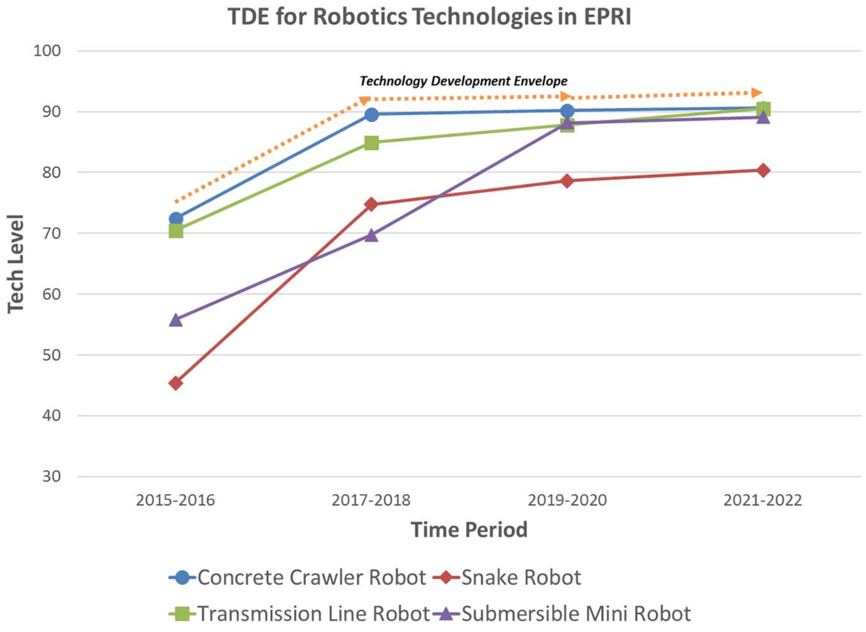

Fig. 16. TDE Plot for technology-focused strategy.

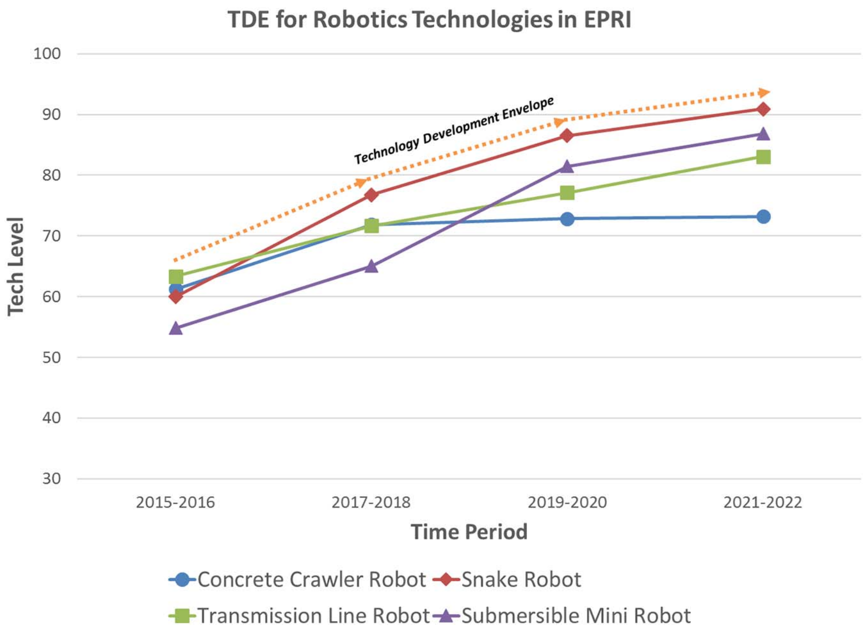

Fig. 17. TDE Plot for user experience-focused strategy.

below:

$$TV_n = \sum_{k=1}^{K}\sum_{j_k=1}^{J_k} w_k \bullet f_{j_k,\ k} \bullet V(t_{n,\ j_k,k}), \tag{1}$$

where

$\sum_{j_k=1}^{J_k} w_k \cdot f_{j_k,\ k}$

: Global weight of a criterion (j_k) with respect to the objective of HDM.

Table 4 shows the 2015-2016 computed technology values of four robotic systems used as technology alternatives. A comparison of the technology values of two different robotic systems shows that “Transmission Line Robot” has higher value than “Submersible Mini-Robot.”

5.7. Future technology estimation

In order to estimate the advancement of each technology alternative in each two-year period between 2015 and 2022, this study conducted a survey of new technological experts who have experience in developing robotic systems similar to each technology alternative in the academic setting.

A standardized form, as shown in Table 5, includes an instructive description in order to help experts understand the concept of each metric, which will enable them to estimate the advancement of each technology alternative in each two-year period. The experts input measurements for the metrics in the form based on their own insights on a specific technology alternative. Table 6 shows the results for “Transmission Line Robot.”

