Applying Six Sigma Quality Methods to Improve Customer Service Satisfaction

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Abstract

A panel of thought leading global experts on manufacturing was convened by the National Academy of Engineering in 1992, and among other major findings in their report "Manufacturing Systems" [1] that panel shared their curiosity about there being "Laws of Manufacturing" and how, if found, would extend industrial engineering methods of that time. Since that time, acceptance of lean six sigma thinking and culture has profoundly and irreversibly changed our management methods. Likewise in that time frame the short comings of MRP systems of the long past, have evolved to ERP systems of today that are viewed at a minimum as beneficial to the end user. In the net-centric, ERP driven supply chains of today, we find the loudest "voice of the customer" in their sales data, and it needs to be given considerable weight in our planning. Presented here is the generalization of "Little's Law" to a much broader utilization in operations management. That generalization is facilitated by six sigma statistical methods applied to data typically available in any contemporary ERP system, to innovate and improve operational planning to drive gains to greater customer satisfaction with the "When" of their orders.

Keywords

Littles Law, supply chain, replenishment period, re-order point, lean manufacturing, six sigma, ERP, bivariate normal distribution, binomial analysis

Management of finished goods inventory levels is an engaging topic in organizations because it impacts so many managers and executives. As an asset, inventory is one of the most liquid, close behind cash, so it gets a lot of financial and accounting executive attention. It has profound impact on customer service satisfaction levels, so marketing executives are concerned. Obviously operations and production executive's days are greatly consumed with planning on how to solve and minimize shortages. Facility and real estate executives have to plan for where to warehouse it and how to move it. Information technology executives have to build systems to operate global enterprise software for users.

For many of the first adopters, of "Just in Time" inventory management, the focus was on unilateral cuts in work in progress and finished goods and they were disappointed with the result. They discovered reducing inventory while maintaining customer service satisfaction is a result, not a means. Later adoption of Total Quality Management, World Class Manufacturing, Lean Manufacturing and Six Sigma set organizations on continuous improvement journeys which facilitated reductions in work in progress and finished goods throughout the supply chain. Concurrently through those years of management cultural transformations, information technology with Manufacturing Resource Planning MRP, evolved into Enterprise Resource Planning ERP, and operation management and production planning improved greatly. A quiet contributor in the supply chain transformation is the express parcel industry and their disruptive introduction of next day parcel delivery. Everyone recognizes the profound transformation of consumer behavior in its aggregate migration from bricks and mortar retail to the internet, as well as business to business online transactions and the monumental impact on supply chains.

Those simultaneous transformations over the last three decades in corporate cultural, enterprise software, express parcel service, and consumer behavior have facilitated the expected level of performance of all supply chain members to same day order fulfillment and next day delivery. The thesis presented here is that while enterprise software has built impressive screens for users, the underlying mathematical theory on which today's inventory management system depends has not been revisited since the work of Hadley and Whitin [2] five decades ago. A superior method with greater accuracy is needed to avoid stock-outs on the back side of the replenishment periods, with a granularity of less than one day.

What did Hadley and Whitin provide us back then? They gave us the expressions, $\mu_y = \lambda \mu_t$ and $\sigma_y^2 = \mu_t \sigma_x^2 + \lambda^2 \sigma_t^2$ for modeling a replenishment period with both the customer demand and the replenishment lead time as random variables. It is essential to note that they assumed that those random variables are Poisson distributions. Why did they choose a Poisson distribution? They chose a Poisson distribution because the mathematical integration problem for Poisson could be solved deterministically. Did Hadley and Whitin endorse this equation for what many are using it for today? Strangely enough, the equation was presented in their textbook as a homework problem at the end of chapter three without comment by the authors on its use.

Modeling the replenishment period problem with customer demand and the lead time as random variables with normal distributions would be superior to assuming Poisson distributions. The reason we should, and the reason Hadley and Whitin did not, is that contemporarily the mathematical integration of the normal distribution can be performed numerically.

