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A Spatially Detailed Locomotive Emission Model and Goods Movement Data Constraints on Public Policy and Planning

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A Spatially Detailed Locomotive Emission Model and Goods Movement Data Constraints on Public Policy and Planning

By

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ABSTRACT

The first part of this dissertation develops a new theoretically consistent GIS based locomotive emission model which improves the accuracy of current inventory methods while also increasing the spatial detail. Greater spatial resolution is important for considering local effects and environmental justice concerns. The model increases accuracy and spatial detail by considering the effect of track grade, train type and the local (route specific) locomotive fleet on fuel consumption. Further improvement is gained by developing emission factors that are specific to the local locomotive fleet. The modeling platform also allows the user to easily change model inputs and view results in a map or table at multiple geographic scales.

How engineering and economic modeling is used to support public financing decisions for the provision of private rail infrastructure is also investigated. Public assistance for private rail infrastructure is a growing national trend in the effort to increase the share of goods moved by rail. Project applications for public funds provided by California's Trade Corridors Improvement Fund which allocates $3 billion for goods movement infrastructure improvements are taken as a case study. The modeling and assumptions completed by each applicant seeking funds for rail projects are reviewed.

The study finds a large variety or mostly ad-hoc modeling methods and unsupported assumptions. The most critical finding is the lack of a theoretically sound method which assesses the cost, benefits and risks of using public funds for private infrastructure projects. Few project applications consider or identify the cause of the problem they are trying to solve. For example, is a lack of rail capacity preventing truck traffic from shifting to rail? Under what conditions would private railroads provide less than the socially optimum level of rail capacity? And is public funding of freight rail the best solution to mitigate negative environmental and health impacts caused by goods movement? This research suggests that public planners and policy makers currently lack the required data, tools and experience to make informed freight rail infrastructure decisions. Focusing on correcting apparent market failures is likely to offer more certain benefits. This research also points to the need for a more standardized framework for evaluating goods movement projects.

ACKNOWLEDGEMENTS

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1 INTRODUCTION

Historically, traffic congestion and air quality problems from transportation have been addressed though strategies targeting passenger vehicles (Weiner 1999; Woudsma 2001) and as a result emissions from light-duty vehicles have been significantly reduced even with a growing number of vehicle miles traveled (VMT) (Figure 1-1). The focus on passenger transportation has also led to the development of relatively sophisticated light-duty vehicle emission models (e.g., MOBILE[1], EMFAC[2] and MOVES[3]) and travel demand models (e.g. the four step model (Ortuzar and Willumsen 2001)) to inform decisions and track progress. The historical focus on passenger transportation can be traced to the rapid suburbanization of American cities which resulted in changing land use and employment patterns that greatly increased VTM resulting in highway congestion and increased air pollution (Weiner 1999). Now, with increasing levels of goods movement driven by growth in imports, lower density development and lean distribution networks[4] (Bertram, Santini et al. 2009), goods movement is receiving more attention at both the federal (GAO 2008) and state levels (AASHTO 2002; State of California 2005). However, the legacy of a focus on transportation planning and modeling for passenger transportation has left some critical gaps in our ability to effectively plan for goods movement.

[1] The U.S. Environmental Protection Agency's vehicle emission modeling software, available at http://www.epa.gov/oms/m6.htm
[2] The California Air Resources Board's vehicle emission modeling software, available at http://www.arb.ca.gov/msei/onroad/latest_version.htm
[3] MOVES or "Motor Vehicle Emission Simulator" is a replacement for the MOBILE model currently under development by the U.S. Environmental Protection Agency's. Portions of the model have been developed and approved for use, it is available at http://www.epa.gov/otaq/models/moves/index.htm
[4] Lean distribution/manufacturing is an attempt to operate businesses more efficiently by keeping a minimal inventory on hand. As a result, more frequent truck trips are required to continuously supply manufactures and retailers.

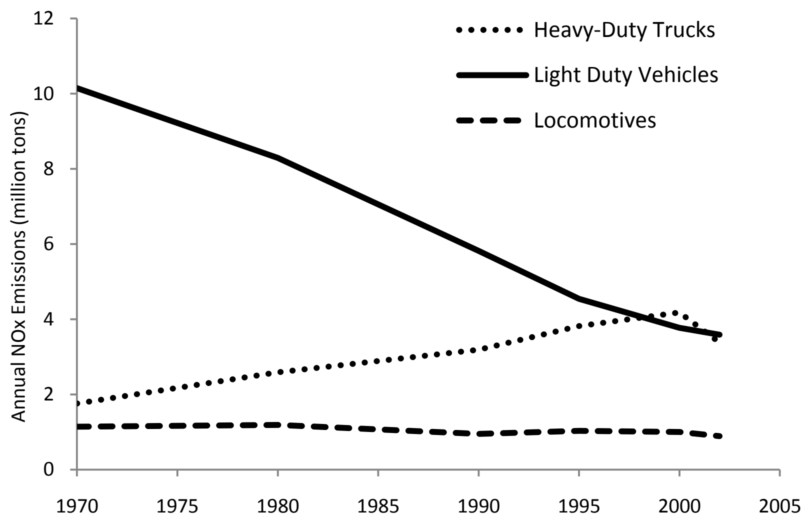


Figure 1-1 Light duty vehicle, heavy duty truck and locomotive emission trends[5]

One of these gaps is methods to evaluate locomotive emissions. While total locomotive emissions are less than those from other mobile sources, they are poised to rise as the volume of imports grows and government policies push to shift more goods movement from highways to railroads. A lack of more sophisticated locomotive emission models results in locomotive emissions also being one of the least understood. Generally, only rough or outdated estimates for large geographic areas are available while contemporary policy questions require more accurate and spatially resolved estimates. For example, policies which increase freight rail activity will need to consider local air quality effects of redistributing criteria air pollutant emissions from areas along highways to railways. Similarly, to gain a better understanding of the net air quality benefits, including carbon dioxide (CO_2) emission reductions, of shifting more goods movement from trucks to freight rail requires a locomotive emission model that can produce route specific emission estimates that can be compared to equivalent truck route estimates.

A second gap is in understanding the constraints posed by the limited information public planning and transportation agencies have about the largely private goods movement sector and

[5] Data sources: Davis, S. and S. Diegel (2006). Transportation Data Energy Book Edition 25. Oak Ridge,TN, Oak Ridge National Laboratory. And BTS Transportation Statistics, table 1-46b available on line at: http://www.bts.gov/publications/national_transportation_statistics/. Accessed on 4/22/2008.

the limited experience public agencies have had in planning for goods movement. While there has been a recent push to publicly fund freight rail capacity projects in an attempt to reduce highway congestion and air pollutant emissions, it is unclear if public planning and transportation agencies have the required data and modeling tools to make effective decisions. Generally, one would expect private railroads which are in this case very competitive with trucking firms for intermodal goods movement to provide themselves with sufficient rail capacity. To show that there is a shortage of rail capacity under such competitive conditions and that granting public funds is the best option to add capacity requires a strong analysis.

