Dell’s Channel Transformation: Leveraging Operations Research to Unleash Potential Across the Value Chain

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Dell pioneered the direct sales model by offering its customers technology solutions through full-system configurability. In 2007, Dell launched several strategic initiatives to drive channel transformation by offering fixed configurations through online channels, retailers, distributors, and other channel partners. Dell’s center of excellence (CoE) in analytics developed solutions that apply operations research (OR) to address key challenges across the value chain and enable profitable growth in the new channels. These solutions include (1) a configuration optimizer to reduce product complexity by identifying fixed hardware configurations (FHCs), which Dell builds and stocks, (2) an online conversion rate accelerator to improve the online customer purchase experience, leading to increased revenues and customer satisfaction, and (3) a retail margin maximizer to improve forecasts, mitigate inventory risk, and recommend promotions to increase margins. Since 2007, OR has helped Dell solve complex business problems and has facilitated its growth in the FHC business to $15 billion. Since 2010, these OR solutions have delivered a margin impact of more than $140 million by reducing markdown expenditures, improving online conversion rates, increasing ocean shipments, and enhancing customer satisfaction.

Keywords: channel; demand clustering; forecasting; multivariate testing; A/B testing; factor analysis; text mining; inventory modeling; ARIMAX, CPFR.
Further, in the emerging markets, Internet penetration was low and consumers preferred to touch and feel the products prior to purchase; therefore, indirect channels were becoming essential to reach a large customer base. This paradigm shift in customer preferences, coupled with macroeconomic changes across the globe, caused Dell to consider changing its business model.

In 2007, Dell started its channel transformation and began to offer fixed hardware configurations (FHCs) through direct and indirect sales channels globally. FHCs are configurations with predefined hardware specifications; they allow customization on only specific software, services, and accessories. The key new channels into which the organization ventured were:

- Retail channel with various retailers, including online retailers, across the globe.
- Distributor and value-added reseller (VAR) networks in emerging nations.
- Ships-fast channel in which popular configurations are built in advance and stocked for shipment within a day of order placement.
- Build-to-order channel in which FHCs are used to build products upon receipt of customer orders.

About 35 percent of Dell’s units are delivered via the CTO channel, 25 percent via the ships-fast channel, 20 percent via the retail channel, 15 percent via the build-to-order channel, and five percent via the VAR network. CTO and FHC models refer to the fulfillment methods used to deliver a customer order. Each can be applied to any Dell product. In the CTO model, a customer visits the Dell website (http://www.dell.com) and configures a unique system from a wide array of components. When the order is placed, Dell manufactures the system and delivers it to the customer within a committed time. Because most of its manufacturing facilities are in Asia and most of its demand is in the United States, Dell uses air transportation for more than 30 percent of its CTO sales. In the FHC fulfillment method, popular configurations are manufactured based on a demand forecast and stocked near the end customer for immediate delivery. FHCs are sold through the ships-fast option on the Dell website and via retailers. Transportation of FHC products from Asia to the United States is by ocean, because these products are manufactured well in advance of their actual purchase.

Dell realized that these new channels could provide it with an opportunity to serve different customer segments. It developed this new channel strategy to accelerate revenues without impacting its CTO business. However, because the business dynamics and constraints were unique to each channel and region, reengineering the processes and driving the transformation were an enormous challenge (Clark and Hammond 1997). They required that we change multiple aspects of the business by leveraging the existing systems and processes that we had built over 25 years. To drive change, business analysts from Dell’s analytics center of excellence (CoE) acted as internal consultants to help the business decision makers. Their main challenge was to deliver profitability in the new channels.

Dell launched three programs as part of its business strategy to implement the transformation. Next, we summarize these programs and their objectives.

1. Client reinvention: Regain competitive differentiation by reducing complexity and providing customers with the choices they value most. Dell moved from a one-size-fits-all approach to a segmented supply chain approach, which consists of build to order, build to plan, build to stock, and configure to order (Simchi-Levi et al. 2013).

2. e-Dell: Leverage Dell’s e-commerce leadership position by enhancing the customer online experience. Dell updated its technology to enhance its online merchandizing capabilities, enable faster fulfillment, provide online support for problem resolution, and improve the overall customer experience.

3. Best-value solution: Develop capabilities and create next-generation solutions that are flexible, efficient, and affordable. Within two years, Dell acquired over 15 organizations in the security, networking, and end-user devices arena. These continuous acquisition and development efforts, in which Dell leveraged its partner network, helped it to build and deliver best-in-class solutions to its customers. Channel transformation was a mammoth task for Dell because most of its business processes and systems were aligned with the CTO business and direct model. As a late entrant to the FHC channel, Dell needed to determine...
a unique selling proposition to stay ahead of its competition. Dell Global Analytics (DGA), Dell’s internal advisory division and analytics CoE, provided expertise in OR and advanced analytics to address key challenges across the value chain (see Figure 1). Since 2009, DGA has been collaborating with Dell senior executives to help the business prosper in the new channels.

In this paper, we cover three high-impact, innovative solutions that DGA designed and implemented across Dell: the configuration optimizer, online conversion rate accelerator (OCRA), and retail margin maximizer (RMM).

