Real-Time Corporate Liquidity and Credit Pricing Using Big Data

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Technology is making it possible for corporates to take advantage of the vast amount of structured and unstructured data at their disposal. A customised big data solution can enable a treasurer to react a lot faster to a sudden, unpredictable change in the operating ecosystem of the company, and can allow the lowest-cost funding choices to be made available at the point of impact before it happens. This article looks at two examples – an insurer tackling an unexpected natural disaster, and an established retailer looking to enter an emerging market – to show how the process works and what its requirements are.

Top Four Liquidity Concerns

While each industry is unique in its liquidity needs, there are certain liquidity issues that all treasurers face. Top among them are:

1. An inability to foresee upcoming market and industry changes that would require sudden, massive shifts in liquidity needs

Companies borrow heavily from credit lines even when maintaining sufficient internal liquidity during periods of economic uncertainty. While this could be due to the unpredictability of markets, such companies can model information about the economy, their customers and suppliers and overlay this with company statistics to identify the least-cost choices for funding.

2. Difficulty tracking connected or linked events and changes that affect the company or its suppliers/customers

For example, the floods in Thailand in 2010–2011 affected car manufacturers, semiconductor manufacturers and other industry players. Companies such as hard drive manufacturers Seagate or WD, which had to switch to suppliers in China, Singapore and Malaysia, had to change their funding choices as well. While the floods were unexpected, their after-effects could have been easily modelled using a Bayesian model and liquidity kept available to be moved as the situation worsened.

3. Poor integration between treasury management systems (TMSs), customer relationship management (CRM) and other systems, preventing a real-time big-picture view

This big-picture view is crucial to predicting liquidity needs based on sudden tax changes,

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etc. Any CFO is bound to appreciate a daily dashboard that predicts with greater accuracy any upcoming, highly probable large-ticket funding needs and next-best funding choices. In the past, it was extremely difficult to implement this due to lack of integration. However, current options like big data analytics enable better understanding of structured and unstructured data, detect patterns between seemingly unrelated events and thus increase the possibility of predicting upcoming changes based on those patterns.

4. A tendency to predict the cost of funding from external sources based on the market's perception of the company rather than the internal view

This is important since the market's view of the company's financial status typically differs from the internal view. The degree of difference determines the spread between what the company thinks should be an ideal interest rate versus the market's rate. Any proposed solution has to track credit default swap (CDS) prices, the company's credit rating, the bank's ratings and perceptions, etc. to arrive at a likely interest rate at which a bank will lend to the company.

A Big Data Based Approach

A solution built using a combination of self-learning and adaptive algorithms can present the treasurer with a dashboard showing the 'top 10' upcoming liquidity needs on a daily basis, and also provide funding recommendations. Both the processes – predicting the liquidity need and matching funding recommendations – occur in real time and are capable of learning from past funding choices and unrealised predictions.

This enables the treasurer to react a lot faster to sudden, unpredictable changes in the operating ecosystem of the company, such as an economic crisis, natural catastrophes, industry changes, competitor bankruptcy, etc. It also allows the lowest-cost funding choices to be made available at the point of impact before the change occurs.

As examples we take two business scenarios – an insurer dealing with a natural disaster and a large retailer looking to enter a growing economy. The proposed approach in this article uses a variation of the Bayesian model to predict, with increasing accuracy, upcoming large-ticket liquidity needs and recommend choices for funding. The approach accepts structured and unstructured data – fed via a big data system that specialises in unifying structured and unstructured data. The accuracy of the system is further refined by using a support vector machine (SVM) to validate the Bayesian model.

The implemented dashboard also allows for the customisation of parameters such as risk appetite and prediction longevity.

Business Scenario 1: Flood Prediction and Price Modelling for an Insurance Company

The large-scale floods in Thailand in 2011 caused total losses exceeding USD45.7bn for the economy as a whole, including a large property and casualty insurer. The insurer was forced to liquidate several of its long-term assets to pay the high amount of claims filed in a short period. Despite possessing extensive prior knowledge about Thailand's frequent flooding, the company did not take into account fully the timing, impact and other factors to create a premium pricing and liquidity model, thereby resulting in significant losses and payouts.

Additionally, delaying a few valid payouts to conserve liquidity led to a shrinking of the customer base, as customers shifted loyalties to the competition.

The following two-part solution would have helped the insurer avoid this catastrophic scenario:

- The first tracks and calculates in real time the flood instances, probable areas and damage, and liquidity needed for quick payouts. This is done by understanding reference data and other weather news,

incidents of weather patterns and changes, customer-base migrations, the business impact of moving liquid assets within and outside the country, etc.
- The second requires quicker processing of insurance claims and point-of-impact approvals using augmented reality technologies, which can help widen the customer base/ premiums and thus reduce seasonal shocks to liquidity.

Towards this end, it would be useful for the insurer to have access to an inclusive and encompassing liquidity, pricing and claims settlement system that processes – in real time – weather patterns such as La Niña, El Niño, global warming, etc. and their fallout, to determine the probabilities of flood and damage, and hence predict liquidity needs and pricing for policies.