This dissertation begins to fill these gaps by developing a new spatially detailed locomotive emission model and conducting a case study to determine what data and methods are currently used by state, regional and local planning and transportation agencies to evaluate the air quality merits of policies aimed at shifting more goods movement from highways to railways. The dissertation is the product of two independent, but closely related research projects. Chapters 2 and 3 are based on research conducted for the California Air Resources Board (CARB) to develop a new geographic information system (GIS) based statewide locomotive emission model which began in the fall of 2006 and was completed in the spring of 2010 (Gould, G. and D. Niemeier, 2010). Chapter 2 provides a literature review which covers basic railroad and locomotive operations and the methods and data currently available to estimate locomotive emissions. Chapter 3 provides a detailed development of the new modeling framework, produces a new statewide locomotive emission inventory and discusses the modeling results. Chapter 4 presents a case study of California's Trade Corridors Improvement Fund (TCIF) which investigates how state, regional and local planning and transportation agencies currently use freight, and particularly rail, data and models to make decisions regarding policies to shift more goods movement from highways to railways. This research was motivated by a review of proposals for TCIF funds which raised serious questions about the quality of emission estimates calculated to support rail related projects. The dissertation concludes in Chapter 5 with a brief summary of the main findings and some thoughts on future research directions, policy considerations and data needs.

2 LITERATURE REVIEW: LOCOMOTIVE MODELING

2.1 Background - Locomotives and Railroads

All mobile source emission models share a basic framework: a measure of activity is multiplied by an emission factor producing an estimate of the quantity of emissions produced in a given time period. Emission factors are typically developed from engine exhaust tests. Because engine emission rates usually vary with engine speed and load, exhaust emissions are weighted by a representative duty cycle. The general modeling framework for locomotives is similar to that for other mobile sources; however, locomotives and railroads also have important unique attributes.

2.1.1 Locomotives

Almost all locomotives in the United States are either diesel-electric or electric, with diesel-electric locomotives comprising the majority of the locomotive fleet (EPA 2008b). Emissions from electric locomotives, commonly used for passenger transportation in urban areas, are not considered here since they occur at the electric power generation source.

Unlike most vehicles, the engines of diesel-electric locomotives are not mechanically linked to their wheels (Hay 1982). Locomotive engines provide mechanical energy to an electric generator (alternator) that powers electric traction motors connected to the wheels. The mechanical decoupling of the engine and the wheels allows the locomotive engine to operate at discrete throttle positions known as notches. There are typically 8 notches for movement of the locomotive in addition to two idle settings and dynamic braking. Dynamic braking uses a locomotive's traction motors to slow the locomotive by transforming the kinetic energy from the wheels to electrical power which is then dissipated in a resistance grid.

The discrete engine throttle positions result in steady state engine operation (Hay 1982), producing a relatively constant fuel consumption rate in each notch (Drish Jr. 1989). The steady state engine conditions also simplify emission testing, producing stable emission rates in each notch. By comparison, the operation of engines in on-road vehicles is transient, fuel consumption and emission rates vary continuously under changing loads and throttle. Locomotive emission rates are determined by sampling the engine exhaust at each notch. The notch specific emission rates are then weighted by a representative duty cycle, the relative amount of time that the locomotive operates in each notch, producing a composite locomotive emission factor.

The duty cycle, along with the particular make and model of the locomotive, determines the locomotive emission rate. Different railroad services and operations determine the duty cycle. Several additional factors also affect the duty cycle: the desired train speed, number of locomotives being used, weight of the train, topography (grades and hills), weather, and operator skill (Hay 1982; William F. Dish 1989; Armstrong 1990).

2.1.2 Operations

Trains can be classified into three categories: intermodal, unit, and manifest. Each type of service makes different tradeoffs between speed, reliability and cost; some tradeoffs affect emission rates. Intermodal trains carry either truck trailers on flat cars (TOFC) or shipping containers on flat cars (COFC), allowing for quick interchange of freight between shipping, trucking and rail. Intermodal trains also compete with trucking, tending to offer quicker service than typical trains (AASHTO 2002). However, intermodal trains have higher costs than other types of trains due to reduced fuel efficiency caused by poor aerodynamics and higher speeds (Hay 1982). Unit trains provide low cost transportation for bulky, low value commodities such as coal, grains, and chemicals. Low costs are achieved by requiring large shipments of single commodities, scheduled service, and improved fuel efficiency from using identical railcars (AASHTO 2002). A manifest train moves a variety of goods using various railcars that are picked up and dropped off along the train’s route. Manifest trains may also require time consuming re-arrangement of cars between trains at rail yards. Dropping off, picking up, and re-arrangement of rail cars results in slow travel times and reduced fuel efficiency for manifest trains. Unit and manifest trains may also achieve greater fuel savings by operating with lower power densities (ratio of power to train weight) given the lower priority on speed.

The type of train operation also influences emission rates. Locomotives perform three general categories of work: line-haul transportation of freight, line-haul transportation of passengers, and switching. Line-haul operations move freight trains between rail yards or passenger trains between stations. Switching operations move railcars around rail yards and sidings, adding and removing railcars from trains. Locomotives used in line-haul operations spend relatively more time in high power notches, while switching locomotives spend more time in lower power and idle notches (EPA 1998). Due to the differing power requirements between line-haul and switching operations, the most powerful locomotives are used for line-haul operations and lower powered, often older, locomotives are used for switching (EPA 2008b).

2.1.3 Regulation

Regulations also affect locomotive emissions. Locomotive emissions were unregulated until 2000 when the first of three tiers of federal standards took effect. The first tier of standards (Tier 0) applies to re-manufactured locomotives originally manufactured during 1973-2001, stricter Tier 1 and Tier 2 standards subsequently took effect for new locomotives manufactured during 2002-2004 and 2005 and later, respectively (EPA 1999). During 2008, EPA established two additional tiers of standards for new locomotives that will be phased in during 2009 and 2014 respectively (EPA 2008a). However, the combination of locomotive lifetimes in excess of 40 years (EPA 2008b) and lack of historical regulation has resulted in a large stock of unregulated locomotives limiting the immediate impact of the new emission standards. Additionally, recent federal standards preempt states and other local governments from regulating locomotive emissions (40 CFR 85.1603).

Regulations also affect locomotive modeling by setting different data reporting requirements for different types of railroad companies. There are three categories of freight railroads classified by the Surface Transportation Board (STB) on the amount of annual revenue they generate: Class I, Class II, and Class III. Class I railroads generate the most revenue;

currently there are 7 Class I railroads in the U.S., which accounted for 84% of all freight rail traffic in 2000 (AASHTO 2002). Class II and III railroads generate less revenue and account for less freight rail traffic though there are several hundred of them in the U.S. The STB requires Class I railroads to submit a detailed report of annual operation and business data which includes fuel consumption, locomotive purchases, and the quantity of freight moved (49 CFR 124.11), Class II and III railroads do not have these reporting requirements.

2.2 Locomotive Models

Locomotive and other mobile source emissions are typically estimated by multiplying an emission factor by an estimate of locomotive activity as shown in Figure 2-1. Ideally, emission factors are known from a large, representative sample of the in-use locomotive fleet and an easily observable (inexpensive and unobtrusive) measurement of activity that is highly correlated with emissions rates. However, this is not the case for locomotives and as with other mobile sources, our knowledge about emissions variability and influencing factors continues to evolve. Activity measurements and emission factors for locomotive emission models are discussed, respectively in the following two sections.

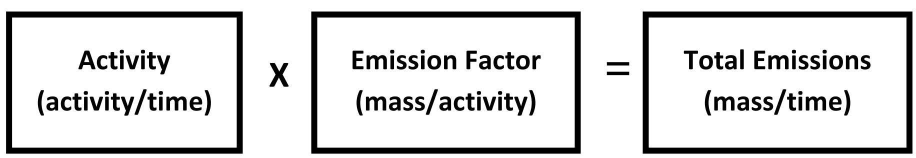


Figure 2-1 Basic mobile source emission model

2.2.1 Activity Measurement

In estimating emissions of any type, a robust measure of activity that is strongly correlated with emissions is critical. If emission factors are unknown or unreliable, the relative amount of activity will still indicate the relative amount of emissions. The most detailed measure of activity is an account of the cumulative amount of time each locomotive spends in each notch because emission rates are stable at each notch. However, such detailed operational data are typically held as proprietary information or are unknown. Exceptions are a few limited studies (Barth and Tadi 1996) which compared emissions from trucks and locomotives along a 140 mile interstate highway corridor, in this case the railroad was willing to provide detailed time-in-notch data.

