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Patent analysis of wind energy technology using the patent alert system

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A B S T R A C T

Using publicly available information effectively is important to remain competitive in technology related industries. The main difficulty in this is determining how to use the information effectively and in a manner that will yield results that can be acted upon. Several different methodologies are being developed in the Technology Watch area of research including the Patent Alert System (PAS) by Dereli and Durmusoglu. By using two different variations of the Patent Alert System, this paper will analyze two different technologies based on wind energy. These variations include Linear Regression based PAS and Fuzzy Logic based PAS. Each approach uses a different methodology to evaluate the available data and generate a trend that will be used to predict future values of patent counts in the applied area of technology. The results of these different approaches are compared in order to determine if either method produces more reliable results which would then lead to better decisions by the organization. In order to connect the results with real-world events, trend changes will be evaluated against global events which should have an impact on technological development in this area.

1. Introduction

Staying on the leading edge of technology is a challenging proposition regardless of the specific industry and the energy industry is no exception. With the push for greener technologies and more efficient power generators, there is a lot of awareness and publicity that affects the decisions of top executives. Therefore getting the best and most recent information regarding what specific technologies are being developed is extremely beneficial and valuable. Patent applications and grants are an effective source of information that is an indicator as to what technologies are being developed in a given area of focus. The problem with using this information is sorting through the large amounts of data and determining whether or not the number of patents is increasing, decreasing, or stable. If this information is extracted from the patents data pool and presented in a clear format, then it could be used to predict which technologies are picking up, which will allow the organization to be well prepared for industry shifts.

With the global focus of energy and the United States' focus and priority on renewable energy, using wind energy technology for this analysis is applicable and current. With political pressures such as the Kyoto Protocol to reduce green-house gas (GHG) emissions [1] and more regional renewable energy portfolio standards in the Pacific Northwest [2–4] green energy and the applicable technological industries will be an appropriate area to analyze with the Patent Alert System.

This paper will show a process for extracting and analyzing patent data called the Patent Alert System (PAS) [5] which will indicate the trend of a technology and also identify when the trend changes based on the number of patent applications per time period. The first question this paper will address will be whether or not the Patent Alert System can be used to compare two similar technologies to determine if they are following two different trends or not. In a real-world environment, the PAS methodology would be applied to several different technologies which would then alert the end user when each specific technology has a trend change. Therefore this paper will replicate this by applying the PAS to two different forms of wind energy technology.

The developers of the PAS model have also identified an alternate methodology for improving their model which utilizes fuzzy regression to identify the trends [6]. This paper will also aim to compare both forms of the Patent Alert System to determine if

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there is a noticeable difference between the two. While this paper will not attempt to determine which method is more accurate, this will be a comparison evaluation to determine if the two different models yield similar results or if there are major inconsistencies between both models.

Finally, the intent of the Patent Alert System is to trigger alerts when major trend changes occur in a given technology. As the patents are affected by multiple organizations across multiple countries, it is believed that global events will have an impact on technological development and therefore patent applications which would then be reflected in our data. Therefore this paper will attempt to identify major trend changes via the Patent Alert System and then correlate the time frames with global events. The purpose of this will be to validate whether global influences will ripple through technology industries and result in significant changes in technological development trends.

2. Literature review

2.1. Technology watch literature review

Technology watch is defined as “the dynamic process of monitoring and strategic analysis of scientific and technological advances and the competitive, trade, environmental and regulatory aspects” [7]. Since technological watch helps organizations lower the ambiguity in markets and recognize the new development areas in a given technology, it enables more refined decision processes in organizations [7]. Technology watch tools contingent on scientific information sources like patents and other scientific publications are widely used in the literature [8]. Patents provide valuable information exhibiting the progress and state-of-the-art of a given technology, technological relations, business trends in long lapses of time [7,9]. Also, patent data is publicly available in most countries [10]. The recent availability of patent documents on Internet via patent databases facilitates the access to electronic copies of those documents and conducting bibliometric analysis [11]. Analyzing patent information would also arouse original industrial solutions and help make investment policy decisions [12,13], since it does not only provide information related to the current situation but also some insights for the future direction and potential for that specific technology.

Patent analysis can be applied to different assessment areas, such as economic growth, intellectual property management, market value and potential, R&D management/technology assessment, mergers and acquisitions, company valuation, competitive intelligence [14,15]. In the literature there are many studies conducted on patents for technology assessment to establish the technology strategy at either national or corporate level. Abraham and Moitra [16] employed patents to conduct a technology trend analysis for Indian Industry. Also Yoon and Park [17] developed a patent network for trend analysis. Wu and Lee [15] used patent analysis to introduce a comprehensive idea of intelligent transportation systems innovations in US, Europe and Japan. The patent analysis conducted by Chen et al. [18] to define “core technologies and key industries” of Taiwan exhibited the development of Taiwan to an “innovation-based economy”. To analyze and arrange the extracted patent information patent mapping approaches are also proposed [19,20]. Lee et al. [21] used patent analysis for technology driven road-mapping. Some studies employed regression models to process the patent data [22]. Bengisu and Nekhili [23] used growth curves to forecast emerging technologies using patent data. Ashton and Sen [24] used patent trend analysis to model the advanced battery technology. Levitas et al. [25] exploited patent analysis to investigate the decisions of a firm on development of new technologies across different technological turbulence in this environment. Daim et al. [10] also forecasted emerging technologies using patent analysis combined with other forecasting tools such as growth curves and scenario planning. Dereli and Durmusoglu [26] used a fuzzy-based clustering approach to determine the trends related to the textile Technologies. They also proposed a patent alert system (PAS) based on regression model to discover the current trend in the examined technology [5] which is the focus of this paper.

2.2. Wind energy technology literature review

Today, wind energy has developed to a stage where it is accepted as one of the utility generation technologies [27]. The development of wind energy technology has been triggered by the oil crises in the beginning of 70’s and the concerns about the environmental effects of acknowledged energy sources [27,28]. CO_2 gases emitted by fossil fueled electricity generation are one of the largest contributions to greenhouse gases and it builds 1/3 of the emitted CO_2 in US. The concern about the climate change caused by greenhouse gases have driven governments to limit the emission of the CO_2 and to look for more green alternatives for electricity generation [29]. Wind energy seems to be the least expensive energy source among the renewable energy alternatives [30].

