Assortment Planning of Automotive Products

Considerations for Economic and Environmental Impacts of Technology Selection

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Abstract

A manufacturer's assortment is the set of products that the company offers to its customers. Assortment planning considerably affects both the sales revenue and product offering costs for the company and it had experienced growing attention across different industries over recent decades. In this study, we propose a modeling framework that seeks to identify the optimal assortment for a manufacturer of configurable products (in particular, automobiles). Our model accounts for environmental considerations (Corporate Average Fuel Economy requirements, tail-pipe emissions, and greenhouse gas emissions related to the production of the fuel used to power the vehicle) during assortment planning. We formulate the economic and environmental requirements in the model through a mixed-integer programming framework and present a hypothetical product case study motivated by an American automaker that involves 120 potential configurations employing different engine technologies (gasoline, diesel, and hybrid technologies). Notwithstanding consideration for consumer perceptions and acceptance, the results of this research work show that diesel technologies are a better choice to satisfy average fuel economy requirements compared to hybrid and conventional powertrains with current technology maturity.

Key words: Assortment planning, configurable products, product substitution, technology selection, sustainability, CAFE requirements, emissions.

1. Introduction

A manufacturer's assortment is the set of products that the company builds and offers to its customers. Kok et al. (2008) describe the goal of assortment planning as finding an assortment that maximizes company's profit subject to various constraints such as limited budget to purchase products and limited shelf space to display products. For configurable products such as automobiles, which are a combination of required and/or optional components (Rodriguez and Goker, 2011), each model comes in a number of configurations; the set of configurations and the associated logic for a configurable product is sometimes termed *product definition*. *Assortment planning* requires a tradeoff between sales revenue and product offering costs for the company (MacDuffie et al., 1996). The automotive product offerings and configurations have steadily

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grown in the U.S. until recent years. For example, the number of car models available in the U.S. market increased from 30 models in 1955 to 142 models in 1989 (Womack et al. 1990). Including nameplates, body styles, and special performance editions, the industry is offering 394 new models in the U.S. market in 2013 (Baumann 2013). However, growing awareness for the costs associated with increasing manufacturing complexity and plant productivity issues under large product configuration assortments is compelling major volume-driven automotive original equipment manufacturers (OEMs) to consider controlling their configuration variety to decrease their operational costs while maintaining their sales and market shares. For example, Ford Motor Company reduced the ordering complexity (i.e., number of orderable configurations) of the 2009 F-150 truck by more than 90%. As for cars, it planned for the 2010 Ford Focus to have just 150 "major" (or "core entity") combinations, a drop of 95% from the 2008 model (Wilson, Automotive News, 2008). OEM data from Pil and Holweg (2004) for a popular vehicle segment in Europe even suggests that there is little correlation between the total number of configurations offered by a brand model and the total sales experienced. While there are a number of factors that influence sales besides product variety (e.g., product quality, value, brand image), overall it appears that automakers are not necessarily driving their strategic decisions regarding product configuration variety based on objective and holistic decision support models.

Besides economic objectives to maximize profit, there are also other factors affecting the final assortment of an OEM. Environmental considerations are important driving forces that impact the automotive industry due to increasingly strict governmental regulations and social expectations (Geffen and Rothenberg, 2000; Koplin et al. 2007). In the U.S., the main federal regulations on vehicle fuel economy have been expressed through Corporate Average Fuel Economy (CAFE) standards by the National Highway Traffic Safety Administration (NHTSA) and the Environmental Protection Agency (EPA). CAFE is the sales-weighted fleet average fuel economy of an OEM, expressed in miles per U.S. gallon (3.785 liters) of vehicles for sale in the U.S., for any given model year. The CAFE requirements were relatively static from 1990 to 2010, with a requirement of 27.5 miles per U.S. gallon (mpg) for passenger cars. Starting in 2011, the CAFE standards are newly expressed as mathematical functions depending on vehicle "footprint," a measure of vehicle size determined by multiplying the vehicle's wheelbase by its average track width. Going forward, the CAFE requirements are tightening: 2016 target fuel economy is 35.5 mpg for car and light trucks and will further increase to 54.5 mpg by model year 2025. The current penalty for failing to meet the standards is \$5.50 per tenth of a mpg for each tenth under the target value times the total volume of vehicles manufactured. In addition, a Gas Guzzler Tax is also levied on individual passenger car models (but not trucks, vans, minivans, or SUVs) that get less than 22.5 mpg. Instead of CAFE requirements, some countries including European states have imposed taxation policy on gasoline and diesel prices (Sterner, 2007; Ekins, 1999). This policy has been considered one of the best ways to fiscally control the amount of energy consumption and emissions from the transportation sector (Steenberghen and Lopez, 2008). This policy often involves significantly increasing fuel price (van Vliet et al. 2010) and motivates customer's evolution toward more fuel-efficient vehicles. This dynamic will be implicitly considered in our model through the impact of vehicle price on primary demand fractions for distinct configurations. Another important measure for OEMs in deciding the product configuration assortment is the emissions footprint from vehicle manufacturing as well as product use and disposal/recycling.

In this paper, while limiting our discussion to the automotive industry, we aim to develop configurable product assortment planning models that take environmental considerations into concern while explicitly accounting for both demand and supply issues . In the past decades, there has been considerable work dedicated to demand aspects of assortment planning (see Kök et al. 2008, for a literature review). However, very little research has been done that integrally considers demand and supply/manufacturing aspects in planning product assortments. This paper proposes an objective decision support modeling framework for configuration assortment planning for individual automotive products by exploiting exogenous demand models. Moreover, and to the best of our knowledge, this is the first work on product assortment planning that takes environmental issues into consideration. The rest of the paper is organized as follows: Section 2 reviews the relevant literature; Section 3 discusses the problem setting in more detail and the main assumptions behind our model. Methodology and problem formulation are discussed in Section 4. Section 5 reports the results from a number of experiments. Finally, we conclude and identify directions for further research in Section 6.

2. Literature Review

Van Ryzin and Mahajan (1999) were the first to study assortment planning and inventory decisions by using a multinomial logit (MNL) model of consumer choice. They assume that each product variant carried in the assortment has an identical unit cost and is offered at an identical price. Later, Mahajan and van Ryzin (2001) study the same problem with substitution under stock-outs. Smith and Agrawal (2000) study assortment planning problem with the exogenous demand model by solving an inventory optimization problem that selects both items to stock and the stock levels for each item in the assortment. Kök and Fisher (2007) solve an assortment planning problem with exogenous demand. They formulate their problem in the context of a supermarket chain and offer a procedure for estimating the parameters of substitution behavior and demand for the stores' products. They also propose a heuristic to solve the assortment planning and inventory problem with one-level stock-out-based substitution in the presence of shelf-space constraints. Honhon, Gaur, and Seshadri (2009) propose an algorithm to determine the optimal assortment and inventory levels under stock-out based substitution for a single period problem assuming that each customer type has a specific preference ordering amongst products and chooses the product with the highest rank according to his type (if any), which is available at the time of purchase. None of these models accounts for environmental considerations, and their treatment of manufacturing/supply complexity is limited. In many industries (including auto-industry), there is an increasing awareness toward addressing environmental issues in their products as well as the processes (see Transportation Research Board-National Research Council, 1997; Sutherland et al., 2004). Goldberg (1998) studies the effects of CAFE standards on automobile prices and sales and the expected environmental effects of CAFE standards. He claims that policies oriented toward shifting the mixture of the new car fleet to more fuel-efficient vehicles are promising, and CAFE provides incentives for OEMs to develop more fuel-efficient vehicles. MacLean and Lave (2000) study the environmental implications of alternative-fueled automobiles with respect to air quality and greenhouse gas trade-offs. They analyze different fuel-powertrain options and estimate fuel efficiency, energy use, pollutant discharge, and greenhouse gas emissions for internal combustion engine automobiles and show that compressed natural gas (CNG) vehicles are giving the best exhaust emission performance while direct injected diesels had the worst. On the other hand, greenhouse gases can be reduced with direct injected diesels and direct injected CNG compared to a conventional fueled automobile. Michalek et al. (2004) study the impact of fuel efficiency and emission policy on optimal vehicle design decisions in an oligopoly market. They evaluate several policy scenarios for the small car market, including CAFE standards, carbon dioxide (CO_2) emissions taxes, and diesel technology quotas. The results show that imposing CO_2 taxes on producers for expected life-cycle emissions results in diminishing returns on fuel efficiency improvement as the taxes increase, while CAFE standards lead to higher average fuel efficiency per regulatory dollar. Although their model decides on design parameters (such as engine size), prices, and production volumes, it is different from our approach on assortment planning by considering no substitution effects. Recently, Hoen et al. (2010) study the effect of carbon emission regulations on transport mode selection in supply chains. Although they study a different sector, their results suggest that introducing a constraint on emissions is a more powerful tool for policymakers in reducing emissions compared to introducing an emission cost for freight transport via a direct emission tax or a market mechanism. In this paper, similar to results of Hoen et al. (2010), we too conduct experiments constraining the average emissions allowed by the OEM during product use rather than introducing an emissions cost.