Fuel consumption is a more convenient measure of activity because it is typically observable and is highly correlated with pollutant emissions (Figure 2-2). Fuel consumption has also been used or recommend as an activity measure for other mobile sources because of the high correlation with emission rates, reducing the importance of the drive or duty cycle (Singer and Harley 1996; Dreher and Harley 1998; Kean and Sawyer 2000). However, fuel based emission rates still vary across throttle notches, most notably in the idle and braking notches (Figure 2-3) and for PM and CO (Figure 2-3 b and c). Therefore, fuel based emission factors should be weighted by a representative duty cycle.

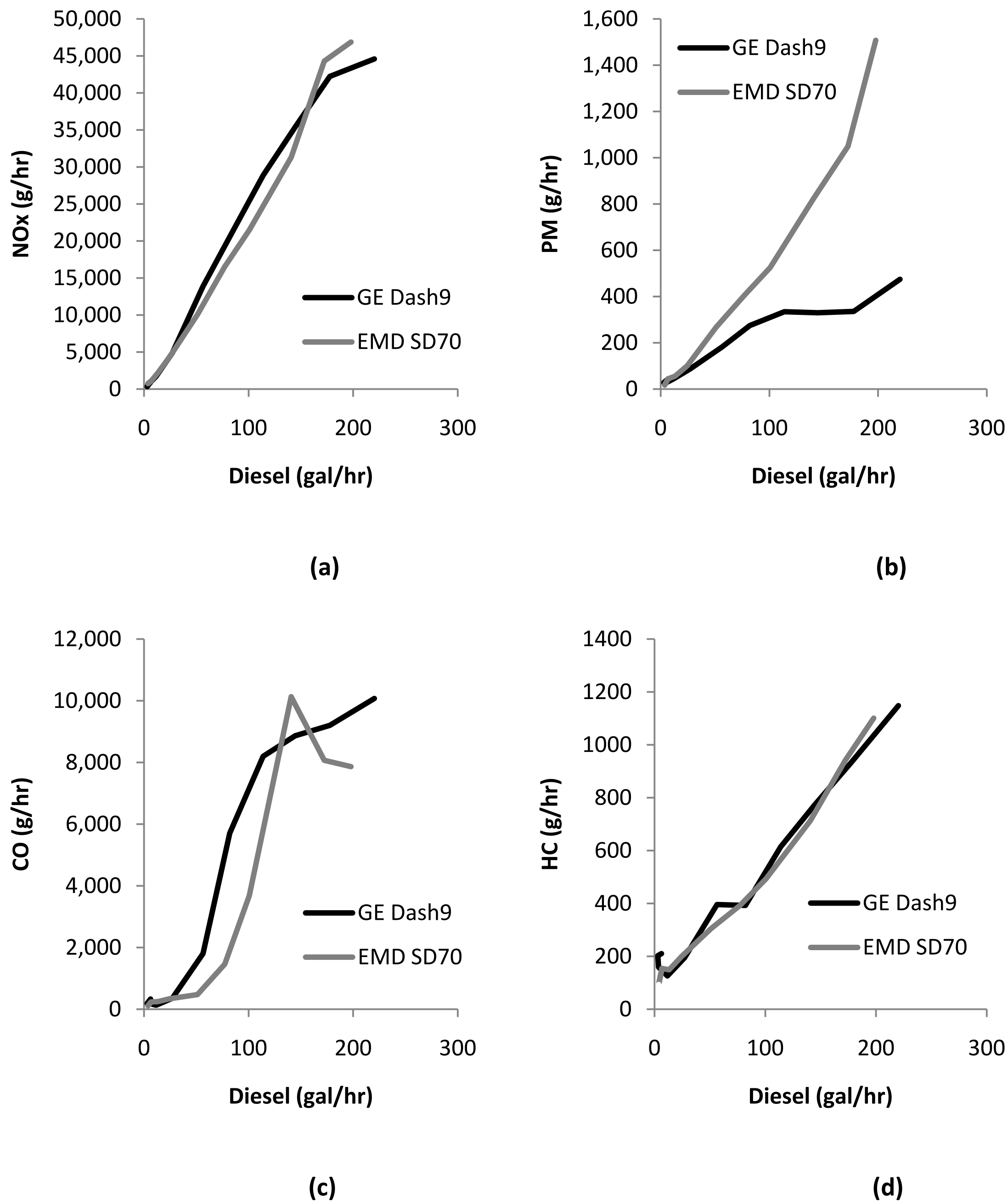


Figure 2-2 Hourly emission rates of (a) NO_x (b) PM (c) CO and (d) hydrocarbons (HC) versus the fuel consumption rates of two common in-use uncontrolled[6] diesel-electric locomotives (chart data derived from (Fritz 2000))

[6] Not certified to any emission control standards.