Wind power has been used for at least three thousand years. Before the end of the 19th century it was only used to produce mechanical power. The first wind turbines to generate electricity were introduced at the beginning of the 20th century [28]. After that, wind power technology has been used and improved as an electricity generation source but it gained the real momentum at the 70’s as mentioned above. “Financial support for research and development of wind energy became available” [28]. This increased interest and available financial resources accelerated the improvement of wind energy technology. According to ABS 2010 Wind Power Report, 1.5% of the electricity generated globally in the year of 2009 was harvested from wind and compared to other renewable energy sources wind energy capacity added in 2009 was the largest [30]. Worldwide capacity growth of wind energy was 31% [30]. As a result of the step by step improvement in the wind turbine technology, also the size, depending on it the capacity, of the wind turbines increased over time. Most of the wind turbines installed in 90’s had a capacity of 50–150 kW, today wind turbines with a capacity of up to 5 MW are commercially available [30].

“Wind turbines generate power by converting the momentum in the wind into mechanical power and converting the rotating mechanical power into a.c. power via standard a.c. generation techniques” [27]. The main two types of wind turbines regarding the rotating mechanical part, rotor, are horizontal axis and vertical axis wind turbines. Horizontal axis wind turbine is the most common type with propeller type, usually two or three blades rotating around a horizontal axis on top of a tower [27]. In case of vertical axis wind turbines “slightly curved symmetrical airfoils” rotate vertically, which make it seem like an eggbeater [28]. Vertical axis wind turbines have the advantage to operate independent of the wind direction and the mechanical parts which link the rotating part to generating part and also generating part are located at the ground level, which is on top of a tower in case of horizontal axis wind turbines. Horizontal axis wind turbines use different type of mechanisms to turn the axis into wind direction. Some disadvantages of vertical axis turbines are no “self starting capability” and “limited speed regulation options” [28]. According to Ackermann and Soeder [28] the period when the vertical axis wind turbines were most popular was 70’s and 80’s. Today most of the commercially available wind turbines are horizontal axis wind turbines.

2.3. Fuzzy regression

Regression analysis is one of the most popular methods to evaluate the functional relationship between the dependent variables and independent variables. Statistical regression analysis uses the concept of measurement error to deal with the difference between estimators and observations. Fuzzy regression analysis is an extension of the statistical regression analysis in which some elements of the model are represented by fuzzy numbers.

The fuzzy regression analysis was first proposed by Tanaka et al. [31]. They assumed the deviation between observed value and estimated value to depend on the indefiniteness of system structure where this structure was represented as a fuzzy function whose parameters were given by fuzzy sets [31]. The fuzzy regression model can be developed by solving a linear program (LP). The fuzzy regression methods with input, output, or both, can be not only crisp values but also fuzzy. Fuzzy regression has been successfully applied to various problems such as engineering [32–34] and forecasting [34–37].

The possibilistic linear regression proposed by Tanaka and Watada [38] is a type of fuzzy regression. In possibilistic linear regression, two types of data are considered non-fuzzy data which are dealt within conventional regression analysis and fuzzy data, which means that outputs are given as fuzzy numbers [38].

The generalized model of possibilistic linear regression can be expressed as [38]:

$$Y = \tilde{A}_1x_1 + \tilde{A}_2x_2 + \ldots + \tilde{A}_nx_n = \tilde{A}^T X \tag{1}$$

Where x_i is an input variable, $\tilde{A}_i$ is a fuzzy interval denoted as $\tilde{A}_i = (\alpha_i, c_i)$ with center α_i and spread c_i, Y is an estimated interval, $X = [x_1, \ldots, x_n]^T$ is an input vector and $\tilde{A} = [\tilde{A}_1, \ldots, \tilde{A}_n]^T$ is a fuzzy interval coefficient vector. The coefficients of the possibilistic regression can be obtained by solving the LP problem.

In the possibilistic linear regression, if the given outputs are fuzzy intervals where the given inputs are crisp, then two regression models are considered, an upper regression model and a lower regression model. And the two regression models are called dual possibilistic models. When the given data are denoted as [6]:

$$\left(Y_j, x_{j1}, \ldots, x_{jn}\right) = \left(Y_j, X_j^T\right) \tag{2}$$

Where Y_j is an interval output denoted as (Y_j, e_j), then the dual possibilistic models are denoted respectively as follows:

$$Y_j^* = \tilde{A}_1^* x_{j1} + \ldots + \tilde{A}_n^* x_{jn} (\text{Upper regression model}) \tag{3}$$

$$Y_{*j} = \tilde{A}_{*1} x_{j1} + \ldots + \tilde{A}_{*n} x_{jn} (\text{Lower regression model}) \tag{4}$$

By solving the following LP problems, the upper and lower regression models can easily be obtained.

$$\begin{aligned} &\text{Min}\, J = \sum_{j=0}^{k} \left(c_i \textstyle\sum_{i=1}^{n} |x_{ij}|\right) \\ &S.t.\ \sum_{j=0}^{k} \alpha_i x_{ij} + (1-h) \sum_{j=0}^{k} c_i |x_{ij}| \geq y_i \\ &\sum_{j=0}^{k} \alpha_i x_{ij} - (1-h) \sum_{j=0}^{k} c_i |x_{ij}| \leq y_i \\ &c_j \geq 0,\ \alpha \in R,\ j = 0, 1, 2, \cdots, k \\ &x_{i0} = 1,\ i = 1, 2, \cdots, n,\ 0 \leq h \leq 1 \end{aligned} \tag{5}$$

Where k is the total number of independent variable, n is the total number of observed dependent variable.

This approach will be utilized in the second half of the analysis when it is added to the Patent Alert System for generating new trends.

3. Methodology

3.1. Patent alert system

As stated in earlier sections, this paper uses the Patent Alert System methodology to analyze patent information from the wind energy industry. This methodology, as developed by Dereli and Durmusoglu [5], uses historical patent data to establish an initial trend and threshold value. The system will then run for each subsequent time unit and compare the actual number of patents with the predicted number based on the previously identified trend. This deviation will be compared to the threshold value to determine if a new trend is warranted or not. If the deviation does not exceed the threshold value the trend will continue for another time unit where a new deviation will be calculated and then added to the previous deviation; this is referred to as the cumulative deviation. This process repeats as necessary until the cumulative deviation exceeds the threshold value. At which point a new trend is created using linear regression with the data since the previous trend and the cumulative deviation is reset to zero. At this time, the end user is alerted to the new trend via e-mail or some other communication method built into the system.

