A Generic Model of Motor-Carrier Fuel Optimization

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Abstract: Fuel optimizers are decision models (software products) that are increasingly recognized as effective fuel management tools by U.S. truckload carriers. Using the latest price data of every truck stop, these models calculate the optimal fueling schedule for each route that indicates: (i) which truck stop(s) to use, and (ii) how much fuel to buy at the chosen truck stop(s) to minimize the refueling cost. In the current form, however, these models minimize only the fuel cost, and ignore or underestimate other costs that are affected by the models' decision variables. On the basis of the interviews with carrier managers, truck drivers, and fuel-optimizer vendors, this article proposes a comprehensive model of motor-carrier fuel optimization that considers all of the costs that are affected by the model's decision variables. Simulation results imply that the proposed model not only attains lower vehicle operating costs than the commercial fuel optimizers, but also gives solutions that are more desirable from the drivers' viewpoint.

Keywords: transportation; motor carriers; fuel cost; linear programming; integer programming.

1. INTRODUCTION

Fuel prices, such as gasoline and diesel prices, have increased dramatically in the last few years. Such a sharp increase of fuel prices has impacted (substantially) the cost of motor carriers. In the United States, many motor carriers were forced to go out of business during the last two years, despite the strong customer demand, because they could not manage fuel costs [9]. Today, the efficient management of fuel cost is a critical issue for all the motor carriers.

Fuel optimizers are decision models (software products) that are increasingly recognized as effective fuel management tools by U.S. truckload (TL) carriers. These models first download the latest price data of nearly all the truck stops in the United States and Canada (updated daily), and then compute the optimal fueling schedule for each route that indicates: (i) which truck stop(s) to use, and (ii) how much fuel to buy at the chosen truck stop(s) to minimize the cost of refueling. These models typically work in conjunction with truck-routing software, so that users can first compute the optimal (shortest) route for a given origin-destination pair (some products consider the highway toll costs when finding the routes), and then optimize the fueling operations along this route. Famous product names include the following: (i) ProMiles, (ii) Expert Fuel, (iii) Fuel and Route, and (iv) Fuel Advice. Vendors of these packages claim that, typically, cost savings range from 4 to 11 cents per gallon of fuel, which convert to an average saving of $1200 per truck per year.

In the current form, however, the commercial fuel-optimizer products merely focus on minimizing the fuel cost (fuel purchasing cost), and ignore or underestimate other cost elements that are affected by the models' decision variables. These "other" cost elements include such items as the vehicle depreciation cost, vehicle maintenance cost, and the opportunity costs associated with fuel-purchasing activities. This pattern implies that, by using fuel optimizers, carriers may be minimizing the fuel cost *at the expense of increased costs for other elements*. Thus, although fuel optimizers are useful tools for managing fuel costs, they may not necessarily provide the optimal fueling solutions to carriers from the overall cost-minimization perspective.

This article proposes a comprehensive framework of motor-carrier fuel optimization that considers not only the cost of buying fuel, but also other cost elements that are: (i) functions of fuel-optimizer decision variables, but (ii) not currently considered by the standard (commercial) fuel optimizers. An interesting feature of our method is that it may be viewed as a "generic" form of the standard fuel optimizers, because our model reduces to the standard fuel-optimizer form if all of the "other" (i.e., nonfuel) cost elements are

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assumed to be zeros. We show that, under this "generic" approach, (i) the optimal fueling solutions will be considerably different from those produced by the standard fuel optimizers, and (ii) the overall vehicle operating cost may become noticeably lower than that attained by the standard fuel optimizers.

2. PRODUCT HISTORY AND LITERATURE

The initial fuel-optimizer product was developed in the mid 1990s by a transportation consulting company based in the United States. The software was designed to address the concern raised by many motor carriers that fuel prices vary, often substantially, from one truck stop to the next within each route. The basic concept of the model is to take advantage of such price variances across truck stops to reduce the cost of buying fuel. The model's goal is to buy more gallons at truck stops where the fuel is cheap, and buy fewer gallons at truck stops where the fuel is expensive. Our literature review indicates that researchers did not consider this type of vehicle refueling problems until recently, despite the proliferation of actual software products in the field.

Probably the first scholarly work that considered the vehicle refueling problem from the operations research perspective is Kuby and Lim [4]. They considered the problem of optimally locating the fueling facilities for limited-range vehicles. Their study, however, was conducted purely from the facility-location standpoint, and did not directly address the "where-to-buy" vehicle refueling problems. More closely related works can be found in Lin [5], Lin et al. [6], and Khuller et al. [3]. Lin et al. [6] considered the fixed-path vehicle refueling problem similar to that addressed by commercial fuel optimizers and developed a linear-time greedy algorithm. Lin [5] extended the work of Lin et al. [6] by developing an algorithm that jointly determines the optimal path from origin to destination and the optimal refueling policies along the path (non-fixed-path refueling problem). Khuller et al. [3] considered, in addition to the fixed-path and non-fixed-path refueling problems, the optimal refueling policies for the traveling-salesman problem (TSP). They developed polynomial-time algorithms to solve the fixed-path and nonfixed-path refueling problems, and developed approximation algorithms to solve the TSP.