Configuration Optimizer

Although the CTO model provided flexibility to customers, it introduced product complexity because it required the company to manage millions of possible configurations (Pil and Holweg 2004). An analysis of historical sales information showed that more than 72 percent of Dell’s notebook and desktop sales were driven by the top 15 percent of configurations sold. This motivated the senior management team to consider adopting the FHC model to reduce the complexity.

The earlier process of creating FHCs was highly subjective and based primarily on third-party market research and the intuition of regional sales teams. Each region followed a different process to develop the configurations; the resulting process was neither scientific nor a unified global process. This drove the product planning and marketing teams to collaborate with DGA to develop a data-driven, standard, and sustainable approach to creating optimal FHC offerings.

In the initial stages of developing a solution, DGA attempted to identify the best FHCs through exploratory analysis (e.g., scatter plots) and online analytical processing tools (e.g., Hyperion and Microsoft analysis services). The challenge in this approach was the large volume of configuration data, the human intervention necessary in the process, and the inability of these methods to handle multiple dimensions and constraints. In 2010, DGA improved the existing Excel-based ranking method by developing the configuration optimizer, which played a significant role in its client strategy. This solution reduced the inherent complexity of the company’s offerings and facilitated building and stocking FHCs well in advance of order placement. It also allowed Dell to realize cost savings by using ocean shipments (e.g., from factories in Asia to warehouses in the United States) instead of air shipments, and enabled supply pooling in sourcing components.

Approach

DGA used historical sales data and relevant factors, including product category (e.g., specific brand of notebook, desktop, or workstation), popular competitor configurations, technology roadmaps, cost implications, and regional considerations, to define its FHCs. We created an initial set of configurations based on techniques such as factor and clustering analysis. We then upgraded these initial configurations with additional options and features, such as operating system upgrades (e.g., Windows XP to Windows 7) and processor upgrades (e.g., Intel i3 to Intel i5), through a quadratic mixed-integer programming model to determine the FHCs that have the highest potential revenue coverage (PRC). In the optimization algorithm, we also consider cost implications resulting from upgrades and the competitive landscape. This solution caters to the business requirements of multiple regions and teams, including product planning, marketing, and product management.

Based on related commodities (e.g., processors, memory) in the order data, SAS/OR solves this quadratic program with an interior-point solver whose solution identifies configuration clusters. These clusters help to define the set of FHCs with the highest PRC.

One innovation of the configuration optimizer is that it considers millions of possible combinations of configurations and recommends an optimal set of FHCs. It also uses qualitative elements, such as technological roadmaps, upgrade preferences, and competitive data. In the following steps, we give additional details.

Step 1: Designing the Initial Set of Configurations

The objective of this step is to determine an initial set of configurations based on historical order
Develop | Market/sell | Fulfill | Support
--- | --- | --- | ---
- What product configurations to offer? | - How to improve marketing ROI? | - How much inventory to stock in the season? | - How to reduce the warranty dispatches?
- What should channel pricing strategy be? | - How to improve online purchase experience? | - How to plan effective channel specific promotions? | - How to improve service level of spare parts availability?
- What supply chain design to adopt for indirect model? | - How to increase store level sales? | - How to reduce distribution cost of quality? | 

Figure 1: OR and analytics applications address challenges across the value chain.

Figure 2: This example shows typical configuration clusters for a specific bundle. Each of the three axes represent all the offerings for the specified commodity.

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information. Using factor analysis (Costello and Osborne 2005), we group correlated commodities; these include performance bundles (e.g., processor, memory, hard drive), security bundles (e.g., optical drive, fingerprint reader), and accessibility bundles (e.g., wireless card, modem, Bluetooth). For each bundle, we employ the demand cluster technique (Joseph and Bryson 1998) to generate configuration clusters. We tested the K-means clustering method and Ward’s method (minimum variance) to determine the possible configuration clusters. However, Ward’s method produced better results in terms of homogeneity of configurations within the same cluster.

Figure 2 shows the configuration clusters for a performance bundle and its related commodities. The FHCs from the performance bundle are further iterated through the security and accessibility bundles to determine an initial set. In the next step, we optimize the given set of configurations based on business factors and constraints to maximize the PRC.

**Step 2: Optimizing the Initial Configurations**

Once we determine the initial set of configurations \( \{FHC_1, FHC_2, \ldots, FHC_N\} \), we use the optimization model to adjust the commodities in each configuration, such that it maximizes the PRC, while satisfying cost constraints and considering competitive data. We deploy SAS optimization solvers with interior-point nonlinear programming options to solve this complex problem, which involves thousands of FHCs.

We estimate (1) the potential unit coverage (PUC), which refers to the number of historical orders that can be mapped to an FHC with defined commodity options, (2) the cost of upgrading the commodities of the FHC, and (3) the revenue opportunity loss incurred by not having FHCs that are equal or close to the configurations of major competitors. We use the previous estimates in formulating five types of optimization constraints (see Appendix A).

A order is mapped to an FHC when an exact match or a permissible upgrade to specific commodities is available. For example, in an FHC with 4 GB of memory, we map all historical orders with 4 GB and also map all orders with 2 GB of memory as one-level upgrades, because we assume that previous 2 GB configurations will progress to 4 GB configurations as a result of the natural progression of technology. The PUC is a complex nonlinear function whose functional form is difficult to estimate. Therefore, we use the Taguchi orthogonal array approach for design of experiments in SAS QC to estimate a linear relationship between commodity upgrades and units coverage from similar configurations.
We estimate the revenue opportunity loss based on the gap between FHC offerings and major-competitor configurations. The fewer the configurations that are equal or close to these competitor configurations, the higher the revenue opportunity loss is. The model’s output is an optimized set of FHCs, which we subject to scenario analysis for validation before recommending it to the business. Appendix A includes details of the model formulation. The marketing and merchandizing teams consider these recommendations in discussions with regional teams and then execute go-to-market plans.

