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Forecasting Emerging Technologies of Low Emission Vehicle

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***Abstract*–The aim of this paper is to propose a patent search strategy in the case of emerging technology fields and to study the development patterns of the Low Emission Vehicle (LEV) technologies. An Automatic Patent Classification (APC) system has been developed based on text mining techniques to facilitate the patent retrieval process. The data was collected from Global Patent Index (GPI) database and interviews were conducted to involve expert's opinion. Technology forecasting method utilized the collected patent data to define the technological life cycles of LEV technology. The growth curves estimates steady growth in LEV technologies including hybrid and battery electronic vehicles, and apparently reaching to saturation point in few decades is inevitable. Plus, patenting activity of hydrogen fuel cell vehicle technology was experiencing the infancy period so far, and further it is anticipated to reach higher growth rate in line with other energy alternatives. The proposed method can help patent researchers in terms of retrieving accurate patents based on their technology target. Moreover, the technology forecasting techniques provide an insight to investors assisting them to allocate their resources properly. The results can benefit car industry stakeholders to anticipate the most promising technology areas in an uncertain dynamic market.**

I. INTRODUCTION

Pressure is mounting on the automotive industry to develop clean and affordable alternatives to the ubiquitous internal combustion engine vehicles (ICEVs), which gained a dominant position at the beginning of the 20th century. Environmental regulations such as zero emission vehicle (ZEV) mandate introduced by Californian air resource board (CARB) in 1990 gave an important impulse to the development of low emission vehicles in California and elsewhere. As a reaction to CARB mandates, the industry currently develops three major options known as low emission vehicles (LEVs) for substituting the existing ICEV paradigm in the future. The three technologies concern battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), and hydrogen fuel cell vehicles (HFCVs). [1–3] This policy regulation has increased R&D and innovative activities of car manufactures and their suppliers. Information about the current progress and future prospects of mentioned technologies would be a great interest of organizations and investors active in this field.

Various methods have been utilized to predict the future of technologies in the industry. Some of these techniques are based on a life cycle approach where technology is expected to follow an S-curve. Databases are valuable sources for such life cycle data or S-curve graphs. One method, which is known to offer different important economic indicators, is the analysis of patents. Patent data represents a valuable source of technical information that can be used to plot the evolution of technologies over time [4–6]. The correlation between the number of patent applications, technological progress, as well as technological forecast has been studied on different levels and for different technologies [7, 8]. The results from a patent data analysis can provide firms an insight about the value of their own patent portfolio as well as activities of competitors [9]. Therefore, obtaining accurate and high-quality patent information relevant to a specific technology is one of the critical parameters to ensure the reliability of patent analysis results.

In this article, we analyze the technology development trend of mentioned technologies as evidenced by their patenting activity. However, several barriers exist in case of retrieving patent information for our target technologies in car industry. Firstly, the enormous increase in the patent application numbers has created a cumbersome challenge for the entire patent system and the professional patent users. Approximately, one million patent applications are being published worldwide each year, thereby increasing the workload causes lower efficiency in patent classification in patent office's [10]. Secondly, the focus of our study is on engine technologies advancement, still the research domain is needed to be expanded to capture all patents related to car components as well [7]. Since, the vehicle advancement does not only hinge on the engine development, but also on the subsystems that make the whole car development package. Thirdly, conventional patent analysis used by previous literature cannot be applied for collection and analysis of patents related to low emission vehicle technologies known as emerging technologies. Because, relevant patent documents to emerging technologies may not be classified under certain section of patent system, which necessitate an accurate systematic patent retrieval process. Last but not least, this patent retrieval system needed to be agile and modified over time to cope with the dynamic nature of LEV technology advancement and ongoing patenting activities.

The above mentioned shortcomings led us to seek for a methodology that would efficiently perform the patent data retrieval and classification in field of LEV technology. With this systematized methodology we would be able to answer the research questions: 1) What is the technology development pace in LEV area? 2) Who are the main innovative industry players in terms of their filed patent applications? The novelty of our study is practicing a modern patent analysis using text–mining techniques to collect patents according to their concepts; regardless of what International Patent Classification (IPC) codes they have been assigned. Moreover, the application of machine learning method which is able to automatically classify the collected patent documents to one of major technology options of LEV. Meanwhile, the involvement of human knowledge and expert screening patent documents will help the whole system to learn and adapt itself to the constantly changing environment. Afterwards, the proper and accurately retrieved patent applications will be prepared for plotting the technology forecasting trends.

The paper continues as follows: In section two we provide the theoretical background to the patent analysis, search strategies and technology life cycle studies. The third section presents our proposed methodology for the automatic patent classification system. Following the fourth section begins the empirical results by illustrating the technology development trends in low emission vehicle (LEV) technologies. The fifth section will discuss the findings, and finally in last section the conclusions are presented.

II. LITERATURE REVIEW

A. Patent analysis in Low Emission Vehicle technology area

Patenting activity in the car industry has been studied quite extensively in relation to the industry's quest for Low Emission Vehicles (LEV) or zero-emission vehicles (ZEV). Reference [5] research results illustrated that both technological variety and organizational competition in LEV technology field have been increased steadily as a response to Californian regulations mandated ZEV in early nineties. The dominant method to classify the pile of filed patent applications is conventionally performed based on International Patent Classification (IPC) system established by the Strasbourg Agreement in the year 1971. IPC code has been traditionally used for searching relevant patents to a technology for patent analysis. However, certain difficulties are encountered in the process.

First, IPC considered too broad to be directly applied to interested subjects. Each IPC code contains a few hundred to tens of thousands of patent documents. Second, no patent categorization method has been developed that can classify patents down to the subgroup level (the bottom level of IPC) so far [11]. Philipp [10] stated that in practice many of patent applications will not be indexed and coded as accurately or completely as they should be. Third, one product or process technology normally consists of a group of associated technologies filed with various IPC codes. For instance, Pilkington, Dyerson and Tissier [7] investigated the Electronic Vehicle (EV) development by using the patent class search B60L11, by which the results showed many irrelevant patents with patent classification search. Because the definition of the IPC group embraces a wide range of EV not just automobiles, therefore the patents included within this classification relate to many other applications apart from EVs. Their study suggested that the data set can be enlarged by adding the other relevant classes, e.g. HVAC[1] covered by B60H1, structures by B62D21–B62D29, hybrid vehicle control is in B60K, electric motors and controllers are in H02K/H02P [7]. Clearly, considering larger scope of IPC may not be a thorough solution since it may again increase the quantity of irrelevant patent documents to LEV technologies area. Moreover, the technology variety of each component of the car must be considered as well. For example, in case of hydrogen cars, there are different ways of hydrogen distributions, hydrogen storage or conversion [12].

