The Pareto Frontier for Vehicle Fleet Purchases
Cost versus Sustainability

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Abstract: Vehicle fleets for large corporations can have thousands of vehicles that are replaced between every few months and every few years. With the emergence of hybrid, plug-in hybrid, and other new vehicle technologies, combined with an increasing focus on sustainability, planning fleet purchases has and continues to become a significantly more complicated undertaking. This paper introduces Ford's Fleet Purchase Planner system designed to present fleet customers with optimal purchase strategies that incorporate their companies' cost and sustainability considerations.

1 INTRODUCTION

Ford's Fleet Purchase Planner (patent pending) is an analytical system, using mathematical optimization methodology, designed to help fleet customers better understand purchase options. It provides customized purchase recommendations that satisfy corporate environmental goals, reduce costs, and analyze trade-offs between company goals.

Sustainability and environmental impact are areas of growing importance to many of Ford's fleet customers. For example, SimplexGrinnell ordered 200 Fusion Hybrids in 2010 to support a Tyco company-wide environmental program, known as "Vital World," to reduce greenhouse gas emissions, waste and water consumption by 25 percent over the next five years (Ford Motor Company, 2010b). Kraft also has goals with its sales fleet program to reduce fuel use and CO_2 emissions and purchased 4 cylinder Fusions in 2010 to help accomplish this (Ford Motor Company, 2010a).

In recent years, several new green vehicle technologies have emerged, e.g., battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), plug-in HEVs (PHEVs), and turbocharged direct injected gasoline engines (e.g., Ford's EcoBoost ®). These technologies provide increasing opportunities for customers to reduce emissions and operating costs, but they also increase the number of purchase options available, making planning a more complicated endeavor.

For example, what is the trade-off cost for purchasing a Focus versus a Focus Electric (BEV)? Can a company recover the additional cost incurred in purchasing the BEV through fuel savings over time? Does a BEV have the same emissions if driven in California as it does in Michigan, Texas or Florida? Decisions become even more complex as customers need to choose which vehicles in their existing fleet to replace, which vehicles they should replace them with (e.g. Focus, Focus Electric, Fusion, Fiesta), and how these choices enable them to meet their cost and sustainability targets.

This paper presents details on our Fleet Purchase Planner (FPP) and is organized as follows. In Section 2, we provide background information on measuring a vehicle's carbon footprint. Section 3 introduces our algorithm and integer programming models used to generate optimal purchase recommendations. In Section 4, we demonstrate our software application on an example fleet. Section 5 contains our summary and conclusions.

2 CARBON FOOTPRINT

As consumers become increasingly aware of the contribution of vehicle greenhouse gas (GHG) emissions toward climate change, they seek opportunities to reduce their global warming footprint. Carbon dioxide (CO_2) is the primary GHG and is the main emission from motor vehicles. CO_2 and water (H_2O) are the end products of combustion, a chemical reaction of hydrocarbon (HC) fuels such as gasoline, diesel, nat-

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ural gas, and coal with oxygen (O_2).

$$HC + O_2 \rightarrow H_2O + CO_2 + \text{energy}.$$

Consumers can reduce vehicle CO_2 emissions by using less fuel. This can be accomplished by selecting vehicles that have better fuel efficiency, using less carbon-intensive fuels, or by driving fewer miles.

We use a well-to-wheels (WTW) approach to quantify the CO_2 emissions from a vehicle fleet. WTW CO_2 includes both the direct emissions from the combustion of fossil fuel by the vehicle, also known as tailpipe emissions or tank-to-wheel (TTW) emissions, as well as the upstream, or well-to-tank (WTT), emissions. WTT emissions are introduced when the feedstock for the finished fuel is extracted or grown, transported, and refined into a usable fuel or used to generate electricity. The WTW emissions represent up to 80% of the vehicle life cycle CO_2, while raw materials, manufacturing and assembly, maintenance, and end of life account for the remainder of vehicle life cycle CO_2 emissions (Notter et al., 2010; Ma et al., 2012). Conventional internal combustion engine vehicles (ICEVs) have about 80% of the life cycle CO_2 in the WTW phase (Notter et al., 2010; Ma et al., 2012). With advanced technologies such as HEVs becoming more prevalent, vehicle fuel efficiency improves, reducing the WTW CO_2. However, the manufacturing or raw materials become more carbon intense; for example, the WTW share of life cycle CO_2 for BEVs can decrease to 50-60% (Notter et al., 2010; Ma et al., 2012).