Implementation and Challenges
In 2010, we started several pilot programs to create FHCs for marketing desktops and notebooks to large enterprise customers in the Americas. A key challenge in the pilot implementation was the availability of data for competitive configurations, pricing, and technology trends. The data we had were inconsistent and scattered across multiple online and offline sources. We designed Web crawlers and competitive matrices and used them to create a single reliable data repository to address this problem. Following the success of the pilot programs, the product managers accepted the solution, its significance, and its value; thus, we were able to globally implement it. However, we had to address country-specific challenges in the Europe and Asia regions, such as technology maturity, customer preferences, and the competitive landscape. We formed regional focus groups to do an in-depth study of these issues. Our objective was to bring business intelligence to the solution’s rollout. During this global rollout, DGA and cross-functional governance teams were involved in overseeing the implementation and measuring its business impact. Regular meetings were conducted to discuss risks and develop mitigation plans for a successful implementation.

Dell’s consumer products division moved to a 100 percent FHC model, which helped it to optimize its product offerings. DGA periodically measured the FHC performance metrics across regions and shared them with business teams to drive adoption.

Benefits and Recognition
Product planning teams and product managers use this solution to make data-driven decisions. Marketing teams use it to make decisions about product positioning and address the key gaps in offerings and pricing (Li and Atkins 2002). Whereas sales teams previously spent large amounts of time sifting through numerous configuration options, they can now easily map customer requirements to specific FHCs and drive sales conversations toward high-margin services.

In 2011, within one year of implementing the configuration optimizer for large enterprise customers in the Americas, FHC offerings grew to 30 percent of this segment’s overall sales. By the end of 2012, they represented 50 percent of these sales. The solution addressed the challenge of configuration complexity by reducing the number of configurations Dell sold globally from 127 million to only a few thousand. It also reduced the number of commodities by 35 percent by pruning product catalogs and supply pooling, which resulted in a two percent improvement in the cost of goods sold (Dell 2012b). Because of a shift in forecasting, based on the probability of a commodity in the CTO model being attached to individual finished-product-level forecasting, the forecast accuracy improved by 40 percent. Forecasting at a commodity level and aggregating it to a CTO model level typically resulted in poor forecast accuracy. The ability to plan for FHC orders in advance has given Dell the flexibility of being able to ship them via the ocean, which has a significant cost advantage over air shipments. Dell has realized $40 million in margin gains since 2010 because of the configuration optimizer.

The optimal FHCs formed a constraint for the online conversion rate accelerator, which we designed to enhance the customer experience and increase Dell’s revenue.

Online Conversion Rate Accelerator
As Dell changed its focus from selling CTO offerings to selling FHCs, prospective customers visited its website to research and purchase, rather than to customize and purchase. As a part of the e-Dell program, DGA collaborated with Dell’s online business managers (OBMs) and developed the OCRA solution
to address this shift in customer preferences. ORCA improved the customer online purchase experience and maximized the conversion rate (i.e., the rate at which prospective customers become purchasers) on the website.

Approach

A Web page consists of various merchandizing and design components. Some of its key merchandizing components are the number of products displayed on each page, the types of products that can be displayed together on the same page, and the manner in which prices and discounts are displayed. Typical design components are navigation options, button placement, and colors used. These components, either solely or in combination, affect the customer conversion rate. We first identify all such components by using several analytical techniques; these include driver analysis, which helps in identifying the key attributes of a Web page that drive the purchase decision, pathing analysis, which helps us to understand a prospective customer’s navigation pattern, text mining, usability testing, and competitive benchmarking. We then measure the conversion rate for a few component combinations using A/B tests and multivariate tests (MVTs). To determine the optimal Web page design, we consider several business constraints, and then further validate this new design by running a final A/B test against the existing Web page to measure the increase in conversion rates. OBMs review the results of the final A/B test and initiate a multiphased implementation across regions. In case of disagreements, we repeat the A/B tests for further validation.

Step 1: Identification of Factors Influencing the Conversion Rate

We integrated a number of analytical techniques to create a comprehensive list of factors that affect the conversion rate. These techniques include driver analysis, text mining, behavioral analysis, which analyzes customer behavior based on responses to a survey (Padmanabhan and Tuzhilin 2003), pathing analysis, a technique that uses clickstream data to analyze browsing behavior (Weischedel and Huizingh 2006), and usability testing, a technique to identify common usability themes in the development of a website (Hinchliffe and Mummery 2008).

Step 2: Preliminary A/B Testing and Multivariate Testing

After we identified the factors that influence the conversion rate and the extent of their influence, we created multiple recipes, which we define as unique combinations of Web page components. We tested some recipes by directing a random sample of visitors to the live Dell website, at which we used A/B tests and MVTs to evaluate the various possible combinations of page components.

