Modeling General Motors and the North American Automobile Market

Philip T. Keenan, Ph.D.
Senior Technical Director
GM Strategic Initiatives
General Motors Corporation
Mail Code 482-C09-C76
300 GM Renaissance Center
P.O. Box 300
Detroit, Michigan 48265-3000
Phone: 313-667-7175
FAX: 313-665-0528
phil.keenan@gm.com

Mark Paich, Ph.D.
Sim Learning/Decisio Consulting

March 24, 2004

Modeling General Motors and the North American Automobile Market

March 26, 2004

Contents

Abstract

This article discusses General Motors' North American *Enterprise Model*, a system dynamics model of the entire North American automobile market. The *Enterprise Model* takes a broad look across the corporation and its marketplace, combining internal activities such as engineering, manufacturing and marketing with external factors such as competition for consumer purchases in the new and used vehicle marketplaces. Eight groups of manufacturers compete monthly for a decade across eighteen vehicle segments, making segment-by-segment decisions about price, volume and investment. The model enables Monte-Carlo analysis of alternative strategies. The goal is to find and assess the likely impact of improved strategies for managing the business that are robust across uncertainty about consumers, competitors, and the macro-economy.

This article presents a high level overview of the model. We discuss why and how the model was built and what sorts of results came from it. We discuss software tools we wrote to supplement Vensim: a profiling tool for finding inefficient equation formulations, and a syntax coloring tool for automatically color coding Vensim sketch diagrams according to selected criteria. Finally, we discuss the limitations of the System Dynamics paradigm for large models, and how Agent Based Models might complement traditional system dynamics.

Keywords: automotive industry, system dynamics modeling, dynamic simulation, Monte-Carlo optimization, consumer choice, multinomial logit, product substitutes, brand loyalty

1 Background

GM Strategic Initiatives (GMSI) is a staff of General Motors Corporation responsible for analyzing major strategic initiatives for the company. As part of our work, we often develop detailed quantitative models of the auto industry or specific parts of it, in order to more accurately assess the likely impact of potential new strategies.

In the mid-1990's, Nick Pudar (recently Director of GMSI) developed a system dynamics model of the impact of leasing on the new and used vehicle markets for Ron Zarella (formerly President of GM North America). Nick's work is described in considerable detail in Chapter 2 of John Sterman's *Business Dynamics* textbook ([6]).

At Zarella's request, and with support from consultant Mark Paich of Decisio LLP, we at GMSI subsequently developed a larger and more comprehensive model of the entire North American vehicle market that combined internal activities such as engineering, manufacturing and marketing with external factors such as competition in the new and used vehicle marketplaces. Known as the GMNA *Enterprise Model*, it simulates eight groups of OEMs competing in 18 vehicle segments for the loyalties of hundreds of segments of consumers. Each manufacturer has an evolving portfolio of product offerings and the ability to make monthly decisions about segment-level price, production volume, and future product investment. The model enables Monte-Carlo analysis of alternative strategies. The goal is to find improved strategies for managing the business that are robust across uncertainty about consumers, competitors, and the macro-economy.

The rest of this article is organized as follows. Section 2 explains why GM decided to build an enterprise level model. Section 3 gives a high level overview of the model. Section 4 delves into the details of the consumer choice model, which is the most complex part of the model. Section 5 illustrates the kind of results that we obtained from the model – though of course the actual results are proprietary. Section 6 explains the reasoning that drove our decisions about level of aggregation and detail.

We built the *Enterprise Model* in Vensim, from www.ventana.com. Although Vensim has many powerful features for system dynamics modeling, it can be difficult to have confidence in the correctness of a very large model – or even to understand how all the parts of the model interrelate. Section 7 discusses some software tools we wrote to supplement Vensim, which helped us deal with such a large model: a profiling tool for finding inefficient equation formulations, and a syntax coloring tool for automatically color coding Vensim sketch diagrams according to selected criteria.

Finally, Section 8 discusses the limitations of the System Dynamics paradigm for large models, and how Agent Based Models might complement traditional system dynamics.

2 Why build an Enterprise Model?

The GM *Enterprise Model* was built to address senior management's problem of determining whether the organization's existing processes, policies, and special initiatives would generate acceptable performance. The model building process was also designed to prioritize broad options for performance improvement. In this case, the two key performance dimensions were market share and profitability. GM was aware that significant improvement was possible in several processes including quality, design, and manufacturing productivity. GM had implemented many successful improvement initiatives but there was concern whether the combination of these initiatives would satisfy the performance objectives.

From a system dynamics perspective, there were reasons for questioning whether the existing initiatives would be sufficient. First, SD stresses the concept of leverage and there was no guarantee that individual initiatives, however sensible, would span the high leverage points. Second, SD stresses the concept of policy resistance due to compensating feedback loops. Well-intentioned attempts to push the system to higher performance levels could be offset by compensating feedback effects.