Vehicle WTT and TTW CO_2 emissions are calculated based on the vehicle fuel economy (miles per gallon, MPG) reported by the U.S. EPA and DOE at fueleconomy.gov. Common liquid fuels are gasoline and diesel, which may be blended with the biofuels ethanol and biodiesel, respectively. A mixture of 10% ethanol and 90% gasoline (by volume) is called E10. E10 is sold as gasoline in most U.S. states. E85 contains 85% ethanol by volume and is used only by flex-fuel vehicles (FFVs), which can operate on any blend from E0 (gasoline) to E85. Each fuel has known TTW CO_2 emissions, calculated from the physical and chemical properties of the fuel. The WTT CO_2 emissions for each fuel are provided by GREET 1.8d.0, a fuel life cycle assessment tool developed at Argonne National Labs (Wang, 1999). Other GHGs are emitted in smaller quantities, primarily during the WTT phase. The GHGs methane (CH_4) and nitrogen dioxide (N_2O) have 25 and 298 times the global warming potential (GWP) of CO_2, respectively, over 100 years (Solomon, 2007). Frequently, the emissions of CH_4 and N_2O are weighted by their GWPs and combined with the CO_2 emissions to provide a single CO_2-equivalent GHG metric (CO_2eq). Table 1 lists the WTT and TTW CO_2eq factors for the fuels used in the model in units of kg/gal.

Table 1: WTT and TTW fuel emission factors.

	GHG (kg CO_2eq/gal)	
	f_{WTT}	f_{TTW}
Gasoline	2.2	8.9
E10 (corn ethanol)	2.5	8.0
E85 (corn ethanol)	4.7	1.3
Diesel	2.47	10.0
B10 (soy biodiesel)	2.49	9.0

The factors in Table 1 include only fossil-based GHG emissions. Renewable biofuels, like neat ethanol E100, have no TTW fossil-based CO_2 emissions because there is no net increase in atmospheric CO_2 concentrations when the fuel is burned. The CO_2 is repeatedly emitted and reclaimed in a closed-cycle in which the ethanol is combusted then absorbed from the atmosphere as the biomass (corn) grows. Fossil fuels like gasoline produce a net increase in atmospheric CO_2 by removing carbon stored underground and releasing it into the atmosphere with no mechanism for returning it underground. Biofuels have only WTT fossil-based CO_2 emissions.

For ICEVs, the annual metric tons of GHG emissions are calculated as a function of fuel economy, distance traveled, and GHG emissions factors in (1). HEVs are treated as ICEVs since the small on-board battery is recharged from the engine, not from an electric outlet.

$$\text{GHG}_{WTW} = VMT \frac{f_{WTT} + f_{TTW}}{1000MPG}, \tag{1}$$

where VMT is annual travel (miles); MPG is the EPA label fuel economy (miles/gallon), f_{WTT} is the well-to-tank (fuel production) emission factor (kg CO_2eq/gallon) in Table 1, and f_{TTW} is the tank-to-wheel (fuel combustion) emission factor (kg CO_2eq/gallon) in Table 1.

BEVs have only WTT CO_2 emissions. Like liquid fuels, electricity may come from both fossil and renewable sources. Renewable sources include hydropower, solar energy, biomass, and wind power and have no WTT CO_2. Fossil fuels' carbon intensities combined with the efficiency of the power plant determine the electricity WTT CO_2 footprint. Table 2 lists the WTT CO_2 factors for electricity by feedstock fuel including 8% transportation and distribution losses (Wang, 1999).

The electricity used to charge the BEV battery varies across the country depending on the regional mix of fuels used in the power plants. The GREET 1.8d.0 database provides mixes for the Northeast and

Table 2: WTT GHG emission factors for electricity generation, by fuel.

	GHG (kg CO_2eq/kWh) f_{elec}
Coal	1.23
Natural Gas	0.64
Oil	1.03
Nuclear	0.02
Renewables	0.00

California. The mix for other regions was extracted from the 2009 Annual Energy Outlook supplemental tables (EIA, 2009), which use regions defined by the National Energy Modeling System (NEMS) shown in Figure 1. Using GREET's CO_2 factors and the AEO2009 regional electricity feedstock mix, we can calculate the weighted average WTT CO_2eq emission factors for a region or state. Table 3 shows the weighted emissions factors for each region and a list of the states included in each region.