Step 3: Incorporation of Business Constraints and Optimization

We built various constraints into the evaluation process to represent design, merchandizing, and website performance attributes; our objective was to identify the combination of website elements that maximize the conversion rates. We then solved the resulting nonlinear mixed-integer program using a primary dual interior-point method. Appendix B provides details of the optimization model formulation.
Techniques to identify influencing factors:
- Driver analysis to identify characteristics of CTO/FHC visitors
- Text mining and behavioral classification
- Pathing analysis
- Competitive benchmarking
- Usability testing
- Learning from previous tests

Multivariate testing

Preliminary A/B testing

Response surface model

Optimizer engine to identify best combination of influencing factors

Final A/B testing and implementation

Figure 3: The flowchart shows the ORCA analytical framework for designing and improving the conversion rates of Web pages.

Complexity reduction
- Most popular configurations, logically bundled
- Low complexity, low cost
- Industry standard service/support

Repeatable process
- Value chain aligned end-to-end
- Customer driven product and supply chain design
- Strong supply chain performance

Higher value focus
- High value product leadership
- Optimized complexity, better value
- Personalization/customization
- Premium care service and support

Popular, preconfigured offers

Consumer eligible ocean ship

Contract manufacturing

Figure 4: In this figure, we show structural channel transformation changes: complexity reduction, repeatable processes, and higher-value focus, delivering improved profitability by increasing the percentage of preconfigured product bundles (i.e., FHCs).

Implementation and Challenges

We piloted several iterations of the region-specific website between 2010 and 2012. Although we implemented each website iteration regionally, the global project management team managed it. As a part of the project, site designers created new designs, merchandising teams created new banners and buttons, information technology teams made code changes, DGA provided analytics support, and OBMs approved the final website changes. DGA analyzed the final A/B test and MVT results and presented them to the OBMs. Changes were deployed across all regional websites. For website changes, the project team monitored performance to ensure that the increase in demand, as projected by the final A/B test, was achieved.

The key challenge in this initiative was identifying an accurate list of constraints, which can vary across regions; for example, customers in China prefer red buttons. We collaborated with the sales, marketing, branding, merchandising, development, and data infrastructure teams to accurately identify the constraints and regional preferences. Another challenge was convincing the OBMs to accept the test results...
because some results were counterintuitive. For example, one previously held erroneous belief was that increasing the number of deal banners on a Web page would increase the probability of converting a prospect to a purchaser. To establish the optimal number of deal banners that maximize conversion, DGA validated the test results by analyzing factors such as historical conversion rate for a given number of deal banners on Dell’s Web pages. Integrating the large data sets that include clickstream, transaction, survey, and campaign data was also a challenge. To address this, we used the SAS integrated environment and MS SQL server to facilitate the development of a data mart to integrate all these data.

Benefits and Recognition

We measured the changes made through OCRA on live Dell website traffic using A/B testing of the control and the test design. Various merchandising changes made as part of OCRA helped increase the online FHC sales mix from seven percent in 2010 to 38 percent in 2012. In the same period, the overall satisfaction of online FHC customers improved from 27 to 45 percent as a result of the simplified purchase path. Since 2010, Dell has realized a margin improvement of $33.5 million because of implementing various changes recommended by these OCRA processes. The calculation we used to determine the margin benefits is as follows:

\[
\text{Incremental margin of a page} = \text{Improvement in revenue per visit (RPV)} \times \text{contribution of that page to total revenue} \times \text{margin\% of the website,}
\]

where the contribution of a page to total revenue is based on a proportional allocation of visits from the landing to the checkout page, adjusting for the abandonment rate from a given page. The landing page refers to the Dell Web page that appears on the user’s screen immediately after that user clicks on a search engine result or online advertisement. Table 1 shows the business impact of implementing OCRA.

The changes made to the website layout simplified navigation for both FHC and CTO prospective customers. Changes in online product merchandising helped FHC customers find the most relevant products within three clicks, whereas the CTO process had required 40 clicks. Improving the product comparison tool and the online configuration tool enabled FHC customers to select the right products and add relevant accessories and services. A product comparison tool is available on the Dell website to compare Dell products.

In 2012, Dell won 8 of 17 awards for OCRA at the WhichTestWon industry awards (Anne Holland Ventures 2012). Its innovative use of OR methodologies helped it create a website optimization technique that positively impacts its business. In addition, this initiative’s return on investment (ROI) caused the online marketing team to change from basing its decision on intuition to basing them on analytics. Dell has also partnered with retailers to reach a larger customer base. In the next section, we describe the company’s activities in the retail channel.

Retail Margin Maximizer

In 2007, Dell entered the retail channel and faced challenges in becoming profitable. Its sales team relied on retailer-generated forecasts, which were usually inflated; the result was high end-of-season inventory, reactive promotions with high discounts, delays in product transition, and loss of sales. By 2010, the sales operations team realized that a presence in the retail channel demands strategic collaboration with original-design manufacturers, retailers, and other stakeholders, and identified collaborative planning forecasting and replenishment (CPFR) as an approach to address this. To enable an extensive analysis of point-of-sales data and predictive analytics, the sales operations executives requested DGA to build a solution.

