Sensitivity of Freight and Passenger Rail Fuel Efficiency to Infrastructure, Equipment, and Operating Factors

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After labor expenses, the cost of fuel is the largest operating budget expense item for freight and passenger rail operations in the United States. Because fuel is such a costly component of operations, the railroad industry is constantly researching and testing new methods either to reduce the volume of fuel consumed or to switch to less-expensive fuels and sources of energy. An understanding of the factors that affect fuel consumption and their interactions is valuable for analyzing the feasibility of a given technology. Such knowledge allows for more intelligent extrapolation of simulation and laboratory results across a range of routes and in-service operating conditions. This research investigates the relative effects of infrastructure, equipment, and operating parameters on fuel efficiency for freight and passenger railroads on a mixed-use corridor. Partial factorial experiments investigate the effects of multiple factors on freight and passenger train fuel efficiency. Rail simulation software is used to run trial cases of single-track lines with heterogeneous traffic and to calculate energy-efficiency metrics. Results from the simulations are used to create two multivariate regression models for freight and passenger rail fuel efficiency. A sensitivity analysis identifies the relative effects of these factors on freight and passenger train fuel efficiency. By understanding the relative influence of various parameters on fuel efficiency, practitioners can focus data collection, modeling, and other fuel-saving efforts on the most significant factors.

After labor expenses, the cost of fuel is the largest operating budget expense item for freight and passenger rail in the United States. Hence, fuel efficiency is critical to the ability of railroads to control operating costs and offer competitive transportation services. As shown in Figure 1, the volume of fuel purchased by freight railroads has not increased substantially during the past 30 years, although freight railroad ton-miles doubled in the same period. This doubling of transportation productivity per unit of fuel consumed can be attributed to heavier axle loads, longer trains, and improvements in diesel–electric locomotive technology. Despite these gains in fuel efficiency, the rising cost of oil in the past decade has caused fuel cost as a percentage of total operating expenses to increase 86% since 1980, and it comprised 23% of all operating expenses in 2011 (*1*). In 2012, fuel costs represented 11% of all operating costs for transit agencies nationwide and 10.8% for Amtrak in 2013 (*2, 3*).

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Because of the impact of fuel on operating costs, the freight and passenger railroad industry is constantly researching and testing new methods for reducing fuel expense. Railroad expenditures on fuel can be reduced in one of two ways: decreasing the total volume of fuel consumed or switching to lower-cost alternative fuels and sources of energy (*4–6*). Although the former approach has been achieved through a combination of operational changes and modifications to conventional diesel–electric locomotives, the latter approach requires the development of entirely new forms of motive power and fuel or energy supply infrastructure. To capitalize on the low costs of natural gas, several railroads have been testing liquefied natural gas locomotives for line haul applications (*7*). Battery hybrid locomotives that reuse regenerated braking energy for traction have been proposed to reduce energy consumption (*8*). Plug-in battery-tender cars could use lower-cost electricity to supplant fossil fuels for portions of train runs. Wayside energy storage is also being explored for electrified passenger and commuter rail applications (*9*). Other technologies such as electromagnetically controlled pneumatic brakes, positive train control, and rail and wheel lubrication have been identified as potential railroad system upgrades that although intended to address other operational and maintenance issues may also reduce railroad fuel expense under certain conditions (*4*).

The capital investment required to develop, test, pilot, commercialize, and implement any of these new technologies is sizeable. To justify this investment, the feasibility of technologies must be analyzed in a manner that is comprehensive yet cost-effective. Previous evaluation of new motive power technology showed that fuel efficiency benefits can vary greatly between routes and between operating environments (*8*). Hence, it is not sufficient to rely on one general estimate of benefits derived from laboratory or limited service conditions. It is infeasible, even with simulation, to determine the benefits of a technology on every route under all possible service operating conditions. An understanding of how various factors affect fuel efficiency is needed for determining the required number and range of case studies that will provide a representative assessment of the potential of a given technology. Likewise, knowledge of the interaction between these factors is useful for extrapolating the results of technology case studies to various operating conditions, such as train speed and traffic volume.