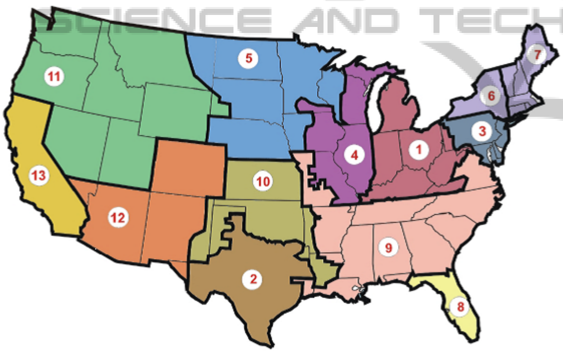

Figure 1: Electricity generation regions used in AEO2009 and GREET 1.8d.0. GREET combines regions 3, 6, and 7 to form the Northeast region. Region names: East Central #1, Texas #2, Northeast #3+#6+#7), Mid-America #4, Mid-Continent #5, Florida #8, Southeast #9, OK, KS #10, Northwest #11, CO, AZ, NM #12, and CA #13. Graphic from (EIA, 2009).

Table 3: Regional and state electricity GHG emission factors.

Region #	kg CO_2eq per kWh	coal	natural gas	oil	nuclear	renewables
1	1.074	84.2%	4.7%	0.3%	10.0%	0.8%
2	0.734	36.3%	44.1%	0.1%	12.5%	7.0%
3+6+7	0.412	29.9%	21.7%	2.2%	33.9%	12.3%
4	0.728	56.2%	4.2%	0.2%	35.2%	4.2%
5	0.893	71.5%	0.8%	0.3%	14.1%	13.3%
8	0.763	34.1%	42.3%	6.6%	14.1%	2.9%
9	0.743	52.3%	13.6%	0.5%	29.4%	4.2%
10	0.990	69.0%	21.0%	0.3%	4.4%	5.3%
11	0.440	31.6%	7.6%	0.1%	3.5%	57.2%
12	0.843	51.9%	31.2%	0.1%	9.0%	7.8%
13	0.338	13.3%	36.6%	0.0%	20.5%	29.6%
US Avg	0.721	50.4%	18.3%	1.1%	20.0%	10.2%

The EPA reports fuel economy for BEVs in MPGe, miles per gallon equivalent, based on the based on the fact that combustion of a gallon of gasoline releases 121 MJ (33.7 kWh) of energy (DOE, 2000). Equation 2 is used to calculate the annual metric tons of CO_2eq emissions for a BEV operating in a particular state.

$$\text{GHGe}_{WTW} = VMT \frac{f_{elec,region}}{1000MPGe} \frac{33.7\text{kWh}}{\text{gal}}, \quad (2)$$

where VMT is annual travel (miles), $MPGe$ is the EPA label mile/gallon equivalent fuel economy, $f_{elec,region}$ is the electricity generation emission factor (kg CO_2eq/kWh) for a state (Table 3), and there are 33.7 kWh/gallon of gasoline.

PHEVs operate using a combination of electricity from the grid and internal combustion energy. PHEV CO_2 emissions are calculated as a weighted average of WTW CO_2 from electric mode and internal combustion mode based on the shares of travel that take place in each mode. The utility factor (λ) is the share of travel in electric mode, often referred to as battery charge-depleting mode. The fuel economy label provides the all-electric range (AER) in miles. Assuming one charge per day, we estimate the annual λ as the AER multiplied by 365 and divided by the annual total mileage. Like BEVs, the carbon intensity of electricity used by PHEVs varies by region of operation. Equation 3 provides the annual metric tons of GHGs emitted by a PHEV operating in a particular state.

$$\text{GHGp}_{WTW} = \lambda \text{GHGe}_{WTW} + (1-\lambda)\text{GHG}_{WTW}, \quad (3)$$

where λ is the share of travel in electric (charge-depleting) mode, GHG_{WTW} from (1) is the emissions from gasoline and GHGe_{WTW} from (2) is the emissions from electricity generation.

