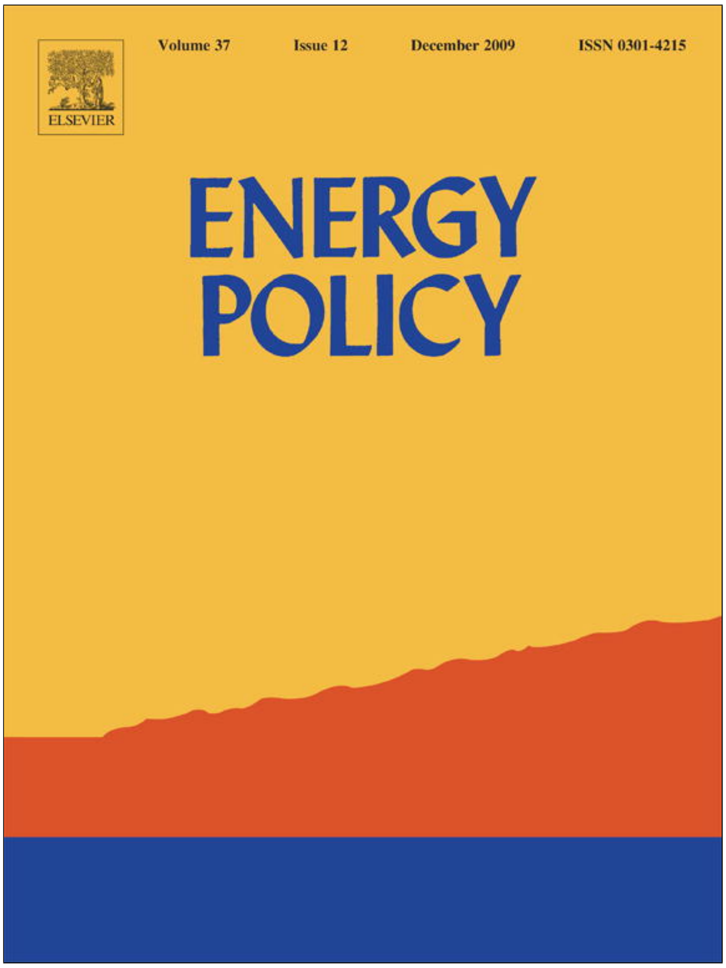
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Diversification in the driveway: mean-variance optimization for greenhouse gas emissions reduction from the next generation of vehicles

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ABSTRACT

Modern portfolio theory is applied to the problem of selecting which vehicle technologies and fuels to use in the next generation of vehicles. Selecting vehicles with the lowest lifetime cost is complicated by the fact that future prices are uncertain, just as selecting securities for an investment portfolio is complicated by the fact that future returns are uncertain. A quadratic program is developed based on modern portfolio theory, with the objective of minimizing the expected lifetime cost of the "vehicle portfolio". Constraints limit greenhouse gas emissions, as well as the variance of the cost. A case study is performed for light-duty passenger vehicles in the United States, drawing emissions and usage data from the US Environmental Protection Agency's MOVES and Department of Energy's GREET models, among other sources. Four vehicle technologies are considered: conventional gasoline, conventional diesel, grid-independent (non-plug-in) gasoline-electric hybrid, and flex fuel using E85. Results indicate that much of the uncertainty surrounding cost stems from fuel price fluctuations, and that fuel efficient vehicles can lower cost variance. Hybrids exhibit the lowest cost variances of the technologies considered, making them an arguably financially conservative choice.

1. Introduction

Global climate change is a topic of great and growing concern, both to planning professionals, and the public whom they serve. The transportation sector is widely regarded as one of the principle culprits behind greenhouse gas (GHG) emissions, and indeed it accounted for 28% of the United States' GHG emissions in 2006 (US Environmental Protection Agency (EPA), 2008). The research community has put forward a daunting array of potential solutions, each with its own costs and benefits (Greene and Schafer, 2003). In addition to possible improvements to system efficiency, scientists and engineers have developed engine technologies (such as the gasoline–electric hybrid), and methods of producing alternative fuels (such as ethanol).

Policy makers are faced with the difficult task of assessing which engine technologies and fuels are the wisest choices for the next generation of vehicles. At first, it might seem that the most sensible approach would be simply to calculate how much greenhouse gasses can be reduced per dollar spent on each potential improvement. Improvements could then be selected, starting with the most cost efficient, until a satisfactory emissions reduction is achieved. Given the resulting "environmental to do list," policy makers could determine what subsidies and regulations are appropriate.

Constructing such a list becomes much more challenging when we acknowledge the high level of uncertainty surrounding vehicle and fuel prices. Furthermore, the costs of different fuels and vehicles are not necessarily independent of each other. If gasoline–electric hybrids are less expensive than we predict, there is a good chance either pure gasoline or pure electric vehicles will also be cheaper, because of the shared materials and manufacturing processes.

Selecting a subset of available options in the face of uncertainty can be a challenging task, but government planners are not the only people facing it. Financial analysts deal with similar obstacles in constructing portfolios. Based on the groundwork laid by Markowitz (1952), modern portfolio theory (MPT) seeks to maximize the expected return, while minimizing risk. MPT takes advantage of correlations between the performances of securities to reduce the overall variance of the return of the portfolio. In his famous paper "Portfolio Selection", published in the *Journal of Finance* in March of 1952, Markowitz introduced modern portfolio theory by arguing that the paradigm of simple return maximization was inherently flawed. It led to naive portfolios with unnecessary levels of risk. He demonstrated quantitatively that diversification could substantially mitigate risk. The model he built sought to provide an efficient frontier of

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portfolios that maximized the expected discounted return, given an acceptable level of risk, represented by the variance of the portfolio (Markowitz, 1952). This concept and the formulation behind it form the foundation of MPT. Although it is most commonly applied to financial markets, MPT can also offer profound insight to other fields. Robison and Brake (1979) applied MPT to analyzing farmer and lender behavior, while Bridges et al. (2002) used MPT to enhance cost-effectiveness analysis of multiple health care procedures.

Modern researchers have applied MPT to environmental decision making as well. Environmental policies must be decided despite significant uncertainties, ranging from the cost and effectiveness of equipment to the magnitude of the health impacts of a pollutant. Researchers have sought to use MPT to minimize risk deriving from such uncertainties in selected cases. Springer (2003) applied MPT to Kyoto protocol mechanisms for GHG emissions reduction. Using quadratic programming, Springer performed a case study on Swedish pilot projects on boilers, finding that portfolio diversification can ameliorate the risks associated with Kyoto protocol mechanisms. Awerbuch (2006) applied MPT to electricity generation planning. He constructed a tradeoff curve to illustrate energy portfolios that maximized return (kWh/cent) for a given level of portfolio financial risk (standard deviation of costs). Awerbuch argued that this risk is important because volatility in energy price is able to depress an economy. MPT was found to be a valuable tool, capable of demonstrating how renewable energy sources can reduce risk, or, for a given level of risk, increase the return. Neither Springer (2003) nor Awerbuch (2006) addressed transportation sector issues, however.