This paper identifies the most significant operational parameters to consider in evaluating potential energy-saving technologies. Practitioners can use this knowledge to focus on a subset of route and operational characteristics when planning experiments to evaluate a technology's potential. Not only can this knowledge reduce the number of simulation trials or full-scale experiments needed to evaluate the technology, and consequently the time and cost of the

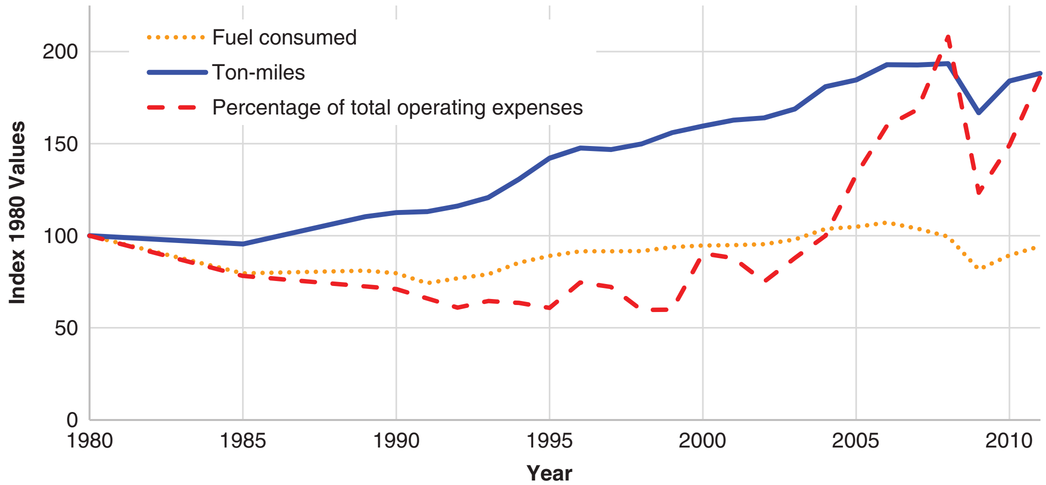

FIGURE 1 Freight rail fuel consumption, ton-miles, and percentage of total operating costs indexed to 1980 values.

investigation, but it also allows engineers to focus detailed data collection efforts on specific factors.

BACKGROUND

Several studies have quantified variation in overall fuel efficiency of freight and passenger operations while taking different approaches to control for it in their respective analyses. Fullerton et al. analyzed several factors related to fuel consumption through single-variable analyses (*10*). Speed, congestion, and stop spacing were examined for both freight and passenger trains on a mixed-use corridor. Since other factors were held constant during each separate experiment, the interactions between factors could not be determined. The analyzed factors were selected because of their relationship to train energy as modeled by the Davis equation for rail rolling resistance (*11*). Other factors unrelated to train resistance, such as traffic volume, were also investigated. Hopkins developed a simple equation for calculating passenger train fuel efficiency as a function of train speed and weight per seat (*12*). Mittal developed an extensive train performance calculation framework for intercity passenger trains that is used to identify the impacts of route conditions and operating characteristics on train energy intensity (*13*). Lukascewicz performed a sensitivity analysis on factors affecting freight locomotive performance, focusing on the mechanical attributes of the locomotive rather than network effects (*14*). Factors studied included running resistance, adhesion, tractive force, braking gain time, and braking release force. Tolliver et al. analyzed freight fuel efficiency by using an analytical model based on the Davis equation as well as a statistical regression model based on observed data (*15*). Although the two methods were consistent, they could not accurately account for all the operating characteristics of the train. Sierra Research, Inc., and Caretto similarly analyzed freight operations in California and accounted for the effect of grades on train efficiency by using a correction factor based on the severity and frequency of grades on a given route (*16*). Liu and Golovitcher created an energy-efficient control algorithm that accounted for constraints on traction and braking forces, train velocity, and curvature and grade resistance (*17*). The ability of the automated train operation algorithm to improve energy efficiency through small changes in throttle settings and speed profiles illustrates the variability and sensitivity of efficiency to these parameters. Several other studies identified how consist management, car placement, and braking profile optimization can affect fuel efficiency (*4, 18*). FRA published a detailed report on the mechanical and operational factors that have helped rail become more efficient in recent decades (*19*). The variation of freight rail fuel consumption between regions, types of terrain, and unit trains versus nonunit trains has been noted several times (*15, 16*). Fullerton et al. also showed how use of advanced train-dispatching simulation allows for better analysis of the efficiency of an individual train subject to delays from interference with other trains on the network (*10*). There is no single resource that combines the relative impact and interaction effects of network congestion, operating parameters, and route parameters on fuel efficiency.