Hence, when more IPC items are included in a patent search, then piles of documents are overloaded for analytical purposes. On the other hand, the technology advances captured through these IPC codes may, or may not, be used in electric vehicle or hydrogen vehicle development at all, and this is a major limitation for utilizing IPC codes or keywords to explore product advances in LEV technology area.

IPC codes are regularly supplemented by the inclusion of keywords. The problem of using keywords is that an inconsistency possibly exists between the users and the inventors. That is to say, the keywords defined in the documents are not the same keywords input by the researchers. Moreover, the database search is based on the match of exact wording; it is merely a means of finding characters without contextual meanings. Therefore, the output of a search generally leads to many patents that are not compatible with the needs. Also, being unfamiliar to the technology area, for which the patent data are being gathered, it would be quite difficult to build an exhaustive keyword list. The efficiency and accuracy of patent retrieval would be improved if the collection process would be based on patents concept and applicability. Plus, the classification and patent sorting could be greatly improved if can be done automatically by computer algorithms.

So far, the majority of patent analysis research previously done in car industry field, have utilized bibliographic fields of patent documents, known as structured data (such as publication date, applicant name, innovator, classification code, …, etc.), for their statistical analysis. Undoubtedly, the technical information and concepts of invention laid in abstracts, titles and descriptions of patent documents (unstructured data), that were not considered in conventional patent studies. To overcome above mentioned limitations, recent studies have applied text-mining and data-mining methods to patent analysis for several purposes and industries. For example, article [13] tried to improve the information retrieval process with text mining in 2007. Furthermore, the application of text summarization techniques showed to be helpful in patent analysis and automatic organization of documents [14]. In addition, there are other research used summarization techniques [15, 16]. Yeap, Loo and Pang [17] used the technique to conduct a trend analysis in the area of nanotechnology, and Yoon and Park [18] suggested text mining for technology keyword clusters for in–depth quantitative analysis.

[1] Heating ,Ventilation and Air Conditioning

The present study is aimed to investigate and conduct a methodology that both elaborate structured and unstructured patent data. In other words, patent documents will be searched, retrieved and classified based on their content rather than their predefined technology categories.

B. Automatic Patent Classification system

The automatic patent classification is mainly based on text categorization of patent documents. The method considers analysis of both structured and unstructured feature of a document based on text mining techniques. These methods have already been used intensively in data mining applications [19–21]. Black and Ciccolo [22] applied machine learning methods to text classification on United States' patent information to automatically differentiate between patents relating the biotech industry and those unrelated. There are many other studies about developing an automated classification of patent applications by employing text processing methods [23–25]. It seems that most of the previous studies addressed the importance of search strategy and data analysis during their patent studies and searched for more efficient methods or algorithms.

Many machine learning algorithms have been developed in the past several years, such as, the support vector machine (SVM) [26–28], Naïve Bayes [29, 30], the artificial neural network [31, 32], K-Nearest Neighbor [33, 34]. Many researches have proven that SVM method has outstanding classification validity [27, 35–37] and therefore it will be applied in our research as well.

Previously, the automatic patent categorization system has only been used in the patent division of major countries, and then mainly as a research project, and has seldom been used in practice [38]. Also, most of the researches were mainly focused on computational models for IPC system rather than using them on real world patents classification cases [25, 38]. Contrary to mentioned research areas, this paper will practice a real world case of patent analysis in low emission vehicle technology area. As a starting point, the unstructured patent data will be transformed to numerical format to be readable by the classification algorithm. Thus, before applying classification categorization algorithms to unstructured data of patent documents, the typical text pre-processing tasks are needed to be performed [39]. Then the extracted words of the documents are transformed into numerical representations for further analysis.

C. Technology development and Forecasting

Patents are important indicators that can be used to explore technological trends and development. According to [40] patent applications are easily retrieved and can measure the impact of R&D activities. Andersen [41] suggests that the accumulations of patents are useful for measuring technology trends and reflect the diffusion of the technology. Therefore, in this research, cumulative patent applications are used for studying the growth curve of LEV technology development trends. Patent application volume reveals the maturity of a new technology. Technology forecasting is the process of predicting the future characteristics and timing of technology [42] which is always a challenging task. Generally it is important to foresee as clearly as possible the probable impact of a rapidly growing technology.

Technological forecasting is not deterministic in a way that its results may not anticipate a single certain future. An exhaustive forecast projects a range of possible futures, of which some may be more likely that the others. Forecasting procedures can be quantitative, qualitative or even the mixture of both. In this research, the prediction will be quantified based of cumulative patent data, which facilitates the estimation of the timing and degree of change in technological parameters, attributes and capabilities.

Prior to forecast the technology development, one should learn about the current stage of technology or technological life cycle. One approach to identify technological life cycles comes from the observation that technological performance data for particular technologies over either time or cumulative R&D expenditures show an S–shaped relationship [43]. The other approach more oriented towards the market effects of technologies which can also be incorporated into S–curve illustration [44]. Porter and Rossini [45] categorized these approaches as trend extrapolation which is a technique to forecast the future development of a specific technology.

It has been empirically observed by Ernst [40] the number of patent applications over time generally follows a trend which resembles an S–shaped curve. If the volume of patent applications is growing, then there are many resources creating the technology and the innovation. In such cases the technology may soon reach its peak. On the other hand, if the volume of applications is declining, then the technology may be is in the processes of being substituted by a new technology and thus entering the decline stage of the technology life cycle.