The *Enterprise Model* was designed to integrate GM's best information into a single planning tool. GM spends significant resources collecting market research and competitive data in addition to its own cost and capacity information. The *Enterprise Model* attempted to pull all this information into a common framework so that it could be applied consistently to the analysis of alternatives. For example, GM does a quarterly study that allows the calculation of switching patterns between vehicle segments and competitors. We found that the switching matrix, when supplemented with data about price and feature elasticities, was a very powerful tool in understanding vehicle market dynamics. Our market model was relevant to many of the decisions that GM makes including product development and production. The *Enterprise Model* made our market model available for the analysis of choices across the entire company even if they were not strictly marketing decisions.

System dynamics was the chosen method because feedback effects and accumulation effects were believed to be important. GM does extensive financial modeling and has an extensive process for integrating forecasts from the vehicle line segments but interdependencies over-time and across vehicle segments were not well accounted for. For example, consumer decisions in the current year feedback to influence future decisions through the strong effect of brand loyalty. The brand loyalty effect is a well-known effect that is very difficult to implement in a financial model especially with multiple vehicle segments and changing vehicle attributes. Our modeling revealed that the brand loyalty mechanism makes a substantial difference in policy analysis. Including loyalty effects significantly changes the structure of good pricing, production, and product development policies.

3 High Level Structure

The *Enterprise Model* includes a number of sectors, described here only at a very high level. Roughly speaking, the model seeks to simulate macro-economic variables such as General Motors's annual profit from North American vehicle operations, from micro-economic analysis of supply and demand interactions at the vehicle segment level. The goal is to enable GM to test "what-if" scenarios in order to make better business decisions, just like the goal of more traditional spreadsheet models. However, unlike most spreadsheet models, the Enterprise model is able to incorporate a number of important dynamic effects, including the interaction of production, inventory, competitive pricing, sales, customer holding time, and the used vehicle market.

Figure 1 is a very high level view of the model.

The *Enterprise Model* puts all the players on a level playing field. Using Vensim's subscripting capability, all manufacturers have the same underlying structure. Each of the 8 manufacturers or groups of OEMs makes monthly choices about how to spend money, in each of 18 vehicle segments. They can spend money:

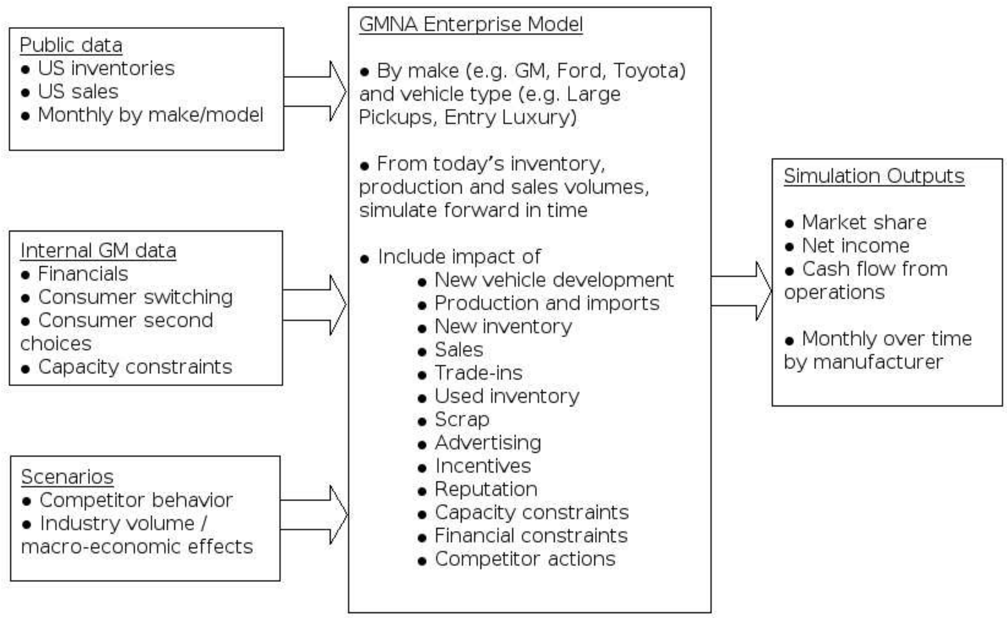

Figure 1: A very high level summary of the Enterprise Model

- in the form of engineering expense and capital, to enhance their future portfolio of vehicle programs
- in the form of material cost, to build actual vehicles in manufacturing plants,
- in the form of incentives, to change the transaction prices experienced by consumers, or
- on various other activities, such as marketing (e.g. advertising to consumers)

In addition, each incurs various ongoing expenses, such as wages based on the size of the Employees stock, and depreciation determined by the aging chain of past capital expenditures. These are not available for monthly decision making, since they are driven by underlying stocks, although it is possible for the players to choose to change those stocks gradually over time, e.g. through their human resource management policy.