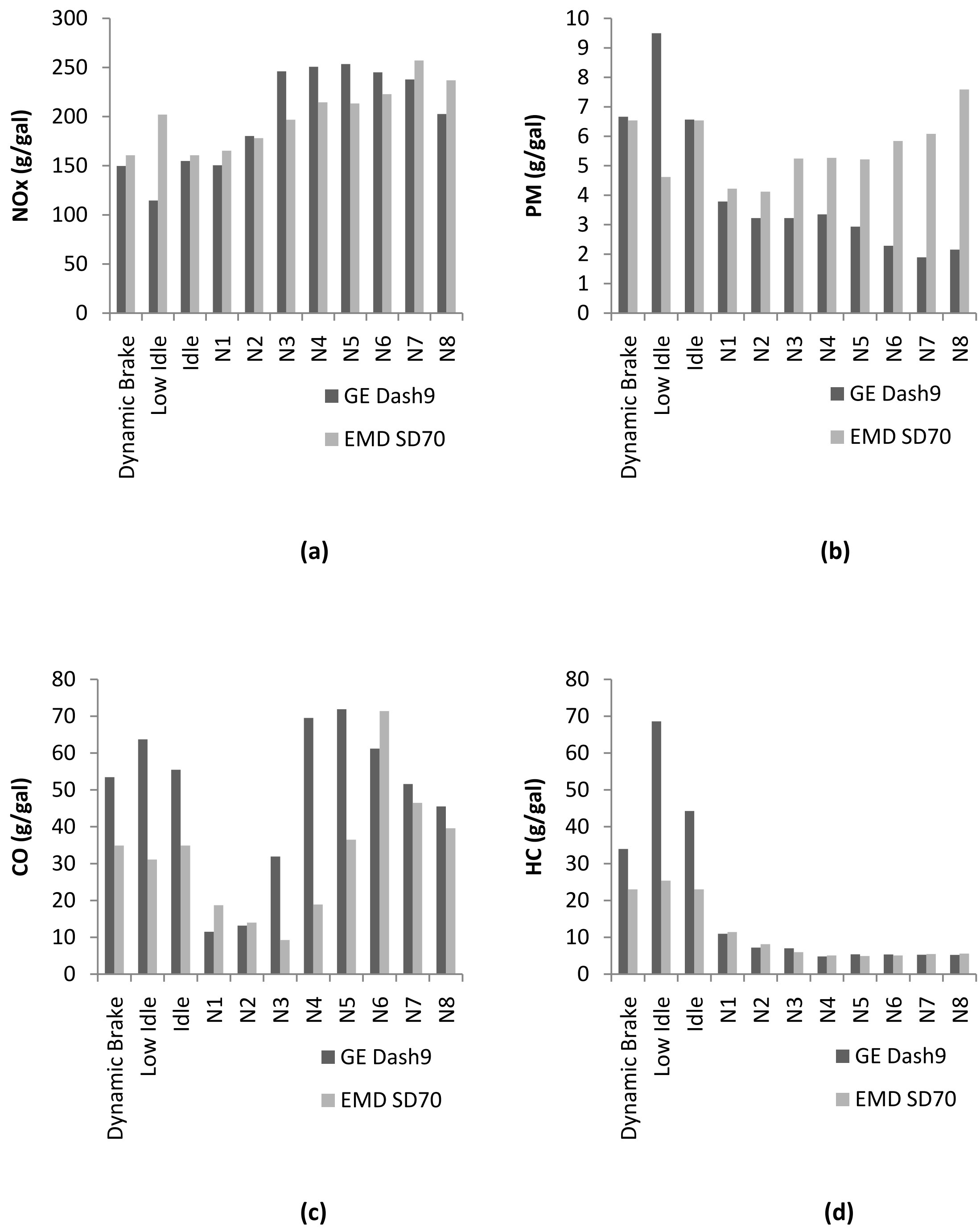


Figure 2-3 Emission rates of (a) NO_x, (b) PM, (c) CO and (d) HC by throttle notch of two common in-use uncontrolled diesel electric locomotives (chart data derived from (Fritz 2000))

While national fuel consumption data are available from surveys (EIA 2008) and the railroads (AAR 1995; APTA 2007; ASLRRA 2007; DOT 2007) and is the preferred activity measure for national estimates, disaggregate fuel consumption data are not available. Estimation of regional fuel consumption from regional fuel sales data (if that were available) is unattractive since locomotives can travel long distances before refueling given their large fuel tanks. No method is currently available to allocate regional fuel sales data to any particular place. And while measurement of locomotive fuel consumption is conceptually simple (no different than measuring the fuel consumption of your car) railroads currently do not collect or are unwilling to provide disaggregate fuel consumption data.

Given the lack of regional fuel consumption data, spatially disaggregate models must rely on alternative activity measures, typically either an estimate of fuel consumption derived from other factors or an estimate of operating hours. Fuel consumption can also be estimated by simulation models based on train-rail dynamics (physical model of train motion). The Train Energy Model (TEM) developed by the railroad industry is the most popular simulation model for estimating energy use; however, a license must be provided by the railroad industry and it requires detailed train, locomotive and route data, making it impractical as a source of activity data (Drish Jr. 1989).

The following sections review the methods used by EPA and CARB to estimate locomotive activity for use in regional emission inventories. The methods differ by each agency, rail class, and rail operations.

2.2.1.1 Class I Line-Haul

2.2.1.1.1 EPA Guidance

EPA has two methods for estimating regional locomotive emission inventories: the National Emission Inventory (NEI) method (ERG 2005) and its guidance for regional inventory preparation (EPA 1992).

The NEI method is simply a disaggregation of EPA's national locomotive emission inventory by county (ERG 2005). The national locomotive emission inventory is estimated by multiplying EPA's national locomotive emission factors (EPA 1997) by EIA's estimate of national railroad fuel consumption (EIA 2008). The national emission inventory is then proportioned to individual counties based on their share of national traffic density (gross ton-miles). County traffic density is obtained from the Bureau of Transportation Statistic's National Transportation Atlas Database (NTAD) which contains traffic density data for each track in the U.S. (BTS 2006). The NTAD does not contain actual traffic density, but 6 ranges of traffic density to maintain the confidentiality of railroad company data; the medians of the traffic density ranges are used.

EPA's guidance for regional inventory preparation provides a more detailed approach as shown in Figure 2-4 (EPA 1992). The first step is estimation of each railroad's fuel efficiency obtained by dividing each railroad's system-wide traffic density by system-wide fuel consumption. Each railroad's system wide traffic density and fuel consumption are reported annually to the STB and may be downloaded from the STB website[7]. Fuel efficiency is then divided by the traffic density of each track segment in a region producing a track segment by track segment fuel consumption estimate. This is carried out separately for each railroad operating in the region and then all the fuel consumption estimates are summed. However, the detailed traffic density data (by track segment or subdivision) is typically considered confidential business information; this method is therefore limited by the willingness of each railroad to provide the data.

[7] Railroad company annual reports available at
http://www.stb.dot.gov/econdata.nsf/f039526076cc0f8e8525660b006870c9?OpenView

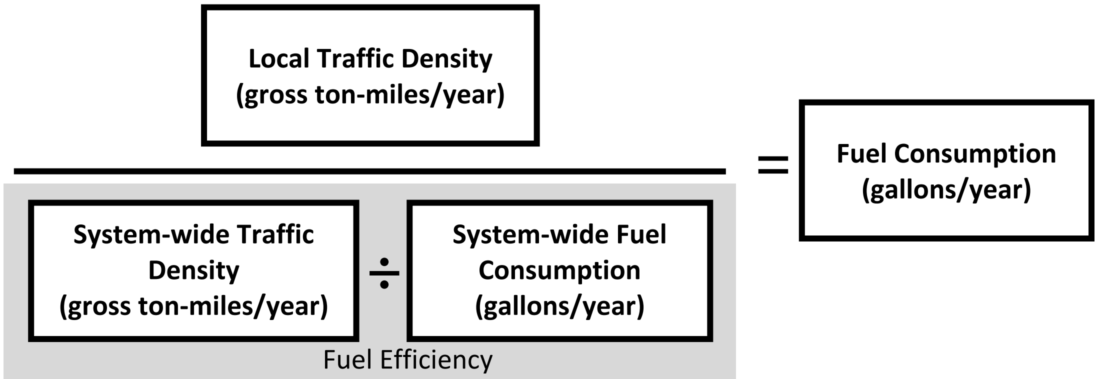


Figure 2-4 EPA's method of estimating regional locomotive fuel consumption

Data issues aside, both of the above methods would be insufficient for most regional and local

Data issues aside, both of the above methods would be insufficient for most regional and local emission modeling applications. The NEI approach assumes a constant mass per gross ton-mile emission rate and the guidance for regional inventory preparation assumes a constant system-wide fuel consumption rate. Each method ignores important local factors: geography and train type, and potentially congestion.

The geography, grades, curves, and wind, associated with track alignment can cause a large increase in the work required to move a train. Because locomotive work directly correlates with fuel use (see Figure 5) grades, curves and wind increase fuel consumption per gross ton-mile. Currently, no data exist that quantifies the effects of these factors. However, because the work required to move a train is proportional to the amount of resistance acting on the train by friction and gravity, it is possible to estimate the effect that grades and curves have on fuel consumption.