The characteristics of technology life cycle have been described by several authors. According to Foster [46], the emerging stage is characterized by a relatively low growth of technological performance compared to the amount of R&D efforts. In the growth stage, the marginal technological progress over cumulative R&D expenditures is positive, whereas it is negative in the maturity stage. In the saturation stage small technological performance improvements are only gained through very high R&D efforts. Based on the S–shaped technological development, strategic R&D decisions can be made. In the maturity stage, further investments in the "old" technology are not recommended, since future technological improvements are only marginal. Instead, it should be looked for a "new" technology (S-curve) with a higher future development potential (Fig 1).

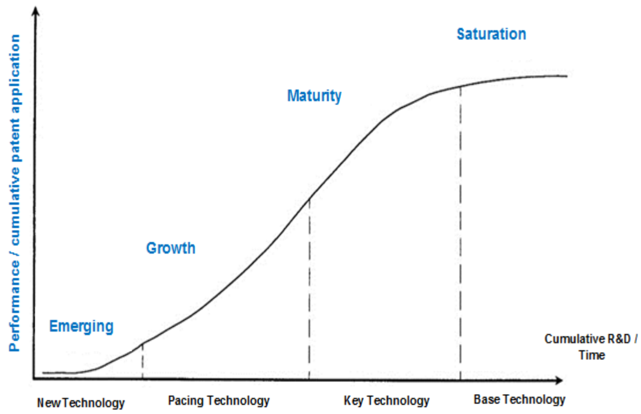

Fig. 1: Technological Life Cycle [40]

Liu [47] added that when technology is in the introduction stage, companies should develop and apply related patent technology as a means to strengthen their position in the industry. If the technology is in its growth stage, the plan should include means to modify the core technology and search for new applications. During the maturity stage, technology developers should be clear on the boundaries of intellectual property and evaluate the advantages of forming strategic alliances to trade IP. Finally, if the technology is in the decline stage, new technology will be created to replace the old and signal new opportunities for research and development. Here it should be noted that these guide lines and theories may vary for each technology field, depending on the nature of the cumulative data and technology nature.

The dominant approaches to analyze Technological Life Cycle (TLC) are Gompertz or Logistic model [48–50]. These growth curves are widely used in technology forecasting field [51, 52]. These methods are mainly based on a projection of a model that takes historical data as containing all the information needed to forecast the future. The number of patents will considered here as the dependent variable. The Gompertz and logistic models are, respectively, presented as equation (1) and (2). Both Gompertz and logistic curve range from zero to L as t varies and are controlled by three coefficients: a, b, and L. All three coefficients are computed using a nonlinear least squared estimation method.

$$y_t = L\, e^{-ae^{-bt}} \quad (1)$$

$$y_t = \frac{L}{1+ae^{-bt}} \quad (2)$$

The choice between these two curves is a very critical task, because the forecast will be seriously in error when the data represents a logistic and a Gompertz is fitted. The choice between these two curves can be performed by using a regression model developed by Franses [53], which tests for non-linearity between the dependent variable and time. The regression model (equation 3) for Gompertz curve is linear in t and the expression for logistic curve is nonlinear in t [53].

$$\ln(\Delta \ln Y_t) = \alpha + \beta t + \gamma t^2 \quad (3)$$

In the case when γ is significantly different from zero, the forecasting method to be used will be based on logistic curve rather than Gompertz curve. All the coefficient estimations are performed using MS Excel software. Trend extrapolation like other forecasting methodologies has basic limitations. Setting an upper bound for growth models heavily affects the trend outcomes [54]. It has been argued in their study [54] that trend extrapolation can produce significantly different results if each time the chosen database, growth model or upper bound varies. In this research, we have carefully estimated the maximum value of L based on both statistical justification and expert opinion.

Moreover, the forecasts conducted by trend analysis usually do not explicitly address the causal forces that drive the patent publication rates [54, 55]. Therefore, the output of the forecast cannot be considered as absolute, since the underlying assumption of the trend analysis techniques is the past and current conditions will continue in future or with less change [56]. Although, patent indicators provide useful forecasting information on technological performances for decision makers in the public and private sectors [57] the forecast may not be certain and contains uncertainty. Porter and Cunningham [55] emphasize treating the trend study results as crude as possible and cautiously interpret the findings. Because, the next year patent data may significantly alter the model and its projection. It is critical to be aware of constantly changing technology environment which necessitates frequent updating of the forecast. The level of uncertainty can be communicated to decision makers by providing the results with confidence intervals (CI) which indicates the reliability of an estimate. According to statistical considerations, for instance a 95% CI implies that only in 5% of the times the actual value would fall outside of the lower and upper bound. In order to diminish the level of uncertainty, the future projection of LEV technologies development will be reported by considering the confidence predictions.

III. RESEARCH METHOD

The main intention of developing an automatic patent retrieval system is to that a patent must be related to the subcategories of low emission vehicle technologies to assure the accuracy of technology forecasting report. The methodology is designed in four phases (Fig.3), which will be described step by step. Data collection and our patent search strategy will be described in first phase. Second and third phases will present the establishment of automatic patent classification system. The implantation of technology forecasting process will be described in fourth step.

In the first phase of the project, authors started getting grasp over car engine technologies by interviewing practitioners and researchers active in mechanical or electrical fields. The knowledge over cars was developed by looking into the problems toward engine development, techniques, product and manufacturing processes. Identification of patents related to integrated technologies, emerging technologies like LEV that has not been clearly defined through patent classes or no definite related patent class exits in the patent system is a challenging task (Fig. 2). Therefore, text processing technique will be applied in this research as a supplement patent search strategy by identifying patents based on their concepts and applicability.

Two different types of queries were formed in this step; one is based on domain of IPC codes (e.g. the patent classifications B60K [2], B60W[3], B60L[4], H01M[5]), which are appeared to be quite broad and contain irrelevant patents to our target technology (See Appendix A). The second query is primarily constituted based on both relevant keywords and IPC. However, the results are not very satisfactory since the word "hybrid" which we used to retrieved "hybrid cars" has resulted us with patents contains "hybrid bike", "hybrid electrode" or "hybrid methodology" in their texts . Both queries were formed on Global Patent Index (GPI) database, and the retrieved patents will be used to establish our automatic patent classification system (APC). The APC system requires a series of LEV relevant patent documents so-called "Training set" to learn the pattern of our data. To form the training set, experts were asked to manually review the patents retrieved by our second query, and define the most relevant ones. Once, the APC model is trained, it will need to be applied on a broader patent collection named "Test set" and filter out irrelevant patent application to LEV technologies. More detailed information about training and testing the model will be provided in next phases.