All the earlier studies have made important contributions to the vehicle refueling literature. However, no studies have explicitly considered the nonfuel cost elements that were mentioned in the previous section, nor investigated how the model that incorporates such nonfuel cost elements may actually perform in the field relative to the standard fuel-optimizer products. In the discussions that follow, we: (i) develop a model that mimics the standard fuel-optimizer products, (ii) enhance the resulting model by explicitly including the nonfuel cost elements into the model, and (iii) empirically investigate the performance of the enhanced model relative to the standard fuel-optimizer products by performing a series of simulation experiments.

3. THE STANDARD FUEL OPTIMIZER MODEL

This section describes the basic framework of the commercial fuel optimizers and derives the mathematical model that mimics them. Our discussions below are based on the interviews with three users and two vendors of fuel optimizers, as well as our experience of using the products. The model derived in this section will later be used in our simulation experiments.

3.1. Basic Framework

Basically, the standard fuel optimizers are mathematical programming models that minimize the cost of buying fuel in a given route by selecting the optimal fueling locations (truck stops) and quantities (gallons). The following factors are considered by the models: (i) truck's tank capacity, (ii) trip starting fuel, (iii) trip ending fuel, (iv) fuel consumption rate (miles per gallon), (v) minimum fuel to be maintained at all times, and (vi) out-of-route distance to each candidate truck stop (the extent to which a vehicle must deviate from the optimal route to reach the truck stop). Our interviews with two fuel-optimizer vendors suggest that the commercial fuel optimizers generally use a linear-programming type method to find the optimal fueling solutions.

Most fuel-optimizer packages allow users to include certain constraints that reflect their corporate policies and preferences, so that the model solutions become not only "feasible," but also "practical" from the execution standpoint. These constraints include the following: (i) eliminating certain truck stops from the models that do not meet the minimum acceptable standards (e.g., those that are more than three miles away from the shortest route, or those that do not have shower facilities), and (ii) forcing the models to consider only the "network" truck stops (those with which the users have purchase contracts) when solving the problem. The models also allow users to specify the minimum amount of fuel to buy at truck stops, so that users can: (i) control the frequency of fuel stops (avoid frequent stops), and (ii) give "free showers" to drivers (in most truck stops drivers can use shower facilities free if they buy 50 gallons of diesel fuel or more).

3.2. Model Formulation

Let Ω be the set of all the truck stops along the (shortest) route from origin o to destination d, and $i (i = 1, 2, \ldots, n)$ be the elements of Ω (see Fig. 1). The required inputs are as follows:

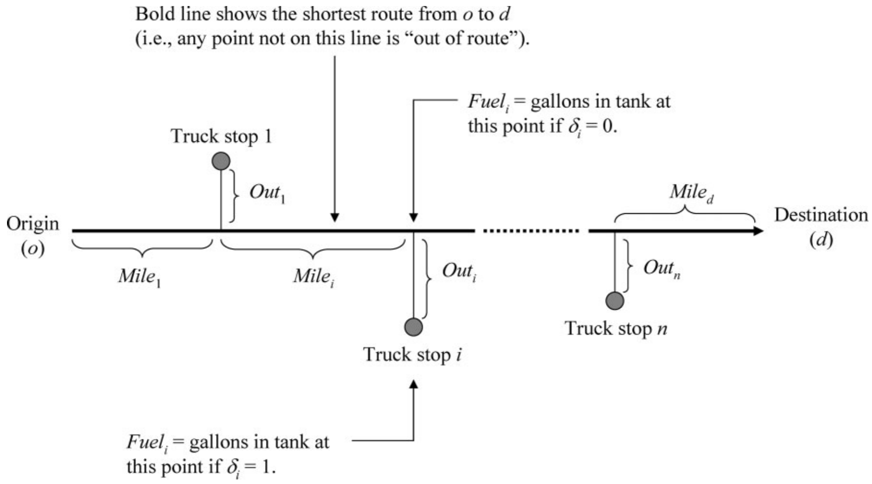

Figure 1. A sample route.

$Price_i$ = retail diesel price (per gallon) at truck stop i

Out_i = amount of miles that a vehicle must go out-of-route (OOR) to reach truck stop i

$Mile_i$ = distance (miles) from truck stop $i-1$ to i (not including Out_{i-1} or Out_i)

SF = amount of fuel (gallons) in tank at origin o (starting fuel)

MG = average fuel consumption rate (miles per gallon or MPG) for the whole trip

TC = vehicle tank capacity (e.g., 200 gallons)

LF = minimum fuel to be maintained in tank at all times (lower bound fuel)

MP = minimum amount of fuel to purchase at truck stops (e.g., 50 gallons)

EF = required amount of fuel in tank at the final destination d (ending fuel)

Given these inputs, the fuel-optimizer problem can be written as a mixed-integer LP model:

$$\underset{\phi_i \geq 0, \delta_i}{\text{Minimize}} \quad \left\{ \sum_{i \in \Omega} Price_i \phi_i \right\} \tag{1}$$

$$\text{Subject to:} \quad \delta_i \in \{0, 1\} \quad \forall\, i \in \Omega \tag{2}$$

$$Fuel_i \geq LF \quad \forall\, i \in \Omega \tag{3}$$

$$Fuel_d \geq EF \tag{4}$$

$$\phi_i \geq \delta_i MP \quad \forall\, i \in \Omega \tag{5}$$

$$\phi_i \leq \delta_i TC \quad \forall\, i \in \Omega \tag{6}$$

$$Fuel_i + \phi_i \leq TC \quad \forall\, i \in \Omega \tag{7}$$

where:

δ_i = 1 if truck stop i is selected as a refueling point, 0 otherwise

ϕ_i = nonnegative amount of fuel (gallons) to purchase at truck stop i

$Fuel_i$ = nonnegative amount of fuel in tank either at truck stop i before buying fuel (if $\delta_i = 1$) or at the point nearest to i along the route (if $\delta_i = 0$) (see Fig. 1)

$Fuel_d$ = remaining fuel at the destination (d)

We calculate $Fuel_i$ and $Fuel_d$ values by using the following formulas:

$$Fuel_i = \begin{cases} SF - (Mile_i + \delta_i Out_i)/MG, & \text{if } i = 1 \\ Fuel_{i-1} + \phi_{i-1} - (\delta_{i-1} Out_{i-1} \\ \quad + Mile_i + \delta_i Out_i)/MG, & \text{if } i \neq 1 \end{cases} \tag{8}$$

$$Fuel_d = Fuel_n + \phi_n - (\delta_n Out_n + Mile_d)/MG \tag{9}$$

where $Mile_d$ is the distance between truck stop n and the destination d (not including Out_n).

Observe that the above model minimizes the cost of buying fuel (refueling cost) between o and d while ensuring that: (i) the remaining fuel in the tank does not fall below LF at any point in the route (constraint 3), (ii) the ending fuel is larger than or equal to EF (constraint 4), (iii) the minimum purchase quantity (of diesel fuel) is MP at any truck stop (constraints 5 and 6), and (iv) the sum of remaining fuel in the tank (before buying fuel) and the amount of purchased fuel does not exceed the tank capacity at any truck stop (constraint 7). We verified that the above model generally gives the same solution as ProMiles (one of the most-widely used fuel optimizers).

4. LIMITATIONS OF THE STANDARD FUEL OPTIMIZERS

A major limitation of the standard fuel optimizers is that they consider *only* the cost of fuel. As mentioned earlier, these models make two types of decisions in each route; i.e., fueling locations and fueling quantities. It should be noted that these decisions determine not only the place and quantity of fuel purchases, but also the following two attributes for each route: (i) total out-of-route miles a vehicle must travel in the route (OOR miles—determined by the choice of truck stops), and (ii) frequency of fuel stops in the route (fueling frequency—determined by the amount of fuel purchased at each truck stop). In this section we point out the cost elements that are affected by the above two route attributes (i.e., the costs that are indirect functions of fuel-optimizer decision variables), but are either ignored or underestimated by the standard fuel optimizers. Our arguments in this section are based on the in-depth interviews with four TL carriers, three over-the-road truck drivers, two fuel-optimizer vendors, and two truck-stop chains.

Vehicle maintenance cost (affected by OOR miles; ignored by the models). Under the standard costing practice, TL carriers incur the cost of vehicle maintenance on a "per-mile" basis, because they "spread out" the cost of maintenance over certain miles. For example, if a carrier pays $500 of preventive maintenance cost per 5000 vehicle miles, this $500 is spread out over 5000 miles so that the carrier incurs the maintenance cost of $0.1 per mile [8]. This condition indicates that the maintenance cost incurred by a carrier in a given route is determined by the total distance of the route, including OOR miles. The vehicle maintenance cost, therefore, is a function of OOR miles such that the longer the OOR miles the higher the cost.

Vehicle depreciation cost (affected by OOR miles; ignored by the models). In general, motor carriers depreciate the cost of equipment (tractor and trailer) purchases over certain amounts of miles (over the expected life of equipment—e.g., 360,000 miles). This accounting procedure allows carriers to allocate the cost of equipment purchases to a variety of loads based on their route miles. This pattern suggests that, like the vehicle maintenance cost, the equipment depreciation cost incurred by a carrier in a given route is determined by the total distance of the route, including OOR miles. Hence, the vehicle depreciation cost is a function of OOR miles.

Fuel cost (affected by OOR miles; underestimated by the models). The standard fuel optimizers consider both the cost of fuel incurred in the "main" segment of the route (mostly highways) and that incurred in the "OOR" segment (mostly non-highway roads). The standard models, however, compute the total fuel cost for each route by applying the same MPG to both the "main" segment and the "OOR" segment. It is well known that the MPG of heavy-duty trucks is substantially worse on non-highway roads than on highways (see, e.g., [7]). This condition implies that, by applying the same MPG to all the segments, the standard fuel optimizers may be underestimating the cost of fuel needed to move trucks on OOR roads.

Opportunity cost of OOR miles (affected by OOR miles; ignored by the models). Theories of transport economics suggest that there are *opportunity costs* associated with OOR miles, because the driver and vehicle times that are used to travel OOR miles have alternative uses. In theory, OOR miles can be completely avoided by using only the truck stops that are "on the route". This condition suggests that, *every time* a carrier requires a vehicle to go "out-of-route," the carrier incurs an opportunity cost because (by adding OOR miles) it is increasing the needed time to finish the *current load*, which can potentially reduce the time to haul *future loads*. In other words, whenever a carrier requires a vehicle to use the truck stops that are "off the route," it is "wasting" certain amount of driver and vehicle times that could otherwise be used to generate additional profits. TL carriers are quite sensitive to this type of cost (possible loss of future profit), but it is not currently considered by the standard fuel optimizers.

