Hidden Markov Model (HMM) in Support of Intellectual Property Risk Management

Lois Onyejere Nwobodo, Hyacinth C. Inyiama

Abstract- An important element of intellectual property (IP) risk management is valuation, forecasting and strategy. Forecasting the optimal likelihood probabilities for the risk can be an audacious exercise, but it is critical in understanding the damage that can be caused by infringement, IP rights litigations etc providing the basis for prioritizing risk management activities and allocating resources. In this paper the occurrence, interactions of risk events as it impacts intellectual property management is modeled as Hidden Markov Model (HMM). The paper presents the HMM as a tool that can be used to optimize IP risk management response. The paper developed a HMM that can be used to predict the maximum likelihood probability for IP risk. This gives substantial information for optimal planning & coordination of IP risk response activities.

KEY TERMS: IP, risk management, HMM maximum likelihood probabilities, IP risk features.

I. INTRODUCTION

Risk is the likelihood that the actual outcome will be unfavorable or undesired. Complexity results from uncertainty piled atop uncertainty [1]. Risk is most often difficult to precisely measure or assess. This paper proposes the Hidden Marker Model (HMM) in support of intellectual property (IP) risk management. An important element of IP risk management is valuation, prediction and strategy, forecasting the impact of intellectual property risk can be an arduous exercise, but it is critical in a proactive understanding of the possible damage that can be caused by infringement, providing the basis for prioritizing risk management activities and allocating resources. Much of the available works on IP risk management focused mainly on managing IP litigation risk. For instance, the reference [2] focused on risk analysis for intellectual property litigation. It modeled the prior risk analysis problem as a supervisor discriminative binary classification task whose goal is to predict the outcome of new IP litigation given relevant prior factors. The HMM technique proposed in this paper is predictive; however the present work looks at IP risk prediction based on a broader framework. It considers the interactions of different IP risk factors or events to arrive at maximum likelihood probability dataset, which provides richer information for optimal IP risk response planning.

This is premised on the basis of pattern recognition or classification from the interaction of IP risk factors. HMM technique is used to identify the most probable IP risk pattern. That is the combination or sequence of risk factors that constitutes the maximum probability likelihood for the organization is identified using the HMM.

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Using the HMM model, this maximum risk interactions events or factors can be identified. Using this as a basis the risk response plan can be optimally formulated.

II. Considerations for IP risk Management

Intellectual property refers to creation of the mind for when property rights are recognized. “Intellectual property” is a subset of “intangible assets”, which includes such things as slogans, non-compete clauses, proprietary sales methods, training methods and customer lists [3]. Patents, copy rights, trademarks and other forms of intellectual property (IP) are among the most significant drivers of competitive advantage for many companies today. Intellectual property is an important measure of corporate value [4]. Protecting intellectual (IP) is not a new concern. Patent protection was recognized by the Greeks at least as early as 500B.C. In the modern economy, protecting IP has taken on heightened importance. IP, not fixed assets, has become the principal sources of shareholder wealth and competitive advantage for many companies [3]. An important, but often overlooked, IP risk management step is assigning monetary value to IP. Valuing IP provides useful information for prioritizing risk management activities and for allocating risk management resources [3]. Not only must companies be vigilant about protecting their IP, they also must be careful to not infringe on the IP of others. Companies can be sued for patent or copyright infringement over products or processes they believe to be unique by their own. If successful, the owner of the IP right will likely demand compensation for past infringement, and may prohibit further use of the IP. Under any circumstance, IP litigation is expensive and can be a drain on management resources [3]. In the light of these realities, companies need analytic tools that are predictive. Such tools that can combine a wide range of possible interactions of IP risk factors or events to give indications of maximum likelihood probabilities in support of optimal IP risk management. If a company sells or licenses its IP, a predictive assessment model such as the proposed HMM enables the company to determine the transient value of its IP based on risk forecast. With this the company can bring in dynamism in its IP risk management strategies.