In total, 124 000 patents related to hybrid vehicles or battery electric vehicles (BEV) covering the years 1987–2013, and 13 134 patents related to hydrogen vehicles (HV) or fuel cell vehicles (FCV) within the time period of 1994–2013 were retrieved and archived for analysis.

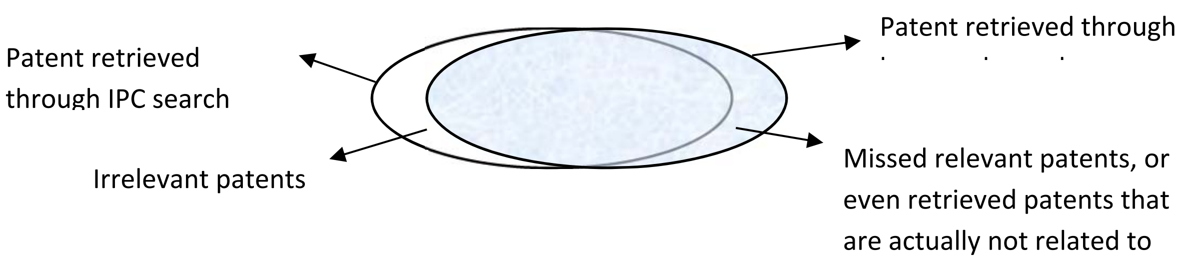

Fig 2: Patent search strategies

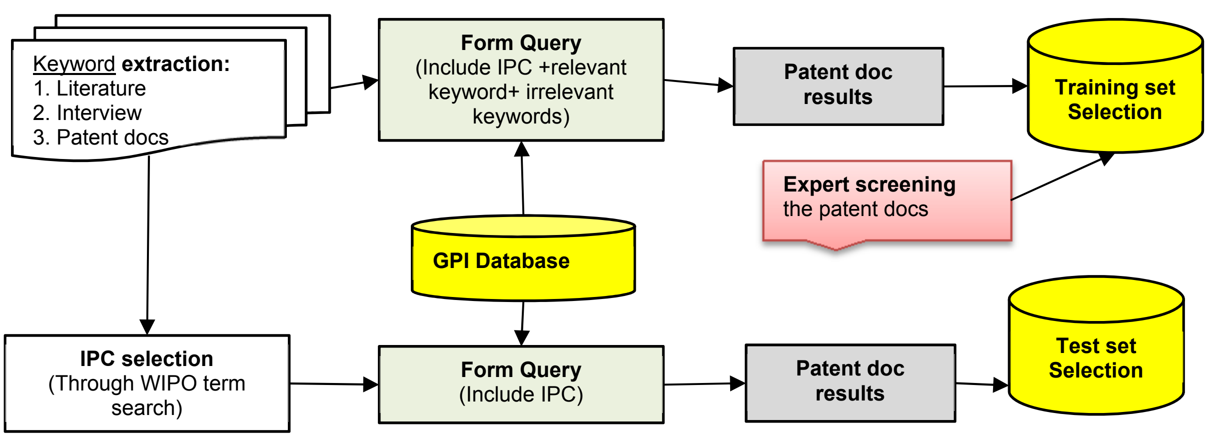

Fig. 3: Patent data collection

[2] Mounting of propulsion units
[3] Conjoint control of vehicle
[4] Propulsion of electrically-propelled vehicles
[5] Processes or means, e.g. Batteries, for the direct conversion of chemical energy into electrical energy

Second phase is a vital step toward developing an automatic patent classification system since it includes training the SVM classifier. Usually the training set for SVM includes both correct (Positive) and wrong documents (Negative), which requires the use of experts to manually review patent documents, regarding LEV technologies development and the selection of about 100 most relevant patent documents for the correct training set. The negative training set would be created with 100 irrelevant patent documents specifically to LEV. To achieve high precision and recall it is critical to structure the training carefully with key patents of technology field. The validated training set will be used to train the automatic patent classification system. Meanwhile, the test set is created based on broad number of potential IPC codes seems to be relevant to LEV.

To establish an automatic patent classification, firstly the training set text need to be pre-processed. The document preprocessing phase includes; feature extraction, feature selection, and document representation as activities [39]. The main idea of text processing is to change the terms of the text to numbers, by which facilitate further document categorization. RapidMiner software package was used to conduct the text processing on training set and test set including patents abstract and title.

Feature extraction is the first step in document text preprocessing. The general problem in this phase is to generate a list of terms that describes the documents sufficiently. The most popular methods for this purpose are: 1) Tokenization; means to remove all punctuations and special characters, 2) Stop-word removal; removes articles, prepositions and conjunctions, which reduces complexity without any loss of information, 3) Stemming; it breaks down words to their roots [39], and 4) N-gram; it creates the combination of tokens (words) in a document to capture the definition of word in that specific context.

Feature extraction is followed by feature selection. The main objective of this phase is to eliminate those features that provide only few or less important information. This time statistical values are used to determine the most meaningful features. The most common indicators are term frequency (TF), inverse document frequency (IDF), which together represents the TF-IDF method. By using TF it is assumed that important words occur more often in a document than unimportant ones. When applying IDF, the rarest words in the document collection are supposed to have the biggest explanatory power. [39]

Document representation as the final task in document preprocessing provides documents, which have been turned to TF–IDF Matrix indicates words or documents weights. TF–IDF Matrix is an input for SVM classifier. For adjusting the SVM parameters on RapidMiner software, the factor C=0, convergence epsilon=0.001 and max iteration set as100000. To validate SVM model we performed a cross validation process with the software. Cross-validation process would hide $1/10^{th}$ of the data from SVM model, and build the model on the remaining $9/10^{th}$ of the data, and then it test the model on the remaining dataset for calculating its accuracy. This validation process may continue for 10 times and the average of accuracies will be provided. Then validation and evaluation step offers three analysis indices: rate of accuracy, rate of precision and rate of recall. We are aiming for the highest rate of accuracy as it suggests that all the patent documents were classified under right category. Therefore, the training set was modified several times under supervision of experts to reach the best classification accuracy. Finally, the selected SVM performance level showed 84% rate of accuracy, 80% of precision and 79% rate of recall.