3. Assumptions

Suppose that for the product under consideration, $N = \{1,\ldots,I\}$ denotes the set of potential configurations that can be made available by the OEM. Assortment planning involves selecting a subset of these configurations for tooling the assembly line and readying the suppliers and dealers/retailers. Due to the long lead times associated with engineering parts/options and their integration into the vehicle, as well as lead times associated with supply chain readiness, the assortment planning decisions have to be made well up front, often several years in advance of product launch. This forces the planners to make a number of assumptions. The major assumptions behind our assortment planning model are as follows, categorized into assumptions related to demand, supply, costs, and environmental issues.

1. Demand
    a. Assumption (A1). We assume that the target market needs to be split into different regions, and $R = \{1,\ldots,r\}$ denotes the set of regions in the market. This is less of an assumption and more of a model feature. Each region is allowed to have its distinct product configuration demand and substitution behavior (e.g., colder northern states generally exhibit less demand for convertible models and have higher demand for features such as heated seats and engine block heaters). From our conversations with subject-matter-experts, this is how OEMs model the market.
    b. Assumption (A2). Given the long lead times associated with assortment planning and the significant uncertainty in fuel prices and their impact on product demand, we consider different potential scenarios for market fuel(s) price(s). A probability is associated with each of the scenarios and the associated product demand mix (i.e., the demand for the different configurations). We impose no restrictions on the structure of the relationship between fuel price and the product demand mix within these scenarios.
    c. Assumption (A3). We assume that every potential customer has a favorite (most preferred) configuration from the set N. Under fuel price scenario $f \in FP$, the potential demand for each configuration $i \in N$, at each region $r \in R$, is assumed to be a known fraction of total market demand, M. The total market demand as well as the demand mix for different technologies could be different across fuel price scenarios. If the customer cannot find her favorite configuration i, she will decide not to substitute with probability $\delta_i^r(s)$; otherwise she will choose configuration j with probability α_{ji}^r. We

assume that customers in a region would only substitute available configurations across the region (and not between regions) if their favorite configuration is missing.

2. Supply
   a. Assumption (A4). Although there are multiple market realization scenarios (in terms of fuel price and associated demand), given the long lead times involved for product development and supply chain readiness the OEM has to decide on a unique product configuration assortment upfront (strategic planning process). The model also has to decide upfront the planned production volumes for each configuration, so that the supply chain can install the necessary manufacturing capacity for producing the parts/options content. While the OEMs can try to adjust these production capacities after launching the product and observing the actual realized demand, this is often a very lengthy and expensive process for highly engineered and complex products such as automobiles and often takes several quarters to a year. OEMs can also rely on tactics such as price rebates to alter demand. These reactionary decisions are more tactical in nature and outside the scope of our strategic assortment planning model. This being a strategic model, we model the production supply and consumption setting as a single-period problem, also known as the newsboy or news vendor model, where the manufacturer would supply the regions with product configurations at the beginning of the time period; we do not explicitly model the ongoing replenishment process with dealers ordering and the OEM trying to fulfill the orders.
   b. Assumption (A5). We allow economies of scale for the OEM in purchasing parts/options from the suppliers as a function of purchase quantity. That is, the OEM could receive discounts on some parts/options if purchased in large quantities. We assume that the information related to discounts is exogenous to our model and purchasing cost is assumed to follow a step-wise non-increasing function as a function of purchase quantity; we assume an all-unit quantity discount model. If parts are shared across models, the step-wise function is expected to capture the incremental price benefits from using the part within the product under consideration. Additional piece-price discounts garnered from using a part within the particular program under consideration will apply to other programs that employ the part as well. This is again less of an assumption and more of a flexible model feature.
3. Costs
   a. Assumption (A6). We assume that each potential configuration j has a variable production/supply cost, $C_j^{variable}$. We assume that prices for each product configuration, p_j, are set exogenously and are available *a priori* for product assortment planning. We assume that each feature/option p, if carried in any final assortment configuration, will incur a fixed cost $C_p^{fixed\_part}$. The fixed cost can be attributable to factors such as incremental design, integration engineering, testing, quality, warranty, and service costs from incorporating the feature into the assortment. Similarly, we make provision for fixed costs from adding configurations to the assortment ($C_j^{fixed\_conf}\,\forall j$).
   b. Assumption (A7). We assume that there is overage cost ($C_i^{overage}$) for leftover inventory at the end of the selling period to cover the cost of additional incentives/marketing necessary to clear the inventory within the distribution pipeline for introduction of product from the next model year.

c. Assumption (A8). We assume that the prices of different configurations are fixed and do not change as a function of the fuel prices encountered in the market.

4. Environmental Factors
   a. Assumption (A9). We assume that the OEM will target a specific average fuel economy (AFE) for the model under consideration in the aim of meeting the CAFE or similar requirements for the overall company across all models. Since CAFE requirements are only mandatory in USA, we would consider our study/numerical experiments more consistent with the US market.
   b. Assumption (A10). We assume that the effect of any tax and excise policy on fuel prices (e.g., policies encouraging diesel vehicles in Europe) and/or financial incentives for purchasing fuel efficient vehicles (e.g., recent subsidies for electric cars in the U.S.) would only affect potential demand for each configuration within these regions and does not incur any cost to the OEM.
   c. Assumption (A11). We limit modeling of greenhouse gas (GHG) emissions to just product use emissions from tailpipe and upstream fuel supply chain GHG emissions. We are aware that production impacts are also critical. However, given that many OEMs have global supply chains, any such analysis, in particular the logistics footprint, requires good understanding for the supply chain configuration and this information is often unavailable at the stage of the product development cycle when assortment planning takes place. In addition, impact estimates from even methods such as the Economic Input-Output Life Cycle Assessment (EIO-LCA) are not very reliable for many countries. We hope that future studies can address this limitation more thoroughly. The data we are using in our numerical experiments is derived from the U.S. fueleconomy.gov website, and those estimates include CO2, methane, and nitrous oxide emitted from all steps in the use of a fuel (from production and refining to distribution and final use—vehicle manufacture is excluded). Methane and nitrous oxide emissions are converted into a CO2 equivalent (CO2e). Future research should also account for emissions from producing the vehicle. We also assume that all vehicle units sold will be used for the same number of years and that any emissions limit is in average U.S. tons/year (1 U.S. ton equals 907.18 kilograms).

Furthermore, we assume that the regulations affecting the assortment decisions do not change during the planning horizon. We also assume that the fuel(s) prices will remain constant during the planning horizon based on one of the fuel price scenarios. There is also no explicit consideration for supply network decisions in the model (e.g., supplier selection, facility location).

4. Methodology

In this section, we present our framework to model assortment planning decisions for automotive products. The mathematical model seeks to maximize OEM's profit subjected to feasibility and environmental constraints. Note that our model only accounts for revenues and direct cost of sales but not overhead costs such as selling/marketing, administrative, and other expenses. Prior to presenting the details of the model, we need to mention that our methodology uses the following inputs:

a. Primary demand fractions, substitution rates, and probability mass function of fuel price scenarios from demand perspective.

b. Information regarding fuel economy as well as annual CO_2 equivalent emissions from environmental perspective.
c. Selling prices, fixed and variable costs, economies of scale, Bill-of-material, and capacity limits from manufacturing perspective.

The model then outputs the optimal set of configurations to be built, production volumes of each configuration at each marketing region, and total units of option ‘p’ and corresponding discount level required for the assortment.