METHODOLOGY

Railways form a complex and dynamic network, resulting in many factors that may ultimately affect the fuel efficiency of a given route or train run. Combinations of these factors may have different effects on fuel efficiency than does any one factor in isolation. The main effects of each factor and primary interactions are best captured with design of experiments (DOE) techniques. However, because of the large number of possible factors and the wide range of potential factor levels, a full factorial experiment for simulating all possible combinations of factors is infeasible. JMP software is commercially available statistical analysis software that uses specific DOE methods to strategically organize permutations of important factors to eliminate the redundancy of a full factorial experiment and reduce the number of simulation trials. JMP software is used in this research to develop a partial factorial set of freight and passenger rail scenarios that are then simulated with railway dispatching software that has a built-in train performance calculator. Fuel consumption results from each simulation are then used to construct a multivariate regression model of freight and passenger rail fuel efficiency. A sensitivity analysis for freight and passenger rail fuel efficiency is used to identify the most significant factors and to better understand the relative magnitude of their influence on fuel efficiency.

Factor Selection

Several factors with demonstrated effects on fuel efficiency for freight and passenger rail transportation are used in this analysis. As shown in Table 1, each factor and representative range of values is selected to reflect real-world conditions on a mixed-use corridor. Previous studies and train energy modeling consider grade one of the most significant factors in train fuel consumption (*10, 15, 16*). The expected grade range for the freight experiment is lower than that for the passenger experiment, since steeper grades are required to make an operational impact on lighter, faster passenger trains. Although existing main-line grades can exceed 3% for short distances, the maximum desired design grade for a freight railroad is 1% (*20*). Use of the steeper passenger grades for the freight experiment would create extreme congestion on the line and distort the results.

Traffic volume is included as a proxy for congestion, representing realistic train volumes for a single-track line with passing sidings. The percentage of freight trains represents the heterogeneity of traffic on the line. Lines with greater heterogeneity have been shown to experience more train delay for a given traffic volume (*21, 22*). The extra delay could disproportionately affect freight train fuel consumption with increased passenger traffic (*23*).

Speed of freight and passenger trains is also considered because of the increased train resistance associated with higher speeds. Train resistance forces also increase with train length and weight, represented by number of cars and gross rail car load. Length is considered for passenger trains, and coach weight is held constant across all simulations. These factors determine the transportation productivity of each run, since they control the number of ton-miles and seat miles used in calculations of fuel efficiency. For passenger trains, the number of locomotives providing tractive effort is also taken into account.

DOE methodology is used to reduce the computing time and power needed to conduct full factorial experiments. For the freight experiment, a full factorial experiment would require 729 unique trials, but the DOE procedure required only 50 to provide results to generate an adequate response surface. The partial factorial passenger experiment required 80 cases, compared with 1,458 total cases for a full factorial experiment. The difference in size stems from the analysis of seven factors in the passenger experiment, compared with six for the freight.

TABLE 1 Factors Investigated in Freight and Passenger Fuel Efficiency Study

Experiment Factor	Low	Medium	High
Freight			
Grade (%)	−1	0	1
Traffic volume (tpd)	8	24	40
Percentage of freight trains	12.5	50	87.5
Freight speed (mph)	20	40	60
Train length (number of cars)	50	100	150
Gross rail load (tons)	131.5	143	157.5
Passenger			
Grade (%)	−2.22	0	2.22
Traffic volume (tpd)	8	16	24
Percentage of freight trains	25	50	75
Passenger speed (mph)	50	79	110
Train length (number of coaches)	6	9	12
Locomotives	na	1	2
Station spacing (mi)	5	120	240

NOTE: tpd = trains per day; na = not applicable.