In the third phase, the well performed SVM classifier will be applied to our test set. The patent applications contain the most relevant technology to low emission vehicles were classified under LEV class, and the remaining irrelevant inventions named as not LEV. Approximately, 59 858 documents out of 124000 and were labeled for BEV and HEV, 4878 out of 13134 patent documents classified under FCV, after removing duplications and were prepared for the further analysis. Finally, the technology life cycle trends are plotted in the last phase using the logistic function. Logistic model has been selected since γ parameter in Franses [53] regression model turned out to be none zero (See Appendix B).

The parameters of the logistic formula (L, a, and b) were computed using a nonlinear least squared estimation method with Matlab and MS Excel (See Appendix C for estimated values). This model can forecast how many patent applications will be submitted for a short time period. Once the possible ceiling value of cumulative applications (L) is determined, the stage of technology life cycle is estimated and time when the saturation of the technology will occur is computed. In this study, similar to [40] and [58] the 10%, 50%, and 90% of the limit L are used to define the cyclical points for classifying the four stages of the technology life cycle. Thus, if y(t) represents the number of patent publications at time t, L is the maximum value of y(t). Then, $y(t)/L < 10\%$, $10\% \leqq y(t)/L < 50\%$, $50\% \leqq y(t)/L < 90\%$, and $90\% \leqq y(t)/L$, mark the range for technology in introduction, growth, maturity, and saturation stages, respectively. For the simple logistic model, reference [47] proposed that the range from 10% to 90% of the limit L represents the growth stage. Additionally, article [39] defines the maturity stage beginning from the inflection point, or 50% of the upper limit, for a simple logistic curve.

IV. CASE RESULTS

A. Patent classification and Analysis

The patent documents labeled as LEV embraces three main alternative technology categories: Hybrid vehicle, battery electric vehicles and fuel cell vehicles. As we have mentioned earlier our study focus is only on LEV technologies and the conventional internal combustion engines (ICE) per se are out of research scope. However, hybrid cars draw energy for mechanical propulsion from both ICE and an electric power storage device. Therefore, distinguishing the patent data related to hybrid cars from ICE or BEV related patents is a challenging task since patents related hybrid cars may contain the word "combustion engine" or "battery" as well. Hence, HEV and BEV classes were considered in one category separately from FCV for patent analysis purpose.

Patent analysis is used to synthesize patent information including patent counts, development trend and assignees analysis. Fig. 4 provides an assumption about the patenting intensity of the two technology group of HEV+BEV and FCV. However, the normalized values (Fig. 5) offers better representation of patenting activity comparing to absolute values. Regardless of volume, it shows how rapidly FCV technology is moving forward along with hybrid and electric cars. The rapid growth of FCV have been previously corresponded to resemble a hype model, where the high rate of prototyping or positive statement announced in media about specific technology only attracts sponsors and disappoint them with failure in commercialization [59, 60]. But without regard to the research volume, Suominen [61] has illustrated that fuel cell research intensity and co-operation have been grown at national level worldwide. This can be considered as an important driving force of one technology commercialization in the future.

The trend shows a drastic increase in patenting behavior around the year 1990, which can be explained by introduction of CARB regulation in the same time period. The sudden stagnancy of both trends in the last two years can be justified by publication time lags in patent system. It usually takes 18 months for applied patents to be published; therefore the decreased amount of patents does not mean the development trend has declined.

Regarding assignees analysis, Table 1 shows the top 10 applicants who are having the largest share of patent applications related to BEV, HEV and FCV. As shown in the Table, Japanese companies (e.g. Toyota, Nissan, and Honda) are the front runner based on their large contribution to patenting in LEV technology field. American companies such General Motors and Ford seems to be actively involved in developing cars with least amount of emission.

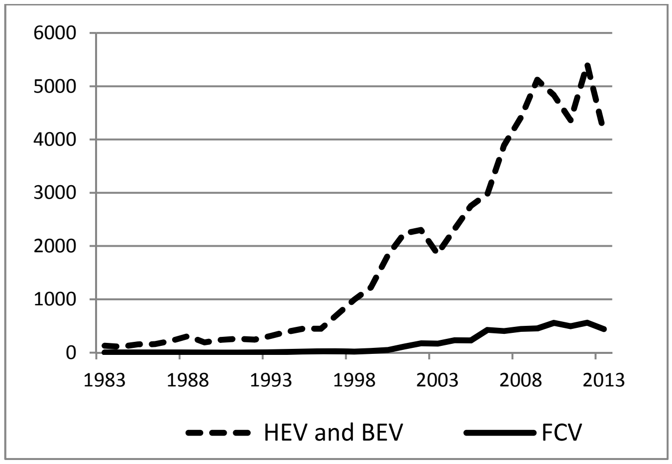

Fig. 4: Patent publication number of HEV+BEV vs. FCV

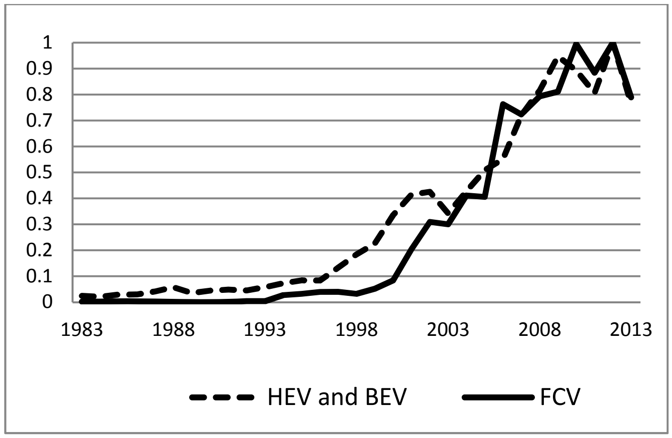

Fig 5: Normalized number of patent publications of HEV+BEV vs. FCV

TABLE 1: TOP 10 APPLICANTS IN LEV (1987-2013)

	HEV – BEV		FCV	
	Applicant name	**Number of patent application**	**Applicant name**	**Number of patent applications**
1	Toyota	8666	Toyota	1156
2	Nissan	3093	Honda	601
3	Honda	2411	Nissan	421
4	Bosch GMBH Robert	2041	Hyundai	161
5	Denso	1066	Renault	106
6	General Motors	820	General Motors	90
7	Hitachi	801	Daimler	74
8	Hyundai	691	Suzuki	69
9	Ford	682	Delphi Tech	51
10	Peugeot	566	Denso	42

B. Technology Forecasting Trends

The current patent application results collected for 30 years (1983-2013) used to plot the technology development trends of the alternative engine technologies. Fig. 6 depicts the S–curve of the BEV and HEV. Using the simple logistic model, the evolution trend of the LEV technologies and the maximum cumulative LEV patent applications (upper limit) are estimated. (See Appendix B for estimated parameters). Similar calculation has been followed for FCV (Fig. 7).