Figure 2 compares the CO_2eq emissions of a 2012 Ford Focus, ICEV versus BEV. We can see that the WTW emissions for the ICEV are about the same as a BEV driven in Michigan with coal-intense electricity, but are nearly 3 times higher than a BEV driven in California with large shares of nuclear and renewable electricity.

3 MATHEMATICAL MODEL

There are two main goals that we aim to achieve in identifying fleet purchase options through optimization: minimizing cost and minimizing emissions. Rather than optimizing to obtain a single purchase recommendation, we aim to present points from the Pareto frontier from which customers can select their preferred levels of sustainability and cost.

Pareto frontier visualization is a classic technique for addressing multi-objective optimization problems.

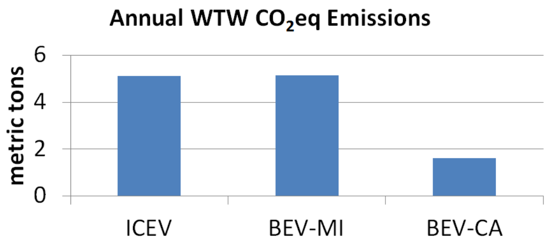

Figure 2: 2012 Ford Focus: ICEV vs BEV, 15000 miles, 55% city, Michigan (MI) and Calfornia (CA) electric grids for BEV.

In the context of sustainability and cost, it has recently been applied to supply chain network design problems (Wang et al., 2011).

To calculate the Pareto frontier for fleet purchases, we developed an algorithm that repeatedly solves the following two optimization problems:

- *Cost* | *Emissions Bound*: this IP minimizes the cost while satisfying the emissions bound e^k, which is initialized to ∞ and is then iteratively reduced until the problem becomes infeasible, at which point the algorithm terminates. The objective function value $\{c^*\}^k$, is used as the required cost in the next IP.

- *Emissions* | *Cost*: this IP minimizes the emissions $\{e^*\}^k$, by selecting the best replacement strategy given the previously calculated cost $\{c^*\}^k$. The optimal emissions $\{e^*\}^k$ are then reduced by a predetermined step size h to set the emissions bound $e^{k+1} = \{e^*\}^k - h$ for the next iteration.

The algorithm is outlined in Figure 3. The result is a Pareto frontier of purchase options that include the types and quantities of vehicles to purchase as replacements for currently owned vehicles in a customer's fleet.

We define the notation that we will use to formulate the IPs and provide a corresponding example, denoted with $\diamond$, as follows:

- R is the set of currently owned vehicles being replaced.

$\diamond$ $R = \{$2010 Ford Fusion 3.5L - 17K miles/year Florida, 2010 Ford Fusion 3.5L - 51K miles/year Michigan$\}$.

- q_r is the number of units of vehicle $r \in R$ being replaced.

$\diamond$ $\vec{q} = [4, 6]$.

- V is the set of vehicles available for purchase.

$\diamond$ $V = \{$2012 Ford Fusion 2.5L, 2012 Ford Fusion Hybrid, etc.$\}$.

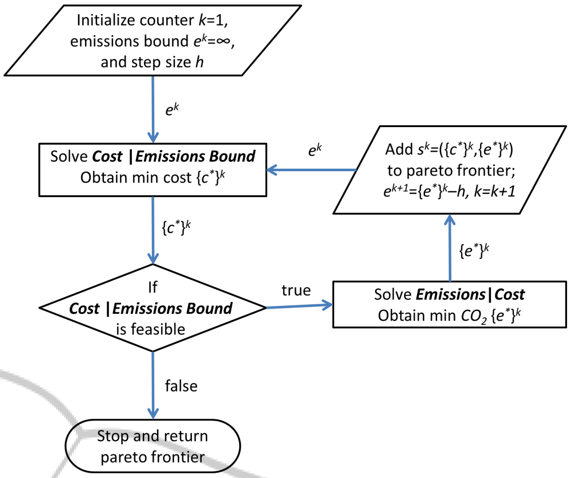

Figure 3: Flowchart for optimizations to produce the Pareto frontier.

- c_v is the cost of vehicle $v \in V$ (e.g. total cost of ownership or purchase price with or without fuel costs).

$\diamond$ $\vec{c} = [\$20705, \$28775, \text{etc.}]$ (starting MSRP price).