Inventory management should provide a rational and balanced end result for the finished goods inventory levels across all SKUs (within customer service classes) without manual intervention and continuous adjustments. Most SKUs should run on autopilot. Secondly, it should provide demand leveling also known as Heijunka, one of the pillars of the lean house. Leveling at the end of the organization eliminates variance in demand of all upstream processes. If one is predisposed to dismiss the correctness of holding finished goods at the end of the supply chain, consider stellar success of dominant internet retailers. Thirdly, it should have a resemblance to the easy to understand Wal-Mart methodology of expressing the likelihood of experiencing a missed delivery. That being we will tolerate one missed shipment in three years. This clear expression of expectation shows that we need to couple Boolean analysis of that repetition of cycles that play out over three years into the choice of the probability of success in a single replenishment period.

Further improvements in production and inventory management should give dashboard visibility on few things. First it should provide a rational and balanced end result for the finished goods inventory levels across all SKUs without manual intervention and continuous adjustments. Most SKU's should run on autopilot over multiple replenishment cycles. Secondly, it should provide demand leveling also known as Heijunka, one of the pillars of the lean house. Leveling at the end of the organization, eliminates variance in demand of all upstream processes. The method should explicitly prioritize target SKU's for improvement. If one is predisposed to dismiss the correctness of holding finished goods at the end of the supply chain, consider dominant internet retailers.

It will be helpful to make clear the use of the term "re-order point" (ROP) to mean the quantity of units on hand at the beginning of a replenishment cycle.

A helpful perspective comes from the familiar general algebraic surface of Z=XY and a cutting plane Z=constant. The intersection of the cutting plane with Z=XY maps out a hyperbolic curve. This curve is of interest because it is the boundary that separates two regions of the surface of Z=XY over non-negative values of x and y. The region between the origin and the curve has all combinations of x and y for which Z is less than the chosen constant. Likewise the region beyond the curve has all combinations for which Z is greater than the chosen constant.

Improvement in production and inventory management will come from utilizing an analytic that in a superior way accounts for (1) the appropriate variance in customer demand, and (2) the appropriate variance in lead time while considering the strategies for the periodic replenishment of inventory.

As it turns out, such an analytic exists and is very straightforward. It can be explained and summarized in a pair of diagrams. Both of these diagrams show continuous surfaces in 3D for all non-negative outcomes of " λ" daily demand rate and "W" replenishment period.

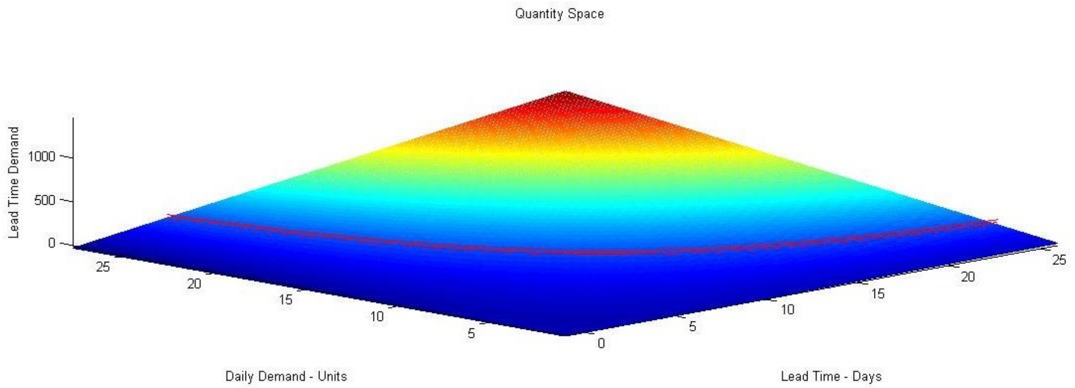

Figure 1: "Littles Law" $L = \lambda W$ with the ROP isoquant (hyperbolic curve in red) separating two regions

The first diagram illustrates in 3D the ubiquitous "Littles Law" $L = \lambda W$ [4]. This is taken here as the number of units "L" demanded by customers during a replenishment period will be equal to the customer daily unit demand " λ" multiplied by the length of the period "W" in days. This diagram shows in the number of units "L" demanded by customers during a replenishment period as a continuous surface in 3D for all non-negative outcomes of " λ" daily demand rate and "W" replenishment period.

