# Enhancing Visibility and Agility in the Electronics Manufacturing Supply Chain

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«Understanding historical activity can predict future productivity. »

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## Abstract

The extremely volatile and competitive electronics manufacturing industry are continually searching for ways to increase efficiency of their supply chain, and reduce manufacturing costs.

In the many current resources that forecast OEM/EMS supply chain demands, the process is conducted through the analysis of current customer inputs and confirmation supplier orders. The limitation of current or present data impedes on the effectiveness of predicting a supply risk, as it does not correctly address historical inputs with the daily emotional activity of all the actors in a market.

The paper will specifically focus on the relationship between ERP historical data and global distributor supply data by profiling each actor in the environment as it relates to fulfilling all necessary components for a product. Thus, we examine the ways in which big data technologies have and will continue to increase the agility of the electronics manufacturing supply chain, by applying our analytic results to three particular issues: the obsolescence risk for overstocked parts, the risk of production cycle interruption induced by stock shortages, and the negative impact of volatile lead times on lifecycle management.

## Introduction

The electronics manufacturing industry is in a constant state of fluctuation with returns in the billions each year. In 2013 alone, the industry is expected to expand by 4.7% (Staff, 2013) with total revenues reaching $404.5 billion (Dinges, 2013). Knowing that these figures change year after year based on the volatility of the market, the question many companies face is: What is/are the best solutions to control market volatility?

The challenge with understanding market volatility resides in the visibility of the supply chain. More specifically, the constant change in supply lead times; the risk of having your production cycle interrupted; the potential for overstock, which leads to obsolete stock. According to Gartner's 2013 annual user wants and needs survey, supply chain visibility has ranked top in companies' investment priorities for technologies across their supply chain, and in the top three of the leading challenges to achieve supply chain goals for

2014 (Titze & Payne, 2013). To protect against these inevitable challenges, companies' have initially turned to solutions that are potentially a quick fix to an ongoing problem, but in essence, they must find solutions that provide continuous visibility over the entire supply chain. This includes not only addressing the input and output of data in the supply chain, but end-to-end solutions with prescribed actions.

As active participants in a rapidly interactive industry supply pool, it is uniquely important to focus on the key elements that optimize productivity. This paper seeks to address the differences between visibilities provided by current technologies that focus on forecasting, against that of new technology frameworks that utilize machine learning on big data. All of which address the volatility of the supply chain for electronics manufacturing. As expressed by Kevin O'Marah, demand volatility is the number one challenge for companies today (SupplyChainBrain, 2012).

## Current Market Products

The manufacturing industry is not blind to technological products that help to manage the increasingly complicated supply chain. At present there are hundreds of different ERP solutions, and hundreds more if you include forecasting and demand-planning solutions, working to optimize supply lead times. Many of these solutions focus on aggregating information and making assumptions on data inputs and outputs to determine appropriate forecasts for supply chain planning, which limit the potential for a precise justification of supply availability.

As stated in the Business Dictionary, forecasting is a planning tool that helps management in its attempts to cope with the uncertainty of the future, relying mainly on data from the past and present analysis of trends (Business Dictionary, 2013).

Much of the software that is presently on the market does just that, forecasts the supplies. This basic approach of predictive analysis has had many successes in the consumer manufacturing industry, but those same tools have been applied to the electronics manufacturing industry in hopes of similar success rates on predicting demand. The assumption that one industry solution will have the same result if used across multiple industries has shown limited success, especially in electronics manufacturing where supply lead times fluctuate and the extreme volatility of demand, which can lead one to believe that forecasting is unpredictable.

Therefore, in a thought process where forecasting demand is believed to be the key to managing uncertainty, we must begin by testing the theory against various industries to verify its validity. What we find is that many forecasting service companies use parametric algorithmic solutions that are generally best at addressing retail industries or seasonal consumer products. In addition, the bulk of a parametric analysis that is achieved by a majority of demand planning and forecasting software is based on techniques that have been created and modified since the 1920's. Research introduced by the MIT Supply Chain Forum, suggests that the continued use of parametric models to create new software for supply demand, has been completed as recently as 2008 (Datta, et al., 2008). The continued use of historical tools puts capacity limitations on overall system effectivity, and thereby restricts supply chain efficiency.

## **Prescriptive Analytics with Machine Learning**

"Prescriptive analytics not only foresees what will happen and when it will happen, but also why it will happen and provides recommendations on how to act upon it in order to take advantage of the predictions" (van Rijmenam, 2013).

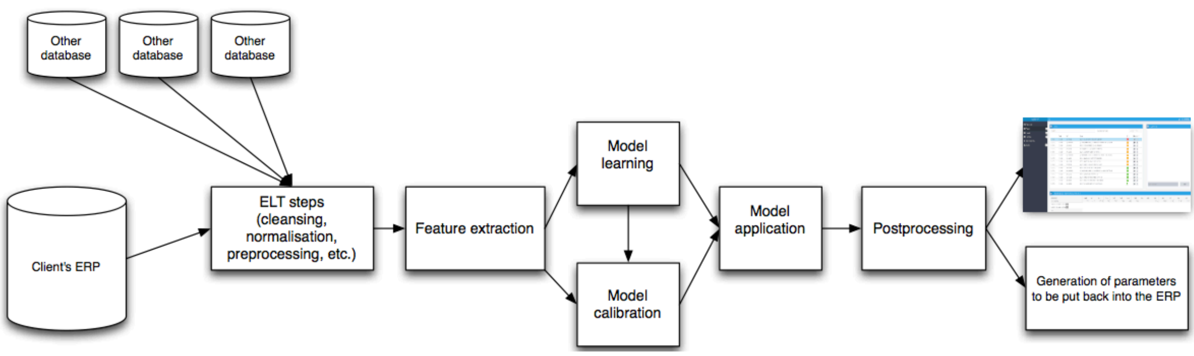
Over the last several years, what has emerged are efficient, to add a form of precision and growth as computers learn based on specific algorithmic models. As early as 1959, machine learning became a common phrase in the mathematics community, as scientist Arthur Samuel first defined this process as artificial intelligence: the field of study that gives computers the ability to learn without being explicitly programmed (Simon, 2013). "Machine learning is concerned simultaneously with statistical soundness and computational efficiency" (Domingos, 2002), which can be seen as what drives accuracy in its heuristic approach.