- $V_r \subseteq V$ is the subset of vehicles available for purchase that are suitable replacements for currently owned vehicle $r \in R$.

$\diamond$ $V_1 = V_2 = \{$2012 Ford Fusion 2.5L, 2012 Ford Fusion Hybrid$\}$.

- $e_{v,r}$ is the emissions produced by vehicle $v \in V$ when replacing vehicle $r \in R$, which is a function of the fuel economy of v and the annual mileage of r, as described in Section 2.

$\diamond$ $e_{1,1} = 6.9$, $e_{2,1} = 4.8$, $e_{1,2} = 20.7$, $e_{2,2} = 14.3$ (metric tons CO_2).

- e^k is the maximum emissions allowed at iteration k.

$\diamond$ $e^k = \infty$ (no limit initially, to minimize price).

- F is the set of vehicle features and categories being considered, for example, moonroof, hybrid, leather, manual, Fusion 2.5L, Focus, etc.

$\diamond$ $F = \{$hybrid$\}$.

- f^l is a lower-bound on the number of vehicles to be purchased with feature $f \in F$.

$\diamond$ hybrid$^l = 2$.

- f^u is an upper-bound on the number of vehicles to be purchased with feature $f \in F$.

$\diamond$ hybrid$^u = 8$.

- f_v is a boolean parameter that indicates whether or not vehicle $v \in V$ contains feature $f \in F$.

$\diamond$ $\vec{hybrid} = [\text{false}, \text{true}]$.

The decision variables in both integer programs are the same: $x_{v,r}$ is the number of units of vehicle $v \in V$ to purchase to replace vehicle $r \in R$.

We formulate *Cost* | *Emissions Bound* as follows:

Cost | Emissions Bound

$$\{c^*\}^k = \min \sum_{r \in R} \sum_{v \in V_r} c_v x_{v,r} \tag{4}$$

$$\text{s.t.} \sum_{r \in R} \sum_{v \in V_r} e_{v,r} x_{v,r} \leq e^k \tag{5}$$

$$\sum_{v \in V_r} x_v = q_r \qquad \forall r \in R \tag{6}$$

$$f^l \leq \sum_{r \in R} \sum_{v \in V_r : f_v = \text{true}} x_{v,r} \leq f^u \qquad \forall f \in F \tag{7}$$

$$\vec{x} \in \{0, 1, \cdots\}, \tag{8}$$

where (4) minimizes the total purchase cost, (5) sets the emissions limit, (6) is a flow-balance constraint that ensures exactly one vehicle is purchased for each vehicle being replaced, (7) provides lower and upper bounds on features or vehicle types, and (8) requires non-negative integer solutions for the number of vehicles purchased.

Continuing our example, we first find the minimal purchase cost with no emissions bound ($e^1 = \infty$), so we have

$$\{c^*\}^1 = \min 20705(x_{1,1} + x_{1,2}) + 28775(x_{2,1} + x_{2,2}) \tag{9}$$

$$\text{s.t. } 6.9x_{1,1} + 4.8x_{2,1} + 20.7x_{1,2} + 14.3x_{2,2} \leq \infty \tag{10}$$

$$x_{1,1} + x_{2,1} = 4 \tag{11}$$

$$x_{1,2} + x_{2,2} = 6 \tag{12}$$

$$2 \leq x_{2,1} + x_{2,2} \leq 8 \tag{13}$$

$$\vec{x} \in \{0, 1, \cdots\}, \tag{14}$$

where (9) minimizes purchase price, constraint (10) that sets the initial emissions bound $e^1 = \infty$ is automatically satisfied, constraint (11) replaces the 4 vehicles in Florida, constraint (12) replaces the 6 vehicles in Michigan, constraint (13) includes between 2 and 8 hybrids, and constraint (14) ensures integrality. An optimal solution (not unique) is $x_{1,1} = 2$, $x_{2,1} = 2$, $x_{1,2} = 6$, $x_{2,2} = 0$, which achieves the lower limit on hybrids of 2 and thereby minimizes purchase cost. The optimal objective value is $\{c^*\}^1 = \$223190$. The emissions level achieved in the left-hand side of (10) is 147.6 metric tons of CO_2. However, this emissions level is not the lowest one achievable for a purchase of 2 hybrids and 8 conventional engine vehicles. This is why we need one more integer program that optimizes emissions for a given cost.