Based on the survey result, the TDE plot was developed by calculating the corresponding technology value of each technology alternative for each period as shown in Fig. 13. The dotted-line connecting the highest value in each time period indicates the technology

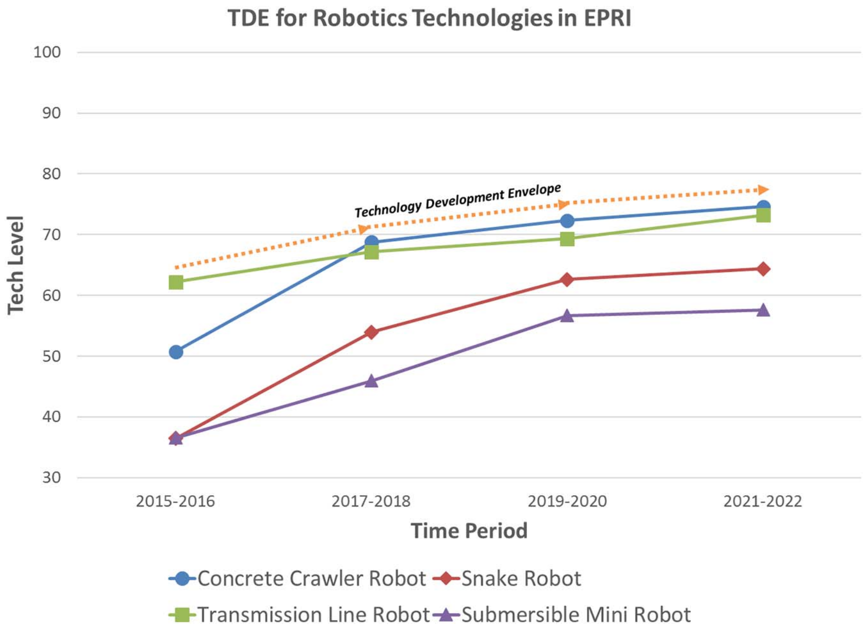

Fig. 18. TDE Plot for electronics-focused strategy.

development envelop (TDE) of this study. Firstly, according to the TDE plot, the concrete crawler robot is expected to have the highest technology level until 2020. Secondly, the technology level of the snake robot will increase rapidly between 2015 and 2018. Third, the submersible minirobot will be expected to show a steep growth of its technology level between 2017 and 2020. Lastly, the transmission line robot technology will have gradual advancement, which will reach the highest technology value in 2022. Additionally, technology levels of all technology alternatives will rise to about 80 in 2022. Therefore, by referring to the TDE, EPRI can establish a strategy to maximize the technological advancements of these four robotic systems for the power industry.

The analysis also identifies the improvements needed for each technology to be an alternative. The needed improvement is the difference of the value of a specific technology and the best technology at a given time. Furthermore future analysis also identifies whether or not that type of improvement will be reached any time soon. Technology developers can choose to increase investment to pull in the development timeline given this possibility.

6. Scenario analysis

There is high uncertainty related to any technology as well as industry. So changes that may happen in the future would impact the values calculated. Scenarios (Amer et al., 2013 and Cinar et al., 2010) are used to conduct how sensitive models like the one presented in this paper are. We developed scenarios as outlined in Table 7. While these are extreme scenarios and other scenario can be developed by varying the perspective weights. The results are presented in Figs. 14 through Fig. 18.

As shown in Fig. 14, in the case of functionality focused strategy, the tech level of the transmission line robot will increase gradually, and be highest between 2020 and 2021. TDE path will be “Concrete Crawler Robot > > > Transmission Line Robot”.

In the case of design focused strategy, the technology value of the snake robot will increase gradually, and be highest after 2021. TDE path will be Concrete Crawler Robot > > > Snake Robot (Fig. 15).

Fig. 16 depicts the technology focused strategy in which case the technology values of Concrete Crawler Robot, Transmission Line Robot and Submersible Mini Robot will reach to around 90 after 2021. The technology value of Submersible Mini Robot will rapidly increase between 2017 and 2019.

User experience focused strategy (Fig. 17) will yield to Snake Robot to have the highest value starting in 2017 until 2022. TDE path will be Transmission Line Robot > > > Snake Robot.

In electronics focused strategy, technology values are all < 80 indicating opportunities for improvement. (See Fig. 18.)

7. Conclusion

This study presents a way to assess the current robotics technologies being used in the power industry today, and to identify the technology that would be the most beneficial to the industry in the future. To establish the technology evaluation model, two expert panels were identified by bibliometric and social network analyses through academic literature. With the dedication of the experts, a HDM model was built with five perspectives and twenty criteria. Based on the judgments of the experts, the relative importance of each criterion was weighted. Simultaneously, desirability curves were developed to present the preference on the technological metric of each criterion. Based on the current technological status of the four technology alternatives, technology values were calculated. Lastly, this study developed the prospect of each technology alternative advancement and the TDE. As a result, “Functionality” was identified as the most important perspective, and the most relatively and globally important criterion was “Multi-application.” Though currently the technology levels of the four technology alternatives are spread widely around a relatively low area, experts are expecting that the technology alternatives will advance continuously and have high technology level in 2022. A scenario based sensitivity analysis provides further insight into how priorities impact technology choices.

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Tugrul U Daim is a Professor and the Director of the Technology Management Doctoral Program at Portland State University in Portland Oregon.

Byung-Sung Yoon is a PhD student at the Engineering and Technology Management Department at Portland State University in Portland Oregon.

John Lindenberg is a Program Manager at Electric Power Research Institute in Charlotte, North Carolina.

Robert Grizzi is a Principal Project Manager at Electric Power Research Institute in Charlotte, North Carolina.

Judith Estep is the Portfolio Manager at Bonneville Power Administration in Portland Oregon, She is also a and adjunct faculty member at the Engineering and Technology Management Department at Portland State University.

Terry Oliver is the Chief Technology Officer at Bonneville Power Administration in Portland Oregon.