Before presenting the model’s objective function and constraints, it is necessary that we introduce the structure of our exogenous demand model. Assume that $d_{i,r,f}$ is the primary (first-choice) demand for configuration i in region r under fuel price scenario f. The effective (or realized) demand for configuration i in region r under fuel price scenario f could be computed as follows:

$$E_{i,r,f} = d_{i,r,f} + \sum_{\forall j \neq i} d_{j,r,f} \cdot (1 - X_j).\, \alpha_{ji} \qquad \text{(Equation 1)}$$

where α_{ji} is the probability that a customer will switch (substitute) to configuration i after not finding her favorite choice, configuration j; X_j is a binary decision variable equal to one if configuration i is a part of the final assortment (i.e., built), and zero otherwise. We can now introduce the mathematical model to find the optimal assortment. For brevity, we introduce the notation and definition of all parameters and decision variables in Table 1.

Table 1: Assortment planning model parameters, sets, and decision variables

Sets	
$i \in 1, \dots, N$	Set of all potential model configurations for the assortment
$r \in 1, \dots, R$	Set of all market regions
$p \in 1, \dots, P$	Set of all options required for assortment production
$l \in 1, \dots, L$	Set of all discount levels for an option
$f \in 1, \dots, FP$	Set of all fuel price scenarios

Parameters	
$d_{i,r,f}$	Primary (first-choice) demand for configuration i in region r under fuel price scenario f when facing a full assortment
$FuelEC_i$	Fuel economy (calculated in miles per gallon) of configuration i
AFE	Average fuel economy target for the vehicle model in support of CAFE requirement for the whole company
CE_i	Annual CO_2 equivalent emissions of configuration i
Max_ACE	Maximum average annual CO_2 equivalent emissions allowed for the whole assortment
α_{ij}	Probability that customer switches (substitutes) to configuration i after not finding the favorite choice, configuration j
p_i	Selling price of configuration i
$C_i^{fixed\_conf}$	Fixed cost of configuration i, if carried in the final assortment
$C_p^{fixed\_part}$	Fixed cost of option/feature p, if carried in any final assortment configuration
$C_i^{variable}$	Variable cost for a unit of configuration i
$C_i^{overage}$	Overage cost of configuration i if not sold by the end of the planning horizon
v_l^p	Amount of discount for each unit of option p if purchased at quantity level l
OP_p	Total units of option p used by other programs in the company

LP_l^p	With respect to economies of scale, the minimum order quantity limit for price level l of option p
β_i^p	Bill-of-material parameter; equal to one if configuration i requires option p (zero otherwise)
$BigM$	A sufficiently large number
Y_{max}	Maximum production capacity of the OEM
X_{max}	Maximum number of configurations in the assortment
$P(f)$	Probability mass function for fuel price scenario f

Decision Variables	
Y_i^r	Number of vehicles of configuration i planned to be supplied to market region r
X_i^{config}	A binary decision variable equal to one if configuration i is built (zero otherwise)
X_p^{part}	A binary decision variable equal to one if option p should be built based on assortment requirements (zero otherwise)
Z^p	Total required units of option p for the production of the final assortment
$\tilde{z}_l^p$	Total required units of option p purchased at discount level l
$Z\_Binary_l^p$	A binary decision variable equal to one if option p is purchased at discount level l (zero otherwise)
$\mathcal{L}_{i,r,f}$	Leftover inventory of configuration i in region r , under fuel price scenario f
$E_{i,r,f}$	Effective demand for configuration i in region r, under fuel price scenario f

Let $\pi(f, Y)$ be the one-period (news vendor) profit for the OEM, from stocking assortment Y, when fuel price realization is f. We have:

$$\pi(f,Y) = \sum_{i=1}^{N}\sum_{r=1}^{R}\left[(P_i - C_i^{Variable}) \cdot (Y_i^r - \mathcal{L}_{i,r,f}) - C_i^{overage}.\mathcal{L}_{i,r,f}\right] - \sum_{i=1}^{N} C_i^{fixed\_conf}.X_i^{config} - \sum_{p=1}^{P} C_p^{fixed\_part}.X_p^{part} + \sum_{\forall p\in P}\sum_{\forall l\in L} v_l^p.(\tilde{z}_l^p + OP_p) \quad \text{(Equation 2)}$$

This profit function consists of revenue associated with product sales minus any fixed and variable costs associated with offering configurations as well as parts/options. The last term in equation (2) captures any savings from economies of scale in purchasing/producing parts/option content. Then, the expected profit across all possible fuel price scenarios would be:

$$E\Pi(Y) = \sum_{f\in FP} \pi(f,Y).P(f) \quad \text{(Equation 3)}$$

Our goal in finalizing the product assortment is to maximize $E\Pi(Y)$ with respect to capacity and feasibility constraints. The complete formulation for the optimization problem is presented as follows:

$$max_{Y,X}\, E\Pi(\boldsymbol{Y},\boldsymbol{X}) = \sum_{f\in FP} \pi(f,Y).P(f) \quad \text{(Equation 4)}$$

s.t.

$$E_{i,r,f} = d_{i,r,f} + \sum_{\forall j\neq i} d_{j,r,f} \cdot (1 - X_j).\alpha_{ij} \qquad \forall i,r,f \quad \text{(Equation 5)}$$

$$\mathcal{L}_{i,r,f} = (Y_i^r - E_{i,r,f})^+ \qquad \forall i,r,f \quad \text{(Equation 6)}$$

$$\sum_{\forall r\in R} Y_i^r \leq Y_{max} \cdot X_i^{config} \qquad \forall i \quad \text{(Equation 7)}$$

$$X_i^{config} \leq \sum_{\forall r\in R} Y_i^r \qquad \forall i \quad \text{(Equation 8)}$$

$$\sum_{\forall r\in R}\sum_{\forall i\in N} Y_i^r \leq Y_{max} \qquad \text{(Equation 9)}$$

$$\sum_{\forall i\in N} X_i^{config} \leq X_{max} \qquad \text{(Equation 10)}$$

$$\sum_{\forall i\in N}\sum_{\forall r\in R} Y_i^r \geq AFE * \sum_{\forall i\in N} \frac{\sum_{\forall r\in R} Y_i^r}{FuelEC_i} \qquad \text{(Equation 11)}$$

$$\sum_{\forall i\in N}(CE_i.\sum_{\forall r\in R} Y_i^r) \leq Max\_ACE * \sum_{\forall i\in N}\sum_{\forall r\in R} Y_i^r \qquad \text{(Equation 12)}$$

$$Z^p = \sum_{\forall i\in N}\{(\sum_{\forall r\in R} Y_i^r).\beta_i^p\} \quad \forall p \qquad \text{(Equation 13)}$$

$$Z^p \leq BigM * X_p^{part} \quad \forall p \qquad \text{(Equation 14)}$$

$$Z^p = \sum_{\forall l} \tilde{z}_l^p \quad \forall p \qquad \text{(Equation 15)}$$

$$\sum_{\forall l} Z\_Binary_l^p = 1 \quad \forall p \qquad \text{(Equation 16)}$$

$$\tilde{z}_l^p \leq LP_{l+1}^p \times Z\_Binary_l^p \quad \forall p, l \qquad \text{(Equation 17)}$$

$$\tilde{z}_l^p \geq LP_l^p - BigM * (1 - Z_{Binary}{}_l^p) \quad \forall p, l \qquad \text{(Equation 18)}$$

$$\tilde{z}_l^p \leq LP_{l+1}^p + BigM * (1 - Z_{Binary}{}_l^p) \quad \forall p, l \qquad \text{(Equation 19)}$$

$$X_i^{config} \in \{0,1\} \quad \forall i \in N \qquad \text{(Equation 20)}$$

$$Z^p \in \mathbb{R}^+,\ X_p^{part} \in \{0,1\} \quad \forall p \in P \qquad \text{(Equation 21)}$$

$$Y_i^r \in \mathbb{R}^+ \quad \forall i \in N, \forall r \in R \qquad \text{(Equation 22)}$$

$$\mathcal{L}_{i,r,f}\ , d_{i,r,f}^E \in \mathbb{R}^+ \quad \forall i \in N, \forall r \in R\ , \forall f \in FP \qquad \text{(Equation 23)}$$

Constraint (5) captures effective demand for configuration i in region r under fuel price scenario f. This constraint consists of original demand ($d_{i,r,f}$) plus any demand arising through substitution from missing product configurations. Constraint (6) determines the leftover inventory of configuration i in region r, which is maximum of zero and production volume minus realized demand. Constraints (7-8) are to ensure that there is no production for a configuration that is not built. Constraint (9) is used to limit the total production while constraint (10) limits maximum number of configurations supplied to the market. Constraint (11) ensures that the assortment satisfies the OEM's target average fuel economy (AFE) for the model in support of meeting overall CAFE requirement for the whole company and is the linearized form of this formulation:

$$\frac{\sum_{\forall i\in N}\sum_{\forall r\in R} Y_i^r}{\sum_{\forall i\in N}\frac{\sum_{\forall r\in R} Y_i^r}{FuelEC_i}} \geq AFE \qquad \text{(Equation 25)}$$

Constraint (12) ensures that the average annual tailpipe and upstream fuel CO_2 emissions in the assortment do not exceed a predetermined threshold (Max_ACE). Constraint (13) calculates total units of option p required for the production of any configuration that entails part p based on the bill of materials. Constraint (14) guarantees that part p will have zero units (either manufactured or purchased) if it is not selected in the assortment. Constraints (15-19) are required to determine the discount level from economies of scale for each option in the assortment. More specifically, constraint (15) links total units of part p to sum over different discount levels of part p. Constraint (16) ensures that only one of the discount levels could be selected and constraints (17-

19) give the lower and upper bounds of units of part p at discount level l. Equations (21-23) declare the model decision variable types.