Opportunity cost of making fuel stops (affected by fueling frequency; ignored by the models). Truck drivers claim that, every time they stop for fuel, they must spend certain amounts of "fixed time" at truck stops in addition to the required time for pumping. This "fixed time" includes the times for (i) waiting in line for pumping, (ii) adjusting the log book, and (iii) making payments. Drivers are especially concerned with the wait times for pumping, because U.S. truck stops are generally congested [11]. This pattern implies that, if a vehicle makes more than m fuel stops in a given route (where m is the minimum number of fuel stops required in the route), it incurs an opportunity cost because (in theory) the driver and vehicle times that are spent for being in line, etc., at these "extra" fuel stops are *avoidable* (can be eliminated by buying the maximum fuel at the first m stops). In other words, whenever a carrier requires a vehicle to make more fuel stops than necessary, it is "wasting" certain amounts of driver and vehicle times that could otherwise be used to generate additional profits. This type of opportunity cost is not currently considered by the standard fuel optimizers.

In short, we argue that the standard fuel optimizers: (i) ignore or underestimate several cost elements that are associated with OOR miles, and (ii) totally ignore the opportunity cost associated with fuel stops. Thus, the models may: (i) favor truck stops that offer cheap prices but are far from the (shortest) route, and (ii) produce solutions that require rather frequent fuel stops (relative to the minimum number of fuel stops needed). Such solutions may minimize the fuel cost, but not necessarily the *overall vehicle operating cost*. In the next section, we develop a comprehensive framework that incorporates all of the cost elements mentioned in this section.

5. THE PROPOSED MODEL

5.1. Framework

Our approach is to minimize the total cost of operating a vehicle in a given route, which includes the costs of fuel, maintenance, depreciation, and driver wage (these four items usually account for over 95% of the vehicle operating cost—see [2]), as well as the opportunity costs associated with OOR miles and fuel stops. The driver wage, however, will not be explicitly included in our objective function. The reason is that, because TL drivers are paid by the billed miles (shortest-route miles) rather than by the actual (odometer) miles, the driver wage in each route is constant (i.e., driver wage will not be affected by the model's decision variables).

5.2. Model Formulation

Our model requires the use of all the inputs from the standard fuel optimizers (section 3.2), as well as the following additional inputs (measurements of these inputs will be discussed later):

$MC =$ vehicle maintenance cost ($ per mile)
$DC =$ vehicle depreciation cost ($ per mile)
$MG(h) =$ standard MPG
$MG(l) =$ MPG on non-highway (OOR) roads
$LPM =$ opportunity cost (lost profit) associated with OOR miles ($ per OOR mile)
$LPS =$ opportunity cost (lost profit) associated with fuel stops ($ per stop)

Let OM be the actual distance (odometer miles) between origin o and destination d which includes the OOR miles. We can calculate the value of OM by using the following formula:

$$OM = \sum_{i\in\Omega}(Mile_i) + Mile_d + \sum_{i\in\Omega}(2\delta_i Out_i) \tag{10}$$

Also let MRS be the minimum number of times a vehicle must stop for refueling between origin o and destination d (theoretical lower bound). MRS can be obtained by evaluating the value of the following formula, and rounding the resulting figure up to the nearest integer:

$$\max\left(0, \frac{\left(\left(\sum_{i\in\Omega}(Mile_i) + Mile_d\right)/MG(h)\right) - (SF - EF)}{TC - LF}\right) \tag{11}$$

Notice that Eq. (11) assumes that a driver: (i) fills up (tops off) the tank whenever the remaining fuel becomes roughly equal to LF, and (ii) uses only the truck stops that are "on the route."

Given these inputs and definitions, the objective function of our model (which measures the total cost of operating a vehicle from origin o to destination d) can be written as follows:

$$\begin{aligned}\underset{\phi_i\geq 0,\delta_i}{\text{Minimize}} \Bigg\{ &\sum_{i\in\Omega}(Price_i\phi_i) + OM(DC+MC) \\ &+ \sum_{i\in\Omega}(2\delta_i Out_i)LPM + \left[\sum_{i\in\Omega}(\delta_i) - MRS\right] LPS \Bigg\}\end{aligned} \tag{12}$$

where the first and second additive terms represent the "direct" costs of operating a vehicle (fuel, depreciation, and maintenance costs), whereas the third and fourth additive terms represent the "indirect" costs (opportunity cost of OOR miles and that of making fuel stops). Notice that we assess the opportunity cost associated with fuel stops by first calculating the difference between the actual number of fuel stops and MRS, and then multiplying the resulting figure by LPS (so that it represents the cost of making *additional* stops *beyond* the minimum number of stops).

Our model is subject to all of the constraints that apply to the standard fuel optimizers, except that $Fuel_i$ and $Fuel_d$ must be measured by the following formulas (in lieu of Eqs. 8 and 9):

$$Fuel_i = \begin{cases} SF - (Mile_i/MG(h)) - (\delta_i Out_i/MG(l)), & \text{if } i = 1 \\ Fuel_{i-1} + \phi_{i-1} - (Mile_i/MG(h)) \\ \quad -((\delta_{i-1}Out_{i-1} + \delta_i Out_i)/MG(l)), & \text{if } i \neq 1 \end{cases} \tag{13}$$

$$\begin{aligned}Fuel_d = Fuel_n + \phi_n - (Mile_d/MG(h)) \\ - (\delta_n Out_n/MG(l))\end{aligned} \tag{14}$$

Notice that these formulas calculate the amount of fuel consumed in the "main" segment of the route and that in the "OOR" segment separately by using different fuel consumption rates (MPG).