Similar to the Z=XY review above, a hyperbolic curve is mapped by a cutting plane for a chosen L=constant. The intersection of the cutting plane and $L=\lambda W$ maps out a hyperbolic curve. This curve is significant to this thesis because it is the boundary that separates two regions of the surface $L=\lambda W$ over non-negative values of λ and W. The region between the origin and the curve has all combinations of λ and W for which L is less than the chosen constant. If the chosen constant is taken as the re-order point, than the region is has all of the combinations of λ and W for which the replenishment period will be successful. Likewise, the region beyond the curve has all combinations for which L is greater than the re-order point and the replenishment period will result in a stock out.

When L is taken as the "reorder point quantity" (ROP) littles law succinctly gives the boundary between regions replenishment period success and stock out as the hyperbolic curve

$$\lambda W = ROP \tag{1}$$

Recall the familiar bell curve representing the normal distribution of a single random variable. The literature has shown we can build on this to consider two random variables, in what is known as a bivariate case with the probability illustrated as a surface over a plot of the two random variables. In this bivariate case the volume under the surface is analogous to the area under the bell curve.

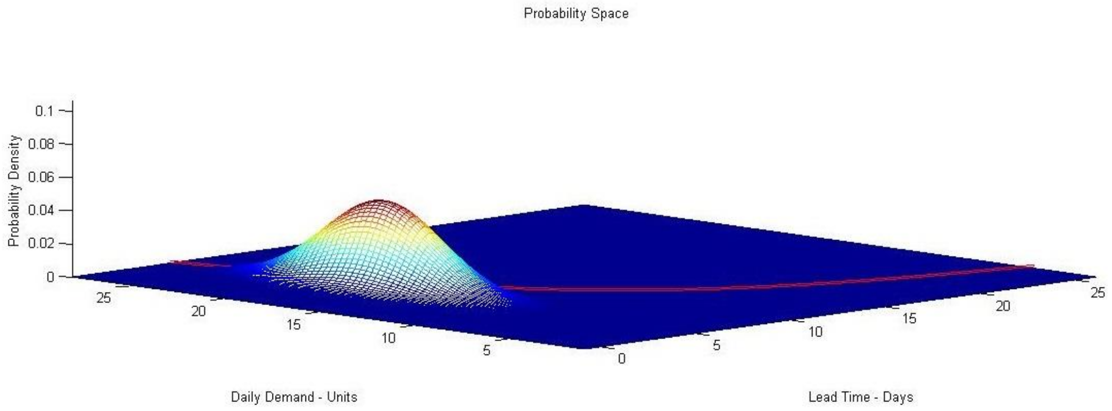

Figure 2 Bivariate normal distribution of a single replenishment period, a single SKU, at a single supply chain echelon with the ROP isoquant (hyperbolic curve in red) separating two regions. The isoquant here is the same in as Fig 1

The second diagram, also in 3d, with the same scales as the first diagram, being the daily demand rate (units per day) and the replenishment period length (days). This diagram shows bivariate probability distribution [3] as a continuous surface in 3D for all non-negative outcomes of " λ" daily demand rate and "W" replenishment period.

The same hyperbolic curve established by the intersection of the reorder point cutting plane with L=λW in the first diagram, can be used in the second diagram. Recall the second diagram is the bivariate probability distribution. The hyperbolic curve boundary separates two regions of the probability distribution over non-negative values of λ and W. The region between the origin and the curve has all combinations of λ and W for which the replenishment period will be successful. Finding the volume under the surface of this region by integration provides an exact value for the probability of replenishment success. Complementary, finding the volume under the surface beyond the curve by integration provides an exact value for the probability of stocking out.

