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A patent quality analysis for innovative technology and product development

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ABSTRACT

Enterprises evaluate intellectual property rights and the quality of patent documents in order to develop innovative products and discover state-of-the-art technology trends. The product technologies covered by patent claims are protected by law, and the quality of the patent insures against infringement by competitors while increasing the worth of the invention. Thus, patent quality analysis provides a means by which companies determine whether or not to customize and manufacture innovative products. Since patents provide significant financial protection for businesses, the number of patents filed is increasing at a fast pace. Companies which cannot process patent information or fail to protect their innovations by filing patents lose market competitiveness. Current patent research is needed to estimate the quality of patent documents. The purpose of this research is to improve the analysis and ranking of patent quality. The first step of the proposed methodology is to collect technology specific patents and to extract relevant patent quality performance indicators. The second step is to identify the key impact factors using principal component analysis. These factors are then used as the input parameters for a back-propagation neural network model. Patent transactions help judge patent quality and patents which are licensed or sold with intellectual property usage rights are considered high quality patents. This research collected 283 patents sold or licensed from the news of patent transactions and 116 patents which were unsold but belong to the technology specific domains of interest. After training the patent quality model, 36 historical patents are used to verify the performance of the trained model. The match between the analytical results and the actual trading status reached an 85% level of accuracy. Thus, the proposed patent quality methodology evaluates the quality of patents automatically and effectively as a preliminary screening solution. The approach saves domain experts valuable time targeting high value patents for R&D commercialization and mass customization of products.

1. Introduction

Patents play an important role in a knowledge based economy since companies use patents to protect innovation. Patents often establish a time period of protection for the intellectual property (IP) and the new products' market domination. For the economics and management of mass customization, product planning considers the customer's needs and the sources of technology. Analyzing related patent documents help design engineers create detailed conceptual plans and understand the underlying component technology. Patent quality analysis furthers the analysis by strategically identifying critical patents for mass customization. High quality patents contain wide claims, refer to few prior art designs, and are highly applicable. Owning high quality patents helps enterprise defend themselves against patent trolls and product infringement.

Mass customization products must consider the risk of patent infringement. Manufacturers must choose the highest quality patents for mass customization to insure commercial production value. High quality patents better enable companies to avoid costly litigation that impedes the production and sales of products in the marketplace. Thus, patent quality analysis facilitates mass customization and product personalization while minimizing the risk of infringing on the intellectual property rights (IPR) of others. For sustainable competitive growth, enterprises must claim and use intellectual property rights effectively.

Recent patent news shows that enterprises often purchase technology specific patents to advance technology and create new products for timely commercialization. There are also incidences whereby manufactures are accused of IP infringement by competitors which impede new products from entering the market. The traditional process of patent trade includes three steps. First, the enterprise collects patents of interest from a patent trading platform. After collecting and organizing the patent collection, domain experts study and analyze the patents. Next, the enterprise evaluates and decides whether to purchase patents or invest in its own

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research and development (R&D) to create new intellectual property that can better protect or yield product development opportunities.

Traditional patent analysis requires significant costs, time, and manpower. Thus, the purpose of this research is to shorten the time required to determine and rank the quality of patents for new product R&D and innovation management. This research develops key patent indicators that are derived from principle component analysis. The patent quality models, created with the indicators as inputs, are trained using the back-propagation neural networks. The degree of patent quality is defined by different evaluators in different situations including patent trade (i.e., sold patents are of high quality), patent litigation (i.e., patents win lawsuits are of high quality), and patent assignment (i.e., patents have assignment processes are of high quality). The proposed approach can be used to build different patent quality models based on the pre-defined situations.

In regards to the patent indicators, they are collected from patent corpuses, including the number of patent citations and the number of International Patent Classifications (IPC). The first step of the process is to extract the key quality impact factors using principal component analysis. The second step uses the key factors as input parameters for a back-propagation neural network (BPN) model. The BPN model is trained to identify technology specific patents. The system then processes the patent collection to rapidly identify patents matching the key identifying quality criteria. As a means to evaluate the methodology, patents that are successfully traded in the marketplace are compared to the model selection. The methodology helps experts rank and set values on patent quality. The key impact factors, when combined with a trained model to evaluate unknown patents' quality, better enable engineers and product designers forecast patent potential for product development.

2. Background and literature review

This section highlights the core background knowledge and related literature of the research, including patent analysis, patent characteristics, indicators of patent evaluation, the principal component analysis approach, and back propagation neural network models.

2.1. Patent analysis

Patent analysis is employed across organizations and is a research approach frequently used by R&D engineers, academics, and technology policy makers. The results of patent analysis are used to estimate trends, profitability, and performance of technology [1]. The patent characteristics are in turn used for prior art searching and information extraction about patent history and activities [2]. The competition among companies is revealed using these characteristics, and careful analysis of this information often results in the discovery of mass customization development opportunities. Yoon and Park [3] proposed a network based patent analysis to show the relationship of domain specific patents within a virtual network, which is then used to evaluate a patent's degrees of importance, degree of technique, and degree of similarity.