5. Numerical Experiments

In consultation with several subject-matter-experts from the U.S. automotive industry, we generated a set of hypothetical product assortment planning problems generally representative of the mid-size sedan segment in the U.S. It should be noted that we have had extensive discussions/collaborations with several subject-matter-experts from two OEMs. Some with extensive R&D experience and routinely support marketing and supply chain analytics studies to inform management in managing product assortments and meeting regulations. Few others have over thirty years of experience each as Chief Engineers in product development and assortment planning. These problems carried 120 potential product configurations for consideration and mostly involve vehicle propulsion technologies and sample optional features such as the presence/absence of sunroof and satellite radio. Note that it is typical for OEMs to limit the strategic assortment planning activity to key vehicle part/option content (e.g., body styles, engines, transmissions) to limit data collection and model formulation complexity and avoid considering relatively simple/cheap accessories such a floor mats and most other dealer-installed content. Colors are also often finalized much later. The proposed modeling framework is generic and is flexible enough to accommodate additional technologies/features and options (e.g., technologies for direct injection, regenerative breaking, cylinder cut-off, and turbo chargers). Space constraints were also a factor in keeping the list of features/options to a select minimum. The subject-matter-experts also provided guidance in generating cost data of each part/option and, subsequently, deriving the unit costs associated with each configuration. The profit margins were set between 15% and 30% of the unit cost (with 15% for cheapest configurations and 30% for most expensive ones) and added to the unit cost to compute the selling price for each configuration.. The overage cost of leftover inventory at the end of the selling period is assumed to be between 4% and 12% of the unit cost of a configuration (4% for cheapest configurations and 12% for most expensive ones). Other data/parameters such as substitution probabilities (α_{ij}), primary demand fractions ($d_{i,r,f}$), fixed costs of offering configuration ($C_i^{fixed\_conf}$), and fixed costs of offering options ($C_p^{fixed\_part}$) were also generated in consultation with subject-matter-experts. In total, the 120 potential configurations employ 15 different major parts/options, which are grouped into powertrain technology choices (with 10 different types consisting of 6 gasoline engine choices, 3 diesel engine choices, and 1 hybrid engine choice), 3 body style choices (sedan, two-door coupe, and hatchback), sunroof option, and finally a satellite radio option. While the sunroof and satellite options are truly optional (meaning that the customer can select a configuration without these options), powertrain and body style choices are choices (e.g., the customer cannot select a configuration without a powertrain). Three different market scenarios are assumed based on low, medium, and high but realistic fuel prices. In each of these scenarios, the customers exhibit different demand for configurations with different levels of fuel economy. Given that the assortment planning problem is a strategic problem and the OEM cannot easily change the product configuration assortment in response to changes in fuel prices (though customers tend to react quickly to big swings in fuel prices, as seen in the last decade), the model aims to find a robust yet optimal assortment that best maximizes the expected profit across all possible fuel-price/demand scenarios. In deriving the settings for our synthetic experiments, we not only relied on the viewpoints of several subject-matter-experts from the North-American OEMs but also the official U.S. government source for "fuel economy information" gathered from http://www.fueleconomy.gov to make sure that the data employed is consistent with the real-world situation. All generated data are presented in detail in the Appendix.

Based on powertrain technology, we categorize the whole set of configurations into conventional, diesel, and hybrid vehicles. Each of these configurations has its specific fuel economy and product use emission footprint, which could affect the optimal assortment through either average fuel economy (AFE) requirement and/or maximum allowed average product use emissions constraints (ACE). Figure 1 shows the primary demand fractions for different vehicles (based on technology class) under different scenarios. As expected for the U.S. market, demand for conventional powertrain technologies (i.e., with gasoline engines) is the highest while there is much less demand for diesel and hybrid technologies. This is very different from other markets such as Europe, where diesel powertrains carry a large market share in many vehicle segments. As evident from the figure, the demand for hybrid and diesel technologies is assumed to increase with higher fuel prices for their higher fuel efficiency.

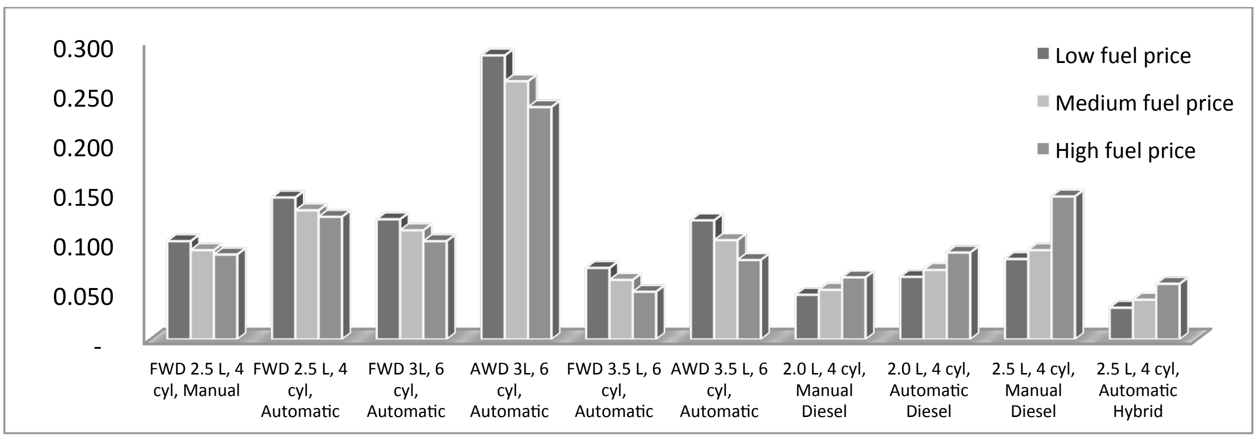

Figure 1: Demand fraction for ten different powertrain technologies under different fuel price scenarios

Table 2: Average margin, overage cost, fuel economy, and greenhouse green emissions for different powertrain technologies

	Powertrain technology	Average margin ($)	Average overage cost ($)	MPG	Greenhouse gas emissions (tons/year)
Conventional	FWD 2.5 L, 4 cyl, Manual	2,500	1,200	25*	7.3*
	FWD 2.5 L, 4 cyl, Automatic	3,000	1,400	26*	7.1*
	FWD 3L, 6 cyl, Automatic	3,000	1,400	23*	8.0*
	AWD 3L, 6 cyl, Automatic	2,800	1,300	20*	9.1*
	FWD 3.5 L, 6 cyl, Automatic	3,000	1,400	21*	8.7*
	AWD 3.5 L, 6 cyl, Automatic	3,100	1,500	19*	9.6*
Diesel	2.0 L, 4 cyl, Manual Diesel	2,600	1,500	26**	7.1**
	2.0 L, 4 cyl, Automatic Diesel	2,500	1,500	33**	6.3**
	2.5 L, 4 cyl, Manual Diesel	2,400	1,600	34**	5.9**
Hybrid	2.5 L, 4 cyl, Automatic Hybrid	1,800	1,300	39*	4.7*

* Numbers are from http://www.fueleconomy.gov
** Numbers are generated based on data for similar class vehicles.