III. Basic Theory of Discrete Hidden Markov Model (HMM)

HMM is a stochastic algorithm capable of statistical learning and classification. This algorithm is adjustable to novel data where there is no complete information about the source from which the data is generated. The difference between Markova cheery and an HMM lies in observations. In HMM, observations are probabilistic function of the related state and its probability distribution function. This feature is an advantage of HMM, which provides more flexibility to overcome uncertainties in a real-world power

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system. The structure of HMM is discussed in the following. An HMM can be defined as π = (N, M, π, A, B), where N is the number of states, M is the number of distinct observation symbols for state, π is the initial state distribution vector, and A and B are the state transition probability and observation probability matrices respectively[4]. The elements of matrix A, aij, is the transition probability from state i to state j, which are defined in Equations (1) and (2) [4] in these equations, q_t is the actual state S at time

$a_{ij} = P[q_{tH} = S_j/q_t = S_i],\ 1 \leq i,j \leq N$ ……………(1)

$a_{ij} \geq 0,\ \sum_{J=1}^{N} a_{ij} = 1$ ……………………………...(2)

The elements of matrix B, bj(k), are defined by equation (3), where V_k is the K^{th} observation in the state. Matrix B and vector π elements follow the rules presented in equation (4). The HMM training process is identical to finding appropriate parameters of A, B and π.

$bj(k) = P\ [0_t = V_k/q_t = Sj],\ 1 \leq j \leq N,\ 1 \leq k \leq M$ ………… (3)

$bj(k) \geq 0,\ \sum bj(k) = 1,\ \sum \pi i =$ ……………………… (4)

where 0_t indicates observation at time t. equation (3) calculates the probability of observation V_k at time t, were $q_t = S_j$ [4].

IV. IP Risk Assessment Based on HMM

The risk evaluation in support of intellectual property management could be regarded as a complicated process by means of pattern recognition. The proposed risk evaluation model is a dynamic i.e Stochastic process model in [5], Davis and Lo define the so-called enhanced risk model as a dynamic version of infections defaults. The portfolio is assumed to be in one of two states: normal risk and enhanced risk. It stands in normal risk, but as soon as a default occurs it moves to enhanced risk, where the hazard rates for all remaining issues are multiplied by an enhancement factor K > 1. The portfolio stays in the enhanced risk state for an exponentially- distributed random time before dropping back to normal risk. The two states can be thought of as a general “good times/ bad times” economic variable. Hence in this paper, according to the above perspective, the IP risk process can be identified as 2 states: normal risk and enhanced risk. However it would still be in order to identify the process as more than two states. It is quite difficult to identify every beginning time and ending time of the 2 states which could be considered ‘hidden’. However the 2 states could be described by some IP risk management parameters, which means the states could be observed, and such IP risk management parameters could be regarded as the feature sets of the observations. So the hidden markov model could be introduced to describe such risk state transitions and the observations are encoded into discrete quantities. The proposed algorithm flowchart is depicted in figure 1. The goal is to predict the risk impact of the organization given relevant prior risk factors or events. The IP risk database is sampled. The sample size (N) should be large enough to permit realistic classification. Regarding the sampling, the features listed in table 1 is picked from the database. The quantification of most of these features could take the form of risk weight, value weight or impact weights assigned to the feature based on IP risk management decision. For example management can assign a weight value to the feature number three: “the organization IP risk tolerance”. The details of the processing step are given by the flowchart in figure 2.