This paper seeks to apply MPT to the problem of selecting the next generation of vehicles. MPT will allow planners to balance the desire for vehicles with low expected cost (akin to maximizing return), with the desire to be certain of cost predictions (akin to the desire to avoid risk in a financial portfolio). Uncertainty around cost predictions can be reduced through selection of technologies with low (or negative) cost correlations, as well as by avoiding fuels with highly volatile prices. This could include reducing dependence on oil, either by selecting more fuel efficient vehicles, or by using alternative fuels, or both. Greater certainty regarding cost can come at the expense of higher expected cost, however. The model presented can produce tradeoff curves showing the relationship between expected cost and the uncertainty of the cost. Additionally, GHG reduction targets are included, which can be viewed as comparable to ethical investing rules.

The model formulation will be presented next. A case study on light-duty passenger vehicles in the United States will follow. Finally, conclusions will be discussed and future research options considered.

2. Model formulation

2.1. Model overview

The model is designed to quantitatively represent the selection of the next generation of vehicles. It is designed to construct national "target" portfolios, given the objective and constraints. It is not intended to model the consumer's decision making process. A policy maker could use the model when deciding which vehicles to encourage people to buy. Vehicles in the initial fleet are assumed to be retired over time until none of the initial vehicles remain. The "next generation" of vehicles is defined as all vehicles purchased before the initial fleet is retired. The costs and emissions of new vehicles are tracked from their purchase until their retirement.

2.2. Sets

The set I (indexed by i or k) includes all general vehicle categories considered. Categories could include passenger cars, light trucks, heavy trucks, school buses, etc. The planner can decide how many categories are needed to represent the fleet. Vehicles within a category are assumed to be interchangeable as far as meeting the basic demands of the users (i.e., they can transport the same quantities of people and goods at comparable speeds). Vehicles in the same category need not have the same emission rates, use the same kind of engine or fuel, operate with the same fuel efficiency, or cost the same amount.

The set T (indexed by t or s) includes all time periods in which emissions are being tracked, or when vehicles can be bought. The first period is period 1. The period after which the entire original fleet has been replaced is called t_f. This is the last period in which purchases are modeled. The period when the last "next generation" vehicles retire is called t_r.

The set J (indexed by j or l) includes all vehicle technologies available. This could include conventional gasoline or diesel, as well as new engine technologies (e.g., gasoline–electric hybrid) or alternative fuels (e.g., bio-fuels). For example, a Toyota Prius would fit into the general category of passenger car, with the technology being grid-independent (non-plug-in) gasoline–electric hybrid.

The set P (indexed by p or q) includes all potential cost components incurred over a vehicle's lifetime (e.g., vehicle purchase, maintenance, fuel).

2.3. Parameters

- F_{ij} number of vehicles in category i using technology j in the initial fleet
- N_{it} number of vehicles in category i needed in the fleet during period t (N_{it} only need be defined for $t \leq t_f$)
- M_{it} expected number of miles a vehicle in category i will travel in period t
- r_{ijt} number of vehicles from initial fleet in category i using technology j that will be retired at the start of period t (r_{ijt} need only be defined for $t \leq t_f$)
- E_{ijt} "well-to-wheel" GHG emissions rate (grams/vehicle-mile) of a vehicle in category i, using technology j bought at the start of period t (includes emissions from fuel production, refining, transport, and use)
- c_{ijtp} expected value of the discounted (to the start of period 1) cost component p for a vehicle in category i, using technology j, bought at the start of period t
- d_i duration (number of periods) that a vehicle in category i will remain in use
- σ_{ijtp} standard deviation of the cost for which c_{ijtp} is the expected value
- $\rho_{ijtp,klsq}$ correlation of the costs for which c_{ijtp} and c_{klsq} are the expected values
- u_{ijt} highest number of vehicles in category i that can be bought with technology j at the start of period t (u_{ijt} is set to 0 if technology j is not compatible with category i)
- G maximum acceptable lifetime GHG emissions from the next generation of vehicles
- V maximum acceptable variance of the lifetime financial cost of the next generation of vehicles

2.4. Variables

B_{ijt}number of vehicles in category i, using technology j, bought at the start of period t (B_{ijt} is only defined for $1 \leq t \leq tf$).

2.5. Constraints

Each B_{ijt} variable must be between zero and its upper bound.

$$0 \le B_{ijt} \le u_{ijt} \forall i \in I,\ j \in J,\ t \in 1 \ldots t_f \tag{1}$$

At the start of every period up to t_f, vehicles retire, and purchases must continue to provide enough vehicles to meet the demand for every category. This must hold true despite any growth in demand.

$$N_{it} = \sum_{j \in J}(F_{ij} - \sum_{s=1}^{t} r_{ijs}) + \sum_{j \in J} \sum_{s=\max\{1,t-d_i+1\}}^{t} B_{ijs} \forall i \in I,\ t \in 1 \ldots t_f \tag{2}$$

Additionally, the planner can enforce a cap on the total emissions from the next generation of vehicles.

$$\sum_{s \in 1 \ldots t_f} \sum_{i \in I} \sum_{j \in J} \sum_{t=s}^{s+d_i-1} B_{ijs} \cdot M_{it} \cdot E_{ijs} \le G \tag{3}$$

Finally, the planner can enforce a cap on the uncertainty around the financial cost. This is accomplished by requiring that the variance of the cost of the vehicle portfolio (the left side of expression (4)) is less than the variance cap, V.

$$\sum_{i \in I} \sum_{j \in J} \sum_{t=1}^{t_f} \sum_{p \in P} \sum_{k \in I} \sum_{l \in J} \sum_{s=1}^{t_f} \sum_{q \in P} B_{ijt} \cdot B_{kls} \cdot \sigma_{ijtp} \cdot \sigma_{klsp} \cdot \rho_{ijtp,klsp} \le V \tag{4}$$

2.6. Objective function

The objective is to minimize the expected total financial cost of the next generation vehicles, given by expression (5).

$$\sum_{t=1}^{t_f} \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} B_{ijt} \cdot c_{ijtp} \tag{5}$$

2.7. Supplementary constraints

The model framework is flexible enough to allow for a wide range of supplementary constraints. For example, a planner may, for energy security reasons, want to ensure that a certain number of vehicles bought every year are capable of using a domestically produced fuel. The planner can simply call this lower bound ψ, the subset of vehicle options using domestically produced fuels J_{df}, and add the linear constraint given in expression (6).

$$\sum_{i \in I} \sum_{j \in J_{df}} B_{ijt} \ge \psi \quad \forall t \in 1 \ldots t_f \tag{6}$$

3. Case study

3.1. Overview

The case study is designed to represent the selection of the next generation of light-duty passenger vehicles in the United States. The primary sources of vehicle inventory and activity data were the EPA's Motor Vehicle Emission Simulator (MOVES) model and the US Department of Energy's (US DOE's) *Transportation Energy Data Book* (Oak Ridge National Laboratory, 2007). The primary source of emission rate data was Argonne National Laboratory's Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model. Cost and fleet data were taken from a variety of sources, many of which were produced by the US DOE.