The creation of a patent portfolio is a combination process including a patent defense strategy. The process is analogous to creating a fence or patent cluster. A patent fence prevents or blocks competitors from registering related core technology. In order to create a defensive technology fence, the company must also develop non-core patent technologies. The fence makes it difficult for competitors to incorporate similar technology without infringement. On the other hand, a patent cluster brings together many patents of alternative technologies, and strategically makes defining the underlying technology trends more difficult. The illustrations of patent fence and patent cluster are shown in Fig. 1.

An advanced patent analysis must consider the characteristics of related patent documents. Most patent analysis techniques focus on the classification of patents using the related prior art, the specific domain technology trend, and the patent defense strategy. Traditional patent quality assessment uses different patent indicators extracted from patent characteristics specified by the domain experts. However, the value or worthiness of patent indicators is changed based on many factors. Thus, the proposed patent quality methodology is flexible for building the patent quality model based on the domain of collected patents and their quality evaluation criteria, e.g., factors related to transaction, litigation, or maintenance.

2.2. Patent characteristics

Patent documentation and analysis use uniform format field, forward and backward analysis of citations, and the creation of patent portfolios. A patent document with a unified form consists of three parts [4]. The first part contains the patent publication number, the application date, the citation number and the international patent classification. The second part describes the background, innovation content, and implementation methods. The third part defines the claims used by the assignees to protect the invention.

Most research focuses on the information contained in the patent citation. Citations provide researchers with a historical trail about the development of technology and provide a means to assess and rank the importance of individual patents. Lai and Wu [5] employed patent co-citation analysis to establish a patent classification system. The classification system reveals the relationship of technologies and the evolution of a technology category. Common technology trend analysis uses forward citation analysis, co-citation analysis, and backward citation analysis. The information contained within cited patents corresponds to specified fields, such as "US patent documents," "foreign patent documents" and "other references". These metadata fields are also useful for evaluating patent quality.

2.3. Patent quality indicators

The primary patent quality indicators are related to investment, maintenance, and litigation, which form a basis for assessing patent quality when the evaluation focuses on the patent's potential for sale. These indicators are briefly described as follows.

2.3.1. Indicators for investment

There are five indicators used by CHI Research to analyze patent portfolios for investment [6,7]. The first indicator represents the number of patent applications from a company and its subsidiaries in the previous year, the second indicator describes the percentage of patent growth in the previous year, and the third indicator is the current impact index. The fourth indicator, science linkage, is calculated using the average number of references which are cited from scientific papers. Finally, the technology cycle-time measures the median age of the cited patents.

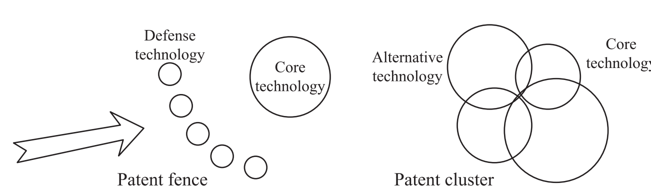

Fig. 1. The purpose of patent portfolios.

2.3.2. Indicators for maintenance

Barney [8] proposes five indicators which demonstrate the competitiveness of patent documents. The five indicators are the number of independent claims, claim length, the length of the written specification, priority claims, and forward citations. The historical patent metadata represents patents having more independent claims and are considered to be more valuable. The larger the number of claims, the broader the scope of protection and the better the likelihood of surviving a validity attack. A longer specification provides better support for patent claims and strengthens the patent against certain types of validity attacks. More priority claims means a patent is entitled to an earlier filing date in more countries, which can be beneficial in fending off patent validity attacks. Intuitively, a high forward citation rate indicates a high level of commercial interest or activity in the patented technology.

The patent maintenance rates generally increase with the number of claims, the length of the written specification, the number of the recorded priority claims, and the forward citation rate. Further, the patent maintenance rates decrease with claim length. Statistical data supports the hypothesis that patents having shorter claims (with fewer limitations and broader scope of protection) are more valuable [9].

2.3.3. Litigation indicators

Allison et al. [10] noted that the identification of valuable patents is needed to win lawsuits. Based on 6861 patents used in litigation, there are five common characteristics. First, the number of claims in a patent provides evidence of its breadth and therefore its value. A patent's claims are the legal definition of the invention. In order to decide whether a patent has been infringed upon, a court must compare the claims of the patent to the defendant's device. Second, the number of references cited (backward citations) in a patent is evidence of a patent's validity. Third, the number of citations received (forward citations) which represent references made by subsequent patents to the patent of interest is evidence of the importance other inventors accord the patent. Furthermore, citations are positively related to patentee decisions to pay maintenance fees [11].

Fourth, Trajtenberg et al. [12] have identified a generality measure which is a means of calculating the dispersion of citations received across different patent classes. They define a function of the sum of the percentages of citations received in each patent class. If a patent is cited by subsequent patents that belong to a wide range of fields, then the measure will be high. Finally, Lanjouw and Schankerman [13] have used the number of different IPCs into which an invention is categorized by the patent and trademark office as evidence of both the breadth and originality of an invention, and hence as evidence of its value.