5.3. Model Features

The proposed model has several interesting features. First, the model considers all of the vehicle operating costs that are overlooked by the standard fuel-optimizer models, yet: (i) retains the desirable linear form of the standard models, and (ii) uses the same number of decision variables and constraints as the standard models. This condition implies that solving our model may be as easy as solving the standard fuel-optimizer models. Our experience indicates that the solution time of our model (using the simplex algorithm in conjunction with the branch-and-bound method) is typically longer than that of the standard models, but the difference is small.

Second, our model may be viewed as a "generic" form of the standard fuel optimizers. Notice that if $MG(h) = MG(l)$ and $MC = DC = LPM = LPS = 0$, our model reduces to the standard fuel-optimizer form. This condition implies that our model allows users to minimize either the fuel cost or the vehicle operating cost (or partial vehicle operating cost), depending on situations. For example, when the economy is soft such that the truck capacity is underutilized, carriers may ignore the opportunity costs ($LPM = LPS = 0$) and focus on minimizing the costs of fuel, maintenance, and depreciation (or just the fuel cost if desired). In contrast, when the economy is strong such that the truck capacity is tight (like in 2005), carriers may wish to use higher *LPM* and *LPS* values to prevent the loss of profit due to inefficient uses of their assets.

Third, from the drivers' viewpoint, our model should give more desirable solutions than the standard fuel optimizers. Notice that our model will most likely: (i) choose truck stops with fewer OOR miles than those chosen by the standard models (to reduce OOR miles), and (ii) buy more gallons per fuel stop than the standard models (to reduce fueling frequency). From the drivers' standpoint, such solutions are desirable because: (i) drivers do not want OOR miles (as OOR miles are "unpaid" miles), and (ii) they do not want frequent fuel stops (they dislike wait times at truck stops, as their goal is to finish the current loads quickly so that they can start the next loads quickly). These conditions suggest that carriers may attain higher driver compliance rates (proportion of fueling occasions in which drivers comply with model instructions) by using our model than by using the commercial fuel optimizers (which implies higher cost savings).

6. SIMULATION EXPERIMENTS

In this section we conduct a series of simulation experiments to investigate how well the proposed model may perform in practice. Our goal is to compare the performance of our model with that of the standard fuel optimizers, so that we can empirically examine how well the proposed model performs *relative to* the standard fuel optimizers. Our experiments do not contrast the proposed model with other vehicle-refueling models (fixed-path vehicle refueling algorithms) proposed in the literature [3, 5, 6]. Because the assumptions of these models differ from those of ours (e.g., they often do not consider certain fuel-optimizer inputs such as *MP* and *EF*), it is difficult to compare these models with the proposed model on the same footing.

To obtain realistic results and implications, we carefully designed the simulation experiments and parameters by referring to a variety of reliable data sources. Our data sources include (but are not limited to) the following: (i) a medium-sized TL carrier based in the United States (referred to as Carrier X), (ii) ProMiles, (iii) interviews with four TL carriers (including Carrier X), (iv) interviews with three over-the-road truck drivers (TL drivers), (v) interviews with two fuel-optimizer vendors, and (vi) a practitioner journal. For clarity, we will refer to the standard Fuel Optimizers as Fuel Optimizer I, and the proposed model as Fuel Optimizer II from now on.

6.1. Experiment

We randomly generate numerous hypothetical (yet realistic) truck-refueling problems, and solve each problem by using both the Fuel Optimizer I and Fuel Optimizer II models. Our experiments are performed according to the following procedure.

First, in each simulation trial (load), the problem details such as the route characteristics (e.g., route distance, number of truck stops in the route) and vehicle characteristics (e.g., starting fuel, ending fuel) are randomly determined (probability distributions of random variables are discussed later). Second, for each truck stop along the route, the store details (e.g., distance from the previous truck stop, out-of-route miles, retail diesel price) are again randomly determined. Third, once the problem details are specified by the above procedure, the problem is solved by using both the Fuel Optimizer I and Fuel Optimizer II models, whose parameters (e.g., minimum gallons to purchase) are set identical throughout the experiment. (We use the simplex algorithm in conjunction with the branch-and-bound method to solve the models). Fourth, after the problem is solved, we compare the solutions given by the two models in terms of both the fuel purchasing cost and the total vehicle operating cost in the route, along with other statistics.

We repeat the above simulation trial 1000 times to complete an experiment (i.e., we solve 2000 mixed-integer LP problems in each experiment). To obtain robust simulation results, we perform three experiments. In each experiment, the expected length of haul (route distance) is varied. The ranges of route distance used for the three experiments are as follows: 500–1000 miles (medium haul–experiment 1), 1000−2000 miles (long haul–experiment 2), and 2000−3000 miles (very-long haul–experiment 3). The simulation took approximately 4, 25, and 120 h for experiments 1, 2, and 3, respectively (on a 1.8 GHz Core-Duo PC). (We used the integer tolerance of "zero" in all the three experiments to avoid "compromising" solutions. In practice, larger values of integer tolerance may be used to obtain quick solutions.)