In the second diagram one can see the visual presentation of two distinct regions, a region of success, and region of failure in regards to stocking out. The parameter that separates success from failure is one that the user can adjust as they see fit. That parameter, which we are all well acquainted with, is simply the Reorder Point Quantity.

To find the probability of replenishment success, which is the volume under the appropriate region (non-negative values only) of the bivariate normal surface, a numerical method by which the integration is accomplished is required. Such a method has been developed as part of this work. Discussion of that method is not appropriate for this level paper and will be the subject of a future paper.

The end customer(s) consumption behavior controls the mean and variance in daily demand. Operations management internal to the supply chain controls the mean and variance in lead time. Evaluation of supply chain performance based on counts of Stock-outs can can be improved by recognizing that a stock out caused by a variance in daily demand which exceeds planning levels is beyond the control of planners and supply chain managers.

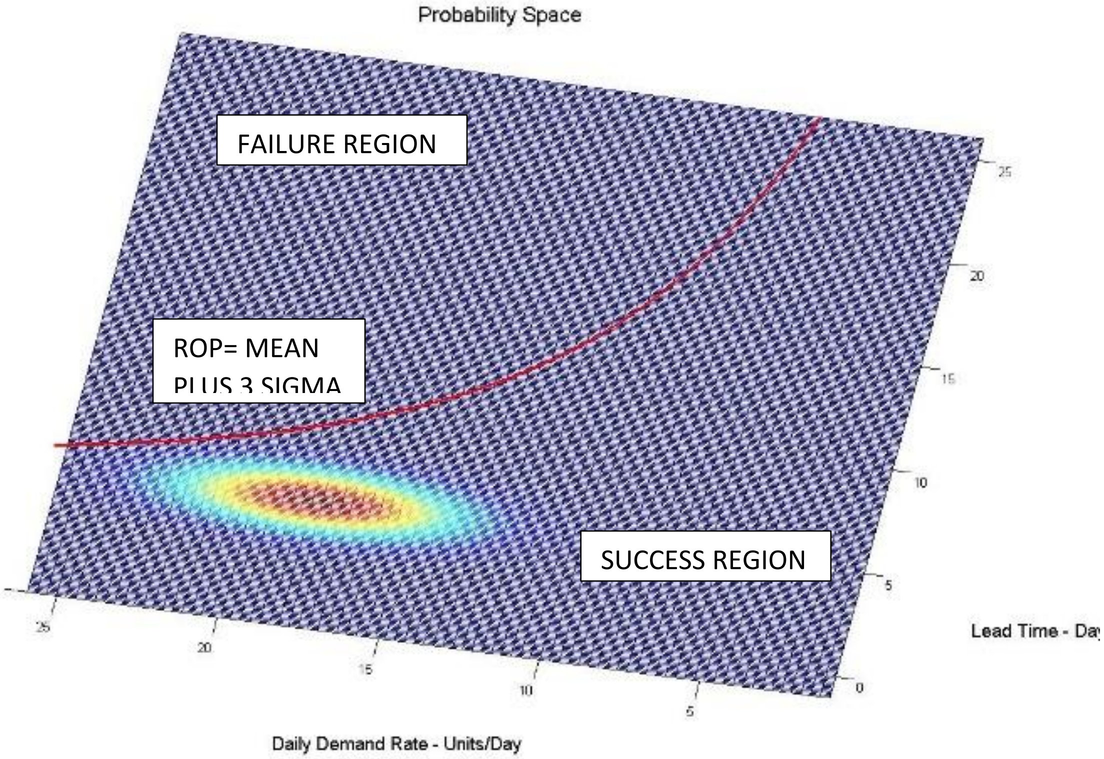

Figure 2 ROP isoquant (hyperbolic curve in red) at 3 sigma from the expected replenishment period demand separating the success region from the failure region.