2.4. Principle component analysis

Principle component analysis (PCA) is a method first proposed by Pearson [14] and later formalized by Hotelling [15]. Principal component analysis transforms several independent variables into a new set of variables which retain the most information. The goal of PCA describes the interrelationship among the variables and transforms the original variables into uncorrelated new variables. Moreover, PCA reduces the dimensions of multivariate data and can solve the colinear problems of linear regression [16].

According to the research of Lai and Chu [17], 17 patent indicators are defined which influence litigation. The report uses the PCA method to find the relationship between indicators and eliminate unimportant indicators. Tsai-Lin [18] used a questionnaire to analyze the value of a patent, and then applied PCA to determine the four factors that influence patent value including the potential to lead technology, the potential for commercialization, the capacity for market application, and ability to defend against litigation. Based on these factors, the study collects a set of valuable patents and clusters the patents into four strategic patent groups. Finally, the study suggests that the value of each patent also depends on its technology life cycle, commercial worth, and legal assessment.

2.5. Back-propagation neural (BPN) network

BPN network models are widely used for classification and forecasting [19]. The BPN network is a fast learning pattern classifier based on a modified back propagation gradient descent algorithm. The BPN network uses a feed-forward and feed-backward flow regulated by an error function. Each network contains an input layer (the neuron number correspond to the number of input vectors), a hidden layer (the weight calculated between the input and output layers), and an output layer (the type of classifications corresponding to the number of output vectors). Using a non-linear transfer function, the BPN network builds the nonlinear relationship of weights between the hidden input layer and the hidden output layer and establishes the target model.

Trappey et al. [20] proposed a new document classification methodology based on a neural network approach. The result yields a significant improvement in document classification and R&D knowledge management. Trappey et al. [21] proposed a combined clustering and S curve approach for technology forecasting of RFID sub-technical groups. Chiang et al. [22] applied a back propagation artificial neural network, a hierarchical ontology, and normalized term frequencies for binary document classification and content analysis. Their approach reduces the effort needed to search and select patents for analysis.

3. Methodology

This research proposes an integrated methodology, combining the Kaiser–Meyer–Olkin (KMO) approach, PCA, and BPN, for determining patent quality based on patent tradability potentials. The structure of the methodology is shown in Fig. 2. First, patent data with IP usage rights are collected from the United States Patent and Trademark Office (USPTO). Second, principal component analysis is used to extract key patent indicators. Third, the key indicators are used as training input parameters for the back propagation neural network model. Fourth, after the BPN model is trained, the technology specific patent model is used to predict the quality of patents and forecast the IP market potential.

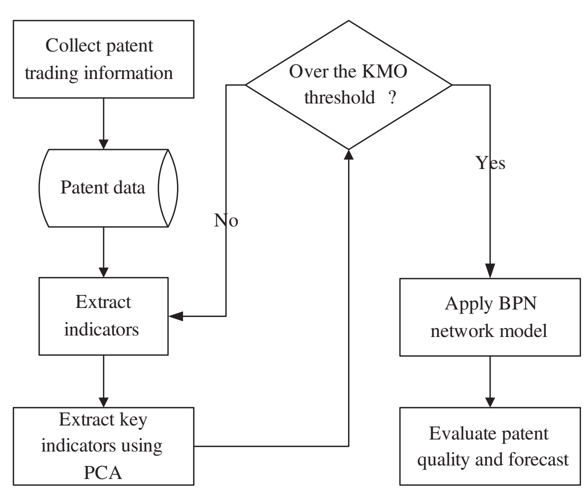

Fig. 2. The patent quality analysis methodology.

Twelve indicators for patent quality are used based on the literature review. The indicator data are used for principal component analysis and the back propagation neural network model. The first two indicators, the patent application and issue date, define the period of patent protection. Next, the international patent classification and US patent classification define the technology specific domain. The indicators describe the technology source and application, including forward citations, foreign citations, and backward citations. The claims and independent claims represent the scope of the lawsuit. Finally, the patent family, the technology cycle time, the science linkage, and the length of detailed specifications are evaluated to quantify the value of patent. The above indicators are located in the patent document as highlighted in Fig. 3.

3.1. Evaluation of patent indicators

After extracting the quality indicators, the Kaiser–Meyer–Olkin (KMO) approach is used for evaluating the strength of the relationship among variables [23]. The Kaiser–Meyer–Olkin measure of sampling adequacy tests whether the partial correlations among variables are small. The KMO measures the sampling adequacy which should be greater than 0.5 for a satisfactory factor analysis. Large values for the KMO measure indicate that a factor analysis of the variables is a good statistical fit. A value of 0.6 is a suggested minimum threshold for the principal component analysis. The KMO function is shown in Formula (1)

$$KMO = \frac{\sum_i \sum_{j(i-j)} r_{ij}^2}{\sum_i \sum_{j(i-j)} r_{ij}^2 + \sum_i \sum_{j(i-j)} s_{ij}^2} \tag{1}$$

where r_{ij} is the correlation coefficients of indicator x_i and indicator x_j. The s_{ij} is the offset correlation coefficients of index x_i and indicator x_j.