For this case study, the length of one period is one year. Vehicles bought or retired in a given year are modeled as bought or retired at the start of the next year. An annual interest rate of 4% is used to discount costs. This is the default interest rate on the US DOE's HEV Cost Calculator Tool (US DOE, 2008).

3.2. Inputs—vehicle categories

Light-duty vehicles are broken into two categories from the MOVES model: passenger cars and passenger trucks. When using US DOE data (such as that from the GREET model, and the *Transportation Energy Data Book*), they are associated with the categories of passenger cars and light-duty trucks 1 (gross vehicle weight less than 6000 lbs), respectively. GREET documentation associates light-duty trucks 1 with midsize SUVs (Argonne National Laboratory, 2007).

3.3. Inputs—vehicle technologies

The case study is designed to examine several near-term technologies which can be implemented widely in the next generation of vehicles. They are conventional gasoline vehicles, conventional diesel vehicles, grid-independent (non-plug-in) gasoline–electric hybrid vehicles, and flex-fuel vehicles running on E85 (E85 FFV). All four are currently commercially available, but the first dominates the light vehicle fleet in the US. Other technologies were excluded because they were not deemed near-term enough, or due to a lack of suitable data sources.

3.4. Inputs—initial fleet and projected usage

The initial fleet was designed to represent the cars and light-duty passenger trucks operating in the United States during the 2008 calendar year. For simplicity, this initial fleet is modeled as 100% conventional gasoline powered. While it is true that hybrid sales have seen rapid growth, they only recently began to account for more than 1% of US vehicle sales, and consequently make up only a very small portion of the current fleet (CBS News, 2006). Diesel engines make up a large portion of heavy-duty vehicles in the US, but they are uncommon in light trucks and quite rare in cars. Diesels have made up less than 1% of US car sales every year from 1985 to 2005 (Oak Ridge National Laboratory, 2007). Approximately 3.7% of trucks under 10,000 lbs sold in the US in 2005 were diesel powered (Oak Ridge National Laboratory, 2007), and the percentage is quite possibly even lower for trucks under 6000 lbs.

Data on historic new car and light-duty truck sales are taken from the *Transportation Energy Data Book*. Future sales are projected using "SalesGrowthFactor" parameters from the MOVES model (US EPA, 2004). Median vehicle lifetimes and survival rate distributions are drawn from the *Transportation Energy Data Book*, as are historic data on the number of cars in use.

The number of trucks in the initial fleet is estimated based on historic sales and light-duty truck survival rates (which have remained relatively constant with respect to model year in recent history) (Oak Ridge National Laboratory, 2007). Car survival rates, on the other hand, have been increasing (Oak Ridge National Laboratory, 2007). The number of cars in the initial fleet was based on a *Transportation Energy Data Book* reported number of cars in the US in 2005, which had appropriate sales added and retirements subtracted (retirements were estimated using a moving average). Retirements from 2008 and later were calculated by assuming all vehicles retire after their respective median lifetimes. This means that all cars in the initial fleet are retired by 2025, and all light-duty trucks by 2024.

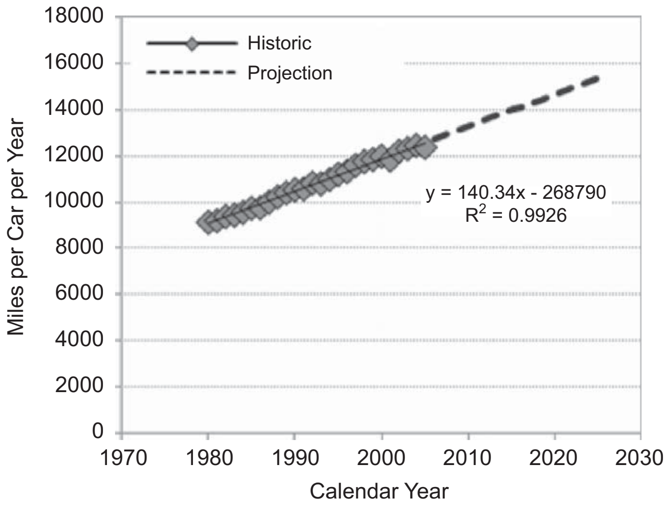

Fig. 1. Average annual car mileage in the United States.

Both car and light-duty truck annual mileages were based on *Transportation Energy Data Book* data. Only 2005 data were available for trucks under 6000 lbs, but data for cars went back several decades. Historic car annual mileages exhibited a highly linear trend, which was used to make future projections for both car and light truck annual mileages (recall that light trucks under 6000 lbs are largely used as passenger vehicles, making it reasonable to assume similar use to that of cars) Fig. 1.

3.5. Inputs—emission rates

Tailpipe emissions measure only part of the environmental impact of running a vehicle. The entire process of producing, refining, transporting, and finally using the fuel is represented by "well-to-wheel" emission rates. All emission rates in this case study are well-to-wheel rates from (or based on) GREET version 1.8a. All emissions are in units of carbon equivalents (GREET considers CH_4 and N_2O as well as CO_2).

GREET also estimates GHG emissions from the vehicle-cycle (including vehicle assembly and recycling), but not for as many vehicle types (Argonne National Laboratory, 2006). In order to compare all vehicles on the same terms, vehicle-cycle emissions are not included. The difference in vehicle-cycle emissions between different technologies is not necessarily significant. According to GREET, a gasoline–electric grid-independent hybrid car produces 154 g/mile less GHG emissions than a conventional gasoline car when both vehicle-cycle and well-to-wheel emissions are considered. When vehicle-cycle emissions are left out, the hybrid produces 156 g/mile less than the pure gasoline car. Leaving out the vehicle-cycle emissions caused an overestimation of the improvement from the hybrid by approximately 1.5%. Vehicle-cycle emissions might make more of a difference when comparing vastly different technologies, but this case study includes only relatively similar short-term technologies.

GREET outputs well-to-wheel GHG emission rates by calendar year, combining emission rates from fuel production and transportation for the calendar year with vehicle emission rates from vehicles made 5 years earlier (Argonne National Laboratory, 2007). The GHG emission rate for a given calendar year is intended to represent the fleet on the road in that year. Hence, the initial fleet's emission rates are GREET's rates for the year 2008. Note that the emission rates from the initial fleet do not actually appear anywhere in the objective or constraints, though they can be used for supplementary calculations. They are considered a "sunk cost". Vehicles bought at the start of 2009 are given GREET emission rates from the year 2014. This ensures that their emission rates are based on vehicle technology from 2009. It also helps ensure that the emission rates associated with fuel production and transport are not overestimated by basing them on 2009 rates.