Rail Traffic Controller

For ideal train runs with no stops, or for a set schedule with known stop locations and dwell, a simple train performance calculator (TPC) can be used to calculate the efficiency metrics for train operations along a route. On single-track railways in North America, however, such free-flow conditions are rarely encountered. Even priority trains are likely to make multiple stops at passing sidings for meets, and differences in train speeds can require running below maximum speed before an overtake. Acceleration, deceleration, and time spent idling while waiting all decrease fuel efficiency, and the frequency of these events will vary depending on the operating characteristics of a given line.

Because North American main lines do not adhere to a strict operation schedule, and because train meets are located by dispatchers in real time, the number of delay incidents encountered by a particular train can vary greatly between runs. This variation and uncertainty in train operating patterns can grow as line operating characteristics change, particularly during simultaneous passenger and freight train operations, decreasing the utility of simple TPC simulations. To capture the variability in operations experienced as traffic congestion arises, more sophisticated simulation software that emulates train dispatching decisions must be used to generate time and distance inputs for train performance calculations. In this study, Rail Traffic Controller (RTC), developed by Berkeley Simulation Software, is used. Each case in the freight and passenger experiment designs is simulated with RTC, and the resulting fuel efficiency is recorded and analyzed.

RTC software is the leading rail simulation software in North America. RTC software considers detailed information, including maximum allowable track speed, curvature, grades, signaling system, train departure time, and locomotive and rail car characteristics, to simulate train movements. The train dispatching logic in RTC generates results by detecting and finding solutions to conflicts among trains as they travel across the representative route. A significant advantage of RTC relative to other software packages is that it may delay or reroute trains according to their priority relative to other trains using the same infrastructure. The emulation of dispatching decisions with consideration of train priorities makes RTC more realistic than other analytical and simulation models. For this study, RTC is used to simulate mixed-use freight and passenger train movements on a 242-mi subdivision of single-track main line with centralized traffic control. The route and train parameters for RTC are shown in Table 2.

Grade is varied for the freight and passenger experiments according to the ranges shown in Table 1 through assigning the positive grade value to one direction of the 242-mi route, the reverse direction representing the negative grade. Fuel consumption results are extracted with respect to consistent directions corresponding to upgrade and downgrade operation. For factors not varied in a given simulation, the middle values are used. To ensure that the results are not dominated by particular train schedule assumptions, and to better emulate the unscheduled North American operating environment, each scenario is simulated for 5 days of traffic with trains being randomly dispatched from each end terminal during a 24-h period. Hence the final efficiency metrics for a particular combination of factor levels represent 5 days of randomly scheduled train operations. The multiple-

TABLE 2 Route and Train Characteristics Used in RTC Simulations

Parameter	Value
Route	
Length (mi)	242
Type	Single main line
Siding spacing (mi)	10
Siding length (ft)	10,000
Signal system	3-aspect CTC
Freight Train	
Locomotive type	SD70-4300
Locomotives	2
Passenger Train	
Locomotive type	GE P-42
Coach type	Amfleet I
Coach weight	55 tons
Coach seating capacity	84 seats

NOTE: CTC = centralized traffic control.

day simulation combined with the simulation being run multiple times provides a reasonable average result. The TPC embedded within RTC generates data on the fuel consumption of every train running through the study corridor. RTC software does this by calculating the speed profile and throttle and brake settings of each train according to the assigned locomotive type and train consist (shown in Table 2). Unlike a stand-alone TPC, service reliability metrics such as train delay are also output from RTC, and the manner in which these metrics affect efficiency can be evaluated.

Multivariate Regression Analysis

Fuel efficiency results from the freight and passenger simulations in RTC are used to construct two multivariate regression models, in which the factors in Table 1 are input parameters and fuel efficiency is the response output. JMP software is used to analyze the results from the RTC simulations and construct the regression models. The models recreate the response surface by using least squares regression. Fuel efficiency in units of ton-miles per gallon is predicted by the freight efficiency regression model. Fuel consumption in gallons is predicted by the passenger efficiency regression model. Efficiency in units of seat miles per gallon is then evaluated separately according to the output of the model and the respective amount of seats in the train consist. This approach was used to avoid overfitting in the software caused by the effects of seating capacity on the relationship between the response variable and the inputs.