In 1926 Davis (Davis Jr. 1926) published a paper containing an equation that estimates the unit (lb/ton) resistance, R_u, acting on a moving train, it became known as the Davis equation. The Davis equation is the basis of the TEM (Drish Jr. 1989) which has been shown to produce accurate fuel consumption estimates (1992b). Hay (1982) provides a "modified" (updated) version of the Davis equation (eq 2-1).

$$\boldsymbol{R_u = 0.6 + \frac{20}{w} + .01V + \frac{KV^2}{wn}}$$ **eq 2-1**

where;

Ru = unit resistance (lbs/ton)
w = weight per railcar axle (tons)
V = speed (miles per hour)
K = rail car drag coefficient
n = number of axles per rail car

Using equation 2-1, the total unit force of resistance for a typical 60 ton rail car is 4.7 lbs/ton assuming a drag coefficient of 0.07 and speed of 45MPH. Hay also shows that the increased resistance caused by a grade is the force needed to balance the downward pull of gravity, and is 20 lbs/ton per percent grade. Therefore, a 1% grade adds 20 lbs/ton of resistance to move the 60 ton rail car, an increase in resistance of 425% over a level track. Curves cause additional resistance because the wheel flanges rub against the sides of the rail, preventing derailment. Based on a series of tests described by Hay, unit resistance caused by curves is estimated at 0.8 lbs/ton/degree, or an increase in unit resistance of 17% over straight tracks. These factors result in large increases in resistance (and thus fuel consumption) and should not be ignored. Hay also reports that wind can cause significant amounts of resistance, the severity depending on wind speed and angle as well as train speed and type.

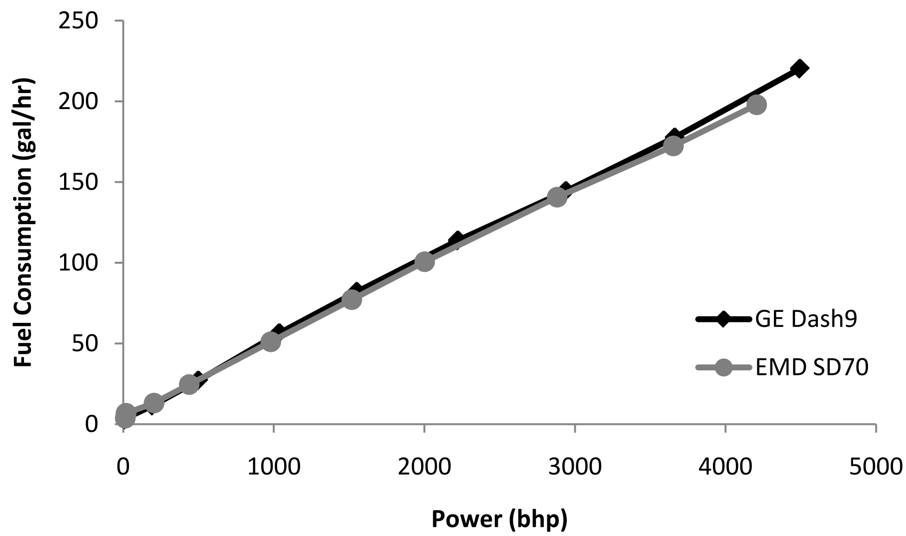


Figure 2-5 Correlation between the fuel consumption rate and power of two common in-use uncontrolled diesel electric locomotives (chart data derived from (Fritz 2000))

The different types of train service (intermodal, unit, and manifest) represent tradeoffs between speed, reliability and cost. Greater speed requires more work, and thus more fuel, to overcome greater air resistance. Additionally, different train configurations also affect air resistance. Substituting the drag coefficient from (Hay 1982) for a COFC into equation 2-1 results in a 17% increase in resistance over a typical rail car and a 64% increase for a TOFC. The prevalence of different train types can vary widely by region, impacting fuel consumption per gross ton-mile. For example, intermodal trains service ports and international trade corridors, while unit trains service coal mines and agricultural regions.

California provides a good example of the problems of using system wide fuel efficiency values and disaggregating national inventories based on traffic density. There are two Class I railroads in California, the Union Pacific (UP) and Burlington Northern Santa Fe (BNSF), and they both primarily provide intermodal train service to the major sea ports. However, nationally, coal accounts for nearly half the tons moved by UP and BNSF, while intermodal trains account for less than 10% (AAR 2001). California is also relatively hilly: all Class I railroads must cross the Sierra Nevada Mountains to leave the state or travel between the northern and southern regions. Therefore, UP's and BNSF's system wide fuel efficiencies are heavily influenced by the fuel efficient transport of coal over relatively level terrain, while rail traffic in California is typified by fuel intensive intermodal service over mountain passes.

Given the short comings of EPA's guidance, a revised inventory method was developed by Sierra Research for the Southeastern State Air Resources Managers Inc. (Caretto 2004a; Caretto 2004b). Correction factors that adjust the system-wide fuel consumption rate in EPA's guidance for the amount and steepness of grade and the proportion of bulk train traffic were developed. However, development of the revised method was limited by data availability, relying on few out-dated data from a previous study, BAH (1991a). Additionally, corrections for the amount of travel across flat terrain were not considered. This may have been an important oversight since the system-wide fuel efficiency is some average of travel over hilly and flat terrain and is therefore unrepresentative of either. Correction factors for other train types were also not developed.

2.2.1.1.2 California's Model

The limitations of the EPA methods, the presence of several large ports, and severe air quality problems probably served as factors prompting California to develop its own locomotive emission model. Booz-Allen Hamilton developed the California model and worked closely with the railroads operating in the state at the time of the study (late 1980s).

For line-haul service, the activity measure is the total annual operating hours in each notch for each type of train (intermodal, unit and manifest) traveling each route as shown in Figure 2-6 (BAH 1991a). The detailed travel times were calculated for each railroad, route and train type with data provided by Class I railroads operating in the state when the study was conducted. The railroads obtained the data from two sources: locomotive event recorders (devices which record time spent in each throttle notch among other things) and train performance modeling software. These data did not include idle time. An average idling time was developed from analysis of data provided by a single railroad which showed 8 hours of idle time per locomotive between arriving and departing from a rail yard.

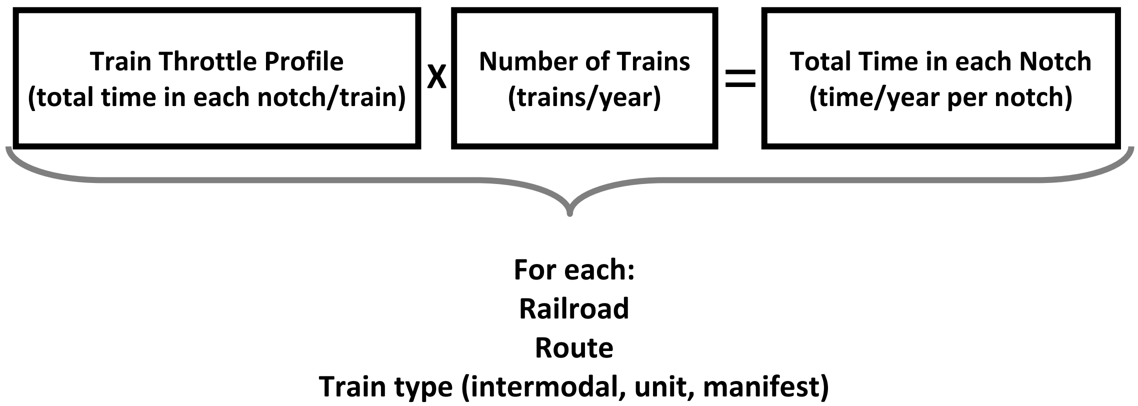


Figure 2-6 CARB’s method of estimating regional locomotive operating hours

The Booz-Allen inventory was only conducted for air basins with large air quality problems and excluded many regions of the state. In a follow up report, Booz-Allen forecasted activity to the remainder of the state and for future time periods (BAH 1992). To forecast activity to the remainder of the state, gram per mile emission rates were calculated for each train in the original study. Route information from the original study was also used to estimate the number and type of trains that traveled routes in the remainder of the state. The number of trains, gram per mile emission rates and distances of the additional routes were multiplied to produce emission estimates for these routes.