Table 2 shows average profit margin, average overage cost, fuel efficiency in miles per U.S. gallon (mpg), and greenhouse gas (GHG) emissions for the different technologies. We make the simplifying assumption that vehicle mpg and emissions are mostly dependent on the powertrain technology and that the impact of feature/option content is relatively negligible. If there are significant interactions between other feature/option content and configuration mpg or emissions, powertrain technology and feature/option content combinations can be aggregated into higher-level aggregate features/options that are part of the assortment planning model. While this comes at the cost of exponential growth in number of aggregate options based on level of aggregation, it can be partially mitigated only by considering combinations that are promising and likely to survive the assortment planning optimization process. As is currently the case, hybrid technologies are the least profitable models but offer the highest fuel efficiency and lowest GHG emissions, while the 3.5-liter automatic all-wheel drive (AWD) powertrain technology builds the most profitable configurations that return the lowest fuel efficiency and release the highest GHG emissions. Our goal is to maximize total expected profit while satisfying AFE requirements and ACE emissions constraints by identifying the supply amount (if any) of each configuration for each region. We used ILOG-CPLEX 11.0 optimization engine to run all the experiments for our proposed mathematical model.

We first investigate the effect of environmental constraints on the optimal assortment. Figure 2 shows the optimal solution for the assortment planning problem under different AFE target levels. First, it shows the optimal solution when there is no AFE constraint, and then by considering AFE requirement at different levels. The first counterintuitive observation is that production shares for different technologies overall look different from their primary demand fractions. As an example, although the AWD 3L, 6 cyl (cylinder), Automatic powertrain has the highest primary demand fraction across all technologies in all fuel price scenarios, this technology is only selected under two AFE requirement levels (no AFE target and AFE = 25) and it has zero production for the other cases. The inconsistency between primary demand fraction and production share is mainly a result of environmental restrictions, product substitutions, and economies of scale. Another unexpected observation is seen by comparing 2.0 L, 4 cyl, Automatic Diesel technology with FWD 3.0 L, 6cyl, Automatic and FWD 3.5 L, 6 cyl, Automatic, and AWD 3.5 L, 6 cyl, Automatic. The diesel technology is getting much higher production share in all AFE levels (in particular when there is no AFE requirement) compared to those conventional technologies, even though the average profit margin is at least 20% less for the diesel technology. The exact reason behind this observation is not clear; however, we suspect that the effect of product substitution is an important factor in determining the optimal share for each configuration.

In addition, one could observe that some particular technologies are not profitable in most AFE scenarios (e.g., 2.5 L 4 cyl Manual Diesel, AWD 3.0 L Automatic, and 2.5 L Automatic hybrids). Since there are many factors affecting the optimal assortment solution (substitution effects, option fixed costs, economies of scale, etc.), it is not straightforward to predict the behavior of the optimal solution. However, one might consider the fact that 2.5 L 5 cyl manual diesel has a lower mpg with regard to other diesel technologies, and hence is not getting a share in the optimal assortment.

One intuitive observation is that the optimal assortment gives a higher share to some of the fuel-efficient technologies when we consider environmental requirements. Also, one might observe that FWD 3.5 L Automatic powertrain technologies get smaller production share with regard to AWD 3.5 L Automatic technologies in most AFE scenarios (except when AFE = 28) even though they have a better fuel economy, which may be the result of having a lower than average profit margin. Another observation is that hybrid technologies seem to be non-profitable (at least with our current settings) due to low profit margins even though they are very fuel efficient. This particular experiment suggests that diesel technologies are a dominant alternative for hybrid technologies in order to achieve higher AFE levels. It is worth mentioning that as Goldberg (1998) and Michalek et al. (2004) discuss on the efficiency of CAFE requirements for OEMs to develop more fuel-efficient vehicles, our experiments suggest that diesel powertrains work as a reliable alternative to help meet average fuel economy target requirements, while hybrid powertrains are not good candidates for product assortments given their currently low profit margins.

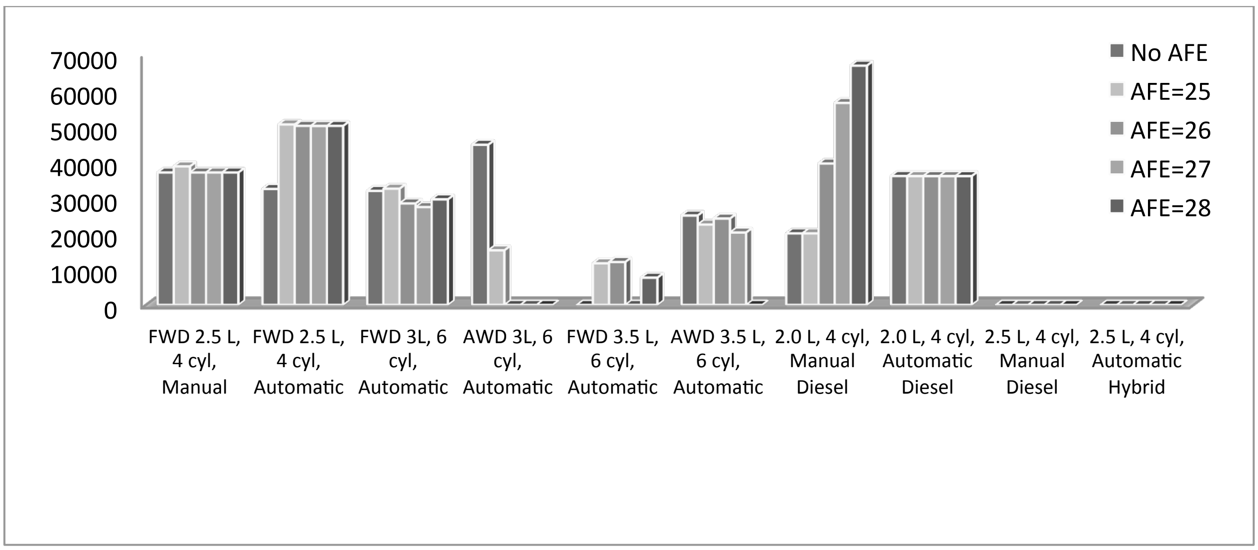

Figure 2: Production levels for different powertrain technologies under different average fuel economy requirements

In terms of profit, Figure 3 shows that satisfying AFE requirements reduces OEM's profit from 0.77% to 6.91% for different AFE target requirements. This is a considerable share of the profit and suggests a need for potential investment in developing fuel-efficient technologies at lower prices. Finally, Figure 4 shows the average annual GHG emissions under different AFE levels, which steadily reduces when satisfying higher AFE levels. This figure shows the potential reduction in GHG emissions by considering more stringent AFE requirements. Considering two extreme AFE levels (AFE=28 and no AFE) in Figures 3 and 4, the net effect is a reduction of GHG emissions by about 200,000 U.S. tons per year (almost one U.S. ton per vehicle per year) and a reduced expected profit of almost 69 million dollars for the OEM (which could be a potential limit on any subsidies spent on GHG emission reduction in the auto industry).

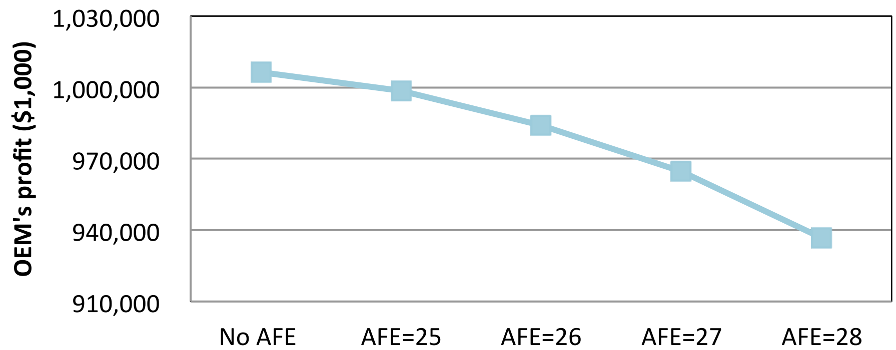

Figure 3: Total manufacturer profit under different average fuel economy requirements