Sensitivity Analysis

After a regression model has been constructed for each experiment, the sensitivity of the response (fuel efficiency) to changes in the inputs (the factors listed in Table 1) can be quantified by the arc elasticity method, as described by Allen and Lerner (*24*). This approach has been used in similar research investigating the influence of various factors on train delay (*25*). The arc elasticity method quantifies how fuel efficiency responds to normalized unit changes in each factor with respect to a base case. Normalization of units is desirable because of the bias that could be introduced through varying the units and order-of-magnitude ranges of the analyzed factors.

The base case for each of the freight and passenger experiments is based on combinations of the medium factor values in Table 1, with a few exceptions. Because the factor ranges used to construct the regression model cover the extreme ranges of each parameter to produce a larger response surface, the high and low values for several factors do not represent a reasonable range of uncertainty or variability in anticipated service conditions. Hence, some of the base, minimum, and maximum factor values were modified in the sensitivity analysis to reflect more realistic ranges. The base, minimum, and maximum values used in the sensitivity analysis are shown in Table 3. Each factor is varied between its low and high values, and the other factors are held constant at their respective medium value and the output fuel efficiency is recorded. The arc elasticity of the fuel efficiency response is then calculated with Equations 1 and 2. The output of each equation is the ratio of the percent change in fuel efficiency and the percent increase or decrease in the factor. Arc elasticity values represent a corresponding percent change in fuel consumption to a 1% change in each input factor. Larger values of arc elasticity indicate that a particular factor has a larger influence on fuel efficiency than factors with lower values of arc elasticity. That is, fuel efficiency is most sensitive to factors with high magnitudes of arc elasticity.

$$e_{\text{high}} = \frac{Y_{i,\text{high}} - Y_0}{\frac{1}{2}\left(Y_{i,\text{high}} + Y_0\right)} \times \frac{\frac{1}{2}\left(X_{i,\text{high}} + X_{i_0}\right)}{X_{i,\text{high}} - X_0} \tag{1}$$

where

e_{high} = arc elasticity with respect to high input variable value,
Y = output variable,
X_i = input variable, and
(X_{i_0}, Y_{i_0}) = base input and corresponding response.

TABLE 3 Base, Minimum, and Maximum Values Used in Freight and Passenger Fuel Efficiency Sensitivity Analysis

Experiment Factor	Minimum	Base	Maximum
Freight			
Grade (%)	−1	0	1
Traffic volume (tpd)	8	20	32
Percentage of freight trains	12.5	50	87.5
Freight speed (mph)	20	45	60
Train length (number of cars)	50	100	150
Gross rail load (tons)	131.5	143	157.5
Passenger			
Grade (%)	−2.22	0	2.22
Traffic volume (tpd)	8	16	24
Percentage of freight trains	25	50	75
Passenger speed (mph)	50	79	110
Train length (number of coaches)	6	9	12
Locomotives	na	1	2
Station spacing (mi)	5	40	75

$$e_{\text{low}} = \frac{Y_{i,\text{low}} - Y_0}{\frac{1}{2}\left(Y_{i,\text{low}} + Y_0\right)} \times \frac{\frac{1}{2}\left(X_{i,\text{low}} + X_{i_0}\right)}{X_0 - X_{i,\text{low}}} \tag{2}$$

where e_{low} is the arc elasticity with respect to the low input variable value.

RESULTS

Results of both the freight and passenger regression models are shown in Table 4. The ranges presented may appear high but are within the valid range of fuel consumption for rail. Previous research showed that individual trains may operate at anywhere from 200 to 1,000 ton-miles per gallon depending on the route and train characteristics (*16*). The only result outside this range for freight is the train traversing a complete downhill grade, a favorable but unrealistic route. The passenger rail efficiencies are higher than expected: analyses of existing passenger lines have shown efficiencies to be between 75 and 157 seat miles per gallon (*26–28*). It is likely that the high priority given to passenger trains within the RTC algorithm combined with the favorable route characteristics is inflating the values. However, this research is focused on the relative magnitude of the values as the input factors are varied.