Of course, each player also gets revenue from actually selling vehicles to dealers.

The model includes an accounting sector which combines all of these cash flows to replicate each player's income statement, so that model results can be calibrated against actual annual reports. It is important that this calibration occur, because it is normally the free cash generated from each company's operations that is available to fund future product development. Just as in real life, the simulated OEMs all face budget constraints based on their profitability.

In addition to these models of the internals of the OEMs, the *Enterprise Model* also has a large external sector. This sector tracks people and their vehicles over time.

Each vehicle moves through an aging chain from production to dealer inventory to its first owner's driveway, to being traded in to become "near new" inventory, to its second owner's driveway, to being "used" inventory, a third owner, and so on, until it finally is scrapped.

People are more complex. They can own or lease a vehicle, or not have one at all. We track how long they have had the vehicle, and when they have had it "long enough", they can trade it in and choose another. The consumer choice process is quite elaborate and will be described more fully in the next section; it includes a mixture of the following influences:

- Current prices of all new and used vehicle choices this month
- Availability (in dealer inventory) of the choices
- Loyalty (i.e. a propensity to repurchase the same type of vehicle from the same manufacturer as last time, all else equal)
- Substitution Effects

The substitution effects are particularly important for accurate assessment of the impact of price-changing strategies involving incentives. For example, Cadillac buyers are unlikely to be influenced by price changes on the Chevy Cavalier or Honda Civic, but they may well pay attention to price changes on the Lexus. The *Enterprise Model* actually captures these effects using detailed market research data collected by General Motors, which measures the cross-substitutability of all pairs of products in the market, both GM and non-GM.

Finally, the model must predict industry volume. An econometric model might try to regress industry volume against the growth in GDP, the rate of employment, and other economic indicators. Although the *Enterprise Model* incorporates such a regression as a starting point for consumer's willingness to trade in their current vehicle, it is only a starting point: actual industry volume and player market shares are *outputs* of the model which depend not only on the "external" macroeconomy, but on the response of vehicle manufacturers, who can impact volume through changes in price.

4 The Consumer Choice Model

Most of the *Enterprise Model* consists of relatively simple structures, the complexity largely occurring in the multiple subscripts. For instance, vehicle development programs, actual vehicles, and capital investments all move through appropriate aging chains. The whole accounting side of the model simply multiplies flows by their unit costs or revenues and adds them up to compute profit and loss. However, the consumer choice section of the model is considerable more complex.

Conceptually, the model simulates a large number of consumers. Some currently own or lease a new vehicle, such as a GM large pickup or a Toyota luxury car. Some currently are the second or third owner of a used vehicle. Some currently have no vehicle at all. Each month, those consumers who have held their vehicle for a long while now evaluate whether they wish to trade it in for something else. To do so, they look at current trends in incentives as well as at the prices and features available to them in new and used models. They factor in their loyalty to their current make and their continuing need for a specific type of vehicle. Their decisions are based on a generalized multinomial logit equation described in [5], calibrated with elasticity and cross-elasticity information. These are in part extracted from a large database of survey information that identifies consumers' second choice preferences. In addition, this database allows us to quantify loyalty effects through measuring the probabilities of switching between manufacturers or vehicle segments. Finally, the generalized logit is calibrated to current market shares for each alternative in the new vehicle market.

The used vehicle market is simulated based on supply and demand. Specifically, when consumers trade in vehicles, the used vehicles are added to the stock of used inventory. As this stock rises, used prices fall to compensate, until enough would-be new car buyers are lured away to the used market to restore equilibrium. Conversely, if there are very few used vehicles available in a given market segment relative to demand, then their price rises.

This dynamic coupling makes it possible to observe a variety of effects. For example, if one manufacturer cuts price on a particular segment of vehicles, it gets an initial boost in sales which gradually declines over time as the used market cuts price to compensate. Thus used prices follow new prices, though with a lag and a reduced amplitude. Moreover, the model simulates competitive reactions, such as the possibility of other manufacturers cutting price as well, in response to the loss in share they might experience. Because we incorporate second choices, this price response can be modeled much more accurately than a standard logit model would permit. For instance, if Honda cuts price on an inexpensive model like the Civic, luxury models like Lexus should lose little if any share, because they are not close substitutes.