Approach

We adopted a threefold approach to manage demand and supply uncertainty through the RMM:
(1) improve forecast accuracy, (2) mitigate inventory risks, and (3) improve promotion planning. RMM comprises demand sensing and shaping. Demand sensing provides better forecasts by leveraging best-of-breed forecasting techniques. Demand shaping provides promotion recommendations by incorporating demand and supply variability and price elasticity. RMM's objective is to answer four questions: Which FHCs should Dell promote? What type of promotions should it run? When should it run these promotions? What should it expect as an ROI?

**Step 1: Demand Sensing**

Each year, the retail business operates through the spring, back-to-school, and holiday seasons. New products are usually launched each season to reflect technology upgrades and shoppers' changing preferences. To ensure good forecast accuracy, at least two years of weekly time-series data at an FHC level are required. However, we did not have the historical data for new products. Therefore, we had to look at the data for prior-season products seasons that have similar attributes (e.g., form factor, brand, price, configuration) to the new product, and create time series. This process is critical because Dell launches new products and product variations each season, thereby making obtaining a configuration-specific sales history difficult. After exploring different time-series forecast models, we selected auto regressive integrated moving average with exogenous input (ARIMAX) because, in addition to time series, it considers the impact of external factors (e.g., price, promotions, events). We used the model's output for multiple planning activities: preseason life-cycle planning, CPFR discussions, and scenario analysis.

DGA generates the preseason life-cycle volume forecasts 60 days before a season commences; the sales operations team uses these forecasts for initial replenishment planning. When a retail season begins, DGA also generates weekly sales forecasts and monitors these forecasts against actual sales. The sales team participates in weekly discussions to verify forecasts and ensure that necessary corrective actions are in place. DGA then uses scenario analysis to determine the impact of several what-if scenarios.

**Step 2: Demand Shaping**

We developed the demand shaping solution to improve margins using systematic promotion planning and execution. Prior to this initiative, promotions were reactive and executed when inventory was high. This solution allows sales operations and supply chain teams to proactively manage inventory risk and recommends promotions based on the effectiveness of historical promotions. It has two major components—an inventory optimization model to determine inventory threshold limits and a promotion uplift model to determine promotions and expedite the supply of products from Dell warehouses.

In the retail industry, inventory is variable across the weeks within a season. At the start of a season, inventory is high—usually six to eight weeks of demand to ensure product availability across all retail stores—and gradually decreases to zero by the end of the season. In the inventory optimization model, we determine the optimal inventory threshold limits based on demand and supply variability. These lower and upper threshold limits define the desirable range of inventory levels. We deployed the PROC IRP procedure within SAS inventory optimization, considering demand variability projections generated by SAS Forecast Studio. We developed customized SAS code to simulate multiple demand scenarios to determine the optimal inventory thresholds based on the simulated stockout and overstocking of products in retailers' shelves. This helps to reduce the solution’s processing time because the customized code runs the simulations in parallel. The projected future inventory levels from demand sensing are used to trigger promotions during high-inventory-risk situations to avoid loss of margins as a result of discounting (Ahn et al. 2009). Similarly, a low-inventory projection necessitates expediting orders to avoid penalties and loss of sales.

The promotion uplift model garners insights from past promotions to recommend effective promotions to increase demand and generate a profit. We applied the product life-cycle (PLC) concept to divide each retail season into four stages (introduction, growth, maturity, and decline) to improve the correlation between discount and uplift. Thus, by using regression analysis, we concluded that the historical promotional uplift captures the price elasticity of a particular product type in similar life-cycle stages. A key innovation in this initiative is its ability to combine inventory optimization and promotion uplift models.
to recommend a list of FHCs to be promoted. DGA uses the inventory optimization model to identify the list of FHCs that are nearing inventory-risk situations based on threshold limits, and the promotion uplift model generates the list of FHCs that will provide the best ROIs. DGA combines these sets of FHCs through a ranking method based on promotion spends and corresponding returns. This helps it to select the critical FHCs for promotion.

Our solution minimizes the total inventory cost; see Appendix C for details on both models. The decision variables in the objective function are discount, supply, and promotion during excess-inventory situations and expediting orders during low-inventory situations. We used SAS IRP and SAS Forecast Studio to perform scenario analyses for different values of decision variables to determine the optimal solution.

Implementation and Challenges
In 2010, we started a pilot implementation of RMM with a large U.S. retailer. We automated the data collection, processing, analysis, and reporting using SQL server tools. Because no off-the-shelf product combines inventory risk with promotion planning, we developed an in-house solution using SAS Forecast Studio, SAS JMP, and SAS IRP. The SAS IRP solution takes the forecasting input from Forecast Studio and the solution provides a list of inventory-risk (i.e., high and low) FHCs. SAS JMP finds the FHC with the maximum ROI on the promotions, and the ranking method helps to combine these two sets of FHC recommendations.

A key challenge from a change management perspective was convincing the demand and promotion planners to adopt this solution. After finalizing the project scope, we involved various teams in the project to get their feedback at various stages of the solution development process. An important success factor was having weekly planning discussions in which we tried to align all stakeholders. After the success of the pilot program, we presented its benefits to other retailers and obtained commitments to replicate this process. The five major retailers viewed RMM as a valuable addition to their business intelligence tools. Each week, marketing teams, demand planners, sales operations teams from Dell, and retailer executives for replenishment and promotion planning use this solution. During the weekly discussions, any market anomalies and recent competitor actions are considered before making final decisions.