The correlation coefficient (R^2) values for the freight and passenger models are 0.575 and 0.989, respectively. The lower value for the freight model is related to the higher variability in the freight outputs, resulting from the low priority of freight traffic during simulations. The results of the sensitivity analyses of these models are shown in Figure 2, *a* and *b*. Orange bars represent the elasticity (as defined earlier) of fuel efficiency in response to increases in each respective factor. Blue bars represent the elasticity of fuel efficiency in response to decreases in each respective factor. A positive elasticity indicates that the corresponding change in each factor causes an increase in fuel efficiency. A negative elasticity indicates that the corresponding change in each factor causes a decrease in fuel efficiency.

TABLE 4 Fuel Efficiency Results from Freight and Passenger Regression Models

Experiment Factor	Minimum	Base	Maximum
Freight			
Grade (%)	2,440	642	219
Traffic volume (tpd)	956	642	329
Percentage of freight trains	851	642	433
Freight speed (mph)	246	642	269
Train length (number of cars)	203	642	1,532
Gross rail load (tons)	520	642	1,553
Passenger			
Grade (%)	1,357	578	134
Traffic volume (tpd)	583	578	492
Percentage of freight trains	575	578	772
Passenger speed (mph)	854	578	478
Train length (number of coaches)	577	578	396
Locomotives	na	578	336
Station spacing (mi)	449	578	716

Sensitivity of Freight Fuel Efficiency

Figure 2*a* shows the results of the sensitivity analysis performed on the freight train fuel efficiency model within the simulation. In this regression model, fuel consumption is most sensitive to changes in gross rail car load, an increase to 315,000-lb cars more than doubling fuel efficiency. The marginal increase in fuel consumption caused by increasing gross rail car load of each car and overall train weight is now divided between an additional 3,000 tons of freight on the train, increasing the efficiency of the operation in ton-miles per gallon. This result reinforces the historical trend in the North American railroad industry to gain economies of scale by increasing the maximum gross rail car weight and payload per car. For bulk commodities, 263,000-lb rail cars have largely been replaced by 286,000-lb rail cars, and 315,000-lb rail cars are the subject of continued study (*29*). Changes in train length generate a similar effect, but to a lesser extent.

Freight speed is the only factor that has a reverse-parabolic response, meaning that both an increase and a decrease in speed from the base case negatively affect efficiency. The duty cycle for a locomotive indicates that the train is less efficient when the locomotive is operating at the higher throttle notches and power levels required to maintain higher speeds (*28*). This appears to contradict the result of a decrease in fuel efficiency with decreased speed. However, as Fullerton et al. explained, slow trains require more time to traverse single-track sections of the line and are given low priority by the dispatching logic, increasing congestion and causing the freight trains to idle within sidings more often (*10*). The increased acceleration and deceleration cycles of these train meets also reduce fuel efficiency. This effect is amplified on high grades because of the large amount of energy required to accelerate the train.

Increases in the percentage of freight trains in the traffic mix lead to decreases in efficiency, and vice versa. Intuitively, the point with equal numbers of freight and passenger trains represents the maximum amount of heterogeneity on the line and should correspond to the minimum fuel efficiency with all other factors held constant. However, it appears that network effects resulting from extreme grades (and hence slower freight trains) affect this relationship. The extreme uphill grades cause uphill freight trains in particular to move more slowly. When the percentage of freight traffic is increased, the number of trains that will be more severely affected by the extreme grades increases, leading to more congestion on the line. Hence the freight trains appear to be most fuel efficient when operating on a line with larger numbers of faster-moving passenger trains.

Although efficiency is shown to be the least sensitive to grade in this analysis, the regression model results and previous studies suggest that grade is one of the most important factors affecting fuel consumption (*10, 15, 16*). As shown in Table 4, the model generates a range of almost four times the value of the base case between the low and high parameters, more than any other factor, suggesting that the sensitivity of fuel efficiency to grade would rank higher compared with the other factors. The equation for arc elasticity is a function of the percent change in the factors. This metric becomes distorted when one of the factor values is close to zero or is very small compared with the other factor level. If the midpoint of a factor range containing positive and negative values happens to be zero, division by zero causes arc elasticity to be undefined. Since the range of the grade values within the model straddles zero, the changes in grade correspond to a large percent change relative to the base case. This somewhat artificially increases the denominator of the arc elasticity