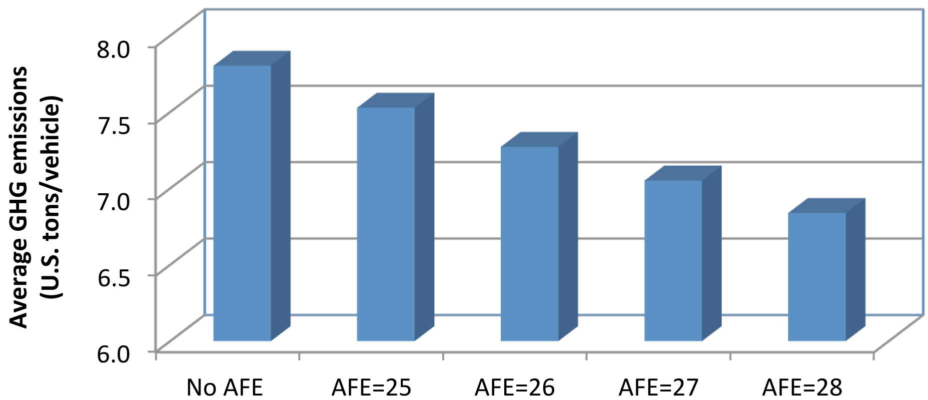

Figure 4: Average annual greenhouse gas emissions (U.S. tons/vehicle) under different average fuel economy requirements

Besides sensitivity analysis with respect to different AFE requirements, we are interested to investigate the sensitivity with respect to changes in other model inputs. For that purpose, we generated two sets of new scenarios to check the optimal assortment under: a) different fuel price scenario probability mass functions, and b) different profit margins. In the first set, we made five scenarios for the probability mass function of fuel price scenario, which can be found in Table V of the appendix. These runs are consistent with our original data set and we chose the AFE target level to be equal to 26 for these runs. As can be seen from the results in Figure 5, the optimal production is not changing considerably under scenarios 1 to 5 and we can conclude that our results are not very sensitive to prediction of this particular parameter although total profit is changing from one scenario to another.

In the second set, we created five other scenarios by changing the profit margins across different powertrain technologies. The average profit margins for these scenarios are reported in Table VI of the appendix. These runs are consistent with our original data set and we once again chose the AFE target level to be equal to 28 for these runs. The production volumes are very similar across the first three scenarios where conventional technologies have higher profit margins compared to diesel and hybrid technologies. However, in the last two scenarios with diesel and hybrid technologies having more similar profit margins compared to the conventional ones, we do see that part of the diesel production has been shifted to hybrid as it better accounts for AFE requirements. This is another indicator that shows necessity for investment in developing more profitable hybrid technologies to make them compatible with other technologies in the optimal assortment.

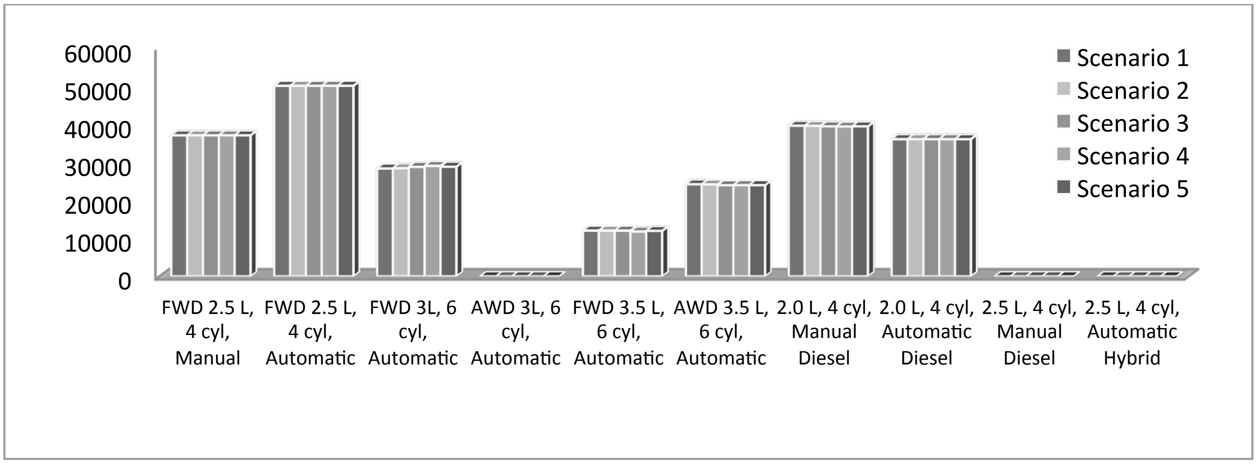

Figure 5: Sensitivity analysis of production volumes w.r.t different fuel price probability mass functions

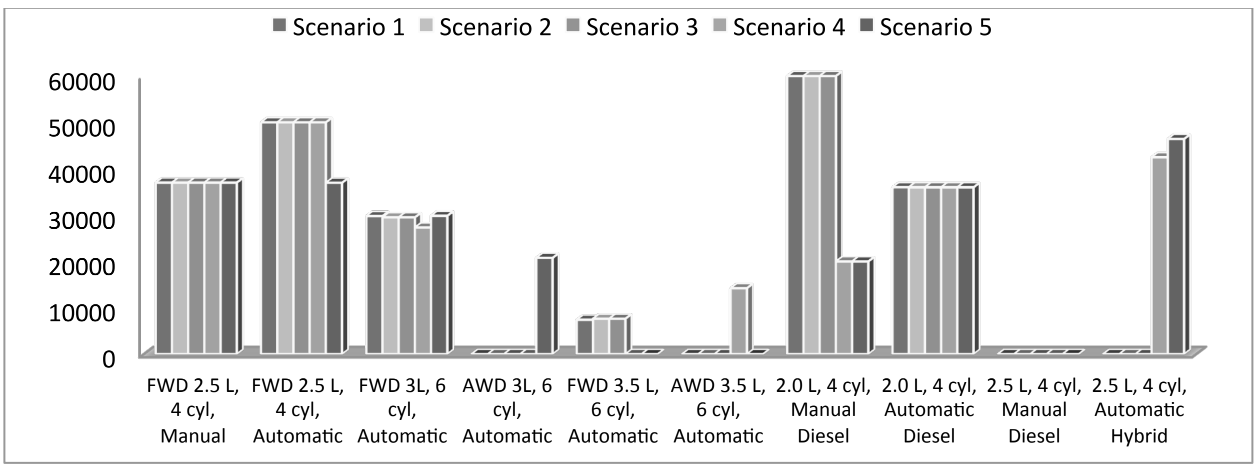

Figure 6: Sensitivity analysis of production volumes w.r.t different profit margins

6. Conclusion

We propose a strategic decision support modeling framework for assortment planning of products, in particular for configurable products--automobiles. We use an exogenous demand model that accounts for substitution across different product configurations when the customer's first choice is not available. The modeling framework supports environmental considerations by allowing targets for the model program's average fuel economy and average product use emissions. Given the strategic nature of the assortment planning process (often carried out years ahead of product launch), we account for uncertainty in market fuel prices and the resulting demand behavior through scenarios and associated probabilities. The proposed mixed-integer program model seeks a robust product configuration assortment that maximizes expected profit across all scenarios.

Our numerical experiments that employ realistic data settings, developed in consultation with subject-matter-experts from the automotive industry and government data sources, suggest that the optimal production volumes can be rather different from the primary demand volumes for different configurations. This can be attributed to product substitution effects, profit-margin differences, economies of scale, and environmental constraints.

The result of our research implies a need for more OEM, government, and public attention toward diesel technologies, at least in the short term, in particular in the United States. Note that there are health concerns regarding traditional diesel engines in particular for the high emissions of nitrogen oxides (NOx) and particulate matter. Although New Technology Diesel Exhaust (NTDE) has been shown to be dramatically cleaner than the Traditional Diesel Exhaust (Hesterberg and Bunn, 2012), new research to deliver even cleaner diesel engines seems necessary by automotive industry. There is also need to improve public perception regarding diesel health based on improved/cleaner diesel technologies.

Another result of our research is to reveal the need for additional investment in cleaner technologies (e.g., hybrids and pure electrics) to make them more cost efficient in the long-term and hence more competitive with conventional and diesel technologies.

Given the strategic nature of the assortment planning problem, in particular for highly engineered/complex automotive products with long lead times for supply network design and capacity planning, we assume a single period single-shot supply setting with no replenishments. As a direction for future research, we suggest building models that account for the effects of the ongoing replenishment process typical in the automotive industry. Another extension to our research could be achieved by developing models that account for endogenous pricing and price-demand elasticity. Finally, the models can be further developed to consider the entire OEM fleet rather than individual vehicle programs, to better account for the effects of common product platforms and commonality.