The highly detailed approach taken by CARB fully addressed the shortcomings of EPA’s methods by considering the differences in activity caused by train type and geography. As previously noted, accounting for the time spent in each notch would provide the most accurate emission estimate. However, the approach is dependent on highly detailed route data which was made available on a one-time basis only to CARB, as part of the initial study. Since that time, CARB has relied on updating its emission inventories using growth factors. The methods and data used to estimate growth factors have changed over time, but generally rely on assumptions related to technological change (of the locomotives) and economic growth (BAH 1992; Alexis, Jaw et al. 2006; Wong 2006).

The reliance on growth factors, which are applied uniformly to all routes in the state, reduces the spatial detail of CARB's estimates. For example, some of the growth factors, which are based on U.S. economic growth or the national average net ton-miles per locomotive, are not specific to California railroads or individual routes within California. Growth factors are unlikely to reflect changes in train length and locomotive power which both affect locomotive duty cycles – and the time spent in each notch. Unlike traffic density or national fuel consumption, which are directly tied to locomotive activity, growth factors based on international trade or economic growth are only partially correlated with locomotive activity. While using national averages in the absence of local information is a reasonable approach, there is little way to verify how these growth factors ultimately impact the emissions estimates.

One additional limitation in CARB's method is the assumption that all line-haul locomotives idle for 8 hours between rail yard arrival and departure. This assumption was derived using data collected from a single railroad at one point in time. It is likely that rail yard arrivals and departures themselves are highly variable, and it is fairly common that locomotives also idle outside of yards at sidings and throughout the lines due to congestion.

2.2.1.2 Class II and III Railroads

2.2.1.2.1 EPA Guidance

EPA recommends using a different approach for Class II and III railroads because they are exempt from submitting annual reports to the STB. EPA's guidance suggests that regional authorities ask each Class II and III railroad to report its fuel consumption, possibly through a survey. The guidance notes that many Class II and III railroads operate locally, so further disaggregation of fuel consumption data provided by the railroads may not be necessary; however, some Class II railroads do cover a relatively large region. To further disaggregate the Class II and III railroad fuel consumption the EPA guidance suggests proportioning fuel use by route traffic density, provided the data are available from the railroad. If not, the guidance recommends proportioning the fuel use by track length.

Provided that fuel consumption data can be obtained from the railroads, EPA's method should provide a reasonable estimate of emissions from Class II and III railroads. Many of these railroads operate only a single route or over a relatively small geographic area, so geographic considerations (variability in emissions over larger spatial areas) are less of a concern. For railroads that operate over larger regions the approach recommended for Class I railroads would be sufficient provided that traffic density data are available; the limitations of this approach as noted for Class I railroads will be reduced because of the comparatively small geographic coverage of even the largest Class II and III railroads. Additionally, small railroads typically offer just one type of train service, further reducing variability between routes. The largest challenge facing this methodology is likely to be obtaining the fuel consumption data. At least one documented attempt by SESARM (a group of 8 southeastern state air quality control agencies) to obtain these data were not successful; railroads did not necessarily collect or archive the required data or did not have personnel available to retrieve the data (Caretto 2004a).

2.2.1.2.2 California's Model

CARB's model also distinguishes between line-haul and "local" service; local service is described as line-haul service provided by smaller railroads (BAH 1991a). For local service, the annual numbers of train trips are used to represent the activity measure. Instead of determining the amount of travel time on each local route, an average travel time is developed for all local service. Event recorder and train performance modeling software data were used to estimate that a local train trip is 10 hours and that there is 10 hours of idling per day per locomotive.

One constraint to this method is that it excludes consideration of almost all regional and local factors. Analysis of the NTAD shows that Class II and III routes vary considerably in length, therefore the time required to travel each route should also vary (BTS 2006). Additionally, geographic and train type differences are also not considered. The relative errors in these estimates is difficult to predict since no distributional data were provided with the average values presented in original (Booz-Allen) inventory report (BAH 1991a).

2.2.1.3 Rail Yard Activity

Both EPA and CARB estimate rail yard activity using a very simplified approach. EPA's method measures activity by multiplying the number of switching locomotives in each yard by an estimate of annual switching locomotive fuel consumption provided by EPA. The EPA guidance recommends asking each rail yard for the number of switching locomotives used. If the rail yard will not provide the data, the guidance suggests going to the yard and counting the number of switching locomotives in use. The California model applies a similar method: the number of locomotives in each yard is multiplied by 24 hours to obtain total operating hours. An average yard duty cycle is then applied to the total operating hours to estimate the total time spent in each notch (BAH 1991a).

Both the EPA and CARB methods assume no variation in the operation of switching locomotives between different rail yards (that is, constant annual fuel consumption or operating hours per locomotive). However, a series of recent toxic air contaminant inventories[8] of major California rail yards completed by the state's Class I railroads to support CARB's rail yard health risk assessments (HRAs) show large differences in operating hours and estimated[9] fuel

[8] Inventories available at http://www.arb.ca.gov/railyard/hra/hra.htm
[9] Locomotive fuel consumption is estimated based on the fuel consumption rate of a representative rail yard locomotive (EMD GP39). For each rail yard, using information from each yard's HRA, fuel consumption is estimated by multiplying, for each throttle notch, the locomotive fuel consumption rate (obtained from EPA test data [7]), the annual yard locomotive operating hours and the fraction of time spent in the throttle

consumption per locomotive (Table 2-1). Table 2-1 shows that applying either the EPA or CARB rail yard method produces estimates that differ from the detailed accounting of individual rail yard operations in the HRAs. The variations in fuel consumption and operating hours per locomotive between the yards are caused by different operating durations (some are 24 hours while others are 8 or 16 hour operations) as well as varying levels of traffic and types of activity (building manifest versus intermodal trains).

The California rail yard inventories show the importance of considering how yard operations differ. For California, the rail yard inventories also provide a detailed source of activity data that could be used to update CARB's emission inventory and study methods to more accurately estimate rail yard activity should such detailed data not be available in the future.

Table 2-1 Difference between activity estimates based on rail yard inventories and EPA and CARB methods

Rail Yard	**HRA**[a] *gallons of diesel*	**EPA**[b] *gallons of diesel*	**EPA Δ**[c]	**HRA** *hours*	**CARB**[d] *hours*	**CARB Δ**[e]
BNSF Wilmington/Watson	68,963	83,220	20.7%	4,200	8,760	108.6%
BNSF Stockton	254,004	249,660	-1.7%	19,612	26,280	34.0%
BNSF Richmond	118,188	166,440	40.8%	17,520	17,520	0.0%
BNSF Commerce/Hobart	358,371	416,100	16.1%	30,112	43,800	45.5%
UP Commerce	244,150	249,660	2.3%	17,520	26,280	50.0%
UP LATC	569,683	499,320	-12.4%	40,880	52,560	28.6%
UP Mira Loma	223,804	166,440	-25.6%	16,060	17,520	9.1%
UP Oakland	488,300	332,880	-31.8%	35,040	35,040	0.0%
UP Stockton	773,142	665,760	-13.9%	55,480	70,080	26.3%

[a]Estimates from rail yard health risk assessment inventories.