GREET 1.8 only provides emission rates through the calendar year 2020, but vehicles are purchased up though 2025 in the case study. The GREET rates were extended by extrapolating the last trend. This frequently proved to be linear, but higher order polynomials were also used when deemed appropriate. For the same vehicle category and year, hybrids had the lowest GHG emission rates, followed by E85 FFV, then diesel (a close 3rd), and finally conventional gasoline vehicles.

Emission rates are assumed not to change with the age of a vehicle. This assumption is consistent with work done by Kim et al. (2004), who state that both fuel economy and CO_2 vehicle emissions are unlikely to change with increased mileage, given proper maintenance.

3.6. Inputs—expected costs

Vehicle costs were broken into three basic categories: initial purchase, maintenance, and fuel. E85 FFVs are assumed to have the same initial purchase and maintenance cost of equivalent gasoline vehicles. The technologies are extremely similar. It generally costs less than a hundred dollars extra to make an E85 FFV instead of an otherwise equivalent conventional gasoline vehicle (Newman, 2008).

Historic purchase prices were collected from MSN Autos (2008a) and MSN Cars UK (2008) for a wide range of popular cars and light trucks using all included technologies. The manufacturer's suggested retail price (MSRP) was used for cars sold in the United States, and the "on the road price" was used for cars sold in Britain. In general, lower end trims were chosen to offset the potentially high MSRP values. Models and trims are frequently discontinued or altered, so efforts were made to select models and trims that could be traced back for a considerable number of years without dramatic changes to the specifications.

For gasoline powered cars, prices came from the Toyota Camry, Honda Accord, Honda Civic, and Nissan Altima. They were the first, second, fourth, and sixth bestselling cars in the US in 2007 (MSN Autos, 2008b). For gasoline powered passenger trucks, the Honda CR-V, the Ford Explorer, and the Toyota RAV-4 were used. The CR-V and the RAV-4 were the best and second best selling SUVs in the US in 2007 (Incantalupo, 2008) while the Explorer was the top selling SUV in the US for some 15 years (MSN Autos, 2008a). For gasoline–electric hybrid cars, the Honda Civic and Toyota Prius were used. For gasoline–electric hybrid passenger trucks, the Ford Escape, Toyota Highlander, and Mercury Mariner were used. As mentioned before, light-duty diesel passenger vehicles are not common in the US, so historic prices were obtained from Britain. This included both diesel and gasoline trim prices for the Ford Focus, which was Britain's bestselling car from 1999–2007 (Trent, 2008), as well as the Land Rover Discovery.

Historic purchase prices generally proved highly linear over time when more than a few years of data were available. Future expected purchase prices were therefore extrapolated from linear regressions. An example plot for conventional gasoline and gasoline–electric hybrid purchase prices is shown in Fig. 2, along with a 95% confidence interval, which is discussed later.

The expected costs of conventional diesel vehicles were computed by adjusting the expected conventional gasoline vehicle costs. The vehicle purchase price was assumed to be 7.5% higher

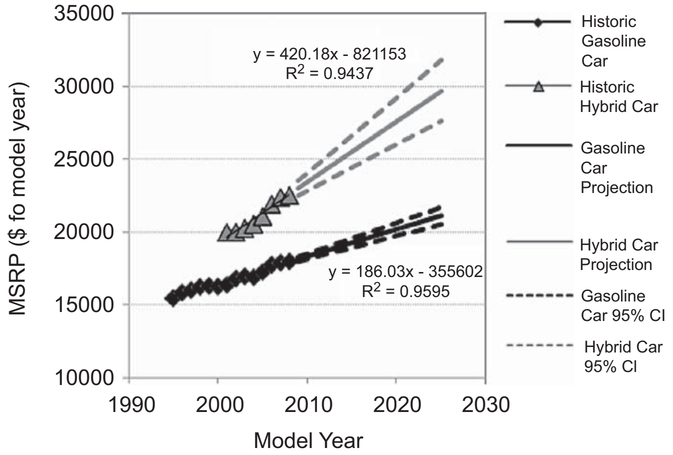

Fig. 2. Conventional gasoline and hybrid car purchase prices and trends.

than that of an equivalent gasoline vehicle. This number is the middle of the 5–10% extra cost estimate presented in Edmondson (2006). This estimate was confirmed by the fact that from model year 2000–2007, the Ford Focus diesel sold in Britain generally cost 3–10% more than the gasoline equivalent (MSN Cars UK, 2008).

Hybrid passenger trucks have only started to become popular in very recent history. Instead of attempting to extrapolate from so few data points, the slope of the regression for conventional gasoline passenger trucks was applied (with the intercept changed so the line passed through the average price of hybrid passenger trucks for model year 2008). A skeptical reader might argue that the slope for gasoline–electric hybrid cars would be more appropriate, but these slopes differed by less than half a percent.

Maintenance costs for conventional gasoline vehicles and grid-independent gasoline–electric hybrids were calculated using the DOE's "HEV Cost Calculator Tool"(US DOE, 2008). The Toyota Camry, which was the top selling car in the US again in 2007 (MSN Autos, 2008b), was used as the base for computing expected car costs. The Ford Escape, which was the third best selling SUV in the US in 2007 (Incantalupo, 2008) (and the best with a hybrid model in 2007) was used as the base for SUV calculations. Other models were used to build an understanding of price variability. The HEV Cost Calculator Tool predicts slightly higher annual maintenance costs for vehicles bought in later years due to higher expected annual mileage. Diesel maintenance costs were assumed to be equal to those of conventional gasoline vehicles, including the maintenance for diesel emissions treatment devices needed to meet modern US standards.

Fuel costs were computed using GREET fuel efficiencies whenever possible. GREET predicts fuel efficiency through calendar year 2020, corresponding to model year 2015. The GREET projections are highly linear, and the trend was continued through all years in which vehicles were purchased. For both cars and light-duty trucks, hybrids achieved the highest miles per gallon, followed by diesel, then conventional gasoline, and finally E85 FFV. Fuel price forecasts through 2030 are taken from the DOE's Annual Energy Outlook (Energy Information Administration, 2009a). Further forecasts are extrapolated from the last trends in these data.

For model year 2010 cars, Fig. 3a summarizes the cost breakdown. As one might suspect, fuel costs make up a larger percentage of costs for conventional gasoline vehicles than they do for hybrids, while the reverse is true of vehicle purchase costs. E85 FFVs have the highest fuel costs.