6.2. Measuring Opportunity Costs

Because the opportunity cost in the transportation industry is defined as "the values of resources in their best alternative use" [2], we measure the opportunity cost of OOR miles and that of making fuel stops in accordance with this definition.

Opportunity cost of OOR miles (LPM). We measure the opportunity cost of an OOR mile by first estimating the amount of vehicle time that is "saved" by reducing one OOR

Table 1. Selected simulation parameters.

	Distribution	Parameters	Data source[a]	Sample size
Random Variables				
Trip miles (medium haul)	Uniform	Min = 500, Max = 1,000	—	—
Trip miles (long haul)	Uniform	Min = 1,000, Max = 2,000	—	—
Trip miles (very long haul)	Uniform	Min = 2,000, Max = 3,000	—	—
$Price_i$ (retail diesel price)[b]	Normal	Mean = 2.62, Std = 0.0918	ProMiles	1,598
$Mile_i$ (miles between TS)	Gamma[c]	L = −0.51, C = 25.17, A = 0.62	ProMiles	1,598
Out_i (one-way OOR miles to TS)	Exponential	1/mean = 2.46	ProMiles	1,598
SF (starting fuel)[d]	Uniform	Min = 25%, Max = 100%	Carrier X	—
EF (ending fuel)[d]	Bimodal	See manuscript[e]	Interview (MC, FV)	4,2
Fixed Parameters				
MP (min. gallons to buy)	—	50 gallons	Interview (MC, FV)	4,2
LF (min. fuel to be maintained)	—	20% of tank capacity	Interview (MC)	4
TC (vehicle tank capacity)	—	200 gallons	Carrier X	—
$MG(h)$ (standard MPG)	—	6.09	Santini et al. [7]	—
$MG(l)$ (non-highway MPG)	—	4.32	Santini et al. [7]	—
DC (depreciation cost per mile)[f]	—	—	Carrier X	1,260
MC (maintenance cost per mile)[f]	—	—	Carrier X	1,260
WC (driver wage per mile)	—	\$0.34	Transport Topics[g]	—
FC (fuel cost per mile)	—	\$0.43	—	—
R (revenue per mile with FSC)	—	\$1.90	Interview (MC)	4
SP (vehicle speed on highways)	—	65 mph	Interview (DR)	3
FX (fixed stopping time at TS)	—	10 min.[h]	Interview (DR)	3

[a] Interview (MC), interviews with motor-carrier managers; interview (FV), interviews with fuel-optimizer vendors; interview (DR), interviews with truck drivers.
[b] The price does not include the state tax. We eliminate the state tax from the fuel price because this is the standard fuel costing practice used by TL carriers. (Some fuel optimizer packages also exclude the state tax from fuel price by default.)
[c] L, location parameter; C, scale parameter; A, shape parameter.
[d] Percentage of the tank filled.
[e] Prob($B = 1$) = 0.5; mean of $EF_1 = 40\%$ of tank capacity; mean of $EF_2 = 80\%$ of tank capacity; standard deviation of EF_1 and $EF_2 = 8\%$ of tank capacity.
[f] These parameters are not reported for confidentiality reasons.
[g] Transport Topics [10].
[h] Our interviews with drivers indicate that they typically spend 10 to 20 min. at truck stops just to wait for pumping.

mile, and then calculating the expected profit that can be generated by using the "saved" time in the best alternative way (hauling another load on non-OOR roads). We use the following LPM formula:

$$LPM = R - (FC + WC + DC + MC) \tag{15}$$

where R is the average revenue per loaded highway mile (including fuel surcharges), FC is the fuel cost per mile (based on $MG(h)$), and WC is the driver wage per mile (i.e., LPM is measured by the gross profit per loaded highway mile.) Here, an implicit assumption is that a vehicle gains one additional "non-OOR" mile (highway mile) by reducing one OOR mile (non-highway mile). This assumption yields a rather conservative estimate of the opportunity cost because, given the faster speed on highways, trucks can gain more than one highway mile by saving one OOR mile.

Opportunity cost of fuel stops (LPS). We measure this cost by first calculating the expected vehicle time that can be saved by eliminating one "extra" fuel stop, and then evaluating the gross profit that can be generated by using the "saved" time in the best alternative way. Thus,

$$LPS = \left(\frac{SP}{60}FX\right) LPM \tag{16}$$

where SP is the average vehicle speed on highways (mph), and FX is the "fixed" (non-pumping) time per fuel stop (minutes). Note that we obtain LPS by multiplying the "expected highway miles per saved time" ($(SP/60)FX$) with the "expected profit per loaded highway mile" (LPM).

6.3. Simulation Parameters

Selected simulation parameters are shown in Table 1. We specify the parameters mainly by referring to three data sources (ProMiles, Carrier X, and interviews). When the actual (or empirical) data are available, the parameters are specified by performing statistical analyses (e.g., fit a variety of distributions to the data and use the parameters of the distribution that gives the best fit). When the actual data are not

Table 2. Comparisons of Fuel Optimizer I and Fuel Optimizer II.