To help visualize consumer preferences, we often build graphs like Figure 2. This example shows a small portion of the complete second choice matrix used in the Enterprise Model, although the data has been randomized to protect proprietary information – real consumers are unlikely to follow any of the patterns illustrated for discussion purposes in the graph shown here. The graph is based on a continuously updated market research survey of a very large number of consumers. Bubbles represent choice alternatives, such as a "GM Large Pickup". Arrows denote second choices, with thicker arrows denoting greater volumes. A complete graph could involve perhaps 200 choice alternatives, with almost 40,000 arrows, which would be as hard to interpret as the corresponding 200 by 200 matrix of numbers. Instead, we graph just the highlights. For instance, we typically suppress all arrows below some threshold in size, concentrating on only the primary interactions. Similarly, in this example we suppress arrows that do not have a GM segment on at least one end – that is, we leave out interactions between say Ford Large Pickups and Ford Medium Pickups. Moreover, the present graph focuses on just a few of the 18 vehicle segments used in the model. One can observe interesting patterns in the real data. In the randomized data shown here, it looks as though the various makes of luxury cars are close substitutes for each other, with a lot of back and forth connections, while there is sufficiently little substitution between luxury and small car models that no arrows are shown connecting them in either direction.

Switching patterns are critical to auto manufacturers and there is much discussion and analysis of brand loyalty. However, marketing models rarely integate switching dynamics with attribute-based models of vehicle choice. Because they have such broad portfolios of partially interacting vehicles, dropping price on one model in an attempt to conquest sales from another manufacturer may in fact result simply in diverting or cannibalizing one's own sales of another model. Thus,

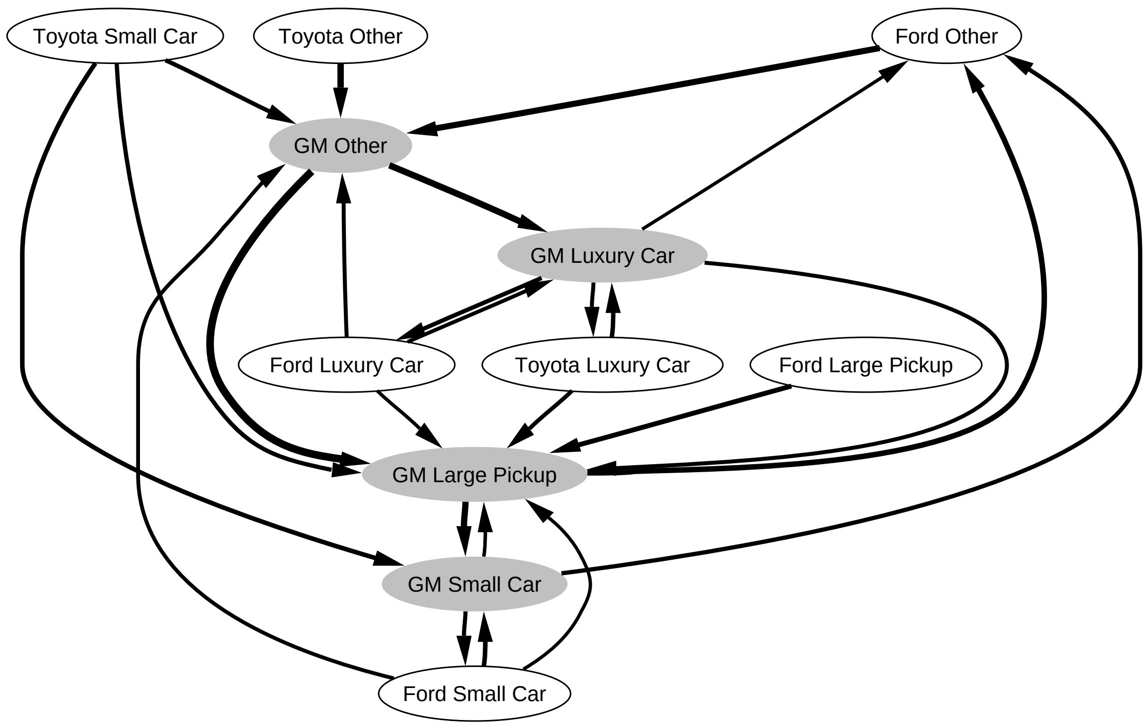

Figure 2: A small piece of a RANDOMIZED second choice matrix

patterns of second choices or *diversions* are very important in accurately assessing the likely impact of alternative marketing strategies.

In fact, though, the situation in the Enterprise Model is even more complex, because consumers can also choose between both new, off-lease, and used vehicles of various ages.