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Appendix: Data Employed for Case Study Experiments[1]

Table I: Total demand and corresponding probabilities for different market scenarios

	Fuel price scenario 1	Fuel price scenario 2	Fuel price scenario 3
Total demand	200,000	200,000	200,000
Probability	0.2	0.45	0.35

Table II: Selling price, unit cost, overage cost, and primary demand fraction for each configuration under different market scenarios

Configuration ID	Powertrain technology type	Selling price ($1,000)	Unit cost ($1,000)	Overage cost ($1,000)	Primary demand fraction in fuel price scenario 1	Primary demand fraction in fuel price scenario 2	Primary demand fraction in fuel price scenario 3
1	FWD 2.5 L, 4 cyl, Manual	17.6	14.6	1.8	0.0241	0.0219	0.0208
2		18.2	15.1	1.9	0.0145	0.0132	0.0125
3		15.5	13.4	0.7	0.0130	0.0118	0.0112
4		15.6	13.5	0.7	0.0097	0.0088	0.0083
5		16	13.9	0.7	0.0080	0.0073	0.0069
6		17.6	14.6	1.8	0.0078	0.0071	0.0067
7		18.6	15.5	1.9	0.0052	0.0047	0.0045
8		20.4	17	2.1	0.0048	0.0044	0.0042
9		15.1	13.1	0.7	0.0043	0.0039	0.0037
10		15.9	13.8	0.7	0.0032	0.0029	0.0028
11		16	13.9	0.7	0.0026	0.0024	0.0022
12		16.1	14	0.7	0.0017	0.0016	0.0015
13	FWD 2.5 L, 4 cyl, Automatic	22.8	17.5	2.1	0.0349	0.0317	0.0301
14		14.2	12.3	0.7	0.0209	0.0190	0.0181
15		17.3	14.4	1.8	0.0188	0.0171	0.0162
16		19.2	16	2	0.0139	0.0127	0.0120
17		18	15	1.8	0.0116	0.0106	0.0100
18		14.7	12.7	0.7	0.0113	0.0102	0.0097
19		15.5	13.4	0.7	0.0075	0.0068	0.0065
20		22.8	17.5	2.1	0.0070	0.0063	0.0060
21		15.7	13.6	0.7	0.0063	0.0057	0.0054
22		17.2	14.3	1.8	0.0046	0.0042	0.0040
23		15.6	13.5	0.7	0.0038	0.0034	0.0032
24		17.2	14.3	1.8	0.0025	0.0023	0.0022
25	FWD 3L, 6 cyl, Automatic	23.4	18	2.2	0.0295	0.0268	0.0241
26		19	15.8	1.9	0.0177	0.0161	0.0145
27		13.7	11.9	0.6	0.0159	0.0144	0.0130
28		14.5	12.6	0.7	0.0118	0.0107	0.0097
29		16	13.9	0.7	0.0098	0.0089	0.0080
30		14.7	12.7	0.7	0.0095	0.0087	0.0078

[1] Probabilities of substitution between configurations are generally derived for these experiments based on price and content similarities between configurations; similar to the a priori substitutability concept discussed by Vaagen et al. (2011). In other words, the more common the parts/options between any two configurations, the higher probability of substitution between the two under stock-out. The (120×120) cell table is not reported here due to space constraints.

31		23.4	18	2.2	0.0064	0.0058	0.0052
32		14.8	12.8	0.7	0.0059	0.0054	0.0048
33		18.6	15.5	1.9	0.0053	0.0048	0.0043
34		25.4	19.5	2.4	0.0039	0.0036	0.0032
35		19.6	16.3	2	0.0032	0.0029	0.0026
36		15.1	13.1	0.7	0.0021	0.0019	0.0017
37	AWD 3L, 6 cyl, Automatic	20.4	17	2.1	0.0697	0.0634	0.0570
38		18.6	15.5	1.9	0.0418	0.0380	0.0342
39		15.1	13.1	0.7	0.0375	0.0341	0.0307
40		15.2	13.2	0.7	0.0279	0.0254	0.0228
41		15.9	13.8	0.7	0.0232	0.0211	0.0190
42		17.7	14.7	1.8	0.0225	0.0205	0.0184
43		17.8	14.8	1.8	0.0150	0.0137	0.0123
44		15.9	13.8	0.7	0.0139	0.0127	0.0114
45		19.5	16.2	2	0.0125	0.0114	0.0102
46		14.2	12.3	0.7	0.0093	0.0085	0.0076
47		24.1	18.5	2.3	0.0075	0.0068	0.0061
48		19.6	16.3	2	0.0050	0.0046	0.0041
49	FWD 3.5 L, 6 cyl, Automatic	14.3	12.4	0.7	0.0176	0.0146	0.0117
50		22.8	17.5	2.1	0.0105	0.0088	0.0070
51		14.2	12.3	0.7	0.0095	0.0079	0.0063
52		15.1	13.1	0.7	0.0070	0.0059	0.0047
53		20.2	16.8	2.1	0.0059	0.0049	0.0039
54		15.2	13.2	0.7	0.0057	0.0047	0.0038
55		26	20	2.4	0.0038	0.0032	0.0025
56		18	15	1.8	0.0035	0.0029	0.0023
57		14.7	12.7	0.7	0.0032	0.0026	0.0021
58		20.1	16.7	2.1	0.0023	0.0020	0.0016
59		13.3	11.5	0.6	0.0019	0.0016	0.0013
60		20.2	16.8	2.1	0.0013	0.0011	0.0008
61	AWD 3.5 L, 6 cyl, Automatic	15.7	13.6	0.7	0.0293	0.0244	0.0195
62		17.2	14.3	1.8	0.0176	0.0146	0.0117
63		23.8	18.3	2.2	0.0158	0.0131	0.0105
64		23.4	18	2.2	0.0117	0.0098	0.0078
65		18.3	15.2	1.9	0.0098	0.0081	0.0065
66		17.1	14.2	1.8	0.0095	0.0079	0.0063
67		13.7	11.9	0.6	0.0063	0.0053	0.0042
68		19	15.8	1.9	0.0059	0.0049	0.0039
69		17.2	14.3	1.8	0.0053	0.0044	0.0035
70		13.7	11.9	0.6	0.0039	0.0033	0.0026
71		14.5	12.6	0.7	0.0032	0.0026	0.0021
72		20.1	16.7	2.1	0.0021	0.0018	0.0014
73	2.0 L, 4 cyl, Manual Diesel	14.1	12.8	0.7	0.0197	0.0219	0.0351
74		14.9	13.5	0.7	0.0118	0.0132	0.0211
75		14	12.7	0.7	0.0106	0.0118	0.0189
76		21.5	17.2	2.1	0.0079	0.0088	0.0140
77		17.3	15	1.8	0.0066	0.0073	0.0117
78		12.3	11.1	0.6	0.0064	0.0071	0.0113
79		21.7	17.3	2.1	0.0043	0.0047	0.0076
80		24.4	19.5	2.4	0.0039	0.0044	0.0070
81		18.8	16.3	2	0.0035	0.0039	0.0063
82		14.5	13.1	0.7	0.0026	0.0029	0.0047
83		21.5	17.2	2.1	0.0021	0.0024	0.0038