The equations for this process are defined by Dereli and Durmusoglu as follows [5]:

$$P(t) = R(t = 0) \tag{6}$$

Where $P(t)$ is the hypothetical line which establishes the predicted patent count in time period t and $R(t)$ is the actual number of patents in time period t. The initial trend is set as a constant line equal to that of the last time period available. The time period t can be set to whatever unit of time desired for the particular application. In this paper, t is based in years as this is how the patent data is reported.

$$\text{dev}(t) = P(t)|R(t) \tag{7}$$

As stated earlier, dev(t) is the difference between the predicted patent count and the real patent count in time period t. This is then used to calculate the cumulative deviation.

$$\text{cumdev}(t) = \text{cumdev}(t-1) + \text{dev}(t) \tag{8}$$

Finally, the cumulative deviation is compared to the threshold value (TV) to determine if a new trend is needed. The threshold value is used to vary the sensitivity of this system and can be modified as needed to adapt to the specific technology area or industry. The developers of this model give three different threshold value options as explained in Table 1.

In the papers where this model is presented, the initial threshold value is established at the beginning of the exercise using the historical data available at that time. Then it is held constant

Table 1
Threshold values.

Sensitivity level	How to calculate	Comments
High	TV = 1	Any deviation will trigger an alert and create a new trend
Medium	$TV = \frac{\text{Average Patent Count}}{2}$	Half of the average historical patent count per time unit t.
Low	TV = Average Patent Count	

throughout the subsequent iterations [5]. For this application, a modification was made to this in order to take into account significant shifts in the number of patents. For example, if the average number of annual patents in a particular area is 4, then the low threshold value would equal four. If a major shift occurs in this area (i.e. emerging technology) then the average number of patents will increase significantly potentially increasing the sensitivity of the Patent Alert System. In order to account for this potential shift, the threshold value was set to low, but was re-calculated every time a new trend was identified. Then, all of the newer historical data was incorporated and accounted for.

3.2. Data

Green technology has been identified as a key area of research and development and specifically the wind energy technology. Therefore this paper identified controlling wind motors as the technology application. As one of the key components of this paper is to compare two different technologies, the patents for horizontal wind motors and vertical wind motors will be looked at. Horizontal windmills are those where the axis of the motor is aligned with the wind direction; vertical windmills are those where the axis of the motor is perpendicular to the direction of the wind. These are the two most common types of windmills and will therefore be used in this paper.

Another key component of this methodology is the use of existing patent classification codes, which are applied to every patent application in an effort to identify and categorize all patents. This classification code is specific to the type of technology being patented and will therefore be useful in distinguishing between the different technologies. For this paper, the International Patent Classification (IPC) codes are F03D7/02 for controlling wind motors with the rotation axis in the direction of the wind and F03D7/06 for motors with the rotation axis at a right angle to the wind direction [39]. The US and European patents were searched using the PATENTSCOPE database from the World Intellectual Property Organization and patent data for these two IPC codes was collected from 1974 to 2009. The first five years were used to establish the initial threshold values and establish the first $P(t)$ value. The values range from 0 patents up to 19 patents on an annual time scale and can be seen in Fig. 1.

3.3. Analysis

Both wind energy technology patent data sets will be analyzed by the Patent Alert System using the linear regression starting from 1980 up through 2009. These will be qualitatively compared to each other as well as the trend line and observations will be made as to the number of trends identified, duration between new trends, and in what direction the last trend is predicting. These comparisons will aim to determine whether or not the PAS can be used to compare competing technologies as stated in the introduction of this paper.

These same data sets will then be analyzed using the modified Patent Alert System which uses "fuzzy logic" [6] to develop the linear regressions. Again, both graphs will be qualitatively reviewed to determine number of trend changes, duration between alerts, and the final trend predictions. The competing technology trends will be compared which should either support or contradict the linear based PAS results. In addition to comparing the competing technologies, the linear based PAS will be compared to the fuzzy logic based PAS. As the same data sets are being analyzed using two different methods, this will allow a direct comparison. Qualitative observations will be made between the two different approaches.

Finally, major trend shifts in both technologies will be identified and these will be compared to global events along the timeline. This should help correlate between major global events and technological development in a related industry. As time is a major resource in technological development, a delay is expected between a major global event and the resulting trend shift. This comparison will help to identify this delay and should confirm the relationship between the cause and events.

4. Patent alert system with linear regression

4.1. Horizontal windmills

The first step in the analysis was to identify the initial threshold value and the initial trend value. As outlined in the methodology section above, the threshold value is based on the historical number of patents per unit of time, which is years for this application. A sensitivity level of low was used for this, which is equal to the average annual patent count. From 1974 to 1979, the average patent

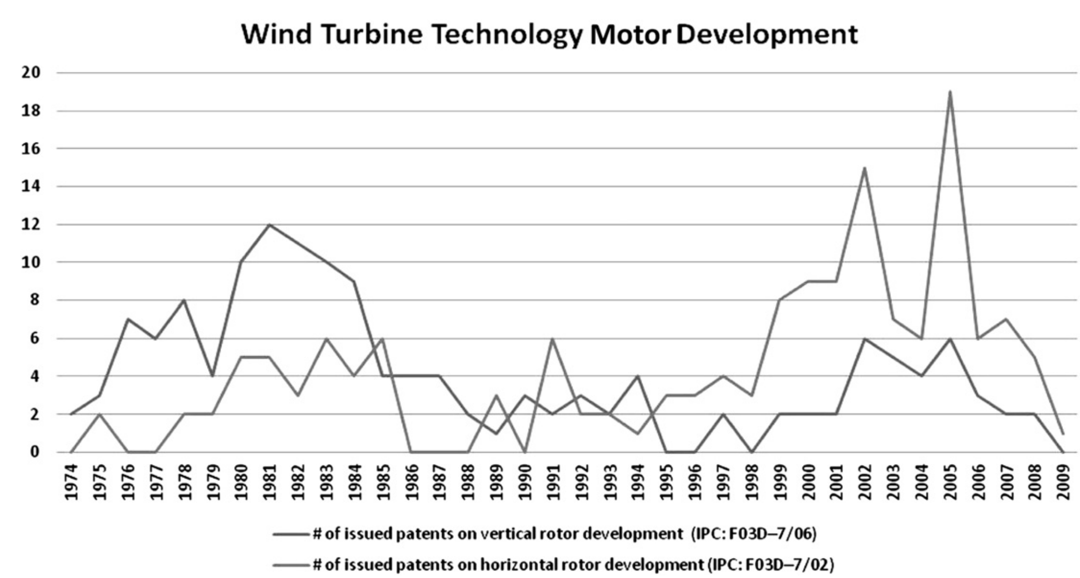

Fig. 1. Patent counts used in PAS analysis.

count was 1. Also, $P(0) = R(t = 0) = \#$ of patents in year 1979 = 2. With the initial variables of the system established, the subsequent time periods were evaluated and can be seen in Fig. 2.