Moreover, brand loyalty plays an important role. Taking a different approach from [3], we implement the loyalty effect by conditioning all the switching calculations on the type of the consumers' present vehicle. In other words, we track separately the population of people who currently own each type of vehicle, so when they come around to trade in their old vehicle and buy a new one, we know their old vehicle type and manufacturer. They make choices using an incremental logit calibrated to the observed switching probabilities of real people who traded in that sort of vehicle, further adjusted for any changes in price since the survey was conducted. We can visualize a switching matrix in much the same way as in Figure 2.

As yet another complexity, the size of the new vehicle market shifts over time in response to the interplay of macro-economic factors (e.g. consumer confidence and unemployment) with the affordability of vehicles (as influenced, in part, by the incentives offered by the manufacturers on new vehicles, and the compensating discounts thereby forced onto the used market by supply and demand). As a result, simulated consumers must also judge (each time step) whether to have a vehicle at all (new or used), or whether to rely on public transportation until the economy improves. Those who lease or buy then keep their vehicle for an appropriate period of time (e.g. the lease term, or a randomly distributed holding time for outright owners), before trading it in and coming back around to the choice part of the model.

5 Results

In this section we will illustrate the qualitative and quantitative insights we can derive from the model.

On the qualitative front, as with any systems dynamics model, one can examine behavior patterns, look for feedback loops, test assumptions, and come up with insights. For example, *incentives are addictive*. This comes about because the behavior rules governing pricing behavior have an element of prisoners dilemma. The behavior rules in the *Enterprise Model*, based on observation of actual industry behavior, suggest that pricing decisions come from balancing a variety of pressures, including the desire to grow market share, the desire to keep plants utilized, and the need to be profitable. If any one manufacturer takes price up in a given segment, it loses disproportionate volume to those who do not follow. This creates strong pressure not to raise price. Moreover, the desire to grow share puts constant downward pressure on prices.

Another part of the equation is the "pull-ahead effect": in the model, consumers come to expect a certain price level. If prices fall below that level temporarily, they perceive a "sale", and are more likely to buy now. If prices rise above it, they decide to wait and buy next month when prices, they expect, will come back down. If one OEM were to raise price unilaterally, it would be hit twice – not only might some shoppers switch to competitors, but even "loyal" consumers might decide to postpone their next purchase temporarily. The resulting fall in volume would then pressure the player to abandon the price increase.

The outputs of the model include forecasts of volume, market share and profitability for each manufacturer, broken down by vehicle segment. One can also observe the overall size of the vehicle parc (that is, the number of vehicles "in circulation"), as well as numerous specific internal details describing the state of manufacturer operations.

Of course, in the real world there is a great deal of uncertainty surrounding many of these points. No one knows how the macro-economy will evolve, let alone how consumer tastes will shift or even what specific new models each manufacturer will launch over the next decade.

Therefore, the next layer of complexity is that we run the Enterprise Model in a Monte-Carlo fashion, coming up with not a single point forecast for demand but rather a large number of possible scenarios. Each one differs in for instance the future course of the economy, and the relative hit-or-dud nature of new product releases. However, all scenarios share the consistent framework of manufacturers producing vehicles and adjusting their relative prices in tandem with consumers making purchase choices. Figure 3 illustrates the output of such a run – in place of a single line graph over time, we can plot confidence intervals showing the likely range of outcomes.

We can think of this as a way to obtain a probability distribution for outcomes such as GM's profitability over the next decade, given a specific set of policies guiding GM's simulated behavior inside this complex market.

Finally, we add an optimization layer, which seeks to find an improved set of policies for guiding GM's investment, production and marketing decisions, such that the overall probability distribution of profit outcomes shifts to the right – in other words, we seek policies that are more likely to make GM more profitable overall.