84		13.2	12	0.6	0.0014	0.0016	0.0025
85	2.0 L, 4 cyl, Automatic Diesel	17	14.7	1.8	0.0154	0.0171	0.0213
86		23.4	18.7	2.3	0.0092	0.0102	0.0128
87		23.5	18.8	2.3	0.0083	0.0092	0.0115
88		15.2	13.8	0.7	0.0061	0.0068	0.0085
89		17.9	15.5	1.9	0.0051	0.0057	0.0071
90		18.7	16.2	2	0.0050	0.0055	0.0069
91		17	14.7	1.8	0.0033	0.0037	0.0046
92		13.6	12.3	0.7	0.0031	0.0034	0.0043
93		13.7	12.4	0.7	0.0028	0.0031	0.0038
94		19.4	16.8	2.1	0.0020	0.0023	0.0028
95		15.4	14	0.7	0.0017	0.0018	0.0023
96		14.3	13	0.7	0.0011	0.0012	0.0015
97	2.5 L, 5 cyl, Manual Diesel	22.2	17.7	2.2	0.0110	0.0122	0.0152
98		17.9	15.5	1.9	0.0066	0.0073	0.0091
99		12.8	11.6	0.6	0.0059	0.0066	0.0082
100		19.3	16.7	2.1	0.0044	0.0049	0.0061
101		12.7	11.5	0.6	0.0037	0.0041	0.0051
102		18.4	16	2	0.0035	0.0039	0.0049
103		22.9	18.3	2.2	0.0024	0.0026	0.0033
104		24	19.2	2.4	0.0022	0.0024	0.0030
105		16.4	14.2	1.8	0.0020	0.0022	0.0027
106		13.1	11.9	0.6	0.0015	0.0016	0.0020
107		18.4	16	2	0.0012	0.0013	0.0016
108		14.9	13.5	0.7	0.0008	0.0009	0.0011
109	2.5 L, 4 cyl, Automatic Hybrid	20.2	17.5	1.6	0.0078	0.0098	0.0137
110		19.8	17.2	1.6	0.0047	0.0059	0.0082
111		16.5	15	1.4	0.0042	0.0053	0.0074
112		14.2	13.5	0.6	0.0031	0.0039	0.0055
113		11.7	11.1	0.5	0.0026	0.0033	0.0046
114		18.2	16.5	1.5	0.0025	0.0032	0.0044
115		21.6	18.7	1.7	0.0017	0.0021	0.0029
116		17.1	15.5	1.4	0.0016	0.0020	0.0027
117		20.7	18	1.7	0.0014	0.0018	0.0025
118		13.7	13	0.6	0.0010	0.0013	0.0018
119		17.6	16	1.5	0.0008	0.0011	0.0015
120		20.2	17.5	1.6	0.0006	0.0007	0.0010

Table III: Bill-of-material for each potential configuration

Configuration ID	Powertrain technology type	4-Door body style	2-Door body style	Hatchback body style	Sunroof	Satellite radio
1	FWD 2.5 L, 4 cyl, Manual	1	0	0	1	1
2		0	1	0	1	1
3		1	0	0	0	1
4		0	0	1	1	1
5		1	0	0	1	0
6		0	1	0	0	1
7		0	0	1	0	1
8		0	1	0	1	0
9		1	0	0	0	0
10		0	0	1	1	0
11		0	1	0	0	0
12		0	0	1	0	0
13	FWD 2.5 L, 4 cyl, Automatic	1	0	0	1	1
14		0	1	0	1	1
15		1	0	0	0	1
16		0	0	1	1	1
17		1	0	0	1	0
18		0	1	0	0	1
19		0	0	1	0	1
20		0	1	0	1	0
21		1	0	0	0	0
22		0	0	1	1	0
23		0	1	0	0	0
24		0	0	1	0	0
25	FWD 3L, 6 cyl, Automatic	1	0	0	1	1
26		0	1	0	1	1
27		1	0	0	0	1
28		0	0	1	1	1
29		1	0	0	1	0
30		0	1	0	0	1
31		0	0	1	0	1
32		0	1	0	1	0
33		1	0	0	0	0
34		0	0	1	1	0
35		0	1	0	0	0
36		0	0	1	0	0
37	AWD 3L, 6 cyl, Automatic	1	0	0	1	1
38		0	1	0	1	1
39		1	0	0	0	1
40		0	0	1	1	1
41		1	0	0	1	0
42		0	1	0	0	1
43		0	0	1	0	1
44		0	1	0	1	0
45		1	0	0	0	0
46		0	0	1	1	0
47		0	1	0	0	0
48		0	0	1	0	0
49	FWD 3.5 L, 6 cyl, Automatic	1	0	0	1	1
50		0	1	0	1	1
51		1	0	0	0	1
52		0	0	1	1	1
53		1	0	0	1	0
54		0	1	0	0	1
55		0	0	1	0	1
56		0	1	0	1	0
57		1	0	0	0	0
58		0	0	1	1	0

59		0	1	0	0	0
60		0	0	1	0	0
61	AWD 3.5 L, 6 cyl, Automatic	1	0	0	1	1
62		0	1	0	1	1
63		1	0	0	0	1
64		0	0	1	1	1
65		1	0	0	1	0
66		0	1	0	0	1
67		0	0	1	0	1
68		0	1	0	1	0
69		1	0	0	0	0
70		0	0	1	1	0
71		0	1	0	0	0
72		0	0	1	0	0
73	2.0 L, 4 cyl, Manual Diesel	1	0	0	1	1
74		0	1	0	1	1
75		1	0	0	0	1
76		0	0	1	1	1
77		1	0	0	1	0
78		0	1	0	0	1
79		0	0	1	0	1
80		0	1	0	1	0
81		1	0	0	0	0
82		0	0	1	1	0
83		0	1	0	0	0
84		0	0	1	0	0
85	2.0 L, 4 cyl, Automatic Diesel	1	0	0	1	1
86		0	1	0	1	1
87		1	0	0	0	1
88		0	0	1	1	1
89		1	0	0	1	0
90		0	1	0	0	1
91		0	0	1	0	1
92		0	1	0	1	0
93		1	0	0	0	0
94		0	0	1	1	0
95		0	1	0	0	0
96		0	0	1	0	0
97	2.5 L, 5 cyl, Manual Diesel	1	0	0	1	1
98		0	1	0	1	1
99		1	0	0	0	1
100		0	0	1	1	1
101		1	0	0	1	0
102		0	1	0	0	1
103		0	0	1	0	1
104		0	1	0	1	0
105		1	0	0	0	0
106		0	0	1	1	0
107		0	1	0	0	0
108		0	0	1	0	0
109	2.5 L, 4 cyl, Automatic Hybrid	1	0	0	1	1
110		0	1	0	1	1
111		1	0	0	0	1
112		0	0	1	1	1
113		1	0	0	1	0
114		0	1	0	0	1
115		0	0	1	0	1
116		0	1	0	1	0
117		1	0	0	0	0
118		0	0	1	1	0
119		0	1	0	0	0
120		0	0	1	0	0

Table IV: Fixed costs and production economies-of-scale information for each part/option

Part/option name	Fixed cost ($1,000)	Volume for all-unit quantity discount	Discount ($)
FWD 2.5 L, 4 cyl, Manual	10,800	37,000	180
FWD 2.5 L, 4 cyl, Automatic	12,000	50,000	200
FWD 3L, 6 cyl, Automatic	13,200	40,000	220
AWD 3L, 6 cyl, Automatic	15,300	16,000	255
FWD 3.5 L, 6 cyl, Automatic	16,500	12,000	275
AWD 3.5 L, 6 cyl, Automatic	18,000	25,000	300
2.0 L, 4 cyl, Manual Diesel	22,500	46,000	375
2.0 L, 4 cyl, Automatic Diesel	24,000	36,000	400
2.5 L, 5 cyl, Manual Diesel	25,500	20,000	425
2.5 L, 4 cyl, Automatic Hybrid	30,000	20,000	500
4-Door Body Style	4,500	95,000	75
2-Door Body Style	6,000	72,000	100
Hatch Back Body Style	4,500	60,000	75
Sunroof	3,600	130,000	60
Satellite Radio	2,400	135,000	40

Table V: Probabilities for different market scenarios

	Fuel price scenario 1	Fuel price scenario 2	Fuel price scenario 3
Scenario 1	0.1	0.4	0.5
Scenario 2	0.2	0.4	0.4
Scenario 3	0.3	0.4	0.3
Scenario 4	0.4	0.4	0.2
Scenario 5	0.5	0.4	0.1

Table VI: Average profit margin for different powertrain technologies

	Powertrain technology	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Conventional	FWD 2.5 L, 4 cyl, Manual	2900	2700	2500	2300	2100
	FWD 2.5 L, 4 cyl, Automatic	3400	3200	3000	2800	2600
	FWD 3L, 6 cyl, Automatic	3400	3200	3000	2800	2600
	AWD 3L, 6 cyl, Automatic	3200	3000	2800	2600	2400
	FWD 3.5 L, 6 cyl, Automatic	3400	3200	3000	2800	2600
	AWD 3.5 L, 6 cyl, Automatic	3500	3300	3100	2900	2700
Diesel	2.0 L, 4 cyl, Manual Diesel	2400	2500	2600	2700	2800
	2.0 L, 4 cyl, Automatic Diesel	2300	2400	2500	2600	2700
	2.5 L, 4 cyl, Manual Diesel	2200	2300	2400	2500	2600
Hybrid	2.5 L, 4 cyl, Automatic Hybrid	800	1300	1800	2300	2800