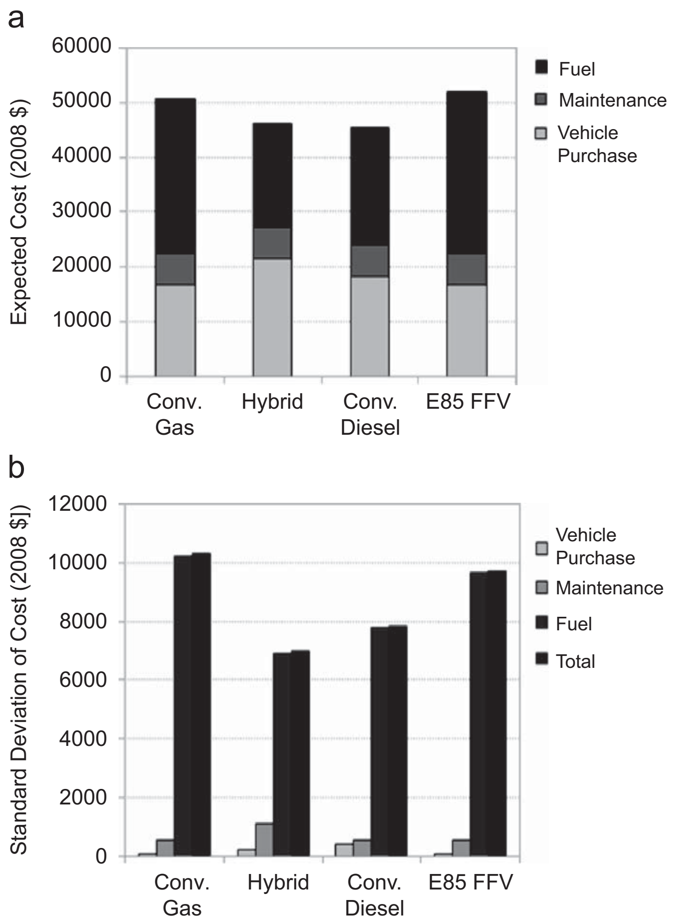

Fig. 3. Cost breakdown for model year 2010 cars (a), and standard deviations of cost components for model year 2010 cars (b).

3.7. Input–component variances

The variances for vehicle purchase cost predictions were computed using the standard equations for uncertainty around linear regressions, given by expressions (7) and (8) (Devore, 2004).

$$s^2 = \sum_{t\in past} \frac{(y_t - y_t^*)^2}{n-2} \tag{7}$$

$$Var(\hat{y}_{x^*}) = s^2\left(\frac{\frac{1}{n} + (x^* - x)^2}{\sum_{t\in past} x_t^2 - \left(\sum_{t\in past} x_t\right)^2/n}\right) \tag{8}$$

where *past* is the set of periods for which there is cost data; n is the number of periods for which there is cost data; y_t is the actual cost in past period t; y_t^* is the cost in past period t back-predicted by regression; s^2 is the sample sum of squared errors divided by the degrees of freedom; x^* is the future year for which the prediction is being made; $y?_{x^*}$ is the cost prediction in future year x^*; x is the average year for the years for which there is cost data; x_t is the year corresponding to past period t.

The variances grow as cost predictions are made for further into the future. More established technologies with longer histories tend to have smaller variances. These two trends are apparent in Fig. 2, which plots expected vehicle purchase prices with a 95% confidence interval for conventional gasoline and hybrid cars.

Recall that the gasoline passenger truck regression slope was applied to hybrid passenger trucks because there was little data for historic hybrid passenger truck prices. The additional uncertainty from this assumption was represented by using a variance twice that of the corresponding gasoline passenger truck cost prediction for each hybrid passenger truck prediction.

Diesel car purchase cost variance was taken to be the variance of gasoline car purchase in the same year, plus the variance of the marginal diesel car cost. The standard deviation of marginal diesel car cost was assumed to be one third of the marginal diesel car cost, and uncorrelated with the rest of the purchase price. This stems from uncertainty regarding what emission reduction technologies will be needed to meet US standards, among other factors.

The standard deviation of national average maintenance costs for conventional gasoline, diesel, or flex-fuel vehicles was assumed to be one tenth of the maintenance costs, in terms of 2008 dollars. For hybrids, the standard deviation was assumed to be 20% of maintenance costs, to reflect the greater uncertainty surrounding their long-term performance.

Projecting fuel prices is challenging. They exhibit considerable volatility. As all projections were from, or based on, the DOE's Annual Energy Outlook (Energy Information Administration, 2009a), the uncertainty surrounding these projections was estimated from the DOE's past success in predicting prices. The DOE's past oil price predictions, and actual historical values, were obtained from Energy Information Administration (2009b). These were used to produce a standard deviation, in terms of percent of predicted price, as a function of how many years into the future the projection is being made. The resulting standard deviations for yearly fuel prices were then translated into standard deviations for vehicle lifetime fuel costs. This required estimating the degree to which fuel prices in different years are correlated. For gasoline and diesel, these correlations were estimated from past oil prices in Energy Information Administration (2009b).

The DOE does not have nearly as much of a track record predicting E85 prices as it does for oil prices. Over the relatively short period for which data could be obtained, ethanol prices were more volatile than gasoline and diesel prices (Energy Information Administration, 2007, 2008a). The standard deviation of E85 price predictions was assumed to be roughly 27% greater than that for gasoline and diesel, based on historic standard deviations of fuel prices. The correlations between E85 prices in different years were estimated from past E85 prices as reported in all of the DOE's Alternative Fuel Price Reports through January 2009 (US DOE, 2009). E85 prices showed less autocorrelation than oil prices.

The uncertainty of the fuel component is consistently higher than that of maintenance and vehicle purchase. For a model year 2010 car, the standard deviations of the cost components are given in Fig. 3b. Uncertainty regarding the vehicle purchase is a relatively small part of the overall uncertainty, though it is significantly higher for hybrids than for conventional gasoline cars or E85 FFV. Diesel cars have the highest standard deviation of vehicle purchase cost, stemming largely from uncertainty surrounding necessary emission control technology.

It is worth pointing out that the E85 FFV cost standard deviations are all based on the assumption that the driver uses E85 exclusively. This is the same assumption made in emissions calculations. Were the driver allowed to choose the fuel, the standard deviation of E85 FFVs' fuel cost could drop significantly, depending on the rule used by the driver. Emissions reductions could also drop significantly, however. Also, note that component cost variances cannot necessarily be added to give the variance of the total cost. Such a calculation requires assumptions regarding the correlation coefficients between components, which are discussed in the next section.