Principal component analysis (PCA) is a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of variables called principal components. The principal components analysis reduces the number of indicators used to represent the entire sample. The correlation of components and indicators are shown in Formula (2)

$$\begin{cases} Z_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1p}x_p \\ Z_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2p}x_p + \\ vdotsZ_m = a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mp}x_p \end{cases},$$

$$Z_1 = [\,a_{i1} \quad a_{i2} \quad \cdots \quad a_{ip}\,] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix} \tag{2}$$

where Z_1 is the subject's value on principal component 1 (the first principal component extracted), x_p represents the subject's value on observed indicator p, and a_{1p} is the regression coefficient for observed indicator p, as used in creating principal component 1. On the other hand, the principal component analysis transfers p indicators to m components (Z_i, i from 1 to m). In this research, the first step of PCA uses the matrix of the correlation coefficients to calculate the indicators, as shown in Formula (3)

$$R = \begin{bmatrix} 1 & r_{12} & \cdots & \cdots & r_{1p} \\ r_{21} & 1 & \cdots & \cdots & r_{2p} \\ r_{31} & r_{32} & \cdots & \cdots & r_{3p} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{p1} & r_{p2} & \cdots & \cdots & 1 \end{bmatrix} \tag{3}$$

where r_{ij} is the correlation coefficient of indicator x_i and indicator x_j.

The second step calculates the principal component weights using a Lagrange equation. The objective function of the Lagrange equation and its constraints are show in Formula (4)

$$\begin{aligned} &Max\ Var(Z) = Var(a'x) = a'Ra \\ &st \quad a'a = 1 \end{aligned} \tag{4}$$

The constraint of the Lagrange equation is $a'a = 1$, which is the normalization of the principal component weights $[\,a_1 \quad a_2 \quad \cdots a_p]$. The Lagrange equation is solved using the objective function minus

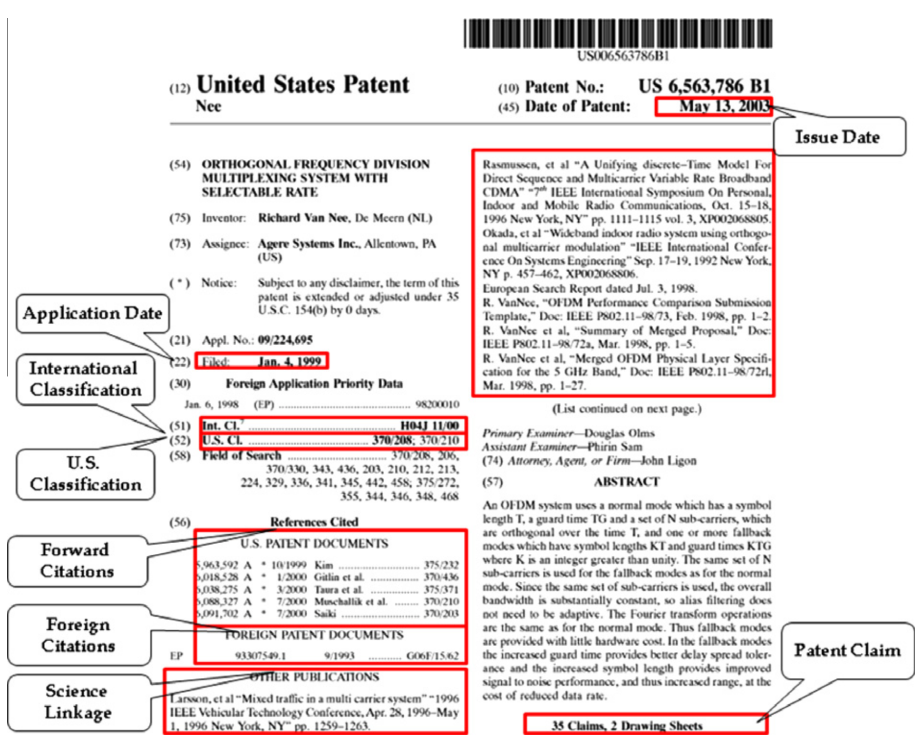

Fig. 3. The partial indicators in a patent document.

the product of the constraint and the Lagrange multiplier, as shown in Formula (5). The results of Lagrange multiplier are the eigenvalues which represent the principal components

$$L = a'Ra - \lambda(a'a - 1) \tag{5}$$

For the third step, the partial differentiation for the Lagrange equation (L) and the Lagrange multiplier (λ) are used to find the weights of the principal components and eigenvalues, as shown in Formula (6). The maximum variance is calculated by Formula (7), and the derivation of principal components is calculated by Formula (8)

$$\begin{aligned} &\frac{\partial L}{\partial a} = 2Ra - 2\lambda a = 0 \Rightarrow Ra - \lambda a = 0 \Rightarrow (R - \lambda I)a = 0 \\ &\frac{\partial L}{\partial \lambda} = a'a - 1 = 0 \end{aligned} \tag{6}$$

$$\begin{aligned} &Var(Z_1) + Var(Z_2) + Var(Z_3) + \cdots + Var(Z_m) \\ &\quad = \lambda_1 + \lambda_2 + \lambda_3 + \cdots + \lambda_m \end{aligned} \tag{7}$$

$$\frac{\lambda_i}{\lambda_1 + \lambda_2 + \lambda_3 + \cdots + \lambda_m} \tag{8}$$