Consider the different echelons of a supply chain for example where fulfillment performance goals are immediate for retail customer, one week for restocking retail from distribution center, one month for shipping production to distribution centers. Traffic costs and material handling logistical issues effect item quantities per transaction as individual sub pack, carton, case, pallet, less then truckload to truckload. At each echelon level the mean and variance of daily demand (unit, case, pallet, truck) as well as lead time will have a different basis (day, week, month) and are calculated independently. It will be independent for each SKU going down each branch of the supply chain to different terminus points. This analytic method accurately computes an exact probability in each case. Modeling each SKU at the various echelon levels provide a means for comprehensive modeling of the SKU throughout the supply chain.

The repetition of the replenishment cycle over years by should be considered. From a real world expression of the likelihood of success, (for example as one stock-out in three years is acceptable), the probability of success for one replenishment period is found by binomial analysis. The binomial analysis will require a choice to be made regarding the number of replenishment cycles that would be expected, (for example over the three years). The required re-order point is determined for that chosen level of success.

If we were to choose a performance goal for a given SKU of no more than one stock-out in three years, how many replenishment cycles would occur in those years? This question brings to the forefront the importance of the selection “order quantity” will have. The expected number of replenishment cycles will be equal to the expected mean demand for a three year period divided by the “order quantity”. The choice of “order quantity” determines the frequency of the replenishment cycles as well as the peak stock level and mean stock level. Recall that replenishment cycles are not synchronized.

The mean value and variance for both (1) customer daily demand and (2) replenishment lead-time is refined from ERP data to facilitate a bivariate normally distributed model for a single replenishment period, for a single SKU, at a single level of the supply chain echelon. Extension of the use of Littles law provides a hyperbolic curve that separates two regions (successful and stock out) of the bivariate normally distributed model. Finding the volume under the successful region of the bivariate surface by numerical integration gives an exact solution to the probability of success for the chosen re-order point quantity that determines the location of the hyperbolic curve which serves as boundary for the integration. The replenishment model is repeated for each SKU of concern. The repetition of the replenishment cycle over years by should be considered. From a real world expression of the likelihood of success, (for example as one stock-out in three years is acceptable), the probability of success for one replenishment period is found by binomial analysis. The binomial analysis will require a choice to be made regarding the number of replenishment cycles that would be expected, (for example over the three years). The required re-order point is determined for that chosen level of success. The replenishment model is employed separately at each level of the supply chain echelon, since the quantities transacted and replenishment periods are different. The separate use of this analysis for all SKU’s, and supply chain echelons for an extended future time horizon becomes the basis for rational production schedule mathematically tied to expected customer service level. The feasibility of that production cycle is qualified by the allowable number of production set ups and available technicians. The coupling of production set ups, and hence inventory turns, to customer service level provides data for a dashboard metric of the future inventory management systems.

As this analytic is applied for all SKUS, and supply chain echelons right sizing all buffers a comprehensive inventory plan is achieved for a chosen level of customer service satisfaction. That inventory plan can be pivoted with unit costs to see a aggregate inventory investment. The chosen customer service level can be adjusted to suit budgetary constraints. From the binomial analysis a frequency of ordering purchase and production lots can be taken. By bolting this analytic onto an ERP system production lot planning, setup labor and resources can be planned to match as well as production labor and assets. Future warehousing and logistics can be planned for that complement the planned production plan.

A great deal more could be covered here about the comprehensive and exhaustive coupling of almost every issue related to operations management and supply chain management to this analytic, but to summarize the core inventory planning result here can be pivoted to put hard numbers behind all operation plans. Equally important, they are inherently synchronized for the first time to the same basis. This extended “Littles Law” is the “Law of Manufacturing” that the 1992 NAE panel contemplated.

Acknowledgements The figures in this paper were produced using Matlab 2014

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