Table 1: IP risk feature set

Item Number	Feature Name
1	Cost of the intellectual property
2	Estimated post litigation cost incurred
3	The organization IP risk tolerance
4	Estimated risk of IP enforcement claims by third party
5	Amount paid by third-party infringements claims
6	Estimated ability to enforce or protect intellectual property rights
7	Available fund for IP rights litigation
8	Range of amount in any IP right controversy
9	Estimated risk in IP right contractual indemnification changes
10	Cost of filed or issued patent and/or trademark application.
11	Value of any licensing deals

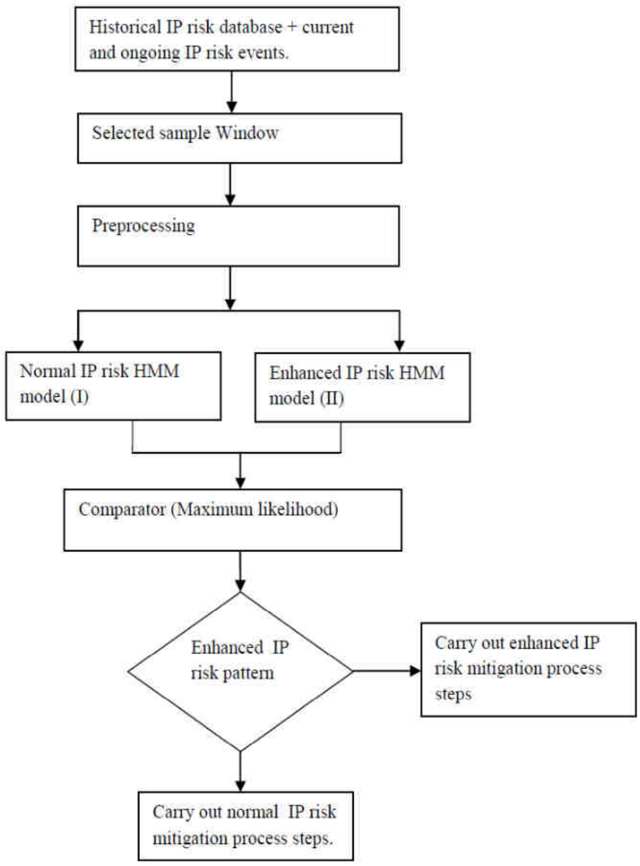

Figure 1: flowchart of proposed IP risk assessment model

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FIG 1: Flowchart of Proposed IP risk assessment model