Based on above steps, the eigenvalues and variance of components are calculated, as shown in Table 1. In general, the cumulative variance should be above 70% for the collective practical principal components. In Table 1, first three components will achieve the 70% cumulative variance level (i.e., 78.06%). Further, Hair et al. [24] defined the indicator thresholds used for explaining different data sample sizes as shown in Table 2. For instance, when the data set example size is 85, the explanation values of the indicators for chosen components need to be above 0.6. Thus, Indicator I (0.656), Indicator II (0.704), Indicator III (0.713), and Indicator IV (0.895) are kept as key indicators to format the three valid principal components.

3.2. Building patent quality model

After the principal components analysis, the key indicators are used as the input nodes for the back propagation neural network model as shown in Fig. 4. The output nodes of the BPN network model represent the quality of patent documents [25,26].

The BPN network model is a supervised learning algorithm used to solve non-linear problems. The feed-forward processing of the BPN network is used to train the data model. The nodes of the hidden layer and the result of output layer are calculated using the activation functions, as shown in Formula (9). Thus, the value of the BPN network from node i of the input layer to the node j of the hidden layer is calculated using Formula (10)

$$f(x) = \frac{1}{1 + e^{-x}} \tag{9}$$

Table 2
The indicator thresholds for different sample sizes.

Sample size	Threshold	Sample size	Threshold
350	0.3	100	0.55
250	0.35	85	0.6
200	0.4	70	0.65
150	0.45	60	0.7
120	0.5	50	0.75

$$net_j^n = \sum_i w_{ij}^h X_i + b_j \tag{10}$$

where w_{ij}^h is the weight from the input layer to the hidden layer, X_i is the node i of the input layer, b_j is the bias of the node j of the hidden layer. Thus, the value of node j representing the hidden layer is calculated using Formula (11). The value of the BPN network from the node j of the hidden layer to the node k of the output layer is calculated by Formula (12)

$$H_j = f\left(net_j^h\right) \tag{11}$$

$$net_k^o = \sum_j w_{jk}^o H_j \tag{12}$$

where w_{jk}^o is the weight from the hidden layer to the output layer. Finally, the value of the node k output layer is shown in Formula (13)

$$O_k = f(net_k^o) = f\left(\sum_j w_{jk}^o H_j\right) \tag{13}$$

where $f(x)$ is the activation function of node k. The error function of the output layer of the BPN network model is described as Formula (14). And, T_k is the real value of the training data

$$E = \frac{1}{2}\sum_k (T_k - O_k)^2 \tag{14}$$

Based on the error function of the output layer, the method which adjusts the weights from the hidden layer to the output layer is calculated by differentiation as shown in Formula (15). Moreover, η is the network learning rate. The error function of the hidden layer of the BPN network model is described by Formula (16). Thus, the method which adjusts the weights from the input layer to the hidden layer can be calculated by the error function of the hidden layer, as shown in Formula (17)

$$\Delta w_{jk}^o = -\eta \frac{\partial E}{\partial w_{jk}^o} = -\eta \frac{\partial E}{\partial O_k}\frac{\partial O_k}{\partial w_{jk}^o} = \eta(T_k - O_k)f'(net_k^o)H_j = \eta\delta_k^o H_j \tag{15}$$

$$\delta_k^o = f'(net_k^o)(T_k - O_k) \tag{16}$$

Table 1
Principal component analysis of patent indicators.

Key indicators	Components matrix				
	Component 1	Component 2	Component 3	Component 4	Component 5
Indicator I	0.040	***<u>0.656</u>***	0.102	0.384	−0.466
Indicator II	***<u>0.704</u>***	0.224	0.482	0.086	0.191
Indicator III	***<u>0.713</u>***	0.177	0.013	−0.100	0.027
Indicator IV	0.194	0.068	***<u>0.895</u>***	−0.024	0.152
Indicator V	0.262	−0.165	0.541	0.796	−0.238
Eigenvalues	3.75	1.62	0.80	0.54	0.06
Variance (%)	31.271	13.471	6.698	4.501	0.483
Cumulative variance (%)	31.27	62.78	***<u>78.06</u>***	92.96	100