Statistically, the closer the R-squared value to unity, the more suitable the forecasting model. The R-squared values for BEV-HEV and FCV technology are estimated as 0.95 and 0.93 respectively. These R-squared values imply that we have used well-fitted models for technology forecasting. The available patent data has been utilized to determine the stage of LEV's technology life cycles. Due to the absolute uncertainty linked to the trend analysis process, the forecast results are reported with confidence intervals (CI). Fig. 6 shows 95% CI for our forecast of HEV and BEV patent activity development. The bounds may widen as the forecasted time series lengthens and the uncertainty would be higher as well. The middle curve labeled as "Actual forecast "is more plausible than optimistic and pessimistic scenario.

According to actual forecast curve, the LEV related patents will experience a steady growth from 2013 up to the year 2033 and remain stable after that. Based on Ernst [40] theory, we can argue that the LEV emergence phase ended 1997 when it reached 10% of total cumulative patent numbers. Then the cumulative patents appeared lower than 50% for following seven years till 2005, which was named growth stage. The next level is maturity level when y_t/L is more than 50% and still less than 90%. Based on the forecasting results, it is anticipated that LEV development may continue and inevitably reach its saturation period. By year 2033, number of patents may reach approximately ~140000, and ~60000 based on positive and negative scenario, respectively.

According to Andersen [41], it is not recommended to invest to existed technology when it is in maturity stage. Instead firms need to investigate and assess a new technology with higher future development potential. It can be observed from Table 2 the saturation point for LEV is projected to occur in few decades. However, it should be noted that patent development trends may represents technical aspects of a specific technology. Investors and decision makers are required to evaluate other business aspects before drawing final conclusions.

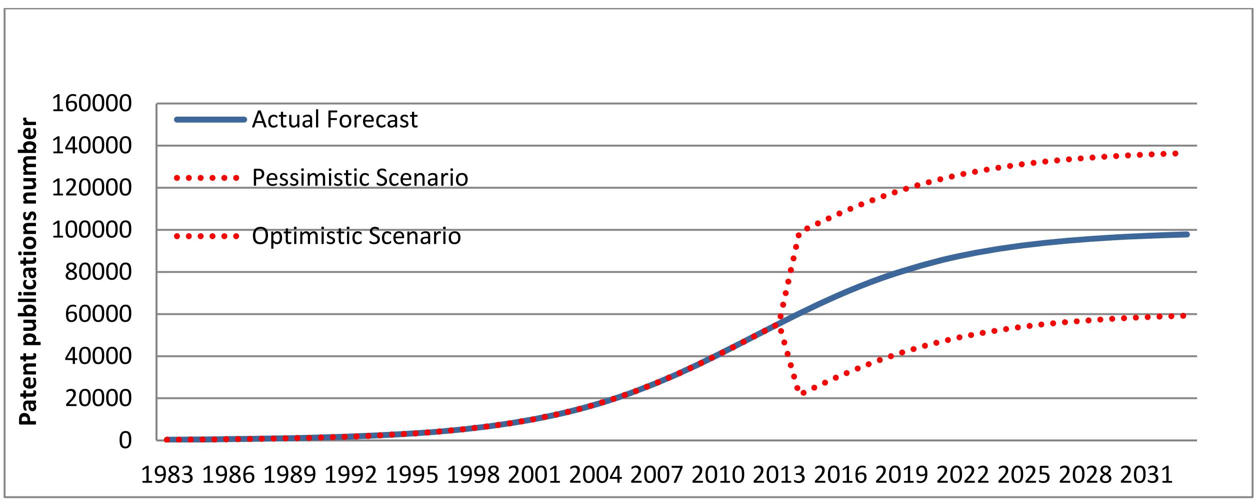

Fig. 6. Actual, predicted and confidence intervals for HEV and BEV

TABLE 2: HEV AND BEV TECHNOLOGY LIFE CYCLE

FCV		**HEV and BEV**			
Patent publications (1994-2020)	**TLC(year)**	**Patent publications (1983-2033)**	**TLC(year)**	**Share of upper limit (%)**	**Stage of technology life cycle**
$y_t = 287$	2002	$y_t = 5780$	1998	$\frac{y_t}{L} \leq 10\%$	Emergence
$y_t = 1002$	2013	$y_t = 27232$	2007	$10\% \leqq \frac{y_t}{L} < 50\%$	Growth
-	2020 < t	$y_t = 50442$	2012	$50\% \leqq \frac{y_t}{L} < 90\%$	Mature
-	-	-	2013 < t	$90\% \leqq \frac{y_t}{L}$	Saturated