Benefits and Recognition
Following the RMM implementation in 2010, our 30-day-forward sales-forecast accuracy at the retailer-FHC level increased by 11 percent and end-of-season inventory decreased by 52 percent at the same set of stores without impacting service levels. The solution has resulted in a positive business impact of over $42 million, largely because of reduced end-of-season inventory, which led to a drastic reduction in clearance spends. It also helped reduce markdown losses across the season because of RMM’s improved forecasting. Table 2 details the savings from using RMM.

Sales and inventory planning have improved as a result of regulating the future replenishments based on RMM recommendations. Reduced end-of-season inventory has enabled timely season transitions and new product introductions. Dell has more in-depth knowledge of its promotions and greater involvement in the promotion planning process with retailers (Kurtuluş et al. 2012). We have also leveraged this solution in other channels (e.g., ships fast and VAR). We are deploying RMM to major retailers worldwide. We presented it at international conferences organized by the Supply Chain Council; examples include the Indian Institute of Management, Bangalore Supply Chain Conference 2012, and Supply Chain World NA 2012.

<table>
<thead>
<tr>
<th>Metrics impacted</th>
<th>Before RMM implementation (%)</th>
<th>After RMM implementation (%)</th>
<th>Business impact ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted-average discount</td>
<td>9.4</td>
<td>3.7</td>
<td>4.2 million</td>
</tr>
<tr>
<td>End-of-season inventory (as percentage of total season volume)</td>
<td>10</td>
<td>5.7</td>
<td>37.8 million</td>
</tr>
</tbody>
</table>

Table 2: The table shows the impact of the RMM implementation on inventory and discount metrics before and after the RMM implementation in 2010.

Overall Results and Benefits
By applying OR, the previous initiatives have collectively helped Dell to achieve channel transformation
benefits, which include profitable growth, increased market share, and operational efficiencies. We have classified the benefits into three categories: channel transformation, OR-based analytical framework, and socioeconomic benefits.

**Channel Transformation Benefits**
From 2007 to 2012, channel transformation enabled the FHC business to reach $15 billion. Dell has also lowered its manufacturing costs by 30 percent, and reduced its cost of goods sold by two percent through commodity leverage and reuse. It now ships over 98 percent of its consumer orders with a one-day lead time following order placement. From 2010 to 2012, Dell posted an income growth of 33 percent, earnings-per-share growth of 40 percent, and return on invested capital of 22 percent, attributing this growth to channel transformation. Additional benefits in terms of complexity reduction, increased ocean shipments, repeatable processes, and higher-value focus are illustrated in Figure 4. Dell has extensively leveraged contract manufacturing (i.e., third-party manufacturing) as a result of the growth of its FHC business (Dell 2012b).

**Operations Research-Based Analytical Framework Benefits**
Throughout its history, Dell has been a proponent of applying analytics to business decision making. For example, it extensively used analytics to establish the distribution network for its CTO business, design the CTO Web page, and develop its direct-to-customer campaigns. Dell realized the power of OR as a result of the channel transformation benefits.

Dell has a panel of subject matter experts who review the impact of each business methodology against a set of established industry standards. Members of this team and Dell financial experts reviewed the methodology and data used to calculate the business impact of each initiative we discuss previously.

Since 2009, the OR-based analytics initiatives have delivered a combined margin improvement of $140 million. These analytics initiatives include the three innovative analytics solutions discussed in this paper and others. Forecast accuracy improved by 40 percent, inventory (across major U.S. retailers) decreased by 52 percent, revenue from effective marketing investments (i.e., in Germany and India) grew by six percent, and the conversion rate increased by 20 percent as a result of pricing optimization. In addition, RPV on Dell’s website increased because of the improved purchase experience, and logistics cost savings rose because of the increase in FHC ocean shipments.

The move to FHCs simplified product design, increased procurement efficiencies, streamlined production planning, and enabled a lower-cost transportation-mode mix. Developing OR solutions required interactions among various business units to identify the key factors and constraints that affect the business, thereby resulting in increased collaboration within the organization. Users in Dell’s various departments readily accepted the solutions because of the compelling pilot results, intuitive interface, effective training provided, and positive impact on their individual performance. Steve Felice, president and chief commercial officer of Dell said, “Our success is a testimony to the value of operations research in solving complex business problems and getting the best returns on our investment in analytics. It is certainly a critical piece of our transformation.”

In-house capabilities and solutions coupled with vendor software lowered the cost of decision making without compromising the outcome. We are currently working on cutting-edge transformational projects in collaboration with universities worldwide.

**Socioeconomic Benefits**
As a result of changing its procurement and manufacturing strategies, Dell increased its percentage of products shipped by ocean, thereby reducing its carbon footprint by 16 percent for the same volume of shipments and avoiding 25 million tons of greenhouse gas emissions in 2012 (Dell 2012a).

**Conclusion**
The success of Dell’s channel transformation is a testament to the power of OR and cross-functional collaboration within the organization. The configuration optimizer, OCRA, and RMM represent the beginning of OR at Dell. Convincing senior management to accept OR as a decision-making tool was a major challenge during the initial phases of the transformation process. However, the success of the pilot programs proved the relevance of OR as an effective
decision-making tool and the implementation results confirmed it. The solutions were later part of large-scale global rollouts, each of which was supported by a robust project management organization. Successful collaboration with channel partners was another key aspect in the success of the transformation.