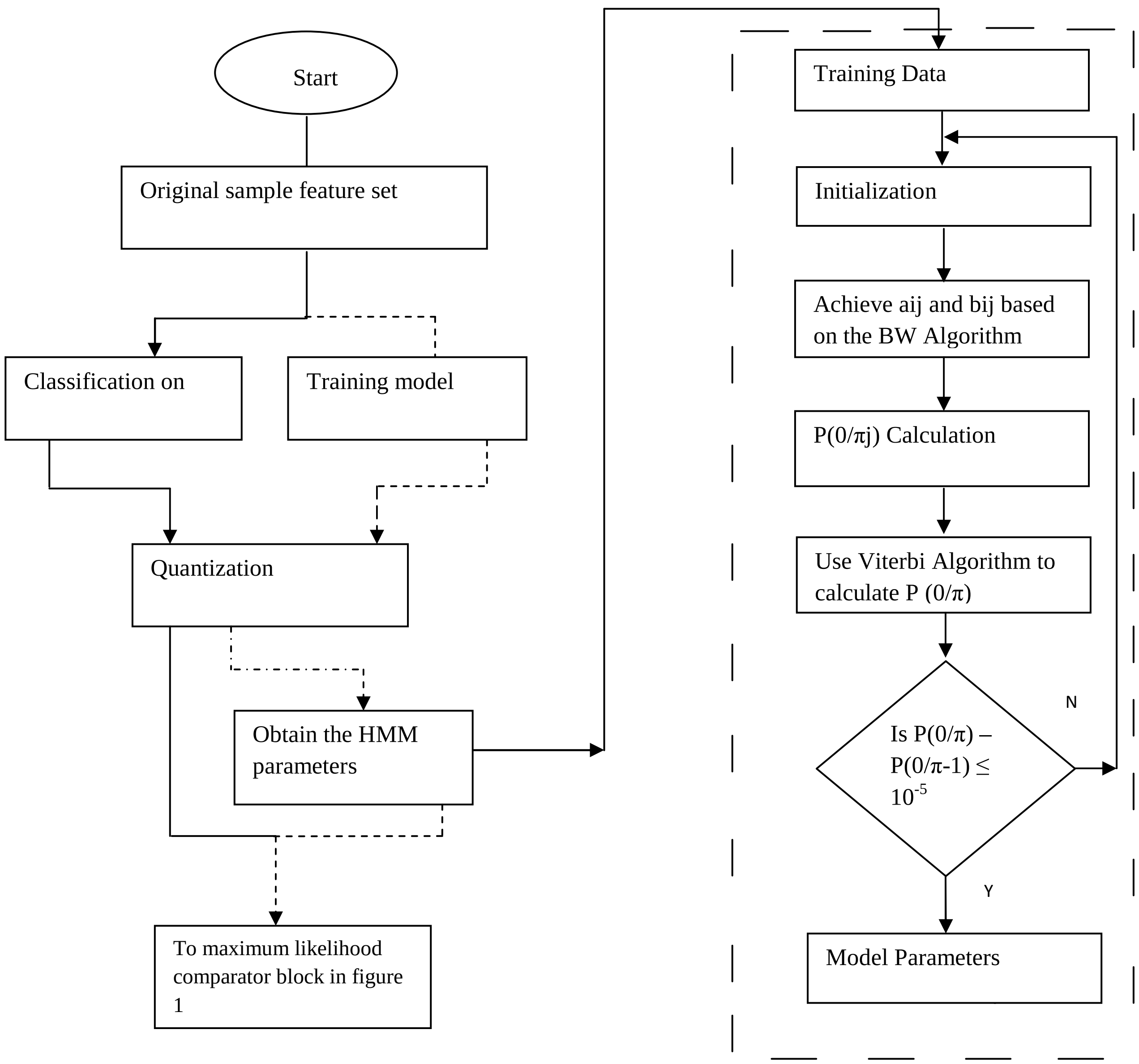

Figure 2: **Flow chart of the details of the processing step of figure 1.**

Referring to figure 2, N samples of IP risk feature sets are taken from the IP risk database. 50% of the N samples are taken as the training data while the other half are going to be classified by the HMM. The training process of HMM is used as part of the process of finding the pattern of interaction of IP risk factors in risk events having the maximum likelihood probability. Finding this gives data that enables optimal risk mitigation plans to be put together.

The identification pre-process starts through the quantization of the input observation data (IP risk data from the data).

In the next stage, the quantized (discredited or coded) data is fed into HMM models. The logarithms of the models output probabilities are then computed in the recuperation stage. Recognition or classification means finding the best path in each trained model and selecting the one that maximizes the path probability for a given input observation O and the model $\lambda_{i} = (A_i, B_i, \pi)$,I = 1, 2….D, where D represents the number of IP risk categorization (based on the company's policy).

4.1. The HMM training process

The training process is as follows:

1. Initialization: Initialize the parameters of the HMM, such as π, A and B.
2. Calculate the new parameters of the HMM based on the Baum Wetch (BW) Algorithm [6]
3. Calculate the optimal condition probability P(O/λj) based on viterbi algorithm [7] with the parameters from [2]
4. Comparer P (0/λj) with P(0/λj-1), if /P(0/λj) – P(0/λj-1)/≤∑, where ∑ is set as a threshold ($\sum = 10^{-5}$), The iterative would finish because of the convergence.
5. If the iterative calculation reached the maximum number of the iterations which is set before the beginning without convergence, if would stop and output the parameters.