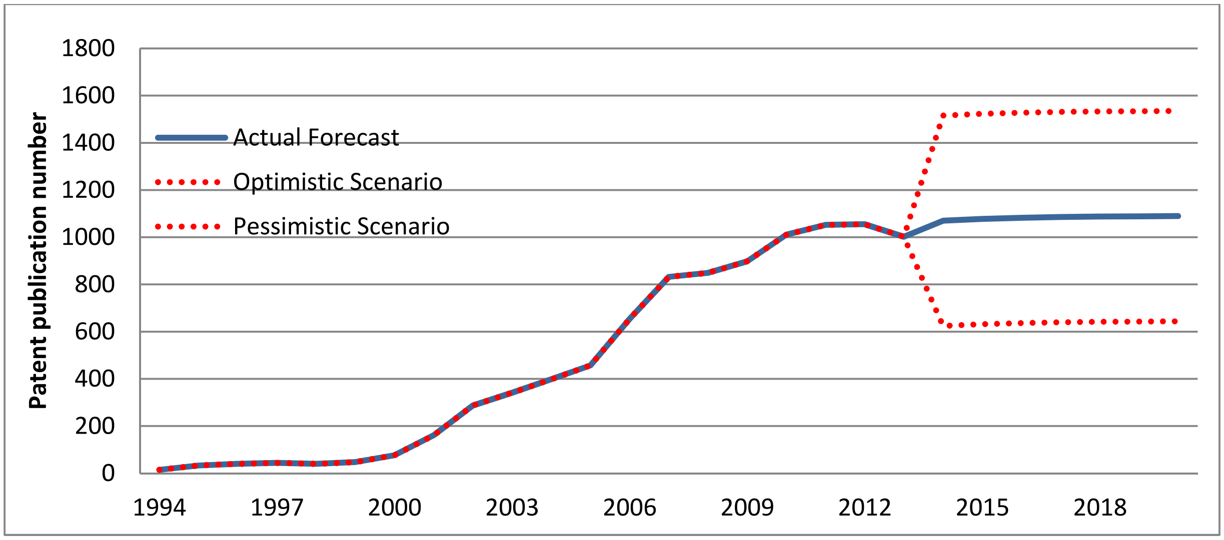

Fig. 7: Actual, predicted and confidence intervals for FCV

The forecast horizon considered to be shorter than previous technologies, since the available patent data starts from 1994. Therefore, the estimation has been done for seven years till 2020. Similar to HEV and BEV, the future development of FCV technology is presented with upper and lower bounds (CIs) (see Fig. 7). The actual forecasting result, the best scenario, of FCV technology development indicates that the technology is probably experiencing its infancy period. The patenting activity was quite low before the year 2003 and results are suggesting that the era of technology emergence was quite long from 1994 till 2002. Based on the S-curve, the growth and maturity level of FCV technology may lay in the future (See Table 2). In addition, we can argue that, number of patent applications may end up ~1100 with optimistic assumptions, or in contrast reach to ~1000 in pessimistic situation.

IV. DISCUSSION

One of the main concerns in retrieving patent data of emerging technologies is how to assure the precision of retrieved patents. The unbiased, accurate and reliable data is main thing to effective decision making, as decisions are only as good as the dates upon which they rely. Incorrect identification may result in wrong collection of patents in a specific technology domain, which may cause serious and inaccurate analyses, even greatly influences the decision-making process in technology forecasting area. Dynamic nature of emerging technologies makes the forecasting situation based on patent data much more difficult. Scientific fields evolve, expand, emerge, and contract over time. This implies the necessity of an agile patent retrieval system that can be updated in terms of mechanism, keyword combinations and classification.

Generally, there are several approaches to search for relevant patents: using patent classification (e.g. IPC codes), keyword search, combination of patent classification and keyword search, and experts reading through the patent. Patent classification has been used by many scholars in low emission vehicle technology area, ended up with relatively unsatisfactory results [7, 12]. Human judgment and expert screening the patent applications manually seems to be an effective method [62], however, it is rather impossible to consistently identify a large amount of patents related to an emerging trajectory. Our research shows that for identifying patents related to emerging technologies that cannot be clearly defined through patent classes or no definite related patent class exists in the patent system, application of text mining methods is an appropriate choice. Text mining offers the possibility to represent patent based on their concept rather than other bibliometric parameters (e.g. IPC codes, application number or date, innovator name …) and then the selection of the most relevant patents to targeted technology would be accurate. The text mining of patent documents has been practiced for a while and successfully has been tested on different technologies [63, 64]. But the recent text mining techniques was rarely practiced in car engine technology field.

Further, the application of machine learning methods in third phase of our methodology not only speeded up the classification process but also will adapt to newly added data set as well. The emerging technologies as LEVs are constantly changing over time and its dynamic nature will be reflected in the patenting behavior as well. The presented automatic patent classification (APC) model addressed this gap by providing an automatic classification that can be modified through its training set. The stored dictionary of terms from training set can be enriched over time and it works as a feedback channel between automatic process and expert opinion. Moreover, our model has involved expert judgment at its early stage of process. Human supervision makes the APC model more agile and increases the performance of classification.

The forecasting model used in the fourth phase, like previous research [47; 58], suggests that analyzing patent data can illustrate the technology life cycle which can be used in management decision making process. The extrapolation trends were statistically fitted very well based on the R-squares values. It should be noted that the growth models such as the logistic model used in this paper has been validated by an abundance of empirical assessments. While, limitation associated with the extrapolation method impacts the findings to a large extent. Meanwhile, trend analysis techniques are vulnerable to cataclysms [65] and apparently do not address the causal mechanism which limits model applicability. The secrecy of publishing R&D results or technical reports limits the validation process of bibliometric studies [66]. Moreover, choosing different upper bound for growth model may produce different trend results [54] with high uncertainty rate.

However, the uncertainty associated to the forecast output can be diminished to some levels by setting the prediction intervals and applying expert opinion. The trend analysis shows that in best scenario, the cumulative number of patent applications related to BEV and HEV would reach the saturation level in few decades. It implies that the technology would be quite mature and market will expect a new complete technology or the combination of previous ones to emerge. On the other hand, it seems that patenting activity in FCV technology area would continue to grow in future, but estimating if and for how long this growth trend will move forward is challenging [54].

Furthermore, due to the limitations stem from patent databases and secrecy of R&D publications the forecast results cannot be used as the only source of decision making process.

Cozzensa et al. [67] added in this regard that quantitative measures have significant potential for technology monitoring but there are limitations to these approaches. Therefore, it is recommended to use quantitative techniques in conjunction with expert methods by focusing the qualitative assessment in particular areas.