In this graph, the red line indicates the actual number of patents granted in that year; the light blue vertical line indicates a new trend was generated at that year. The trend line was developed using linear regression with the patent data since the previous trend change, and this trend is displayed with the dark blue lines. The predicted patent counts, $P(t)$, are shown in the dotted lines. It is the difference between this dotted line and the red line which created the cumulative deviation which is compared to the threshold value.

From Fig. 2, periods of high instability can be seen in the mid-2000's where several new trends are calculated and the switch significantly between negative and positive directions. There are also a few periods of stability where the trend line proves accurate (within the sensitivity of the model) over as many as 5 years. A more detailed evaluation will be completed further on.

4.2. Vertical windmills

The same process above was repeated with the data set for vertical windmills. There were more patents per year during the historical time period which resulted in an initial threshold value of 5. The initial trend was identified as $P(0) = R(t = 0)$ # of patents in 1979 = 4. Again, the Patent Alert System was applied to the remaining years from 1979 to 2009 and the graph is shown below.

Again, the red line indicates the actual patent count in year t, R(t), and the vertical light blue line represents a new trend line was generated. The trend line is displayed with the dark blue lines with the hypothetic line, P(t), shown in the light gray dotted line. As shown in Fig. 3, there are several trend changes over the course of the evaluation period. The level of instability is not as high as the previous technology as indicated by the duration between trend changes. However, the results are fairly consistent with the Horizontal Windmills in the fact that a new trend is identified every few years with the max duration at about 5 years.

5. Patent alert system with fuzzy regression

5.1. Methodological modifications between linear and fuzzy regression based PAS

Similar to linear regression based PAS procedure mentioned above we have used the patent count data belonging to the years between 1974 and 1979 for creating the first fuzzy regression. Initially we have attempted to integrate threshold value by taking the average number of patent count data between 1974 and 1979. However we have experienced that if fuzzy regression based PAS procedure was applied there was a trend change alert in pretty much every year or two years. Mathematical reason behind this has been observed to be the fact that threshold value of fuzzy regression based PAS was a product of derivations from the actual data and both upper and linear regression lines. Thus, taking average of previous years' patent counts for determining a threshold value was creating relatively smaller values.

As an implication, since the procedure requires any latter regression model to be created with the data that is between the previous trend change point and the given current point, in some cases newly created fuzzy regression models required upper and linear regression lines to be very close to each other so that they appear to be collapsing on top of each other. Reason behind this situation has been observed to be the fact that due to high frequency of trend alerts, newly created fuzzy regression models were fed only by data that belongs to only a few years back. This problem could be addressed by making use of more robust methods for predicting a threshold value such as making use of expert judgment however due to lack of expertise in the technology specific development this option was not viable. Although we believe an established threshold value can still be applicable in case of mature technology areas where technological developments are rather saturated however they may not always be applicable in case of relatively rapidly developing technology areas.

Due to dropping threshold value method, need for determining a new way to identify trend change points has emerged. Since fuzzy

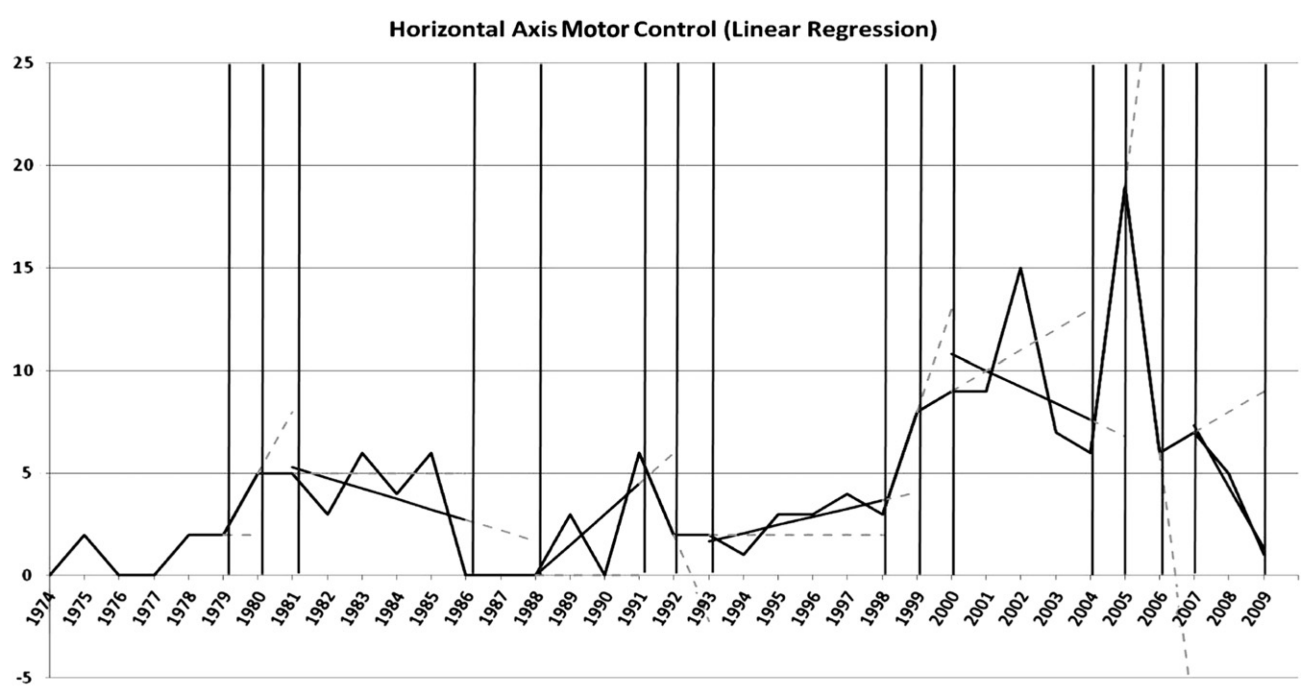

Fig. 2. Horizontal axis motor control with linear regression based PAS.