Going forward, Dell’s strategy is to be the best technology company in which to work and with which to do business. One of Dell’s objectives is to make technology simple by understanding its customers’ needs better than any other company. This will be driven by the launch of new products and services with one simplified catalog of global offerings. We are evolving as an end-to-end solutions provider; hence, this new strategy is critical for our future business.

The various OR analytical frameworks and techniques discussed in this paper can be leveraged by organizations across industries to move into multiple channels and simplify their business offerings, while also maximizing their profitability. The learning and organizational development team at Dell has developed customized OR course offerings, which all Dell employees can access to further their knowledge of OR-based analytics within the organization. To conclude, OR has become an integral part of Dell’s decision-making system. It has become an indispensable tool for analytical decision making and has marked a major cultural shift from the era of qualitative decision making.

Michael Dell, chairman and CEO of Dell said, “Using operations research, we can optimize profitable growth across various sales channels with a level of insight that was never before possible. This is a critical advantage as Dell expands both our offerings and our sales partnerships into new areas.”

Appendix A. Configuration Optimizer

**Input**
- \( p_i \) = average selling price of \( i \)th FHC.
- \( b_{ijk} \) = weighting factor for revenue loss.
- \( c_{ijk} \) = additional cost of \( k \)th option of \( j \)th commodity of \( i \)th FHC.
- \( BC_i \) = bound on upgrades cost on \( i \)th FHC.

**Variables**
- \( X_i \) = potential unit coverage (PUC) of \( i \)th FHC.
- \( Y_{ijk} \) = binary variable indicating whether \( k \)th option of \( j \)th commodity is chosen in \( i \)th FHC.

\( C_i \) = additional cost because of upgrades to features from base configuration.

\( L_i \) = revenue opportunity loss because of the gap in features of \( i \)th FHC versus competitor configurations.

The objective function is to maximize revenue coverage from FHCs, while considering additional costs because of any upgrades to commodities or loss because of a gap between Dell’s and competitor’s configurations. This quadratic function is

\[
\text{Maximize } Z = \sum_{ijk} [p_i - C_i - L_i]X_{ijk}.
\]

The constraints in the model are as follows.

1. The function for the potential units covered (PUC) for an FHC based on historical order data depends on the commodities of the FHC. For this we use a configuration mapping algorithm that maps the historical orders to the FHC based on proximity of commodities and technology roadmaps. The exact functional form is difficult to derive; hence, we use the Taguchi orthogonal array approach to estimate the direct effects \( (d_{ijk}) \) on the PUC of each commodity option of an FHC. Using the direct effects coefficient \( (d_{ijk}) \), we can estimate how many units from historical configurations can be mapped to the \( i \)th FHC. Therefore, the PUC constraint is

\[
X_i = \sum_{j} \sum_{k} a_{ijk} Y_{ijk}.
\]

2. The additional cost for an FHC as a result of features upgrades is

\[
C_i = \sum_{j} \sum_{k} c_{ijk} Y_{ijk}.
\]

3. Revenue loss is the result of a gap in commodities of an FHC versus a competitor configuration. Based on business knowledge from competitive marketing research and market share data, if a commodity of an FHC is not comparable to a competitor’s configuration commodity, we estimate revenue loss for each option of the commodities of an FHC as

\[
L_i = \sum_{j} \sum_{k} b_{ijk} Y_{ijk}.
\]

4. The bound on total upgrade cost of an FHC is

\[
\sum_{j} \sum_{k} e_{ijk} Y_{ijk} \leq BC_i.
\]

5. Only one option of each commodity can be selected:

\[
\sum_{k} Y_{ijk} = 1.
\]

Appendix B. Online Conversion Rate Accelerator Optimization Model

We define the following:

- \( i \in I \) : the set of all influential page components; the size of this set is the number of deal banners possible in a page.
to maximize the conversion of FHC prospective customers

tains deal banner can be displayed simultaneously;

feasible based on the following logic:

seconds to load, where

The objective function of the site optimization problem is to maximize the conversion of FHC prospective customers into buyers:

Maximize

\[
\text{conversion rate} = \sum_{i \in I} a_i x_i + \sum_{j \in J} b_{ij} x_{ij} x_{i'j'},
\]

Constraints

We define the following constraints:

- Each page component can take only one value: \( \sum_{j} x_{ij} = 1 \quad \forall i \).
- A minimum of three and a maximum of four configurations should be displayed on a product page:

\[3 \leq \sum_{j} x_{ij} \leq 4 \quad \forall k \in \text{All available configurations for a page.}\]

- Some combinations of component attributes are not feasible based on the following logic:
  
  - Merchandising: only certain combinations of FHCs can be displayed simultaneously;
  
  \[\text{Component combination} = \sum_{\text{Formusable Combinations}} x_{ii} = 1;\]

  - Pricing: products on a page should have prices within a prespecified band;
  
  - Page layout: based on previous A/B tests, only certain combinations of calls to action, icons, and mastheads can form potential successful recipes;
  
  - Navigation elements: specific combinations of navigation elements should not appear together;
  
  - Load time: the pages should not take more than \( T \) seconds to load, where \( T \) is the time beyond which the rate of users leaving the page exceeds the acceptable limit.