3.8. Input—component correlations

The correlations between cost components were derived from a variety of data sources and assumptions. Data were taken from sources cited in previous sections on expected costs and component variances. Key assumptions for vehicles bought the same year are listed below:

1. Fuel cost for any vehicle is perfectly correlated with fuel cost for other vehicles using the same fuel.
2. Fuel costs have zero correlation with vehicle purchase and maintenance costs. Recall that fuel costs are a function of fuel prices for well over a decade past the vehicle's purchase year.
3. Correlation coefficients are assumed to follow certain symmetries. For example, hybrid light-duty truck purchase is assumed to have same correlation with gasoline light-duty truck purchase as hybrid car purchase does with gasoline car purchase.
4. Maintenance costs for different vehicles have the same correlation coefficients with each other as purchase costs do for the same vehicle pair.
5. Maintenance costs are assumed to have a correlation coefficient of 0.5 with vehicle purchase costs for vehicles of the same type. The reasoning for the moderate positive correlation is that the two require similar, but not identical, inputs, and that maintenance uses those inputs over a greater time span.
6. Maintenance costs are assumed to have half the correlation with the purchase cost of other vehicle types that the vehicle purchase of its vehicle type has with the other vehicle's purchase cost.
7. Flex-fuel vehicle purchase and maintenance costs are assumed to have the same correlations as the corresponding costs for gasoline vehicles.

Additionally, correlation coefficients are assumed to decrease by 5% of the same-year value for each year between the purchases (with a lower bound of zero).

3.9. Additional ethanol assumptions

"Gasoline" vehicles actually use a relatively small amount of ethanol. GREET models gasoline vehicles as using a mix of "conventional gasoline" and "reformulated gasoline". Conventional gasoline uses no oxygenate, but reformulated gasoline uses ethanol as an oxygenate. The percent of gasoline of each type is a function of the year, with reformulated gasoline steadily gaining market share from 59% in calendar year 2013 (used for model year 2008) to 100% in calendar year 2020. Ethanol must make up at least 6.6% of reformulated gasoline by weight to meet oxygen requirements (6.3% by volume).

All ethanol is all assumed to be corn-based. For E85, the gasoline portion is 50% reformulated and 50% conventional. For both fuel efficiency calculations and price projections, E85 is assumed to have an actual year-round average ethanol content of 74%. This assumption was also made by the Energy Information Administration of the US DOE (Energy Information Administration, 2008b). E85 is treated as viable only in the Midwest, as defined by the US Census region (ND, SD, NE, KS, MN, IA, WI, MO, MI, IN, IL, OH) (Census Bureau, 2008a). US Census projected year 2010 population estimates are used to estimate that 22% of the US population will live in the Midwest (Census Bureau, 2008b). Correspondingly, no more than 22% of the vehicles of any category sold in any year can be E85 FFV.

3.10. Solving the quadratic program

The model formulation was coded into AMPL, as were scripts to prepare the input data. The program was then solved using the MINOS 5.5 solver, which employs a variant of the simplex algorithm designed to handle nonlinear objectives and constraints, as well as the Ipopt 3.4 (and later 3.6) solver (Wðchter and Biegler, 2006), which employs a derivative-based interior point method, using Harwell Subroutine Library packages MA27 and MC19 (Hyprotech UK, 2008).

Both solvers were able to solve the linear problem (without the variance constraint) quickly. The two solvers produced very similar results for a range of parameter values. The largest percentage difference in cost was 2.22E-7 percent. Typically, something on the order of ten vehicles would be purchased differently, out of the millions in the portfolio. When the variance constraint was included, Ipopt proved more robust. Warm starts were used to improve performance.

3.11. Results

First, the model was run with the assumptions outlined above, without constraints on GHG emissions or financial risk. Because fuel price emerged as a key factor, two alternate fuel price scenarios were also run for sensitivity analysis. The "low fuel price" and "high fuel price" scenarios had fuel prices one half standard deviation below and above the original predictions, which are the "mid fuel price" scenario. A summary of the minimum cost portfolio for each of these scenarios is contained in Table 1, along with a summary of the portfolio which results from minimizing cost variance or GHG emissions. The portfolio which minimizes GHG emissions is the same as the portfolio which minimizes cost variance: all hybrids. This makes some intuitive sense, as GHG emissions are highly correlated with fuel consumption and the vast majority of financial risk stemmed from fuel price uncertainty. Selecting a vehicle technology designed to conserve fuel can mitigate both problems.

Without GHG emissions or financial risk constraints, the minimum cost portfolio in the low fuel price scenario is nearly all diesel vehicles, with a few E85 FFVs. These E85 FFVs are bought in later years, because in this scenario E85 prices are projected to drop while gasoline and diesel prices rise. With the higher fuel prices in the mid and high scenarios, E85 FFVs are no longer in the minimum cost portfolio, and hybrids make up an increasingly large portion. With higher fuel prices, fuel efficiency becomes more important in determining cost.

Next, the model was run for the mid fuel price scenario, with a range of different caps for GHG emissions and cost variance. For each set of bounds, the model produced the lowest cost portfolio along with its associated cost, emissions inventory, and cost variance. Fig. 4a plots the expected financial cost for each combination of GHG emissions and cost variance caps. Several points are labeled with letters corresponding to portfolios in Table 1. When the financial risk or GHG emission constraints are strict enough, the portfolio is the same as if the cost variance or GHG emissions were being minimized.

Figs. 4b and c plot the GHG emissions and standard deviation of cost for each combination of GHG emissions and cost variance caps. In order to be able to view the whole surfaces, Figs. 4b and c look from a different angle than Fig. 4a. It is worth noting that the GHG emissions are not always equal to the cap. GHG emissions can be forced down by stricter GHG emission caps, as seen along the upper left edge of the surface. GHG emissions can also be forced down by stricter cost variance caps, as seen along the upper right edge of the surface. Fig. 4b shows that constructing a vehicle portfolio to avoid financial risk can also reduce GHG emissions. Similarly, Fig. 4c shows that constructing a vehicle portfolio to reduce GHG emissions can mitigate financial risk. This is made possible by the fact that both financial risk and GHG emissions are so strongly tied to fuel consumption, which can be reduced through the use of hybrid technology.

Given that mean-variance optimization is designed to construct portfolios which reduce financial risk, it is natural to ask how such a portfolio would perform if prices deviate from projections. Portfolios were selected to minimize cost using mid fuel prices for a range of financial risk caps. The extra cost if fuel prices are half a standard deviation above their expected values was then computed. The results are plotted in Fig. 5. Even with the strictest possible financial risk caps, an unexpected increase in fuel prices can cause well over a trillion dollars in unexpected costs. Nonbinding financial risk constraints are obviously of no help, but binding risk constraints can reduce the unexpected costs by over $180 billion. Half a standard deviation is a relatively small error in prediction. The difference would be substantially greater if fuel prices were a full standard deviation higher than expected, or more.

4. Conclusions

It is possible to apply modern portfolio theory to the task of selecting technologies for the next generation of vehicles, though it does require significant data preparation and assumptions,

Table 1
Vehicle portfolio summaries for various objectives, with no financial risk or GHG emissions constraints.