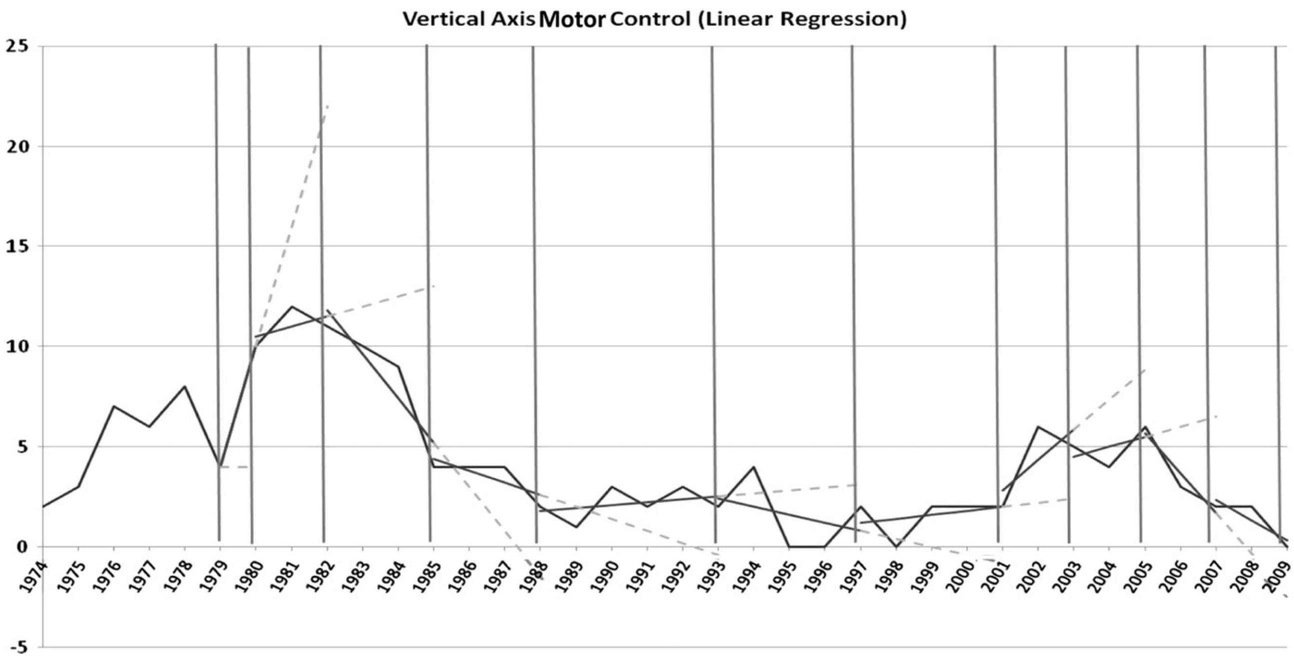

Fig. 3. Vertical axis motor control with linear regression based PAS.

regression methods create both an upper and a lower regression line the range between these lines has been accepted as the expected range of possibilities and in case any observed data went out of the expected range that time point has been regarded as the beginning of a new trend. In order to address the issue of selecting range of data fed into the fuzzy regression model moving average method, that makes use of previous 10 years at the time a trend change alert has been encountered, has been adopted. As technology application involves in energy related development range of moving average can depend on multiple perspectives which might be social, political, environmental and technological developments. In this case range has been determined as 10 years, but could better be improved with an expert help. Although use of moving average has also required small modifications regarding selection of range of the data to be fed into the model we will mention about those in the next section as they are not directly related to methodological modifications. We believe use of moving average can be more applicable to relatively rapidly developing technology areas in order to make the regression models more adapting to the significant changes.

5.2. Horizontal windmills

Results of fuzzy regression based PAS method for horizontal and vertical motor control data can be observed in Figs. 4 and 5 below. Red lines represent actual patent data counts observed throughout the years where as dotted lines are regression lines representing expected range of possibilities created between trend changes. As realized, range of possibilities has been varying for different years. The reason behind this occurrence is the fact that expected range of possibilities determined by upper and lower regression lines are created by using 10 years of previous data points and these years might have relatively high and low patent counts. In some cases such as years after 2003 expected ranges of possibilities are relatively wide due to the fact that there have been major changes in patent counts and PAS model tends to take all those into consideration while predicting the upcoming years. An implication that can be drawn from this situation is that due to rapid changes relative to previous years, expectations for the latter years are uncertain and might actually require organizations to better focus on the technological development.

5.3. vertical windmills

As mentioned before, in the previous section there was a need for modifying range of range of moving average. In the Figs. 6 and 7 below you can see the results in the case where moving average was always product of previous 10 years. As encountered, fuzzy regression model producing Fig. 6 (expected range of possibilities from 1989 to 2009) has been modified by only using previous 7 years where as fuzzy regression model producing Fig. 7 (expected range of possibilities from 2002 to 2004) has been modified by using previous 9 years. As can be observed the reason for modifying fuzzy regression model for horizontal motor control case, the expected range of possibilities appeared to be too wide that it did not really give any significant information about what might actually happen in the upcoming years where as in the case of vertical motor control we observed the trend to go down a little unexpected since the previous years' data seemed to create stable forecast expectation. We believe these results are product of local optimum points that may not have been caught by the algorithm of the software package we are using.

6. Results

The alerts for all applications of the PAS were identified and listed in Table 2. This table shows each time an alert was issued for each different application of the Patent Alert System. An alert is identified with an X in the corresponding year. The Linear Regression (LR) is compared to the Fuzzy Logic (FL) based PAS and each time they trigger an alert in the same year the cells are shaded.

When comparing both wind energy technology alerts using Linear Regression, it can be identified that there were 15 different trend changes for the horizontal motor axis technology while there were only 11 trend changes for vertical motor control patents. This is an expected outcome as the patent graph (Fig. 1) shows more fluctuation and volatility in the horizontal motor control patents,