4.2. The Initialization of the HMM

The IP risk prediction model is identified as 2 states:

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normal IP risk situation and enhanced IP risk situation which is mapped into 2 states of the HMM (S = 2) . The state transmission probability distribution A is a 2 x 2 matrix and observation symbol probability distribution 0 should contain the features listed in table 1. Based on the reference [8], the initial state distribution A could be set as shown in equation [5] and [6], and the observations value probability distribution B should be set according to normal distribution.

$$\pi = [10000] \ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

$$A = \begin{pmatrix} 0.5 & 0.5 & 0 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0.5 & 0.5 & 0 \\ 0 & 0 & 0 & 0.5 & 0.5 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \ldots\ldots\ (6)$$

4.3. Computing the HMM parameters

The HMM classifies the IP risks by comparing the maximum likelihood probability of the risk data (from its IP risk database) for trained models. Thus, an HMM model should be trained for each kind of IP risk category. In the HMM training process, the parameters are recalculated iteratively to statistically match to a group of training data.

As indicated in figure 1, it is necessary to build two separate HMM blocks for normal IP risk and enhanced IP risk. The HMM block inputs are observation vectors O = O, O_2 …………….O_T, which are feature data samples (or IP risk data). In the training process, the maximum likelihood probability denoted by equation [7a] should be maximized indirectly using the logarithm of the above probability (log lik) which is presented in equation [7b].

$$P(O/\lambda) = \sum P(0/Q,\lambda)\, P(Q,\lambda) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (7a)$$

$$\text{Loglik} = \log[P(0/\lambda)] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7b)$$

Where Q q_1,q_2 …………..q_T is a fixed state sequence and T is the number of observations. The Baum-Welch algorithm is used in the problem [10,I1] Baum-Welch first defines Y_t (i,j) (the posterior probability of transitions being in state i at time t and making a transition to state j at t + 1, given the observation sequence) . It can be computed as equation 8, and the variable y_t (the posterior probability of being in state i at time t, given the observation sequence) is defined by equation 9.

$$Y_t(i,j) = P(S_t = i, S_{tt1}, = j/O,\lambda) = \frac{\alpha_t(i)\, a_{ij}\, b_j\, O_{tt1})\, \beta_{tt1}(j)}{P(O/\lambda)} = \frac{\alpha_t(i)\, a_{ij}\, bj\, (O_{t1})\, \beta_{tt1}(j)}{\sum_{kEQf} \alpha_T(k)} = \ldots\ldots\ldots\ldots\ldots (8)$$

$$Y_t(i) = P(S_t = i/OY) = \frac{\alpha_t(i)\, \beta_t(i)}{P(O/\lambda)} = \frac{\alpha_t(i)\, \beta_{t1}(j)}{\sum_{KEQF} X_T(k)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

where α_t (i) is the forward variable for model λ. This is the probability of the partial observation sequence O (until time t) and state S_i at time t. Another parameter is β_t (i), which is a backward variable that refers to the probability of the partial observation sequence from t + 1 to the end, given S_i at time t and the model λ. Q_f is a set of final states.

$$X_t(i) = P(O_1,O_2 \ldots\ldots\ldots, O_t, 9_t = S_i/\lambda) \ldots\ldots\ldots\ldots\ldots (10)$$

$$\beta_t(i) = P(O_{t+1}, O_{tt2}, \ldots\ldots, O_T/9_t = S_i,\lambda) \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

This specifies the probability of the partial observation sequence O_{tt1},O_{tT2} ………… O_T, given state $9_t = S_i$ and model λ (λ i.e IP risk model, a particular and unique combination of IP risk factors/events including their value estimates from the IP risk database).

If $\alpha_1(i) = \pi_i b_i(O_1)$, then α can be calculated as follows:

$$X_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha\, t\,(i)\, a_{ij}\right] bj\, (O_{tt1}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

If β_T (i) = 1 (initialization), then the following holds true:

$$\beta_t(i) = \sum_{j=1}^{N} a_{ij}\, b_j\, (O_{tt1})\, \beta_{tt1}(j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

parameters a_{ij}, bj, π of the re-estimated new model λ can be computed as follows:

$$\overline{aij} = \frac{\sum_{t=1}^{T-1} y_t(i,j)}{\sum_{t=1}^{T-1} y_t(i)} \ldots\ldots\ldots\ldots\ldots (14)$$

$$\overline{bj}(k) = \frac{\sum_{ttO_t=vk} y_t(j)}{\sum_{t=1}^{T} y_t(j)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

$$\pi_i = y_1(i) \ldots\ldots\ldots\ldots\ldots (16)$$

This re-estimation continues by replacing λ, instead of ~~λ,~~ until P(O/λ) converges to a maximum.