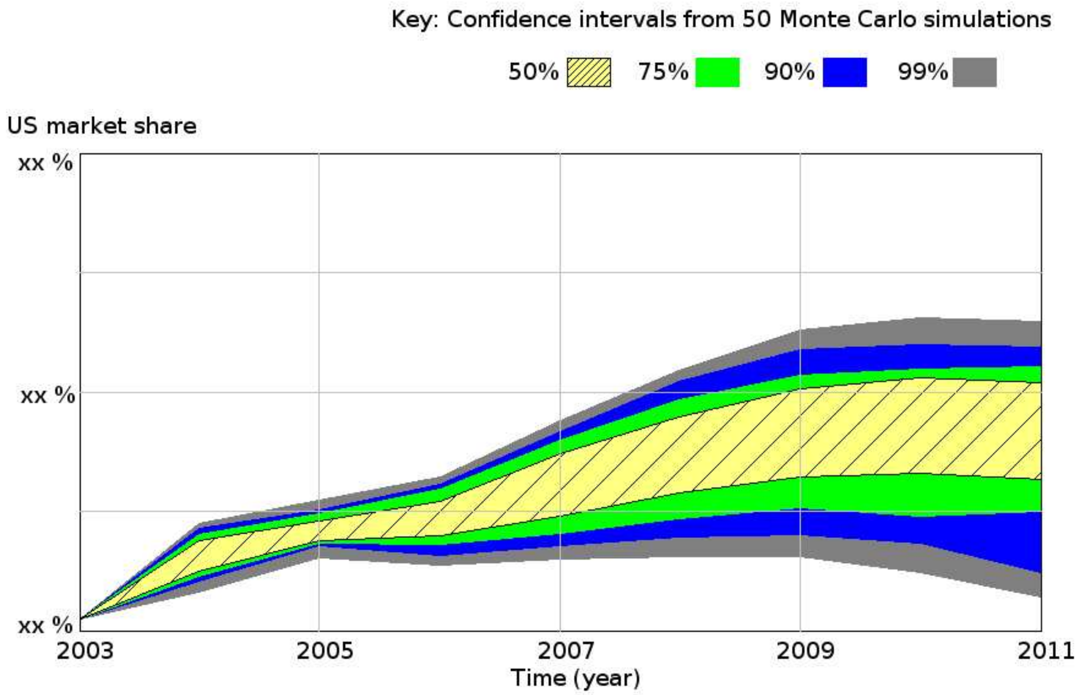

Figure 3: Confidence bounds on market share given a particular operating policy

The goal is to create graphs such as Figure 4. This example shows that Strategy B, while still subject to many sources of uncertainty, tends to produce more profit than Strategy A. Not only is the mean higher with B, but the whole curve shifts to the right. This means that the higher expected profit does not come at the expense of taking on a higher risk of really bad downside outcomes. This sort of graph enables senior management to make an informed comparison and choose their preferred strategy with much more information than a single point forecast would provide.

6 Why Model So Much Detail?

General Motors extends beyond GM North America into overseas regions like Europe and Asia, and beyond Automotive into Financial Services through the General Motors Acceptance Corporation (GMAC), which handles vehicle leasing and financing, as well as insurance and even home mortgages.

Despite its name, we knew from the start that we would need to limit the scope of the *Enterprise Model* to North American Automotive operations. We initially made the model much simpler,

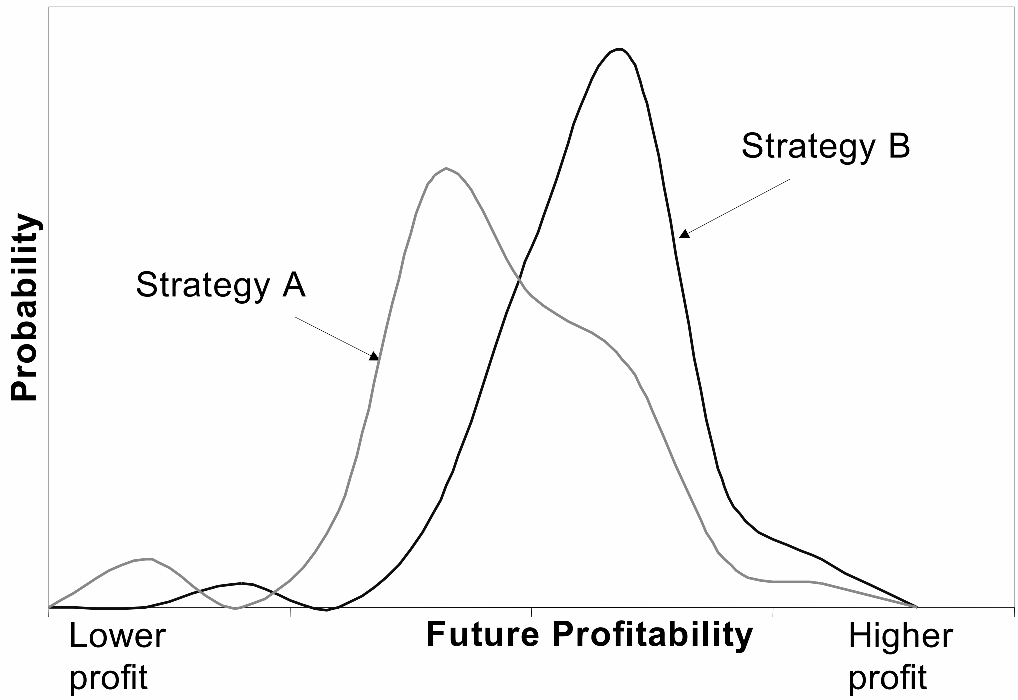

Figure 4: Comparison of an initial policy (A) and an improved policy (B)

representing just GM and "the competition" (instead of 8 different groups of OEMs) and only distinguishing "cars" and "trucks" (instead of 18 vehicle segments).