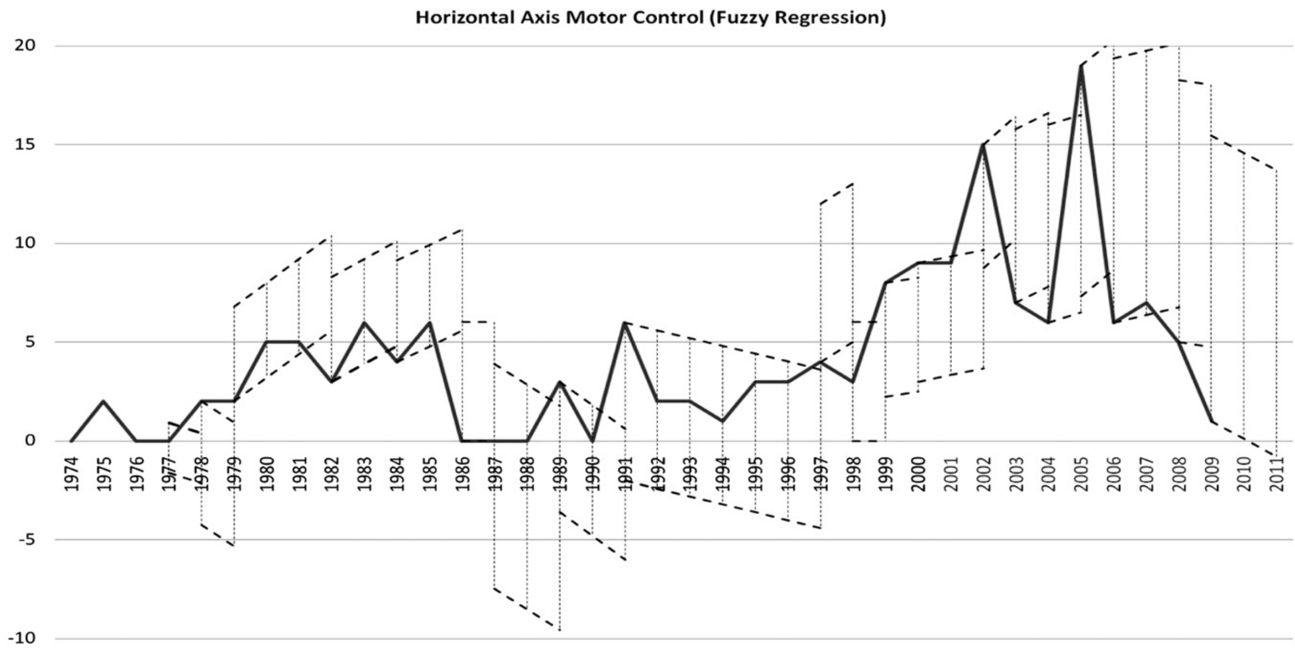

Fig. 4. Horizontal axis motor control with fuzzy regression based PAS.

especially in the late 90's and 2000's. However, both technologies ended the time period on a negative trend.

The longest stretch without an alert when using the Linear Regression PAS was 5 years, which occurred twice for Horizontal Motor Axis patents. The first span was from 1981 to 1986 and again from 1993 up to 1998. Vertical Motor Axis analysis also identified a five year span from 1988 to 1993 where there were no alerts generated. However, there were several occurrences during the analysis of Horizontal Motor Axis patents where an alert was generated the next year following a new trend. Another observation regarding the different alerts is that most of the new trends were in a different direction than the previous trend (i.e. trend went from negative direction to neutral or positive). Only twice in the Horizontal PAS did a new trend continue the same direction as the previous trend with just a slope adjustment. The Vertical Motor Axis PAS resulted in five occurrences where the new trend was in the same direction. This is indicative of false alerts where the trend is generally in the same direction, but the slope has deviated enough to exceed the threshold value. It could be a modification to the PAS software which will allow the user to determine whether they would like to be notified of these trend changes or not.

Similar results were observed when using the Fuzzy Logic based PAS. The Horizontal Motor Control patent analysis triggered 17 different trend changes with the longest span from 1991 till 1997 without an alert. However, from 1997 to 2009, there were only 2 years which did not trigger a new trend. For the Vertical Motor Control patent analysis, only 10 new trends were identified and this analysis had the longest valid trend from 1995 to 2002 (7 years).

When comparing the Linear Regression based PAS with the Fuzzy Logic based PAS, there are several occurrences where each method triggered an alert for the respective technology. These alerts are highlighted in Table 2 and identify 9 years where either method identified a new trend when analyzing the Horizontal Motor Control patents. In addition, there were 7 years where both methods did not

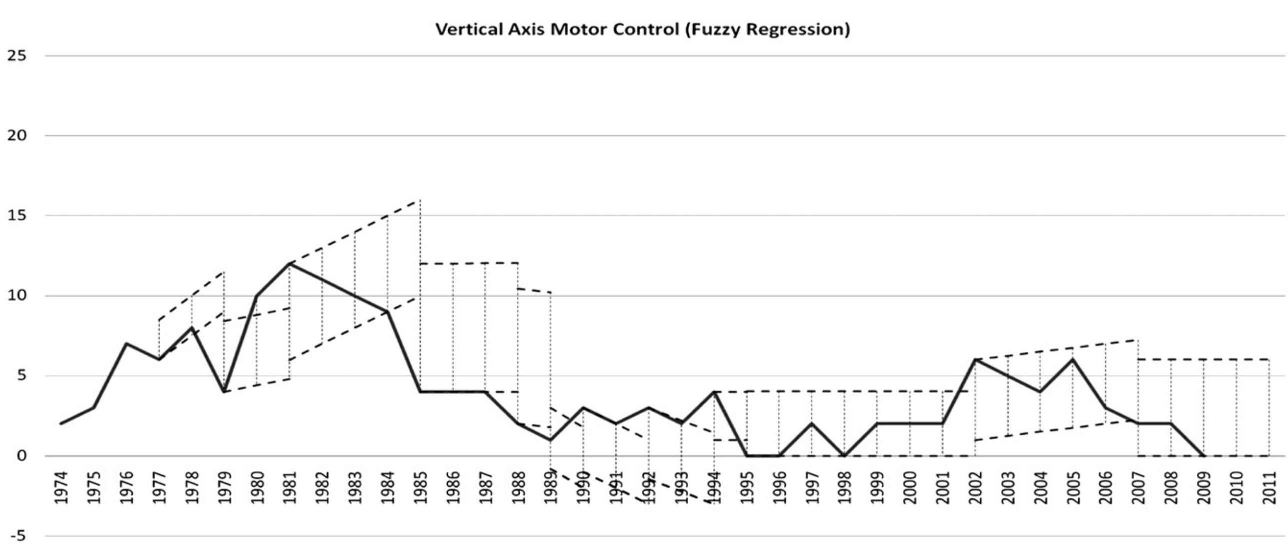

Fig. 5. Vertical axis motor control with fuzzy regression based PAS.