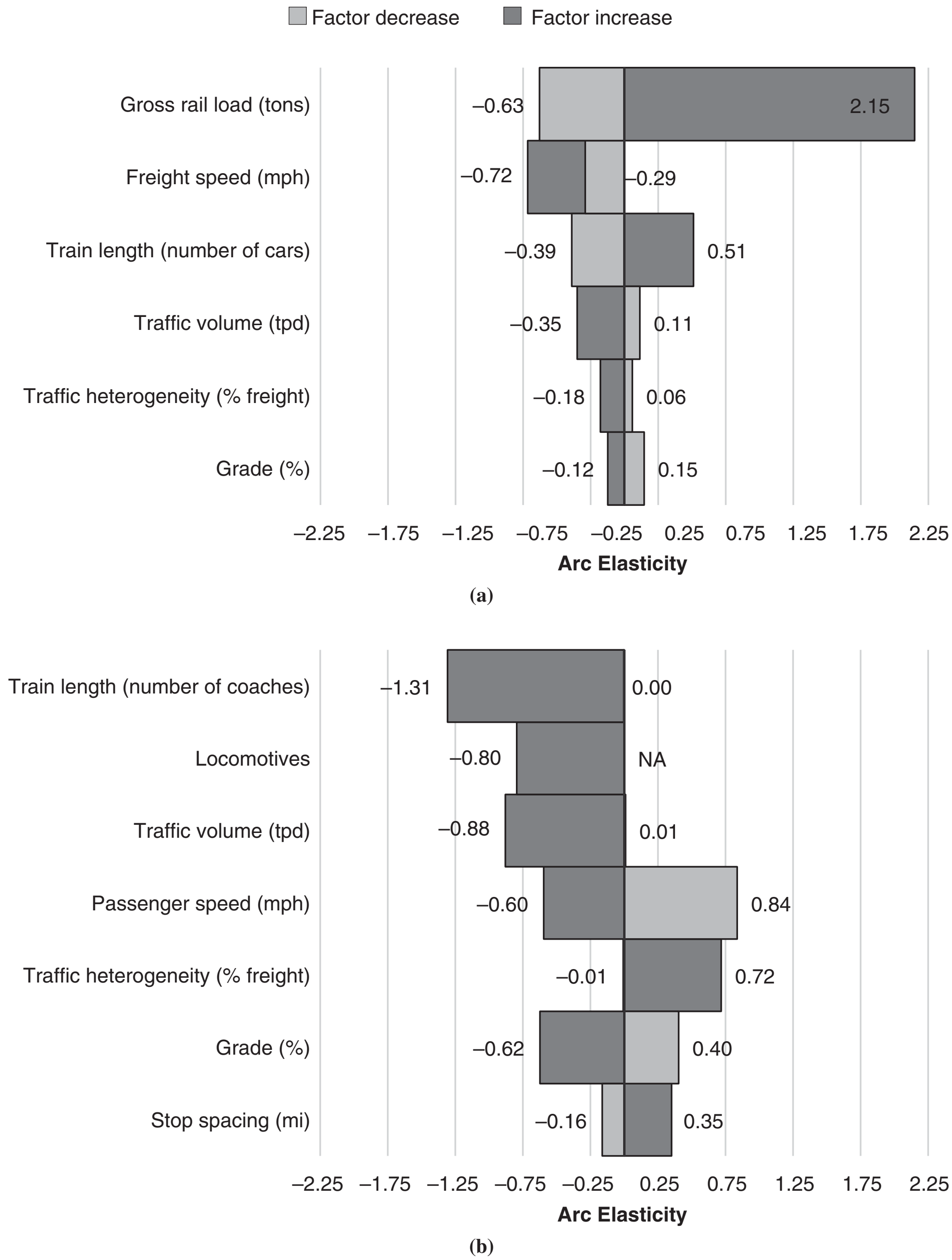

FIGURE 2 Sensitivity analysis results of regression models: (*a*) freight and (*b*) passenger (no. = number; NA = not available).

equation, decreasing the apparent sensitivity to that factor. This is also seen with the sensitivity of efficiency to grade in the analysis of passenger trains.