We formulate *Emissions* | *Cost* as follows:

Emissions | Cost

$$\{e^*\}^k = \min \sum_{r \in R} \sum_{v \in V_r} e_{v,r} x_{v,r} \tag{15}$$

$$\text{s.t.} \sum_{r \in R} \sum_{v \in V_r} c_v x_{v,r} = \{c^*\}^k \tag{16}$$

$$\sum_{v \in V_r} x_v = q_r \qquad \forall r \in R \tag{17}$$

$$f^l \leq \sum_{r \in R} \sum_{v \in V_r : f_v = \text{true}} x_{v,r} \leq f^u \qquad \forall f \in F \tag{18}$$

$$\vec{x} \in \{0, 1, \cdots\}, \tag{19}$$

where (15) minimizes emissions, (16) ensures the purchase cost is the same as the optimal solution $\{c^*\}^k$ of *Cost* | *Emissions Bound* in (4), and constraints (17) - (19) are the same as (6) - (8). The resulting $s^k = (\{c^*\}^k, \{e^*\}^k)$ is added to the Pareto frontier, and the value for e^{k+1} is reduced to $\{e^*\}^k - h$, where h is a predetermined step size.

Continuing our example, we have

$$\{e^*\}^1 = \min 6.9x_{1,1} + 4.8x_{2,1} + 20.7x_{1,2} + 14.3x_{2,2} \tag{20}$$

$$\text{s.t. } 20705(x_{1,1} + x_{1,2}) + 28775(x_{2,1} + x_{2,2}) = 223190 \tag{21}$$

$$x_{1,1} + x_{2,1} = 4 \tag{22}$$

$$x_{1,2} + x_{2,2} = 6 \tag{23}$$

$$2 \leq x_{2,1} + x_{2,2} \leq 8 \tag{24}$$

$$\vec{x} \in \{0, 1, \cdots\}. \tag{25}$$

The optimal solution (unique) is $x_{1,1} = 4$, $x_{2,1} = 0$, $x_{1,2} = 4$, $x_{2,2} = 2$. While the same vehicles are purchased as in *Cost* | *Emissions Bound*, the optimal emissions level achieved of $\{e^*\}^1 = 139$ metric tons of CO_2 is 6% lower; this emissions reduction emphasizes the importance of placing the vehicles optimally. $s^1 = (\{c^*\}^1, \{e^*\}^1) = (\$223190, 139 \text{ metric tons } CO_2)$ is added to the Pareto frontier, and the value for e^2 is reduced to 138 metric tons CO_2, where the step size is $h = 1$ metric ton CO_2.

We continue our algorithm to compute the second point in the Pareto frontier by substituting $e^2 = 138$ metric tons CO_2 into the right-hand side of constraint (10) and resolving *Cost* | *Emissions Bound*. An optimal solution (again not unique) is $x_{1,1} = 1$, $x_{2,1} = 3$, $x_{1,2} = 6$, $x_{2,2} = 0$, which includes 3 hybrids. This is the minimum number of hybrids that can be purchased while satisfying the emissions bound of 138 metric tons CO_2. The optimal objective value is $\{c^*\}^2 = \$231260$. The emissions level achieved in the left-hand side of (10) is 145.5 metric tons of CO_2. Similarly to the first iteration ($k = 1$), this emissions level is not the lowest one achievable for a purchase of 3 hybrids and 7 conventional engine vehicles.

To find the emissions level for the second point in the Pareto frontier, we substitute $\{c^*\}^2 = \$231260$ into the right-hand side of constraint (21) and resolve *Emissions* | *Cost*. The optimal solution (unique) is $x_{1,1} = 4$, $x_{2,1} = 0$, $x_{1,2} = 3$, $x_{2,2} = 3$. While the same vehicles are purchased as in *Cost* | *Emissions Bound*, the optimal emissions level achieved of $\{e^*\}^2 = 132.6$ metric tons of CO_2 is 9% lower. The resulting $s^2 = (\{c^*\}^2, \{e^*\}^2) = (\$31260, 132.6 \text{ metric tons } CO_2)$ is added to the Pareto frontier, and the value for e^3 is reduced to 131.6 metric tons CO_2.