[b]Estimates from EPA Procedures for Inventory Preparation *(28).*

[c]Percent difference from HRA estimates ((EPA-HRA)/HRA*100)

[d]Estimates from CARB/Booz Allen method *(37).*

[e]Percent difference from HRA estimates ((CARB -HRA)/HRA*100)

position. The fuel consumption estimates for each throttle position are then added up, providing an estimate of annual yard locomotive fuel consumption.

2.2.2 Emission Factors

Emission factors describe the rate that pollutants are emitted from vehicle operation. Performing engine exhaust measurements is the most straightforward, and most common, method of estimating emission factors. Engine exhaust measurements have been made on locomotives since the early 1970's (SP 1972) but our understanding of locomotive emission rates remains relatively limited. This section describes how emission factors are estimated and discusses the issues concerning the accuracy and precision of the emission factors.

Emission factors for locomotives are based entirely on laboratory studies; in-use measurements have never been made or remain unpublished. Like other mobile sources (e.g., see the brief literature review in Appendix A), emission factors derived from laboratory studies of locomotive emissions are limited by the degree that tested locomotives represent the actual in-use fleet and how representative test duty cycles are of real world locomotive operation. In general, there has been very little testing completed on locomotives, resulting in an unknown but likely large amount of uncertainty in these laboratory measurements.

2.2.2.1 The In-Use Fleet

The EPA defines fleet average emission factors based on a projected in-use locomotive fleet (EPA 1998). Fleet average emission factors are determined by weighting individual locomotive emission factors by relative fuel consumption. In turn, relative fuel consumption is estimated as a function of the age, horse power and number of each make and model of locomotive. Future fleets are projected based on the retirement of old locomotives determined by age, and the penetration of new locomotives to make up for power lost from the retired locomotives. The EPA method allows for projection of future emissions based on a continuously evolving fleet, accounting for expected changes in new locomotive fuel efficiency and emission rates. However, no updates have been made to EPA's original projections from 1997 (EPA 1997) and they have never been verified against the actual in-use fleet. The original 1997 fleet was based on data obtained from a railroad book[10] (EPA 1998) written for railroad enthusiasts and toy train modelers[11]. Few other sources of information about past or current in-use fleets are publicly available.

In the 1991 Booz-Allen report commissioned by CARB, fleet average emission factors were estimated for each railroad by weighting notch specific emissions factors for each locomotive by the number of locomotives, horse power and typical availability (% of time not in maintenance)(BAH 1991b). Locomotive rosters were provided by Class I railroads. Future emission rates were then projected based on a number of assumptions about future locomotive technology, efficiency and traffic levels (BAH 1992). For example, it was assumed that by 2010 mixed (manifest) and bulk traffic would increase by 2% to 4% and intermodal traffic would increase by 46% over 1986 levels, the rated power of new locomotives would be 5,200 bhp and fuel efficiency would increase by 8% due to new locomotives, reduced aerodynamic drag and increased rail lubrication. These assumptions may have been reasonable, and CARB has indicated that many were refined and updated as the inventory was revised over time.[12] We cannot comment on the robustness of the assumptions in general, for either the Booz-Allen or the subsequent CARB updates, because the available documentation is limited. It is very difficult to build inventories that can be used to reliably forecast trends. In general, models must take into consideration underlying economic mechanisms to produce robust forecasts. For example, some of the Booz-Allen forecasts have not aligned well with recent national railroad statistics. According to the AAR (AAR 2006), between 1990 and 2005 gross ton-miles have increased by 65%, intermodal traffic has doubled and fuel efficiency has increased by 20%; the maximum rated power of new locomotives is 4,400 bhp. And some trends cannot be reliably predicted with

[10] Official Locomotive Rosters and News, 1997 special edition – Class I railroads, James W. Kerr, July 31, 1997 (EPA's citation). No publisher information could be found for the cited edition; however, current editions are published by DPA-LTA Enterprises, Lewiston, NY)

[11] The Union Pacific Railroad lists its current in-use fleet on its website; however, important details such as the Tier certification level, remanufacture history, and age of the locomotives is not included.

[12] CARB comments on final report (dated March 2010)

current knowledge. For example, since the Booz-Allen study was carried out before EPA emission regulations were considered, future fleets do not currently account for any penetration of lower emitting locomotives – the assumption was that emission reductions would come from improved fuel efficiency rather than (newer) cleaner diesel locomotives. Forecasting future trends in inherently uncertain and developing new modeling tools that facilitate incremental updates will help to increase overall robustness.

In both cases (EPA's and CARB's emission models) the emission estimates are likely to exhibit some error because of the underlying assumptions about the actual in-use locomotive fleet. EPA's data on the base in-use fleet comes from a source of unknown validity; in contrast, CARB's data comes directly from the railroads. However, CARB's projections rely on unsupported assumptions (e.g., forecasts of traffic growth, locomotive technology and efficiency and do not account for EPA emission regulations; EPA's projections are somewhat more sensible yet lack any sort of verification.

2.2.2.2 Locomotive Duty Cycles

Steady state emission rates estimated for each locomotive throttle notch are weighted by a duty cycle to create a single emission factor (the average locomotive emission rate for typical operation). EPA uses a national average line-haul and switching duty cycle while CARB uses average duty cycles for each rail segment and train type for line haul operations and a single duty cycle for all switching operations (BAH 1991a; EPA 1992; EPA 1998; ERG 2005). Dunn (Dunn and Eggleton 2002) conducted a study which evaluated the impact of various duty cycles on emission factors, finding that they had relatively little impact. However, the study only considered average duty cycles, that is, duty cycles which represent operations over large geographic areas (e.g. Canada, California and the United States). Actual duty cycles for a specific track segment can be highly variable, depending on topography, train type, congestion and the particular locomotives in use. Given the variability in emission rates across throttle notches (see

Figure 2-3) actual duty cycles can produce substantially different emission factors than average duty cycles. The use of fuel based emission factors, as opposed to hourly emission factors, overcomes some of the differences that occur as a result of using average duty cycles.

Yanowitz (Yanowitz and Cameron-Cole 2003) noted that locomotive test procedures are designed to measure steady state emission rates but average continuous time-in-notch data provided to EPA by several railroads (Table 2-2) indicate that actual operation of locomotives may be more transient (EPA 1998). The federal locomotive test procedure (40 CFR 1033.515) requires emissions to be sampled from all notches for 5 to 10 minutes, except for notch 8 which is sampled for 10 to 15 minutes, from the time that the throttle is changed. The maximum PM emission sampling time can be extended so that a sufficiently large sample can be collected to accurately weigh. The previous federal test procedure (40 CFR 92.124) required a minimum sampling time of 6 minutes in all notches, except notch 8 which had a 15 minute minimum sampling time, from the time that the throttle is changed. The relatively long sampling times mask the effect of emissions during throttle changes.

Table 2-2 Average time continuously in notch

	Minutes	
Throttle Notch	**Line-Haul**[a]	**Switching**[a]
Idle	2.8	1.7
Dynamic Brake	5.6	N/A
N1	0.5	0.5
N2	0.5	0.5
N3	0.5	0.5
N4	0.5	0.3
N5	0.5	0.9
N6	0.6	0.4
N7	0.5	0.3
N8	4.9	0.9

[a]Data from EPA (EPA 1998)

Yanowitz (Yanowitz and Cameron-Cole 2003) estimated the impact of throttle changes on PM emission rates by comparing PM emission rates calculated from two different length sampling times. The necessary data are available from (Fritz 1995); two PM measurements were collected under identical conditions, with the exception of the sampling time length, for several common in-use locomotives. A system of equations can be specified to solve for the impact of the notch change since the sampling time is known and all other factors should be constant. Using the same data and methods as Yanowitz, but converting the results to a bhp-hr basis, Figure 2-7 shows that actual in-use emissions of PM may be two to three times greater than estimates based on the federal test procedure (FTP).