Sensitivity of Passenger Fuel Efficiency

Figure 2*b* shows the sensitivity analysis of the passenger fuel efficiency model. Fuel efficiency results from this model are most sensitive to increases in the train length (number of trailing passenger coaches), which correspond to decreases in fuel efficiency. Decreasing the number of trailing coaches has a much smaller effect on fuel efficiency. If trailing coaches are added, an increase in fuel efficiency is expected because of an increased seating capacity, despite the increased train weight. The extra coaches provide additional seats over which to distribute the locomotive resistance, analogous to increasing the weight and length of the freight trains. However, the severe grades used in this experiment amplify the effects of the added weight of additional passenger coaches. Furthermore, the freight trains move slowly on the severe grades while adhering to a fixed horsepower per trailing ton ratio. The passenger trains attempt to maintain their maximum speed along grades, with increased fuel consumption for the longer and heavier trains. This appears to be enough to offset the extra seating capacity of additional coaches.

Increases in traffic volume, a proxy for traffic congestion, yield a decrease in fuel efficiency. Decreases in traffic volume have a much smaller, albeit positive, effect on fuel efficiency. As discussed by Fullerton et al., traffic congestion does not severely affect the fuel efficiency of passenger trains until a “network saturation point” at which congestion increases enough to have a severe impact on fuel efficiency (*10*). Decreases in passenger speed lead to increases in fuel efficiency and vice versa. As the percentage of freight trains increases, the fuel efficiency of the passenger trains increases. This increase can be attributed to the priority of the passenger trains. As the number of conflicts between passenger and freight trains increases, the number of conflicts between passenger trains decreases, and the passenger trains are dispatched more favorably. This scenario decreases the number of acceleration and idling cycles, improving fuel efficiency. Relative to freight trains, passenger train fuel efficiency appears more sensitive to changes in traffic volume and the percentage of freight trains. This effect can also be attributed to the higher priority of the passenger trains and the negative impacts of additional conflicts between passenger trains. Adding a second locomotive to a passenger consist yields a decrease in fuel efficiency.

Similar to the freight train experiment, increases in grade result in decreased fuel efficiency. The opposite is true as well. Grade has a smaller effect on the fuel efficiency of passenger trains compared with other factors in this study. The elasticity of passenger train fuel efficiency with respect to grade is larger than that of the freight fuel efficiency model. However, a direct comparison of the effect of grade on freight and passenger trains is difficult because of the distortion of the arc elasticity metric for factor ranges very near to and spanning zero. A possible explanation for this result is that, compared with freight trains that travel at relatively lower speeds, passenger trains are more negatively affected by congestion arising from slow-moving freight on steep grades.

Increased distance between station stops leads to an increase in passenger train fuel efficiency; shorter distances decrease fuel efficiency. This relationship is supported by previous single-variable analysis of stop spacing (*10*).

CONCLUSIONS

DOE software was used to create partial factorial experiments for investigating the effects of several factors on the fuel efficiency of freight and passenger trains. Rail simulation software was used to run trial cases, as prescribed by the DOE software, and to calculate the energy consumption of each for single-track operating conditions with delays caused by meets and passes. Results from the simulation software were used to create two multivariate regression models for predicting fuel efficiency of freight and passenger trains. A sensitivity analysis of these models identified the relative effects of these factors on fuel efficiency. For both passenger and freight trains, the equipment, and hence the weight of the train, has the greatest influence on fuel efficiency. Grade has a large and consistent effect on both freight and passenger train fuel consumption and efficiency. However, this effect may be underestimated in these experiments by the difficulty in calculating reasonable arc elasticity values for factor ranges that are very near to or span zero, where elasticity is undefined.

For continued competitive, cost-effective transportation service, the consideration of fuel consumption has an increasingly important role in freight and passenger railroads because of rising fuel costs. To reduce the cost of their second-largest operating expense, railroads are investigating fuel-saving technologies and options for transitioning to less-expensive fuels and sources of energy. Every factor studied has a significant impact on fuel efficiency, so no one factor should be weighted differently than the others in studies or data collection for a systemwide analysis. In addition, this research provides a means to validate research on the effects of individual factors on rail system fuel efficiencies.

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