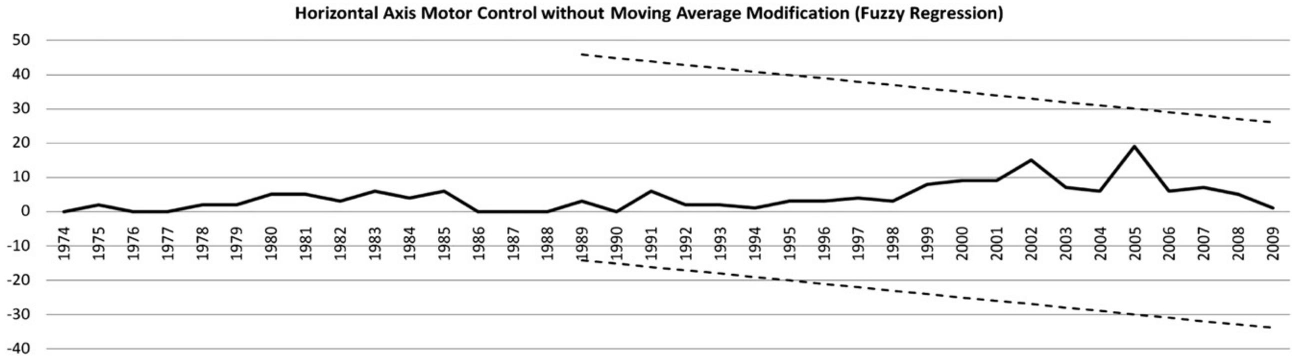

Fig. 6. Horizontal axis motor control without moving average modification (Fuzzy regression).

identify a new trend. However, there were 14 instances where one method identified a new trend and the other did not.

There was even less consistency when comparing the Vertical Motor Control patent analyses. During the 30 year time frame, both models identified a trend in only 3 years. An additional 12 years were identified where neither system generated an alert. Therefore 15 alerts were generated where it was not also identified by the other method.

Another difference between the two models was the number of new trend identified with a similar direction slope as the previous trend. When using the Fuzzy Logic to analyze the Horizontal Motor Control patents, 11 trends were created with the same direction as the previous trend (i.e. positive, negative, or neutral). There were fewer occurrences when reviewing the Vertical Motor Control patents which only had 5 instances.

7. Discussion

While several differences have been identified, it is difficult to evaluate each method to determine which approach yields better results. The value of each system is not realized unless the end user can make informed decisions on the future development of a given technology. Also, the review and evaluation of the data by subject matter experts may result in different conclusions as to which model is better. However, it can be determined that using the Patent Alert System on different technologies can be beneficial for determining which technology is trending up or down. This can be applied to several similar technologies and should provide useful information regarding all of them. Therefore the first objective of this paper has been completed.

The second objective of this paper was to compare the linear regression against the fuzzy logic and determine if one is more useful than the other. As stated above, this is very difficult without additional expertise in this particular area of technology. However, one observation clearly indicates the linear based regression is more appropriate. This was the number of alerts generated with the same trend direction as the previous trend. The end user most likely wants to be notified when the trend direction has significantly changed; either completely changed directions (negative to positive) or has significantly changed in the same direction (slightly positive to very quick increasing trend). While this may be modified by programming changes, this application of the fuzzy logic Patent Alert System triggered several new trends with varying slopes in the same direction. This was mainly caused by the moving range used to calculate the trend line. Many times a new trend was triggered, but many of the same data points were used to create the next trend. This was addressed earlier by adjusting the moving range, but was not fully implemented within the scope of this paper.

This is actually a critical issue that affects both methodologies and is one that may be addressed in future research. Both methodologies try to systematically calculate a new trend line based on the logic in the system. For the linear based regression, the values used to create the trend were only those since the last trend was created. For the fuzzy logic, the system used the trailing 10 years worth of data. Therefore the actual trend could be missed, or either misidentified depending on where it aligned with the generation of a new alert. This could be addressed by adding a review by a subject matter expert to determine the actual number of years to include in the new trend. This would allow some flexibility to include intuition and judgment when creating the new trends. However, this might go against the original intentions as the Patent Alert System was designed to be "hands-off" and simply provide automatic notifications if a new trend was developed.

Finally, the last objective of this paper was to correlate major global events with trend changes identified within these two technologies. In the early 1970's, with the oil crises led to oil price

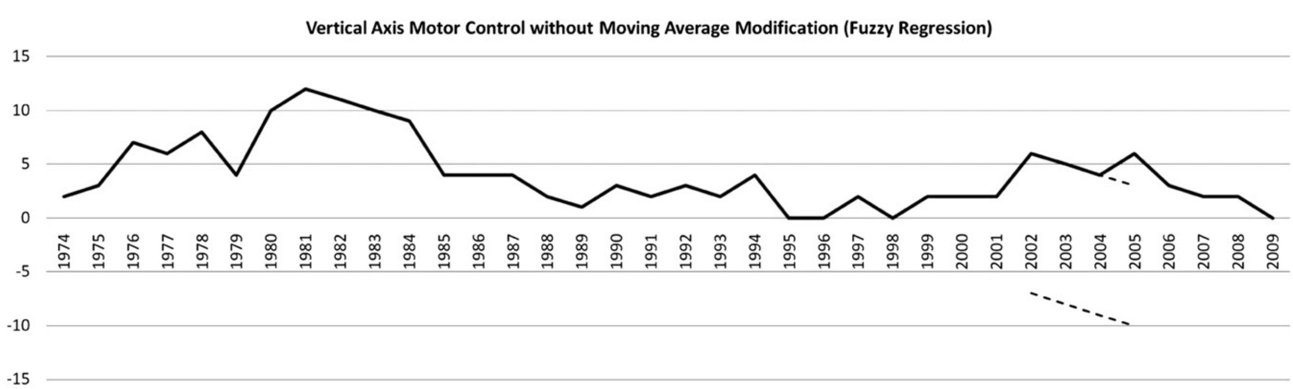

Fig. 7. Vertical axis motor control without moving average modification (Fuzzy regression).

Table 2
Comparison of trend alerts in each PAS application.

	Horizontal motor axis		Vertical motor axis	
	LR	FL	LR	FL
1979	Initial Trend	Initial Trend	Initial Trend	Initial Trend
1980	X		X	
1981	X			X
1982		X	X	
1983				
1984		X		
1985			X	X
1986	X	X		
1987		X		
1988	X		X	X
1989		X		X
1990				X
1991	X	X		
1992	X			X
1993	X		X	
1994				X
1995				X
1996				
1997		X	X	
1998	X	X		
1999	X	X		
2000	X	X		
2001			X	
2002		X		X
2003		X	X	
2004	X	X		
2005	X	X	X	
2006	X	X		
2007	X		X	X
2008		X		
2009	X	X	X	

shock, the interest in wind power generation began to increase. The financial support for research and development of wind energy technology became available. Some countries, such as Germany, USA and Sweden, used this money to develop large-scale wind turbine technology in the MW range [28]. The Public Utility Regulatory Policies Act was passed in 1978 by the United States Congress as part of National Energy Act [40]. It led to the first wind energy boom in recent history. Huge wind farms were installed on the west coast of USA. These may be one reason why the patent numbers of wind turbine rotor technology were increasing in the 1970's. It is shown in Fig. 8.