While we report our early results here, there remains scope for future work both in terms of methodological improvements usable, updating the APC model, and in terms of exploring the technology developments in LEV field. First of all, the dictionary of keywords can be improved to a large extent by more in-depth interviews with expert of each technology field. We have tested different classifiers such as K-NN[6] and Bayesian that showed classification performance lower than SVM which has 86 % accuracy level. There is still room for improving the classification accuracy with same or modified machine learning algorithms. Modern patent information analysis requires sophisticated and specialized computer software tools [68] . We have utilized three different software tools; Global Patent Index, Rapidminer and Matlab to retrieve, analyze and visualize the patent information. We are not aware of a single product that could support the entire methodology workflow. However, the integration of other available tools in the market may help the improvement process.

[6] K-Nearest Neighbor

V. CONCLUSION

This research was designed to identify the most efficient methodology in terms of retrieval and analysis of patent data relevant to Low Emission Vehicle (LEV) technologies. The main challenge in patent retrieval process of emerging technologies like LEV is that there are no certain patent classes or keyword available to form the reliable search strategy. Hence, an Automatic Patent Classification (APC) system has been proposed which would employ text mining for patent identification, and machine learning techniques for patent classification. The performance evaluation result shows that the developed APC model has a high level of accuracy.

Furthermore, the predicted progress of LEV technology trend has been illustrated on S–curves. These growth curves initially will face a slow starting phase and a rapid growth rate afterwards. Thus, reaching to a saturation point is inevitable. More thoughts and efforts should be focused on estimating the technology cycles in terms of time and amount of patent applications. The result of forecasting would be more reliable if the upper bound of trends set up with careful market investigation and qualitative research. In other word, if the managerial actions need to be taken based merely on the quantitative based forecasts, further studies are required to cover expert opinion and qualitative evaluations.

The research methodology provides a solid framework to develop efficient patent classification methods and this paper is just the beginning of this research line. The model can be improved, since the proposed approach is able to dynamically classify patent documents by recording and learning the knowledge and logic of experts. It means by improving the training set the whole classification process would be improved.

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APPENDIX A

Relevant IPCs			Irrelevant IPCs	
Group	**Main group/ sub-group**	**IPC scope**	**Main group/ sub-group**	**IPC scope**
B60K	B60K 6/00	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. hybrid propulsion systems comprising electric motors and internal combustion engines	B60K 6/08	Prime-movers comprising combustion engines and mechanical or fluid energy storing means
	B60K 6/20	the prime-movers consisting of electric motors and internal combustion engines, e.g. HEVs	B60K 6/24	characterized by the combustion engines
	B60K 6/42	characterized by the architecture of the hybrid electric vehicle		
B60W	B60W 20/00	Control systems specially adapted for hybrid vehicles, i.e. vehicles having two or more prime movers of more than one type, e.g. electrical and internal combustion motors, all used for propulsion of the vehicle	B60W 10/06	including control of combustion engines
	B60W 30/00	Purposes of road vehicle drive control systems not related to the control of a particular sub-unit, e.g. of systems using conjoint control of vehicle sub-units	B60W 30/085	Taking automatic action to adjust vehicle attitude in preparation for collision, e.g. braking for nose dropping
	B60W 30/02	Control of vehicle driving stability	B60W 30/16	Control of distance between vehicles, e.g. keeping a distance to preceding vehicle
	B60W 30/192	Mitigating problems related to power-up or power-down of the driveline, e.g. start-up of a cold engine	B60W 30/165	Automatically following the path of a preceding lead vehicle, e.g. "electronic tow-bar
	B60W 40/10	related to vehicle motion	B60W 30/17	with provision for special action when the preceding vehicle comes to a halt, e.g. stop and go
	B60W 40/103	Side slip angle of vehicle body	B60W 30/18	Propelling the vehicle
	B60W 40/12	related to parameters of the vehicle itself	B60W 40/00	Estimation or calculation of driving parameters for road vehicle drive control systems not related to the control of a particular sub-unit
	B60W 10/00	Conjoint control of vehicle sub-units of different type or different function (for propulsion of purely electrically-propelled vehicles with power supplied within the vehicle B60L 11/00		
	B60W 50/00	Details of control systems for road vehicle drive control not related to the control of a particular sub-unit		
	B60W 50/12	Ensuring safety in case of control system failures, e.g. by diagnosing, circumventing or fixing failures		
B62M	B62M 23/02	characterized by the use of two or more dissimilar sources of power, e.g. transmissions for hybrid motorcycles (transmissions for wheeled vehicles using rider propulsion with additional source of power	B62M 3/00	Construction of cranks operated by hand or foot
	B62M 6/00	Rider propulsion of wheeled vehicles with additional source of power, e.g. combustion engine or electric motor	B62M 5/00	Foot-driven levers as pedal cranks which can be immobilized as foot-rests
	B60L 11/00	Electric propulsion with power supplied within the vehicle (B60L 8/00, B60L 13/00 take precedence; arrangements or mounting of prime-movers consisting of electric motors and internal combustion engines for mutual or common propulsion	B62M 25/00	Actuators for gearing speed-change mechanisms specially adapted for cycles
B60L	B60L 8/00	Electric propulsion with power supply from force of nature, e.g. sun, wind		
	B60L 13/00	Electric propulsion for monorail vehicles, suspension vehicles or rack railways; Magnetic suspension or levitation for vehicles		
	B60L 11/18	using power supplied from primary cells, secondary cells, or fuel cells		
H01M		PROCESSES OR MEANS, e.g. BATTERIES, FOR THE DIRECT CONVERSION OF CHEMICAL ENERGY INTO ELECTRICAL ENERGY	H01M 4/00	Electrodes (electrodes for electrolytic processes C25)
	H01M 2/00	Constructional details, or processes of manufacture, of the non-active parts		
	H01M 8/00	Fuel cells; Manufacture thereof		

APPENDIX B. RESULT OF THE SELECTION OF THE GROWTH MODEL

Technology	α	β	γ	**Growth model**
HEV and BEV	4.656	-0.185	-3.12	Logistic
FCV	9.64	0.25	-7.55	Logistic

APPENDIX C. R-SQUARED VALUES AND ESTIMATION OF L VALUE

Technology class	**L**	**a**	**b**	**Inflection point(Time)**	***Application numbers***	R^2
HEV and BEV	56000	500	0.1	2007	27232	0.95
FCV	2000	70	0.15	2014	3401	0.93