		Objective (minimization)			
		A *Expected Cost* (*Low Fuel Prices*)	B *Expected Cost* (*Mid Fuel Prices*)	C *Expected Cost* (*High Fuel Prices*)	D Cost *Variance* or GHG *Emissions*
Cars	Gasoline	0.0%	0.0%	0.0%	0.0%
	Hybrid	0.0%	0.0%	82.4%	100.0%
	Diesel	98.7%	100.0%	17.6%	0.0%
	E85 FFV	1.3%	0.0%	0.0%	0.0%
	Total	100.0%	100.0%	100.0%	100.0%
Light-duty Trucks	Gasoline	0.0%	0.0%	0.0%	0.0%
	Hybrid	0.0%	41.1%	71.8%	100.0%
	Diesel	96.9%	58.9%	28.2%	0.0%
	E85 FFV	3.1%	0.0%	0.0%	0.0%
	Total	100.0%	100.0%	100.0%	100.0%
GHG Emissions (*Billion Tons*)		31.1	29.7	26.1	24.7
Cost *Std. Dev.* (*Trillion 2008$*)		1.99	1.92	1.76	1.73

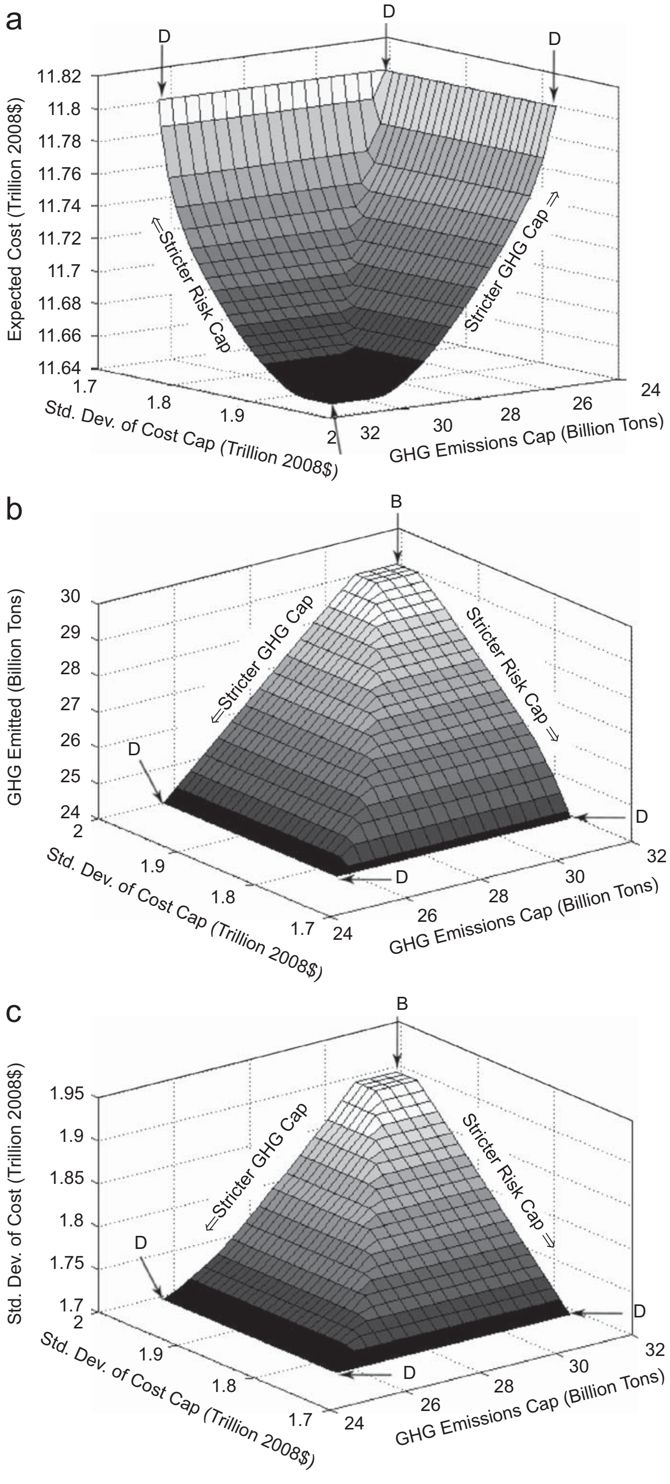

Fig. 4. Minimum cost portfolios (mid fuel prices) were found for 468 GHG emission cap and financial risk cap combinations. The resulting expected cost, GHG emissions, and financial risk are plotted in (a), (b), and (c), respectively.

particularly in the construction of the covariance matrix. The quadratic program developed can help provide insight into the most cost effective strategy for meeting greenhouse emissions reduction and financial risk reduction goals. It can produce tradeoff curves, and it can reveal situations in which altering the vehicle portfolio will improve all three metrics (i.e., cost, financial risk, and GHG emissions).

Shifting away from a conventional gasoline vehicle fleet by purchasing more fuel efficient diesel and hybrid vehicles can be

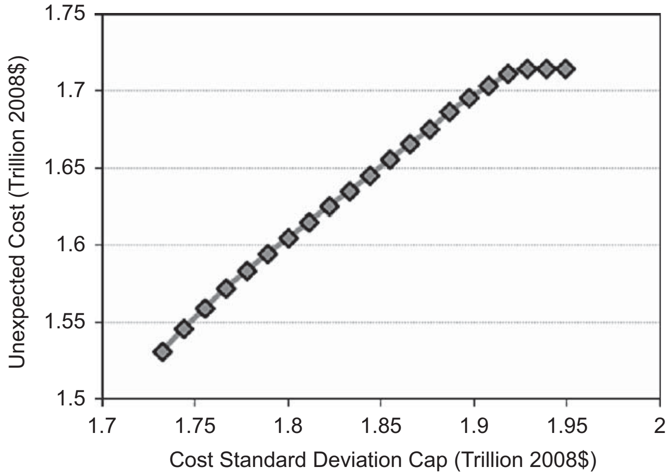

Fig. 5. A portfolio is selected to minimize cost (mid fuel prices) for a range of financial risk caps (*x*-axis). The extra cost if fuel prices are half a standard deviation above their expected values is then computed (*y*-axis).

one such "win-win-win" switch. Financial risk and GHG emissions are both strongly linked with fuel consumption, and both can be reduced by switching to these more fuel efficient vehicles. This is true even when complicating factors, such as the higher carbon content of diesel fuel, are considered. The expected lifetime cost of the fleet can also be lower, depending on the fuel price forecast.