From 1981 to 1998, The World Nominal Oil Price had slow shock. The patent numbers of wind turbine rotor technology had the similar trends. The oil price had a sharp increase from 1990 to 1991, the second Iraq war period. The patent numbers of wind turbine rotor technology also had the similar trends. After 1998, OPEC 10% Quota Increase and Asian financial crisis happened, the oil price was increasing. With growing concerns about carbon dioxide (CO_2), global warming, and increasing fossil fuel prices, wind energy became very attractive. The increased interest in wind energy produced a new wave of technology development. So the patent numbers of wind turbine rotor technology were quickly increasing after 1998.

In 2009, US President Obama signed the American Recovery and Reinvestment Act of 2009 [41]. It means that more money will be invested to renewable energy. Until 2010, the renewable portfolio standard was adopted by many countries, such as USA, Germany and China [42]. The wind energy advantages include zero fuel cost, non-depleting supply, and minimal environmental impact is becoming a hot investment topic. Therefore, in the future, the patent numbers of wind turbine rotor technology will be quickly increasing. This paper builds on prior research [43] by creating practical tools based on patent analyses.

8. Limitations

While the Patent Alert System is a relatively new tool in the Technology Watch arena, there are several benefits that can be realized from its use. By identifying trends in any given technology industry an organization may have an advantage in decision making and strategic planning. However, there are still some issues that need to be addressed before this methodology can be fully implemented. One issue already discussed is the use of data ranges when developing the new trends. This automated logic in the PAS

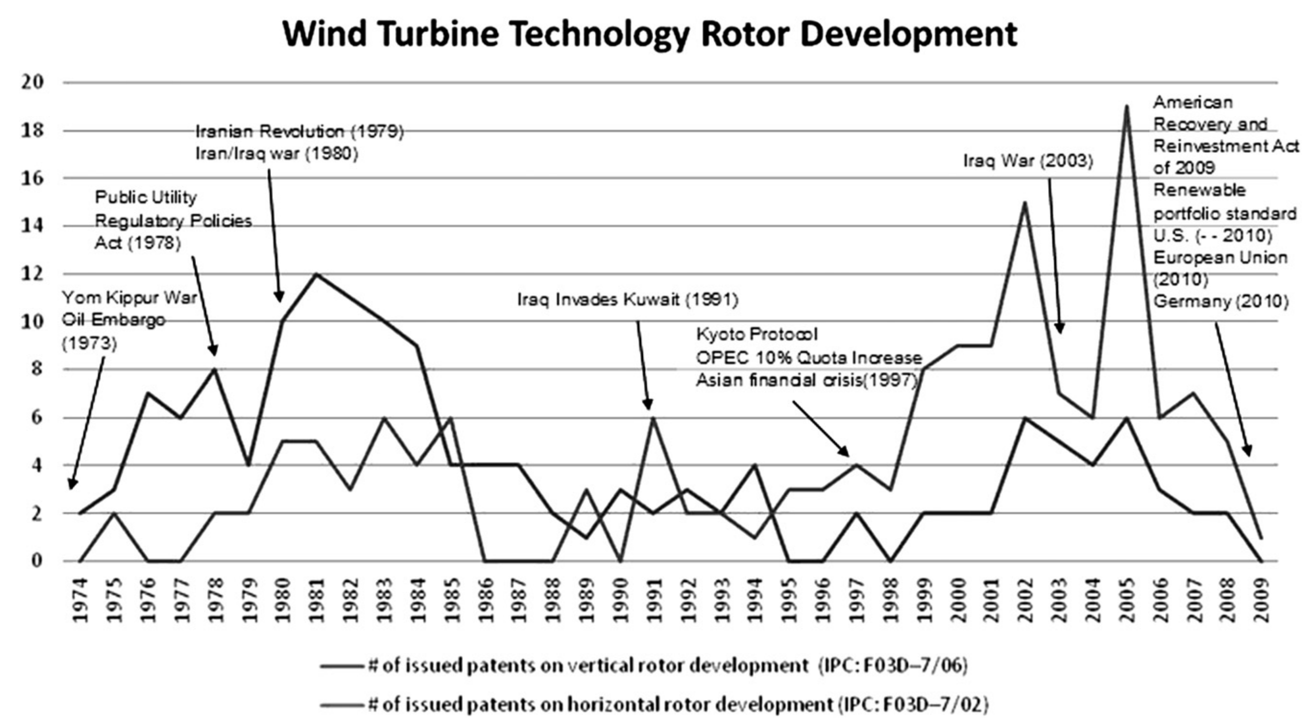

Fig. 8. Wind turbine technology rotor development with world events.

may overlook trends or exaggerate (or minimize) the actual trend based on insufficient data. This can be seen with the Linear Regression application to the Horizontal Motor Control patents in the years from 2004 to 2007. As a new trend was triggered each year, the system only used the data since the last trend, which resulted in a new regression based on two points. The spike generated a new trend with a significantly steep slope. If an organization would have reacted to this as an indicator of future direction, then they could have been completely caught off guard when the next trigger was generated the next year with an equally drastic negative slope. If somebody was able to review the data and provide input they might have either included more years in the development of the trend, or they could have identified it as a spike and not an indication of a new trend.

While the choice of a fuzzy regression perspective helps to reduce the uncertainty, it still does not provide an accurate prediction, but rather a useful description of a changeable environment. Other researchers can argue that the system being modeled in this paper is a stochastic one which may be represented with the discrete distribution. However this view represents an ongoing debate among differing approaches to such problems. It would be a better approach to use multiple modeling methods and compare the results as decisions are made. The specific strengths of the model used in this paper are a robust and non-parametric approach to dealing with uncertain data, and a relatively hands-off and therefore objective algorithm for characterizing change. As indicated before the model also has weaknesses which are an inability to characterize stochastic processes, thereby perhaps finding artificial trends or patterns in the data.

Another area of further refinement is scope and application of this system. In the examples in this paper, the average numbers of annual patents were fairly low as the lowest level IPC codes were used. Therefore the threshold values were low in comparison to the volatility in the system. As patent counts are discrete units, the scale of applications does have an effect on the results of the system. Therefore it would be beneficial to apply this approach to larger (patent) classifications of technology where the average number of patents is in the hundreds. This would result in a larger threshold value, but it is difficult to predict whether the results would be more accurate or beneficial at this time. Along the same lines, it would be interesting to apply this methodology to new emerging technologies as well as more established and mature technologies. Is there a point in the technology life-cycle where this approach yields better results? Finding the best scope to apply this Patent Alert System would go a long way toward more fully validating the system and increasing its adoption.

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