	Fuel Optimizer I	Fuel Optimizer II	Difference (II–I)
Experiment 1 (500–1000 miles)			
Number of fuel stops per trip[a]	1.55	1.30	−0.25 ***
Out-of-route miles per trip	0.57	0.41	−0.16 ***
Purchased fuel per stop (gal.)	75.67	89.75	14.08 ***
Total purchased fuel per trip (gal.)	117.01	116.49	−0.51 *
Fuel purchasing cost per trip	285.66	285.82	0.16
Total vehicle cost per trip	513.32	510.60	−2.73 ***
Experiment 2 (1000–2000 miles)			
Number of fuel stops per trip[a]	2.80	2.27	−0.53 ***
Out-of-route miles per trip	1.00	0.68	−0.32 ***
Purchased fuel per stop (gal.)	83.64	102.72	19.08 ***
Total purchased fuel per trip (gal.)	234.03	233.27	−0.76 *
Fuel purchasing cost per trip	568.74	569.01	0.27
Total vehicle cost per trip	1032.35	1027.22	−5.13 ***
Experiment 3 (2000–3000 miles)			
Number of fuel stops per trip[a]	4.57	3.64	−0.93 ***
Out-of-route miles per trip	1.65	1.11	−0.54 ***
Purchased fuel per stop (gal.)	87.80	110.12	22.32 ***
Total purchased fuel per trip (gal.)	401.51	401.26	−0.25 ***
Fuel purchasing cost per trip	972.44	975.41	2.97 ***
Total vehicle cost per trip	1755.69	1749.21	−6.47 ***

* P-value < 0.05, ** P-value < 0.01, *** P-value < 0.001 (paired t-test).
[a] Average *MRS* values (minimum required stops) were 1.215, 1.974, and 3.022, for experiments 1, 2, and 3, respectively.

available, the parameters are determined by using the inputs obtained from carrier managers, truck drivers, fuel-optimizer vendors, or a practitioner journal. The parameters reported in Table 1 should be mostly self-explanatory to readers. In the paragraphs that follow, we describe those parameters that need further explanations/clarifications.

Fuel cost per mile (FC). This cost is obtained by first calculating the average amount of fuel consumed per mile, and then converting the resulting figure into the dollar value. Specifically, we use the following formula to calculate the per-mile fuel cost:

$$FC = E(Price_i)/MG(h) \tag{17}$$

where $E(Price_i)$ is the average fuel price in our simulation (see Table 1). Observe that $MG(h)$ is used in Eq. (17), rather than $MG(l)$, because FC is used *only to calculate the opportunity costs*.

Ending fuel (EF). Many fuel-optimizer users prefer to set the ending fuel of a truck such that: (i) EF = large value if the expected fuel price of the next route is higher than that of the current route (so that the truck may avoid buying expensive fuel in the next trip), and (ii) EF = small value if the expected fuel price of the next route is lower than that of the current route (so that the truck will buy cheap fuel in the next trip). In our simulation, EF is specified by using a bimodal distribution to incorporate such a pattern. The actual formula used to generate EF is:

$$EF = (B)EF_1 + (1 - B)EF_2 \tag{18}$$

where B is a random Bernoulli (0/1) variable, and EF_1 and EF_2 are two normally-distributed random variables that have the same variance but different means (see Table 1 for further details).

7. RESULTS AND IMPLICATIONS

7.1. Simulation Results

Simulation results are reported in Table 2. The most important findings are as follows. First, the OOR miles (per trip) of Fuel Optimizer II are *significantly* lower than those of Fuel Optimizer I (in this article we use the term *significant* to indicate the differences of values that are statistically significant at the 99.9% confidence level). As expected, therefore, Fuel Optimizer II tends to choose the truck stops that are "closer to the route" than Fuel Optimizer I. This condition implies that, if one's objective is to minimize the total vehicle operating cost (rather than just the fuel cost), it may not always make sense to travel an extra mile or two "off the route" to reach "cheap" truck stops. Second, the fueling frequency of Fuel Optimizer II is significantly lower than that of Fuel Optimizer I, but is somewhat higher than MRS. This pattern suggests that, to minimize the total cost, a vehicle should not buy fuel

Table 3. Annual cost savings of Fuel Optimizer II (over Fuel Optimizer I) by carrier size.

	Medium Carrier (1000 trucks)	Large Carrier (5000 trucks)	Very-Large Carrier (10000 trucks)
Exp. cost saving per mile ($)[a]	0.00321	0.00321	0.00321
Exp. saving per truck per year ($)[b]	385.74	385.74	385.74
Overall cost saving per year ($)	385,741	1,928,704	3,857,408

[a]Average of three simulation experiments.
[b]Annual mileage of 120,000 per truck (class-8 tractors) is assumed (see, e.g., [1]).

too frequently (to avoid the "fixed cost" per fuel stop), but should not over-reduce the fueling frequency either (as this action will limit the choice of truck stops substantially).

Another interesting finding from Table 2 is that the amount of purchased fuel *per stop* is higher for Fuel Optimizer II than for Fuel Optimizer I, while the amount of purchased fuel *per trip* is lower for Fuel Optimizer II than for Fuel Optimizer I. These results are intuitively sound because: (i) Fuel Optimizer II should buy *more* fuel *per stop* than Fuel Optimizer I (to reduce fueling frequencies), but (ii) Fuel Optimizer II should buy *less* fuel *per trip* than Fuel Optimizer I (as Fuel Optimizer II requires less OOR miles per trip than Fuel Optimizer I; i.e., the former requires less fuel to operate a vehicle from origin to destination than the latter). These conditions imply that Fuel Optimizer II may give "greener" or "more environmentally friendly" solutions than Fuel Optimizer I by reducing the amount of fuel needed to operate a vehicle in each route.