The algorithm, summarized in Figure 3, continues to iteratively solve the *Cost* | *Emissions Bound* and *Emissions* | *Cost* IPs for $k = 3,4,5,6,7$ to provide us with additional points s^3, s^4, s^5, s^6, s^7. At $k = 8$, no further emissions reductions are achievable due to the limit of 8 hybrids, which yields an infeasible *Cost* | *Emissions Bound* IP, and the algorithm terminates.

The Pareto frontier for this example in Figure 4 shows solutions for all iterations $k = 1,\ldots,7$. These solutions describe which combinations of vehicles to purchase to replace the 10 vehicles: the solution varies between 2 and 8 HEVs and ICEVs. While the points in Figure 4 are spaced evenly with respect to price, the CO_2 reductions become smaller when 7 and 8 HEVs are chosen for purchase; this can be explained by the higher mileage on the 6 Michigan vehicles, where hybrids are first optimally placed, compared with the lower mileage of the Florida vehicles, where HEVs 7 and 8 are placed. This example is sufficiently concise to solve with logic and intuition alone; with large fleets containing vehicles with variable mileage and more vehicles considered as candidate replacements, the Pareto frontier is quite useful in identifying strategic purchase decisions.

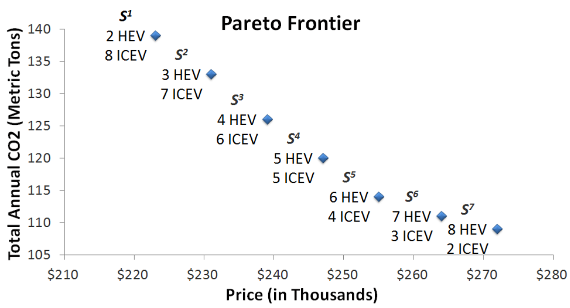

Figure 4: The Pareto frontier.

While we have concentrated on formulations that minimize purchase price in this section, additional objectives are also useful in practice; two such noteworthy objectives are minimizing purchase price plus fuel costs for a given number of years and minimizing total cost of ownership.

4 SOFTWARE APPLICATION

We have developed a Microsoft Excel user interface for the Fleet Purchase Planner. Fleet customers upload information on their current fleets to the template shown in Figure 5. Data collected includes year, make, model, and powertrain, which are mapped to EPA fuel economy data. Combining this with annual mileage, city driving share, and region of operation, we calculate the current state CO_2, as described in Section 2. The input for "quantity to replace" in Figure 5 is used to generate the flow-balance constraints (6), (11), (12), (17), (22) and (23).

Year	Make	Model	Powertrain	Quantity to Replace	Miles/ yr/veh	City driving share	Region of Operation
2010	FORD	FUSION	3.5L, V6, Auto, 2WD	4	17000	55%	Florida
2010	FORD	FUSION	3.5L, V6, Auto, 2WD	6	51000	55%	Michigan

Figure 5: Input for the set of vehicles being replaced, R, from the example in Section 3.

To determine candidate replacements V_r for those vehicles $r \in R$ listed in Figure 5, we use vehicle segmentation data. For example, we look up "2010 Ford Fusion 3.5L, V6, Auto, 2WD" in our segmentation database and find that this is a midsize car. We then refer to the spreadsheet user interface in Figure 6, which lists Fusion as a suitable candidate replacement for midsize cars. This interface offers the flexibility to list multiple candidate replacements, so customers can explore various options; for example, the choice for replacement vehicles could move down in size to a compact car or up to a crossover utility vehicle.

Segment	Consideration	Consideration
MIDSIZE CARS	FUSION	

Figure 6: Segmentation lookup table for vehicles available for purchase.

The interface in Figure 6 is used to narrow down the subset of candidate replacements V_r from all Ford vehicles to all Fusion vehicles. However, in the example from Section 3, we considered only two Fusion vehicles as a candidate replacements: the automatic 2.5L ICEV and the HEV. In practice, we achieve this through our feature sets F and constraints (7) and (18). The information required to generate these constraints is input by the user in the spreadsheet interface shown in Figure 7. For example, a maximum of 0 "Manual" removes manual transmission Fusion vehicles from consideration. This is also where we in-

	Min Number to Purchase	Max Number to Purchase
HYBRID	2	8
ELECTRIC		0
PHEV		0
1.6L, EcoBoost		0
Start/Stop		0
FFV		0
Manual		0

Figure 7: Upper and lower limits, f^l and f^u, respectively, on the features and categories, $f \in F$, for vehicles available for purchase.

troduce the range of 2 to 8 HEVs for constraints (13) and (24).