Today, the world of technology is quickly evolving, with new ways to see and understand data to improve the quality of business transactions. "Machine learning algorithms can figure out how to perform important tasks by generalizing from examples. This is often feasible and cost-effective where manual programming is not. As more data becomes available, more ambitious problems can be tackled" (Domingos, A Few Useful Things to Know about Machine Learning, 2012). Machine learning is an evolution, that is taking steps beyond predictive analytics into a continuum that elicits data precision and efficiency. Machine learning is designed to directly optimize prediction accuracy (Tennant, 2013).

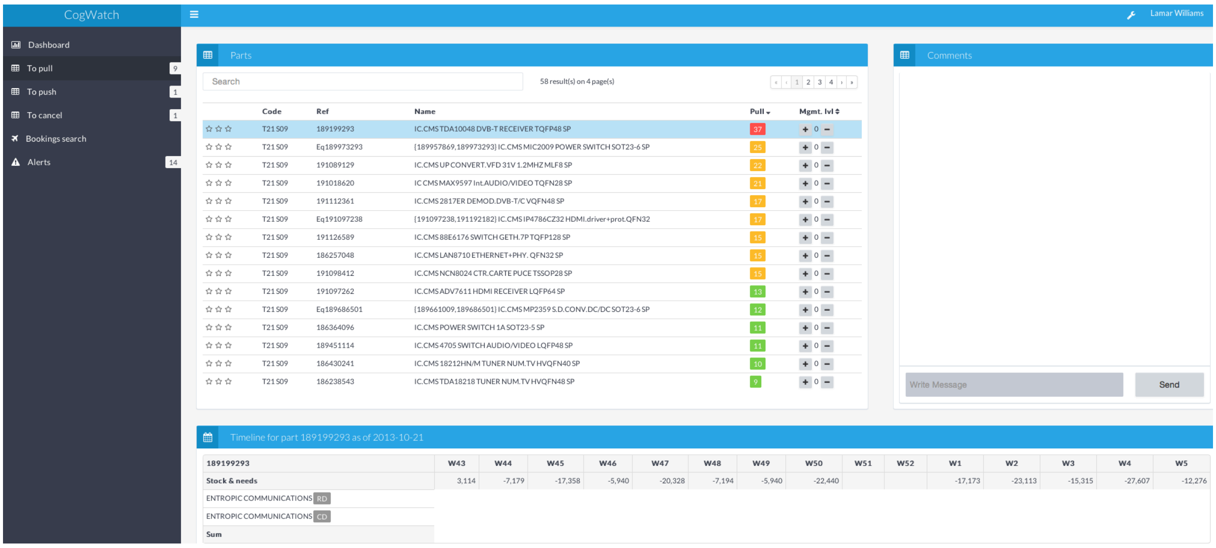
Therefore, the integration of machine learning and its foundational structure, serve to provide a new disruptive framework to precisely increase business practice efficiencies, while reducing expenditures.

In the advancement of today's technology, there is an air of criticality within the many industries, as more and more businesses must compete for clients, based on razor thin margins. In a market, such as electronics manufacturing, where corporate growth is based on the ability to manage production cycles with end-to-end visibility over product development, it is important to have tools that can give you a competitive advantage. In volatile industries, such as this, machine learning simplifies the process of identifying challenges in the supply chain, and redirects reactionary planning to a proactive approach for quick resolutions to future disruptions.

In the following diagram, we have listed an example of how machine learning is applied in the solution provided by Precogs. In the initial stage of example shown below, supply chain data is introduced from several sources (ERP & Distributors). The historical data is then cleaned to extract the necessary information to be analysed with an algorithm, so that it may learn and develop a model for current and future datasets. The algorithmic model is now applied to current datasets, and the output is then pushed into Post-processing. During Post-processing individual data components are formatted into critical risk levels, thus providing a prescriptive solution of actionable items for management teams.



The individual action items are then displayed in a web application, and are coded numerically by critical risk from low-to-high (scale of 0-100). The priority scale highlights the critical risks that must be acted upon to avoid supply chain interruptions and to assure production efficiency.




## Conclusion

The difference between the tools of the past, with that of machine learning is in the application of the data. Forecasting and demand planning use a process of understanding the inputs and outputs of a given process from past and present data to predict future events. This parametric, model-driven process of analysing data produces interesting results, but the accuracy of machine learning provides a basis for solid data results and prescriptive solutions for supply chain optimization.

Additionally, the introduction of big data principles on machine learning permits the synchronization of analysis for continued system learning and development. The depth of information that is acquired from tools that utilize these concepts allow for exponential expansion of industry capabilities, as it relates to market supplies and getting product to clients.

As explained by Gartner, visibility seeks to reduce business and partner risk, while improving lead times and performance, as well as identifying shortage and quality problems along the supply chain (Titze & Payne, 2013). Supply Chain Management is the cornerstone of what is necessary to succeed in the volatile industry of electronics manufacturing. And, “the deeper concerns of business…will be addressed through more mature Supply Chain Management Models. It is not just efficiency and optimization of operations that Supply Chain Management of the future will address – it will likely make the difference between success and failure” (Dhekne & Chittal, 2011).

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