A Bayesian front-end model to understand relative impact probabilities, coupled with a back-end Monte-Carlo simulation to determine probabilities of weather events can easily be used to predict liquidity needs and suggest premium changes in real time (see Figure 1). The solution can ensure proactive claims processing by requiring claims officers to visit affected areas and empowering them to fill out claim forms, approve claims on the spot and ensure the payout happens within the hour.

Figure 1: Simulation of a Cost Prediction and Price Modelling System based on Big Data Analytics

Step	Action	Response
1	Real-time access enabled to: • Weather reports, historical global weather data patterns and studies by weather institutes. • Reports on environmental changes such as dam levels, river changes, etc.	The solution's first task is to model – in real time – the probabilities of flood occurrences in insured areas. This requires using a triage model to understand and display the probability of flood event occurrence in a grid model, which is overlaid with information about insurance coverage in terms of the dollar value for that area and potential payout amounts.
2	During 'normal times', insurance officers upload periodic pictures of the insured property, which is overlaid with local water table information acquired from the municipalities.	The solution correlates this information with that of the water table to constantly update the capacity of the soil/ ground to absorb flood waters before damage occurs. E.g. A flood in a desert-like area will actually be less susceptible to damage than a perennially wet, humid area, which is likely to cause more devastation than normal. This input is required to calculate the potential payout when presented with a claim.
3	The solution detects seasonal changes and more frequently monitors news, weather reports and local liquidity held at branch offices, etc.	The solution activates the real-time claims processing system onto the mobile devices of claims-handling managers already deployed. The claims-handling system uses augmented reality to quickly capture proof of flood damage with GPS-encoded data to reduce fraudulent claims.

4	Based on the Danish Hydrological Institute's 100-year estimates, the solution overlays the reservoir capacity on the flood protection area in heavily insured areas.	The solution correlates rainfall and tides to determine whether the upcoming flood will be less damaging after the dams have been repaired (based on news reports). It also establishes that since the flooding happens on a regular pay week, employees/contractors must continue to be paid.
5	The solution ascertains that past floods cut off communications between the head office and branch offices.	It recommends empowering claims officers to settle claims on the spot via smart applications (apps). Funds to settle claims are moved to multiple bank branches nearer the point of impact.
6	Once flooding occurs, the solution tracks the images of the same and overlays it with the insured parties' locations to confirm flooding.	Claims officers use apps that have been provided with the addresses and GPS coordinates of insured parties who appear to have been affected by flooding, based on visual examination or calls from affected parties.
7	The solution directs claims officers to the most-affected insured parties after verifying insurance validity.	Claims officers visit insured parties and use smart apps on their mobile devices to capture damage assessment details. The claims officer takes photos of the visual damage and creates and populates the claim form with evidence and the insured's e-signature. The augmented reality app ensures the overlaid photos are attached to the digital claim form. The photos are tamper-proof and GPS-encoded to confirm the location of the incident.
8	The solution receives the uploaded photos from the claims system and correlates them with news/media reports of flood damage and locations.	The solution validates the claim submitted by the claims officers by matching the visual evidence with known/confirmed news sources to assess damage. The decision to proceed is given after confirming the damage, but the assessment of damage is left to claims officers who are at the location.
9	The claims officers assess the damage on a video call with their branch offices or other claims officers.	This is to assess the financial cost of the losses and insurance payout. The affected insured party is also included in the video call with the branch to directly discuss the payouts involved.
10	The branch approves the assessment and insurance payout.	Claims officers prepare a claim form and submit digital acceptance of the insurance payout from the insured party via e-signature or video acceptance. The acceptance of the claim kicks off a disbursement event by the solution.
11	Once approved, the payout is paid to the insured's bank account.	The solution transfers the necessary funds to the insured's bank account. The entire claims process can be completed within an hour after the claims officer visits the site.

Source: Infosys

Business Scenario 2: Liquidity and Credit Pricing for a Retailer Expanding Overseas

A large UK-based retailer seeks to expand to India and projects a long-term investment need of GBP5bn and short-term initial funding needs of about GBP80m.

The assumption is that the retailer will open about 21 stores in high-value cities in four states, with sourcing to be done primarily within India.

The treasury has to identify sources of funding – including a mix between internal and external sources – unexpected and contingency funding expectations and a degree of cash flow reuse to determine the mix of local currency and foreign exchange needs.

Towards this end, the treasury inputs details about the target economy, target liquidity reserve and operational needs for the solution, as detailed in Figure 2.