The analytical engine for the Fleet Purchase Planner is implemented in Java and CPLEX 12.4 is used to solve the IPs. These IPs are easily solved for fleets with up to several thousand vehicles, with solve times under 1 second on an Intel Core i5 2.5 GHz CPU with 8GB RAM running 64 bit Windows 7.

In addition to the Pareto frontier shown in Figure 4, there is other information that could be useful to the customer. The report shown in Figure 8 highlights the improvement in sustainability corresponding to each point on the Pareto frontier compared with the current state of the fleet. This report may also include comparisons of fuel expenditure over a given time period versus purchase price, further illustrating the relationship between cost and sustainability.

	Current	s^1	s^2	s^3	s^4	s^5	s^6	s^7
Total CO2/year (metric tons)	191	139	133	126	120	114	111	109
Change in CO2		-27.2%	-30.6%	-33.9%	-37.3%	-40.6%	-41.8%	-42.9%
Price		$223K	$231K	$239K	$247K	$255K	$264K	$272K
2012 Ford Fusion 2.5L		8	7	6	5	4	3	2
2012 Ford Fusion Hybrid		2	3	4	5	6	7	8

Figure 8: Summary report for multiple purchase options corresponding to points $s^1, \cdots, s^7$ on the Pareto frontier.

The second report in Figure 9, provides the optimal placement of each vehicle purchased for the various scenarios. It can also include summary statistics for annual fuel expenditure and CO_2 emissions on the individual vehicle level, compared to the current level for the vehicle being replaced. Each new vehicle being purchased appears below the vehicle it is replacing. Notice that in the min cost scenario s^1, the two HEVs purchased replace the higher mileage vehicles in Michigan. As the upper bound on emissions e^k is lowered at each iteration k, more vehicles in Michigan are replaced with HEVs. Only after all the Michigan vehicles have been replaced with hybrids, at s^5, is a vehicle in Florida replaced with a hybrid.

Model	Powertrain	Region	Qty.	s^1	s^2	s^3	s^4	s^5	s^6	s^7
FUSION	3.5L, V6, Auto, 2WD	Florida	4	-	-	-	-	-	-	-
FUSION	2.5L, I4, Auto, 2WD	Florida	-	4	4	4	4	4	3	2
FUSION HYBRID	2L, I4, Auto, 2WD	Florida	-	0	0	0	0	0	1	2
FUSION	3.5L, V6, Auto, 2WD	Michigan	6	-	-	-	-	-	-	-
FUSION	2.5L, I4, Auto, 2WD	Michigan	-	4	3	2	1	0	0	0
FUSION HYBRID	2L, I4, Auto, 2WD	Michigan	-	2	3	4	5	6	6	6

Figure 9: Detailed report for multiple purchase options corresponding to points $s^1, \cdots, s^7$ on the Pareto frontier. The vehicles being replaced are shown with a black background and white font, with their corresponding replacements below.

5 CONCLUSIONS

Ford's Fleet Purchase Planner is a software system designed to identify the most cost effective opportunities for vehicle fleets to improve their sustainability through new purchases. FPP leverages several data sources, including vehicle fuel economy, segmentation, customers' current fleets and driving patterns. The IP models we have introduced generate the Pareto frontier, which demonstrates the relationship between cost and sustainability. This technology, for the first time, provides customers with current emissions levels of their vehicle fleets and compares that with levels achieved by various purchase options.

FPP has already been used in collaboration with large fleet customers, with significant demonstrated financial benefits over more traditional vehicle replacements strategies. For example, one such strategy is to select a single new midsize vehicle, such as a Ford Fusion EcoBoost, to purchase for any midsize vehicle being replaced. We can show the minimum cost purchase to achieve the same level of sustainability using the Pareto frontier, thereby highlighting the value of optimization.

FPP has the potential to change the way many of Ford's fleet customers plan their purchases, and more importantly, the decisions they make regarding what to purchase.

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