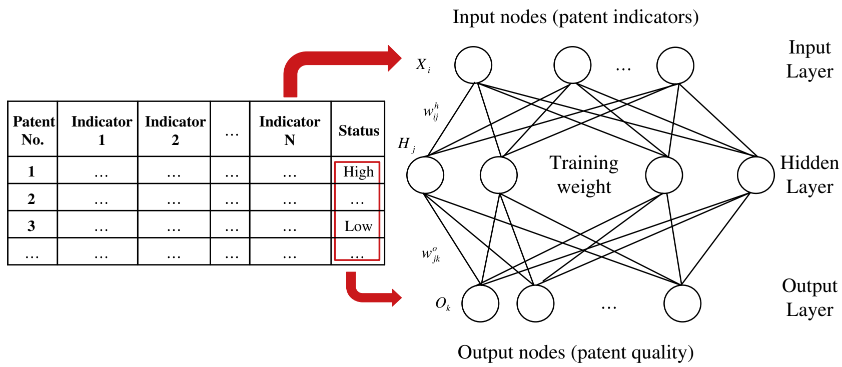

Fig. 4. The BPN network model structure.

$$\Delta w_{ij}^h = -\eta \frac{\partial E}{\partial w_{ij}^h} = -\eta \frac{\partial E}{\partial h_j} \frac{\partial h_j}{\partial w_{ij}^h} = -\eta \frac{\partial E}{\partial O_k} \frac{\partial O_k}{\partial H_j} \frac{\partial H_j}{\partial w_{ij}^h}$$
$$= \eta \sum_k (T_k - O_k) f'(net_k^o) w_{jk}^o f'(net_j^h) x_i$$
$$= \eta \sum_k \delta_k^o w_{jk}^o f'(net_j^h) x_i = \eta \delta_j^h x_i \quad (17)$$

After calculating these values using the formulas defined by Beale and Jackson [27], the weights of the BPN network are trained. The trained model is then used to evaluate the testing data for classification or forecast. Thus, the purpose of this research is to build the patent quality model for evaluating the tradability potential of patents. The patent indicators are extracted from patent documents which have been sold and have changed IP usage rights. These transactional indicators are used to train the BPN patent model and the R&D and intellectual property engineers use the trained model to evaluate the quality of patents.

4. System implementation and case study

For the verification of the patent transaction model, this research collects issued patents that have been sold or licensed to others to build the patent quality system. The proposed system automatically calculates the patent indicators, and uses principal component analysis to extract the transactional indicators. Moreover, the patent transaction model is built for testing the unknown quality of patents using the derived key indicators. The quality of patents can be classified and evaluated after importing the collected patents. The case study collects 399 patents licensed or sold from news of patent transactions. Those patents are used to train the patent quality of the transaction model. The trained patent quality model focuses on patent transactions including digital screens, light emitting diode (LED), information transfer, semiconductors, and cell phones. Each specific domain contains sold or licensed patents and unsold patents for analyzing the patent indicators for different transaction types. Therefore, the well trained high-tech industry transaction model quickly evaluates the quality degree of the unknown patents. News about related patents is collected to verify the performance of the proposed patent quality model.

The transaction model contains five technology specific domains including 78 digital screen patents, 90 LED patents, 52 information transfer patents, 71 semiconductor patents, and 108 cell phone patents. The first group consists of screen patents sold from Hitachi and Samsung. The usage rights of LED patents were transferred from OSRAM to YaHsin Industrial Company (Taiwan). Third, news describes that the information transfer patents were sold by Agere System and GI. Fourth, Acer purchased semiconductors patents developed by the Industrial Technology Research Institute (ITRI). Finally, the case study collects all current cell phone patents owned by Nokia and Sony. In total, the case study has 399 sample patents, containing 283 patents sold or licensed (i.e., considered in higher quality category) and 116 non-traded patents (i.e., in lower quality category) in the just described five technology domains.

After building the patent list from the news, the proposed system downloads patents from the USPTO patent database and automatically extracts patent indicators based on the proposed methodology. The extracted indicators are application length (between application date and issue date using the unit month), the number of international patent classification (IPC), US patent classifications (UPC), forward citations, foreign citations, backward citations, claims, independent claims, patent family (i.e., a set of patents in various countries taken to protect a single invention), technology cycle time [6], science linkage [7,28], and the length of detailed specification, as shown in Table 3.

Table 3
Sample values of indicators from five patents.

	Patent indicators	US Patent No.				
		5075742	5101478	5131006	5146465	5151920
1	Application length	11.6	44.5	18.9	19.5	12.7
2	Number of IPC	8	2	3	9	7
3	Number of UPC	5	1	4	3	2
4	Forward citations	3	25	3	4	6
5	Foreign citations	1	2	7	0	0
6	Backward citations	1	2	1	4	1
7	Number of claims	4	24	14	14	10
8	Independent claims	1	7	4	1	7
9	Patent family	5	7	9	2	1
10	Technology cycle time	3	8	1	1	2
11	Science linkage	1	0	1	0	0
12	The length of specification	3175	231621	6099	4123	4208

4.1. Evaluation of patent indicators

The Kaiser–Meyer–Olkin approach is used to evaluate the appropriateness of the principal component analysis. The KMO analysis yields a value of 0.721 from the extracted 12 patent indicators. The eigenvalues, variance and cumulative variance of components are shown in Table 4. This research assumes that the value of cumulative variance should be above 70% to sufficient collection of principal components. The cumulative variance represents the explanation of components. Therefore, the top five principal components are sufficiently chosen for building the patent quality model. The five components explain and represent the patent indicators respectively in various strength as calculated and listed in Table 5.