Unfortunately, while this simple model contained all the basic dynamic features of the full model, and hence sufficed to demonstrate general principles such as "incentives are addictive", it was insufficiently rich to satisfy busy senior executives who are constantly confronted with questions at the level of specific models, specific plants, and specific geographic regions.

General Motors is a large and complex organization, and it collects and utilizes a large and complex set of data in decision making. The *Enterprise Model* still leaves out many important factors, most notably geography and the detailed operation of dealerships. Even with 8 manufacturers and 18 vehicle segments, various terms of leases and outright ownership, the new and used markets, and so forth, the model still falls short of providing the level of detail needed in many parts of the organization. Indeed, we have subsequently built even more detailed models of specific parts of the organization, such as the revenue management process, the dealer network, the vehicle development process, and the human resource system, to provide answers to more focused and function-specific questions. The bottom line is that for this problem, significant detail around competitors and vehicle segments was the price of entry into senior management decision making. Because the price, cost, and regulatory constraints are very different between vehicle segments, market performance could not be assessed with a simple model.

7 Tools for Building Complex Models Robustly

We built the *Enterprise Model* in Vensim. While Vensim is a great tool for traditional system dynamics models, we wished it had a number of additional capabilities to help us reliably manage such a large model. Since it did not, we provided some of the missing capabilities ourselves, in the form of auxiliary programs (Perl scripts) that read in the text form of the Vensim model file and either assessed it or enhanced it.

7.1 A Vensim Profiler Tool

It was particularly important that the consumer choice sector be efficient. To get a feel for scope of the consumer choice sector, consider the size of the choice set used in the *Enterprise Model*. We partitioned the vehicle market into roughly 10 (in round numbers) major manufacturer groups, such as GM, Ford, Toyota, and so on. These multiply against the partition of vehicle offerings into roughly 20 vehicle segments, such as Large Pickups and Small Cars. Already this means there are 200 alternatives in the choice set. Multiply this by another 10 or so choices between new, used, and various lease durations. Multiply by another 200 if we want to include loyalty effects in the consumer choice process. Moreover, if we want to simulate in monthly time steps for a decade, we will need 120 iterations of this consumer choice calculation, resulting in on the order of 10^7 computations, each involving at least an exponentiation. And this is before we try running an optimizer that may try hundreds of runs with different parameters!

The profiling tool reads a vensim model and estimates the relative CPU time and memory requirements for each equation in the model. To do this, it reads the text version of the model and parses the equations into their constituent variables, subscripts, functions and mathematical operators. It then estimates the number of arithmetic operations and the number of bytes of storage required by the equation. It prints out a large table of results. We then use Microsoft Excel to sort the results, pinpointing which equations are likely bottlenecks. This approach enabled us to improve the run time of the model by roughly an order of magnitude, because we discovered that the way you write equations in Vensim can have a big impact on their run time. For example, the equation

```
marketshare[make] = volume[make]/sum(volume[make!])
```

actually computes the sum of the volumes 8 times, once per make, even though it is the same sum each time. This equation will run faster if you re-write it as the pair

```
totalvolume = sum(volume[make!])
marketshare[make] = volume[make]/totalvolume
```

because now the sum is computed only once. In this simple example, it makes no real difference, but in the *Enterprise Model*, a typical equation involved 5 or 6 subscript ranges simultaneously, so the impact of this sort of code rewriting is magnified enormously. Thus, Vensim modelers who have a background in programming in languages such as C or Fortran should be aware that Vensim does not automatically perform the sorts of code optimizations, such as common subexpression removal, that many modern compilers perform. Instead, Vensim modelers should explicitly factor out common subexpressions and assign them to temporary variables.

Just as when profiling C or Fortran code, we found that the distribution of CPU time and memory is very skewed – in a model like Enterprise, the top few equations may take as much resources as all the rest combined.

7.2 A Vensim Syntax Coloring Tool

The syntax coloring tool reads the Vensim model file in text format, parses the equations so it understands what variables depend on what others, and then writes the model back out, with some changes in the sketch portion of the file that determine the color of objects in the view. This allows a number of interesting possibilities, such as coloring the model according to

- Inputs and Terminals. In a large, multiple-view model, it is no longer easy to tell whether a particular variable is used by others, or whether a shadow variable is a raw input or a calculated quantity.
- Units. One can color the vehicle aging chain differently from the consumers or from the accounting/financial ones by keying the colors off of the units (vehicles, people, money).
- Bugs. One can color code variables according to whether the equation is missing units, or whether it contains inefficient formulations such as unused subscripts on the left hand side of an equation, or whether it contains likely bugs, such as multiplication by zero within an equation to "temporarily" turn off certain terms.