\[\text{Load time} = \sum_{\text{Formusable Combinations}} \text{TimeToLoad}_{ij} \cdot x_{ij}\]

\[\leq \text{AcceptableLoadTime}.\]

Appendix C. Demand Shaping

The goal of demand shaping is to consistently meet demand with minimal inventory across the retail season, subject to the requirement of near-zero inventories at the end of the season. The inventory at any point in a season (\( I_t \)) can be calculated as shown next:

\[I_{t+1} + S_{t} - LT - D_{t} = I_t \quad \forall t = [1, 2, \ldots, T],\]

where

\( I = \text{inventory in units}; \)
\( t = \text{current week of the season}; \)
\( LT = \text{supply lead time in weeks}; \)
\( S = \text{supply in units}; \)
\( D = \text{demand in units.} \)

In the retail industry, variable inventory is maintained across different weeks within a season. At the start of a season, inventory is high (typically six to eight weeks of demand), and gradually falls to zero by the end of the season. The high inventory level at the beginning of the season ensures product availability across all retail stores. The required safety stock (\( S \)) is calculated as follows:

\[S = Z \sqrt{\sigma_2^2 \cdot LT + \sigma_1^2 \cdot D^2},\]

where

\( LT = \text{lead time (approximately one week from Dell warehouse to retailer warehouse)}; \)
\( D = \text{average weekly demand over last four weeks}; \)
\( \sigma_2 = \text{standard deviation of weekly demand}; \)
\( \sigma_1 = \text{lead time variability in weeks.} \)

The supplies to retailers are made using finished-goods inventory at Dell’s distribution centers. Hence, we calculate safety stock assuming lead time (\( LT \)) of one week; for illustration purpose we use a service level of 99 percent:

\[S = 2.33 \sqrt{\sigma_2^2 + \sigma_1^2 \cdot D^2}.\]

We calculate an upper inventory threshold, \( U_t = P_t + S \), and lower inventory threshold, \( L_t = P_t - S \) where \( P_t \) is the target inventory profile at time \( t \). The projected inventory \( I_t \) is monitored every week against these thresholds. The difference between them can lead to either excess (\( E_t \)) or deficient (\( F_t \)) inventory:

\[I_t = \begin{cases} U_t + E_t, & h \geq U_t \\ L_t - F_t, & h \leq L_t \end{cases} \quad \forall t = [1, 2, \ldots, T].\]

At the end of the season (time \( T \)), we are left with either excess inventory (\( E_T \)) or deficient inventory (\( F_T \)). The excess inventory (\( E_T \)) can be partly consumed through end-of-season markdowns and promotions (\( \alpha_e \)), and the leftover inventory can be either sold in the next season (\( \alpha_d \)), or written off because of aging (\( \alpha_a \)):

\[E_T = \alpha_e E_T + \alpha_d E_T + \alpha_a E_T \quad \text{s.t. } \alpha_e + \alpha_d + \alpha_a = 1.\]
The cost to clear this excess inventory is represented as

$$C_e = \text{Cost}(E_t) = C_m \alpha_t E_t + C_d X + C_f \left( \frac{\alpha_t E_t}{R} \right) + C_p \alpha_p E_t,$$

where

- $C_m =$ cost of markdown or discount per unit;
- $C_d =$ cost of running a promotion;
- $X = \begin{cases} 1, & \text{if promoted;} \\ 0, & \text{if not promoted;} \end{cases}$
- $C_f =$ cost of delayed launch for next-season SKU per week;
- $R =$ weekly sales run rate;
- $C_p =$ cost of obsolescence per unit.

Similarly, the deficient inventory ($F_t$) can be partially filled by expediting the order process ($\alpha_t$), which results in premium freight costs because of air shipment. The balance of demand ($\alpha_t$) is the lost opportunity:

$$F_t = \alpha_t F_t + \alpha_d F_t \quad \text{s.t. } \alpha_t + \alpha_d = 1.$$

The cost of deficient inventory is

$$C_f = \text{Cost}(F_t) = C_d \alpha_t F_t + C_f \alpha_d F_t,$$

where

- $C_d =$ cost of expediting per unit;
- $C_f =$ cost of lost revenue per unit.

**Objective Function**

The total cost of both excess ($E_t$) and deficient inventory ($F_t$) for an FHC can be described as follows:

$$\text{Total Cost for an FHC} = Z_t = (C_e + C_f) = C_m \alpha_t E_t + C_d X + C_f \left( \frac{\alpha_t E_t}{R} \right) + C_d \alpha_t F_t + C_f \alpha_d F_t$$

$$\forall i = [1, 2, \ldots, N].$$

The objective of demand shaping is to minimize the costs of both excess ($E_t$) and deficient inventory ($F_t$) across FHCs:

$$\text{Minimize}(Z_t) \quad \forall i = [1, 2, \ldots, N].$$

The model is subject to following constraints and conditions:

1. Supply lead times:
   - $8$ weeks, in case of ocean shipment;
   - $4$ weeks, in case of air shipment.

2. Fixed markdown and promotion budget, $\sum C_m \alpha_t E_t \leq$ marcom budget.

3. Fixed order expediting budget, $\sum C_f \alpha_t F_t \leq$ expedite budget.

4. Season transition should not be delayed by more than four weeks, $((\alpha_d E_t)/R) \leq 4.$

**References**


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