As described in Section 3, the thresholds of indicators for explaining different sample sizes are shown in Table 2. The case study collects 399 patents. Thus, the threshold of indicator of the case study should be above 0.3. Thus, the first component selects "Forward Citation", "Claims" and "Independent Claims" (as underlined in column one, Table 5). The second component selects "IPC", "UPC", and "Backward Citation". The third component selects "Technology Life Cycle", and "Science Linkage". Moreover, the fourth component selects "Foreign Citation" and "Patent Families". Finally, the fifth component only selects "Application length". In

Table 4
The principal component analysis of extracted patent indicators.

Components	***1***	***2***	***3***	***4***	***5***	6	7	8	9	10	11	12
Eigenvalues	***3.47***	***1.73***	***1.42***	***1.18***	***0.90***	0.88	0.71	0.61	0.48	0.39	0.12	0.07
Variance (%)	***28.91***	***14.42***	***11.83***	***9.84***	***7.56***	7.33	5.95	5.14	4.06	3.29	1.02	0.60
Cumulative variance (%)	***28.91***	***43.33***	***55.16***	***65.01***	***72.58***	79.92	85.87	91.01	95.07	98.37	99.39	100

Table 5
Five principal components collectively represent the indicators in various degrees.

Patent Indicator	Component Matrix Component 1	Component 2	Component 3	Component 4	Component 5
Application Length	0.053	0.058	−0.091	0.036	0.933
IPCs	0.232	0.672	−0.339	−0.168	−0.272
UPCs	−0.161	0.738	−0.197	0.376	0.101
Foreign Citations	−0.142	−0.257	0.072	0.505	0.113
Forward Citations	0.309	−0.343	−0.006	−0.150	0.101
Backward Citations	0.232	0.516	0.372	0.498	−0.176
Claims	0.814	0.108	−0.525	0.148	0.57
Independent Claims	0.863	−0.185	0.405	−0.449	0.196
Patent Families	0.115	0.131	0.253	0.678	0.349
Technology Cycle Time	−0.145	−0.104	0.913	0.103	0.552
Science Linkage	0.019	0.085	0.414	0.269	0.114
The length of specification	0.162	−0.049	0.075	0.035	0.254

Training Pass	Learning Rate	Momentum	Iteration	Error Rate	
1	0.1	0.8	8000	Train	0.17
				Test	0.42
2	0.2	0.8	8000	Train	0.18
				Test	0.35
3	0.2	0.8	10000	Train	0.16
				Test	0.29

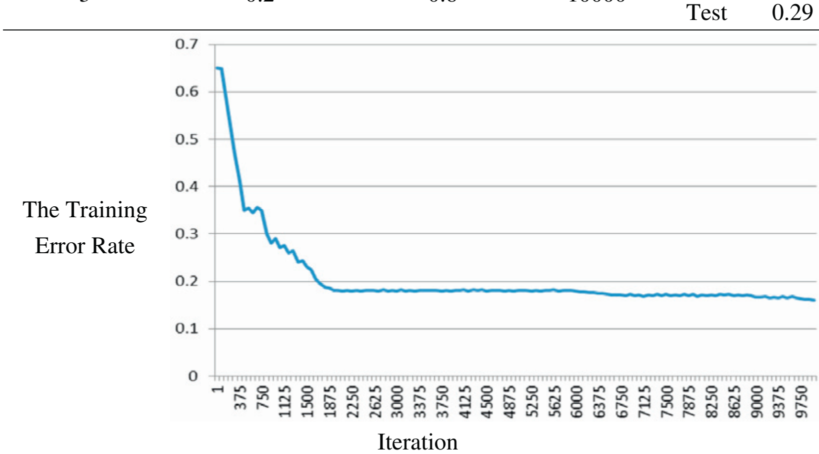

Fig. 5. The training result of the patent transaction model.

Table 6
The information of the patents sold and unsold.

Current assignee	Domain	Type	Patent no.
Stragent LLC	Network communication	Purchased from inventors	US6848972; US7028244; US7320102; US6832226; US6665722; US6393352; US6285945; US6604043; US7289524; US7543077; US7095753
ACER	Computer technology	Licensed from ITRI	US5977626; US6188132; US6280021; US6788257; US5101478; US6075686; US5903765; US5870613; US5410713; US5214761; US5581122
Lutron Electronics Company	Light switches	Unsold	US4893062; US5248919; US5637930; US5905442; US5949200; US7190125; US5982103; US4797599; US5736965
Litepanels, LLC	Light emitting diode (LED)	Unsold	US6948823; US7163302; US7510290; US7429117; US6749310

Table 7
The results of the tradability-based patent quality analysis.