8 Limitations of the System Dynamics Approach

Returning to our estimate in Section 7 of the computational complexity of the model, if we make 100 random Monte-Carlo draws from the model for each policy, and if the optimizer tests 1000 alternative policies, then we need a total of 10^5 runs, each of which involved 120 consumer choice calculations across a large set of alternatives. Even neglecting some of the complexities mentioned above, such as the interaction with the used market, we see we need about 10^7 consumer choice computations among around 10^3 alternatives in order to do a single policy optimization run. In order that we be able to learn by assessing the results, making changes to the model and iterating the process, a policy optimization run cannot take longer than overnight. Thus it becomes important that the consumer choice process be time efficient.

Unfortunately, these considerations severely limit the scope of what we can model using a system dynamics "stock and flow" approach. For instance, we would like to model consumers at the level of individual households. We would like to track how many vehicles are in the household's fleet, when they were purchased, and what kind they are, because all of these factors influence their subsequent purchase behavior. We would also like to track their past history, because hysteresis effects can be very important. For example, if an OEM offers poor quality vehicles, dissapointed customers may be come permanent "avoiders", who refuse to try that OEM's vehicles in the future – even if the OEM brings its quality level back up. Their past experience keeps them from trying the more recent – and significantly higher quality – offerings. Similarly, the number of vehicles in the fleet is very important – sales rose considerably as Americans shifted from one vehicle per family to two over the last couple decades, and manufacturers would love to see the trend continue.

Consider trying to model these effects *in detail*. We emphasize *in detail* since as discussed above, it is not sufficient to build a classical unsubscripted SD model at the "conceptual" level to discuss "avoidance" and similar behaviors qualitatively – senior executives are well aware of the existence of the reinforcing feedback loops. Their question, instead, is where specifically shall we intervene – where shall we place our scarce resources, given GM's huge portfolio competing for attention (depending on how you count them, GM offers many dozens of models, with a dozen or so new ones launched each year, all of which compete for investment, incentive and advertising dollars).

In detail, if each household can have 0, 1, 2, or 3 vehicles in its fleet, and if each vehicle is categorized as being in one of 10 manufacturer groups, and one of 10 vehicle segments, and one of 10 age groups, then we need 10^3 buckets to categorize one vehicle, and 10^9 buckets (subscripted stocks) to categorize the possible combinations of up to 3 vehicles in one household's driveway. At this point, there are more buckets than there are vehicles in America! Thus, the bucketing approach characteristic of system dynamics models, quite sensible in the 1960's as a way to save computer time, can become a limitation in the 2000's when computer time is cheap.

For this reason, we are now turning our attention toward Agent Based modeling. In the agent based approach, we model each vehicle and each household individually. This puts an upper bound on the number of agents we need to consider, regardless of how much information we want to keep track of – the combinatorial explosion problem goes away. Software packages like *AnyLogic* by XJTek allow us to build agent based models efficiently, while preserving our ability to use system dynamics approximations (aggregating individual events into a continuous flow and solving the resulting differential equations) where appropriate, seamlessly integrated into the agent framework. We expect this hybrid approach to bear great fruit over the coming years.

9 Conclusion

Over the years, we have built a wide variety of quantitative models at General Motors in support of improved managerial decision making. They involve a variety of approaches, including system dynamics, agent based modeling, game theory, and real options. No one approach is ideal for all problems. Some problems require a mixture of approaches. Many problems do not even require building a model, but can be solved successfully with back of the envelope analysis. We have written this article about one particularly complex model, the *Enterprise Model*, in the hope that other modelers will find it interesting to see the sorts of issues we have addressed, the kinds of approaches we have taken, the type of results we have obtained, and to understand some of the limitations of the approach.

References

[1] Anderson, Simon P.; De Palma, Andre; and Thisse, Jacques-Francois: Discrete Choice Theory of Product Differentiation MIT Press 1992.

[2] Ben-Akiva, Moshe and Lerman, Steven R.: Discrete Choice Analysis: Theory and Application to Travel Demand, MIT Press 1985.

[3] Bordley, Robert: *Relaxing the Loyalty Condition in the Colombo / Morrison Model*, Marketing Science 8,1 (1989).

[4] Brownstone, David and Train, Kenneth: *Forecasting new product penetration with flexible substitution patterns*, Journal of Econometrics 89 (1999) pp. 109–129.

[5] Keenan, Philip T.: *Incorporating Second Choice Data Into Logit Consumer Choice Models*, submitted for publication.

[6] Sterman, John: Business Dynamics: Systems Thinking and Modeling for a Complex World, McGraw-Hill/Irwin 2000.

[7] Warren, Kim: Competitive Strategy Dynamics, John Wiley & Sons 2002.