The vehicle portfolios described in this paper are by no means intended as a prescription. There are other valid goals relevant to the task of selecting the next generation of vehicles. For example, there are numerous emissions other than greenhouse gases which have important environmental impacts. These could be added to a future version of the model. Also, the heterogeneity of the population, and their vehicle usage, could be further incorporated, as could additional technologies. Parameters which are currently considered exogenous, such as prices, could be made endogenous to better capture the market effects of large changes in vehicle purchase patterns. Though the model uses a substantial number of input parameters, it is quite compact in terms of the number of decision variables, and showed no signs of nearing computational limitations on size.

References

Argonne National Laboratory, US Department of Energy, 2006. Development and Applications of GREET 2.7—The Transportation Vehicle—Cycle Model (ANL/ESD/06-5), US DOE, Argonne, IL.

Argonne National Laboratory, US Department of Energy, 2007. Operating Manual for GREET: Version 1.7 (ANL/ESD/05-3), US DOE, Argonne, IL.

Awerbuch, S., 2006. Portfolio based electricity generation planning: policy implications for renewables and energy security. Mitigation and Adaptation Strategies for Global Climate Change 11, 693–710.

Bridges, J.F.P., Stewart, M., King, M.T., van Gool, K., 2002. Adapting portfolio theory for the evaluation of multiple investments in health with a multiplicative extension for treatment synergies. The European Journal of Health Economics 3, 47–53.

CBS News, 2006. Hybrid Vehicle Sales More Than Double: As New Vehicles Come on the Market, viewed May 9, 2008, 〈http://www.cbsnews.com/stories/2006/05/04/tech/main1584978.shtml〉.

Census Bureau, 2008a. Census Regions and Divisions of the United States, viewed May 29, 2008, 〈http://www.census.gov/geo/www/us_regdiv.pdf〉.

Census Bureau, 2008b. US Population Projections, viewed May 29, 2008, 〈http://www.census.gov/population/www/projections/regdivpyramid.html〉.

Devore, J.L., 2004. Probability and Statistics: For Engineering and the Sciences, sixth Ed Thomson Brooks/Cole, Belmont, CA.

Edmondson, G., 2006. Clearing the Smoke on Diesel: A New Wave of Cleaner Diesel Engines Will Give Hybrids a Run for Their Money, says J.D. Power's Al Bedwell, Business Week, viewed May 9, 2008, 〈http://www.businessweek.com/autos/content/feb2006/bw20060208_589016.htm?campaign_id=aolautos〉.

Energy Information Administration, US Department of Energy, 2007. Biofuels in the US. Transportation Sector, viewed May 29, 2008, 〈http://www.eia.doe.gov/oiaf/analysispaper/biomass.html〉.

Energy Information Administration, US Department of Energy, 2008a. Weekly Retail Gasoline and Diesel Prices, viewed May 29, 2008, 〈http://tonto.eia.doe.gov/dnav/pet/pet_pri_gnd_dcus_nus_w.htm〉.
Energy Information Administration, US Department of Energy, 2008b. Ethanol, viewed May 29, 2008, 〈http://www.eia.doe.gov/oiaf/ethanol3.html〉.
Energy Information Administration, 2009a. Annual Energy Outlook 2009 (DOE/EIA-0383(2009)), viewed June 1, 2009, 〈http://www.eia.doe.gov/oiaf/forecasting.html〉.
Energy Information Administration, 2009b. Annual Energy Outlook Retrospective Review: Evaluation of Projections in Past Editions (1982–2008) (DOE/EIA-0640(2008)), viewed June 1, 2009, 〈http://www.eia.doe.gov/oiaf/analysispaper/retrospective/index.html〉.
Greene, D.L., Schafer, A., 2003. Reducing Greenhouse Gas Emissions from US Transportation, viewed June 18, 2009, 〈http://www.pewclimate.org/docUploads/ustransp.pdf〉.
Hyprotech UK, 2008. HSL, A Collection of Fortran codes for large-scale scientific computation, viewed July 9, 2008, 〈http://hsl.rl.ac.uk/archive/hslarchive.html〉.
Incantalupo, J., 2008. Top 10 Best-selling SUVs. Newsday, viewed July 23, 2008, 〈http://www.newsday.com/classified/automotive/ny-auto-suvs,0,4952384.story〉.
Kim, H.C., Ross, M.H., Keoleian, G.A., 2004. Optimal fleet conversion policy from a life cycle perspective. Transportation Research Part D 9, 229–249.
Markowitz, H., 1952. Portfolio selection. The Journal of Finance 7, 77–91.
MSN Autos, 2008a. Car Information, New Car Prices, Used Car values, Used Car Reviews, New Car Reviews, viewed May 9, 2008, 〈http://autos.msn.com/default.aspx〉.
MSN Autos, 2008b. Bestsellers of 2007: Overall Sales Are Down in the US, but it's not All Bad News, viewed May 9, 2008, 〈http://editorial.autos.msn.com/article.aspx?cp-documentid=434478〉.
MSN Cars UK, 2008. Car Reviews, Road Tests and News on the Latest New and Used Cars Plus Motor Shows, Insurance, and Motorsport, viewed May 9, 2008, 〈http://cars.uk.msn.com/〉.
Newman, R., 2008. Corn Ethanol. US News and World Report, viewed July 23, 2008, 〈http://www.usnews.com/articles/business/your-money/2008/01/11/corn-ethanol.html〉.
Oak Ridge National Laboratory, US Department of Energy, 2007. Transportation Energy Data Book: 26 (ORNL-6978), US DOE, Oak Ridge, TN.
Robison, L.J., Brake, J.R., 1979. Application of portfolio theory to farmer and lender behavior. American Journal of Agricultural Economics 61, 158–164.
Springer, U., 2003. Can the risks of the kyoto mechanisms be reduced through portfolio diversification? Evidence from the Swedish AIJ program. Environmental and Resource Economics 25, 501–513.
Trent, D., 2008. Top 10: Europe's Best Selling Cars. MSN Cars UK, viewed May 9, 2008, 〈http://cars.uk.msn.com/News/Top_ten_article.aspx?cp-documentid=7319152〉.
US Department of Energy, 2008. Alternative Fuels and Advanced Vehicles Data Center HEV Cost Calculator Tool, viewed May 9, 2008, 〈http://www.eere.energy.gov/afdc/hev_calculator/single.php〉.
US Department of Energy, 2009. Clean Cities Alternative Fuel Price Report January 2009, viewed June 1, 2009, 〈http://www.afdc.energy.gov/afdc/pdfs/afpr_jan_09.pdf〉.
US Environmental Protection Agency, 2004. MOVES2004 Highway Vehicle Population and Activity Data: Draft (EPA420-P-04-020), US EPA, Washington, DC.
US Environmental Protection Agency, 2008. Inventory of US GHG Emissions and Sinks: 1990–2006 (EPA 430-R-08-005), US EPA, Washington, DC.
Wðchter, A., Biegler, L.T., 2006. On the implementation of a primal-dual interior point filter line search algorithm for large-scale nonlinear programming. Mathematical Programming 106, 25–57.