4.4. Computing the optimal conditional probability.

In this stage (refer to figure 2), the viterbi algorithm finds the best state sequence Ɵ[10] [9]:

Initialization for all state i:

$$\delta_1(i) = \pi_i b_i(O_1),\ \varphi(i) = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (17)$$

Recursion from time t = 2 to T and all states is:

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$\delta_t(j) = \max_i [\delta_{t-1}(i)a_{ij}]b_j(O_t)$ …………………….. (18)

$\varphi_t(j) = \arg_j \max (\delta_{t-1}(i)a_{ij})$ ………………………. (19)

Termination:

$P = \max [\delta_T(i)]$, $q_T = \operatorname{argmax} (\delta_T(i))$ …………………. (20)

State sequence back tracking from T – 1 to 1:

$q_{t}^{*} = \varphi_{tt1}(q_{tt1}^{t})$ ………………………………………. (21)

The maximum likelihood probability P(O/λ) could be achieved, given the best path Q and observation O (observation vector of the IP risk dataset). The categorization of the risk can then be identified by comparing (figure 1) the logarithm of the likelihood probabilities (loglik) of the models. The model (risk dataset) with higher loglik shows the risk category. The type of risk response block (see figure 1), where the risk categorization HMM block give the computation output, becomes higher; otherwise, the risk dataset (model) will be identified as a normal risk resulting in the company's management following response processes for normal risk.
The HMM procedure, based on the analysis carried out on data samples from the risk database, categorizes the emerging risk to the organization as either normal or enhanced. This enables the company's IP management team to be more proactive quantitative, objective and accurate in the risk mitigation steps. The HMM technique gives this predictive ability to the organizations IP risk managers. This enables the company's to exploit optimization in dealing with IP risk.

V. Risk response based on the HMM output.

The dataset (HMM risk mode) identified as having the maximum likelihood probability can be used to quantify possible cost options, and sequencing of the risk response efforts. The HMM output, the maximum likelihood probability model (dataset) should help the organization to properly align its IP risk response strategies.
The identified risk dataset (i.e the HMM model): normal IP risk HMM model or the enhanced IP HMM model, gives the risk attributes (i.e types of risk factors or events and associated values or estimates). This gives huge information that helps the organization to optimally evaluate its available risk mitigation options.
The HMM output should provide the information that enables the organization to optimally budget for the risk management. The HMM identified risk dataset (the HMM risk model) having the maximum likelihood impact enables management to get (in advance) a sense of the size, impact and hence is enabled to objectively prioritize the budget allocation.

VI. Conclusion

The predictiveness of the proposed HMM technique helps shorten or eliminate the time required for management to identify, assess and respond to IP risk. Organizations often develop a schedule to accommodate risk, risk analysis and risk reaction. With the proposed technique, the indications of risk impact can be flagged in advanced. This gives the IP managers enough time to plan mitigation activities. By providing risk scoring information (normal risk, intermediate risk, enhanced risk) the HMM technique provides an invaluable management decision support capability to IP managers. This advance risk scoring helps to give the quantification of the nature of any impending risk on the firm. For instance the maximum likelihood probability output gives substantial information for making decision such as determining (based on the HMM prediction) which IP insurance policies, might be right for mitigating the identified risk. All companies have the potential to be sued for IP infringement. A company is vulnerable if it is simply making, using or selling a product and or service or if it holds sought-after technology on products and/or processes. The proposed technique helps the company to quantitatively get a sense (in advance) of the nature of its IP risks, helping it to identify areas of inacceptable risk and giving the information that helps it to devise strategies and tactics for possibly shedding that risk to contractors.

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