Patent no.	Assignee	Strength	Score
US6188132	ACER	Strong	98.5
US6285945	Stragent LLC	Strong	98.4
US6280021	ACER	Strong	97.8
US5581122	ACER	Strong	97.3
US7320102	Stragent LLC	Strong	97.2
US6604043	Stragent LLC	Strong	96.6
US7543077	Stragent LLC	Strong	96.5
US5903765	ACER	Strong	96.4
US6393352	Stragent LLC	Strong	95.5
US5870613	ACER	Strong	94.8
US6075686	ACER	Strong	94.2
US7028244	Stragent LLC	Strong	93.3
US7095753	Stragent LLC	Strong	93.2
US5949200	Lutron Electronics Company	Strong	92.3
US5977626	ACER	Strong	90.5
US5736965	Lutron Electronics Company	Strong	88
US6848972	Stragent LLC	Strong	87.5
US6832226	Stragent LLC	Medium	67.2
US5410713	ACER	Medium	66.3
US6665722	Stragent LLC	Medium	66.2
US7163302	Litepanels, LLC	Medium	64.9
US7289524	Stragent LLC	Low	36.5
US5101478	ACER	Low	33
US5214761	ACER	Low	32.2
US4893062	Lutron Electronics Company	Low	32
US5982103	Lutron Electronics Company	Low	29.1
US7510290	Litepanels, LLC	Low	28.8
US5248919	Lutron Electronics Company	Low	26.9
US7190125	Lutron Electronics Company	Low	26.9
US7429117	Litepanels, LLC	Low	25.9
US6788257	ACER	Low	25
US5637930	Lutron Electronics Company	Low	24.3
US6749310	Litepanels, LLC	Low	23.9
US6948823	Litepanels, LLC	Low	22.3
US5905442	Lutron Electronics Company	Low	21.2
US4797599	Lutron Electronics Company	Low	20.6

summary, this case study selects eleven key indicators (excluding indicator "Length of specification"). Thereafter, values of these eleven indictors are extracted from training patent documents to train the patent quality model using BPN approach.

4.2. Training the patent transaction model

The extracted indicators are reduced to 11 significant indicators. These indicators are then used as the input layer for training the BPN network model. The nodes of the output layer contain the trading quality of the patents and the non-trading quality of patents. The case study prepares 260 training patents (182 sold or licensed and 78 unsold patent documents) to train the patent transaction model. The test patents include 101 sold or licensed patents and 38 unsold patent documents. The training parameters include learning rate, momentum, and iteration. The results of the patent transaction model are shown in Fig. 5.

4.3. Verification of patent quality model using historical patent cases

After analyzing the principle components and building the patent transaction model, this research collects total of 36 historical patents as test data to verify the proposed methodology. These patents include 22 sold or licensed patents and 14 unsold patents. Eleven network communication patents were sold from patent owners to Stragent LLC – a company focusing on development, acquisition and licensing of patented technology [29]. Further, eleven computer technology patents were licensed from Taiwan ITRI to ACER Computer using for litigations [30]. These patents, considered as high quality patents, are traded by organizations (e.g., Stragent, ACER, and ITRI) to pursuit or defend legal cases. The testing sample also includes 9 light switch patents owned by Lutron Electronics Company [31] and unsold LED patents owned by Litepanels, LLC [32]. The trading statuses (licensed, sold or unsold) of these 36 patents are depicted in Table 6.

The trained patent transaction model is used to analyze the potentials of these 36 historical patents (purchased, licensed or unsold). The results of the tradability-based patent quality analysis are shown in Table 7.

The predictions for the 36 patents include 17 in the strong/high, 4 medium, and 15 low quality ranges. Eighteen out of 22 patents sold or licensed are classified by the model as high quality, while 11 out of 14 patents unsold are classified as low quality and low potential for patent transactions. The matching between the analytical prediction and the actual trading status reached 85% accuracy. Therefore, the proposed patent quality analysis can be effectively used to evaluate the quality of unknown patents for pre-evaluation and preliminary screening. After extracting the high quality patents, the R&D engineers can confirm the patent claims and advances of inventions.

5. Conclusion

Patent news shows that enterprises often purchase technology specific patents to advance technology or make new products. Enterprises use patents to protect their innovations and to establish a time period of protection. However, traditional patent analysis requires significant costs, time, and manpower to evaluate the quality of patents. Thus, the purpose of this research is to shorten the time required to determine and rank the quality of patents with respect to their potential values in IPR marketplace. The proposed patent quality analysis uses principal component analysis to identify critical patent indicators. These indicators in turn are used to build the patent quality model using BPN network approach. The research has made contribution in applying the patent quality model in real application. The case study uses data set of 399 patents in five high-tech domains to identify the most suitable 11 key indicators. Then, 260 patents' data set are used for training the BPN model and, finally, 36 historical patents to test the model. The case has yield 85% accuracy in patent quality prediction, which is considered a valid result for automatically pre-evaluating huge number of patents for commercialization. The patent quality prediction and methodology can be further refined by adding other criteria and factors for patent quality evaluation. More case studies should be conducted for the practical applications when many companies are increasingly concern about patent infringement and IPR litigations, particularly for rapid product development and mass customization.

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