With regard to the cost, we find the following. First, the total vehicle operating cost of Fuel Optimizer II is lower than that of Fuel Optimizer I. The table shows that, in all the three experiments, Fuel Optimizer II attains significantly lower total costs than Fuel Optimizer I, and that the average amount of difference (the amount by which the former outperforms the latter) is about 0.32 cents per mile (roughly equivalent to the cost-saving of 2.05 cents per gallon of fuel). As expected, therefore, Fuel Optimizer II does a better job of minimizing the overall vehicle cost than Fuel Optimizer I. Second, Fuel Optimizer I attains the lower fuel purchasing cost than Fuel Optimizer II. Table 2 shows that, in all the three experiments, the fuel purchasing cost is lower for Fuel Optimizer I than for Fuel Optimizer II. This means that, in terms of minimizing the fuel purchasing cost, Fuel Optimizer I does a better job than Fuel Optimizer II. It should be noted, however, that the difference of fuel purchasing cost between the two models is not always statistically significant (observe in Table 2 that only in experiment 3 the difference is significant).

Table 3 shows the amount of cost saving that may be attained by using Fuel Optimizer II *over and above* the saving attained by Fuel Optimizer I. The table indicates that, although Fuel Optimizer II outperforms Fuel Optimizer I by only a few dollars on a "per-trip" basis, these small figures may convert to large cost savings on a "per year" basis. The table shows that, for example, large carriers that have over 10,000 trucks (such as J.B. Hunt Transport and Schneider National) may attain *additional cost savings* of nearly $4 million per year by using Fuel Optimizer II. Assuming the cost saving of $1200 per truck per year for Fuel Optimizer I (the amount typically claimed by fuel-optimizer vendors), the above pattern implies that the cost saving given by Fuel Optimizer II may be about 32% higher than that given by Fuel Optimizer I.

Readers should note, however, that the numbers reported in Table 3 may be somewhat exaggerated for the following reasons. First, they include the savings of opportunity costs which may not be realized under certain conditions (e.g., when the economy is soft). Second, they are calculated based on the assumption that the driver compliance rate is 100% (which is rarely true). Readers are advised to interpret the figures shown in Table 3 as the "upper-bound" cost savings.

7.2. Managerial Implications

The following implications may be derived from our study results. First, fuel-optimizer vendors may wish to seriously consider modifying their models (software) to incorporate all the "nonfuel" costs that are affected by the fuel-optimizer decision variables. Development of such models will allow carriers to minimize their costs from the overall company perspective, rather than from the fuel-cost minimization perspective. Simulation results imply that such models not only achieve significantly lower vehicle operating costs than the standard Fuel Optimizers, but also produce more desirable solutions from the drivers' point of view (by reducing both the OOR miles and fueling frequencies). Our interviews with four TL carriers (three of which are fuel-optimizer users) suggest that they will welcome this type of model because, given the practicality of solutions to drivers, it may improve the driver compliance rates. (Fuel-optimizer vendors claim that driver compliance rates typically range between 50% and 70%).

Second, carriers that are currently using the standard Fuel Optimizers may wish to adjust the model parameters to obtain solutions similar to those of Fuel Optimizer II (especially when capacities are tight; i.e., when opportunity costs are high due to strong demand). Our results indicate that Fuel Optimizer II solutions almost always have fewer OOR miles and fuel stops than Fuel Optimizer I solutions. This pattern implies that Fuel Optimizer I users may obtain solutions similar to those of Fuel Optimizer II by: (i) forcing the model to consider only the truck stops that have small OOR miles (e.g., $Out_i \leq 1 \; \forall \; i \in \Omega$), and (ii) restricting the minimum purchase quantity to be large (e.g., $MP = 80$). Our experience indicates that this approach gives solutions that are fairly similar to those of Fuel Optimizer II. It should be noted, however, that this approach does not always give feasible solutions, because it tries to improve solutions by using hard constraints. Truly the optimal solutions are obtained only from Fuel Optimizer II.

8. CONCLUSIONS AND FUTURE RESEARCH

This article has proposed a new type of fuel-optimizer model that considers not only the fuel cost, but also the costs of vehicle operations which are either ignored or underestimated by the standard (commercial) fuel-optimizer products. A unique aspect of our model is that it is a "generic" version of the standard fuel-optimizer models, so that users (carriers) can freely (flexibly) choose the cost element(s) to be minimized by the model. Simulation results suggest that our model may: (i) attain significantly lower vehicle operating costs than the standard fuel optimizers, and (ii) produce more desirable solutions than the standard fuel optimizers from the drivers' point of view (by reducing both the OOR miles and fueling frequencies). Our interviews with TL carriers suggest that they will welcome this type of model. Fuel-optimizer vendors may want to seriously consider developing the type of model proposed in this paper.

One limitation of the proposed model is that it assumes a homogeneous fuel consumption rate (MPG) for all the OOR roads. While this assumption may be reasonable in some routes, it will not apply to all the routes because MPGs are known to vary from one road class to another. Thus, an interesting extension of our work is to incorporate the road-class information (MPG by road class) into the model and improve the accuracy of $Fuel_i$ calculations. Although this type of MPG database is not available yet, several attempts are being made in the industry (by combining GIS database and the MPG data of carriers). We leave this topic for future research.

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