Figure 2: Simulation of a Corporate Liquidity and Credit Pricing Solution based on Big Data Analytics

Step	Action	Response
1	The target economy, internal funding choices and expected risk appetite details are input.	The solution takes the risk appetite and target economy into consideration as an initial input. It starts to filter information specific to the local areas within the region where the retailer intends to open outlets. The solution also identifies the suppliers for each specific store, customer demographics, local gross domestic product, employment factors, political volatility, etc. These factors are fed into the Bayesian model.
2	Each store's predicted funding needs – salaries, initial setup costs, etc.– are identified.	It overlays the same with calculations of the probabilities of unexpected funding needs based on the region's non-statistical, informational data such as protest factors, income gaps, etc. This is to determine worst-case scenarios.
3	The non-mathematical costs of sourcing funds from local banks versus importing funds from UK banks are examined.	While a pure mathematical model might accurately predict that it is cheaper to fund liquidity using a fresh credit line from a UK bank and secured by the retailer's UK assets, the Bayesian model predicts a higher probability of success if the borrowing was from a local bank collateralised by local assets. This is based on its understanding of India's tax system as per recent tax cases (e.g. the Vodafone tax dispute). In this case, the local bank would have a stake in the running of the store, and would help mitigate any tax implications and local concerns. The cost of local credit lines will be higher than an UK credit line. However, the same can be offset against the higher probability of eliminating tax implications. The solution predicts the probability of GBP3.2m in unexpected funding being required for three stores due to a worsening of the already volatile economic condition. This is to meet fixed expenses, tax liabilities, insurance and supply chain payments during a sudden temporary closure of the stores.

4	A 67% probability of the event happening is calculated.	The solution identifies that if the event occurs, liquidity will be needed in multiple, simultaneous payments in local currency. Since this is a highly probable event with a large outlay, the solution calculates the costs in funding it using internal liquidity or by arranging for a contingent credit line. It determines that GBP1.1m be used from internal liquidity sources and recommends putting the amount in a government-owned local bank in the form of a fixed deposit. It recommends the rest of the amount be a contingent credit line that can be drawn down anytime within the next three months. The fee for the undrawn portion is covered by the fixed-deposit returns.
5	The solution updates the probability of various events happening on a real-time basis.	Based on a news report that strikes have forced the closure of two stores out of 11, the solution calculates the recurring and landed costs of the closed stores. Since it calculates a higher probability that the stores will remain closed for more than 15 days, while the cash flow from remaining stores have increased sharply due to their novelty value, it recommends diverting liquidity to keep the two stores funded from internal sources.
6	The solution ascertains a higher probability of increase in corporate tax liability in India.	It recommends this would entail a 4% increase in tax paid and, based on the risk appetite of the retailer in India, would recommend either: • Moving additional 4% of funds to a higher-return investment within India. • Bringing in additional funds from the UK as foreign exchange (FX) and putting them in higher return deposits in GBP and hedging them for the next three months.
7	The solution learns from the media that seasonal rains have failed in South India. The solution detects increasing FX spreads in forward contracts based on similar experiences.	Based on past patterns, this essentially means South India will import additional food grains from elsewhere. This would mean that five stores in South India would need a marginal increase in funding liquidity to accommodate increased transport costs and higher product prices. The solution also recommends increasing hedging of both food imports and currency outflows. It recommends increased forward purchases of INR to lock in benefits of current perceptions.

Source: Infosys

Requirements and Related Concerns

Required Inputs

The proposed approach is heavily dependent on real-time information flowing through the solution. This information includes data (in various formats) from the TMS, order books, cash-flow data from various countries, and market information from Bloomberg, LIBOR rates, bank portals, CRM, social media, etc.

This approach requires a variety of internal and external structured and unstructured data sets:

- Data passing through the company's various systems, especially CRM and financial data;
- Industry-specific data from news media, publications, company annual reports, etc.;
- Economic data about the local and external economy;
- Patterns identifying specific actions and reactions of the company and industry under various economic/material changes (e.g. automotive companies spend more on research and development for hybrid cars during a recession);

- Behaviour of the corporate treasury on specific recommendations/inputs provided by the solution. If the treasurer does not choose specific recommendations (such as holding funds overseas), the learning is incorporated into the system as a pattern based on the similarity of conditions;
- Prediction/actual success rates – the more successful a prediction, the more reinforced the solution would be to produce a similar recommendation under similar conditions; and
- Monitoring the market for CDS prices against the company and default probability, along with credit ratings.

Concerns and How to Address Them

Unlike typical TMSs and liquidity systems that operate on purely structured data stored in a relational database management system (RDBMS), any solution built using this approach would also need to handle unstructured data in the form of news reports, text data and asymmetrical data that cannot be correlated. This can be handled by a big data platform that specialises in unifying structured and unstructured data.

The other challenge would be to operate the solution in real time on a 24/7 basis. The system would need to monitor a variety of information sources and identify patterns that could affect liquidity. It would also need to learn from a treasury's choices and actions taken on the recommendations made.

Finally, there are some nuances that cannot be modelled or form a pattern, and a person is required to successfully interpret the data where the system would be unable to. For example, in the light of information received about a proposed company takeover, the system could predict that additional liquidity is required, which would be best funded by borrowing from multiple banks simultaneously. However, the treasurer might know better – that the proposed takeover is simply a ruse to mislead rivals.

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