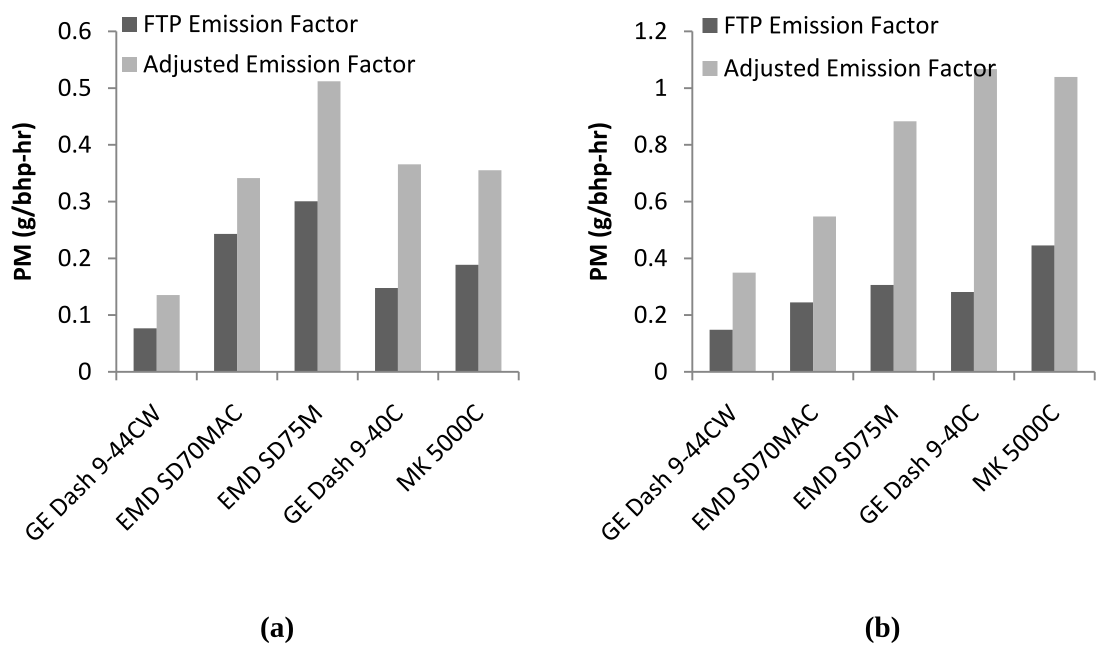


Figure 2-7 Comparison of (a) line-haul and (b) switching duty cycle weighted federal test procedure (FTP) and adjusted emission factors

Similar data to estimate the throttle change effects for other criteria pollutants are not available. The FTP requires that measurements of NO_x, CO and HC exhaust concentrations are made continuously, but the instantaneous mass rate is not available, only the average mass rate during the sampling time period. Concentration data recorded during throttle changes cannot be readily transformed to a mass rate without knowing the exhaust gas volumetric flow rate, which is unknown. However, concentration plots of exhaust emissions can provide information about emission trends, and are therefore helpful.

Continuous exhaust emission concentration (ppm) plots for several late model locomotives are presented in (SP 1972). The concentration plots show elevated concentrations of NOx, CO and HC during throttle changes. Peak concentrations of CO were 300% to 640% higher than steady state concentrations in notch 8 (maximum steady state concentrations) while rapidly increasing the throttle from notch 1 through 8. Similarly for NO_x and HC, peak concentrations recorded during rapid throttle advancement were 20% to 500% higher than notch 8 steady state concentrations. Minimum concentrations, approximately 75% to 100% less than notch 1 steady state concentrations (minimum steady state concentrations) were recorded while decreasing the throttle from notch 8 to 1 for CO, NOx and HC. These results, though out dated, provide some evidence that the current FTP may be significantly underestimating CO, HC and NO_x emissions by overlooking emissions generated through transient operation in throttle notch changes.

2.2.2.3 Emission Test Data

Measurements of exhaust emissions under controlled laboratory conditions are relatively accurate since analytical equipment can be calibrated and the accuracy measured. Locomotive emission testing follows standard EPA mobile source analytical procedures (40 CFR 1065). However, uncertainties in the accuracy and precision of emission factors are likely large, though unknown, because outdated emission test data are used, empirical emission rate data from a few tested locomotive models are extrapolated to estimate emission rates for untested models, and there is a general lack of repeat testing.

Older emission factors were derived from inferior analytical techniques (EPA 1991a)[13] and empirical test data extrapolated from stationary test engines (EPA 1991b) and a small sample of actual locomotives (EPA 1991a). Some of the older emissions factors continue to be used,

[13] A copy of this difficult to obtain document is included in Appendix B.

despite these issues. For example, the emissions factors for all pollutants from GE locomotives, and the PM emission factors from all locomotives presented in BAH (1991a) and EPA (1998) all have serious problems.

The emission test data for GE locomotives originally presented in BAH (1991b) and later in the more widely cited EPA (1998) were derived from a single, stationary GE test engine at Southwest Research Institute (SwRI) in 1978 (BAH 1991b). SwRI extrapolated the data to other engines based on the number of cylinders and horse power without any validation of the approach (EPA 1991a). During the time that the CARB locomotive study was conducted, emission measurement methods were only just being developed for PM. These PM measurement data were considered unreliable (BAH 1991a; EPA 1991b) and were not available for any of the locomotives presented in (BAH 1991b), all PM data reported was extrapolated from testing at SwRI (BAH 1991b) of one EMD and GE locomotive respectively.

The lack of clear documentation is also a serious concern. Emission factors presented in (BAH 1991b) have been used by EPA for its regional inventory preparation guidance (EPA 1992), emission standard rule makings (EPA 1998; EPA 2008b), national locomotive fleet emission factors (EPA 1997), and the National Emission Inventory (ERG 2005). The various EPA reports and guidance have subsequently been used by states, regional government agencies and the railroads to evaluate locomotive emissions from the early 1990's to the present. However, EPA has failed in all of its documentation to cite the original source of most of the data: the CARB Locomotive Emission Study and its Appendices (BAH 1991a; BAH 1991b). Instead, EPA cites its inventory preparation guidance (EPA 1992) which then cites an unpublished EPA memo which was subsequently lost by EPA and replaced with a draft of that memo (EPA 1991a). The CARB locomotive Emission Study, the original source of data, discusses the sources and limitations of the test data. Since EPA has failed to clearly document the source of its data, important information concerning the sources and accuracy of the data are largely inaccessible to most users. The draft memo cited by EPA does acknowledge the CARB Locomotive Emission Study as the source of its data, but does not discuss how the PM data were created and provides a conflicting account of the methods used to measure NO_X emissions.

The data sources and methods used to derive past emission factors continue to exert a heavy weight on locomotive emission modeling. Figure 2-8 provides a time series account of line-haul emission factors used or reported in the most influential reports from 1991 to present. The relative contribution of each locomotive test data to each inventory is represented by the height of each bar. The contribution of each emission factor is assumed to be proportional to the corresponding number of locomotives it applies to in each study. While this simple method holds for some of the studies, it does not for others where the locomotive fleet is also weighted by measures of activity such as horsepower. However, this account should still indicate of the significance of past testing on current inventories and studies.

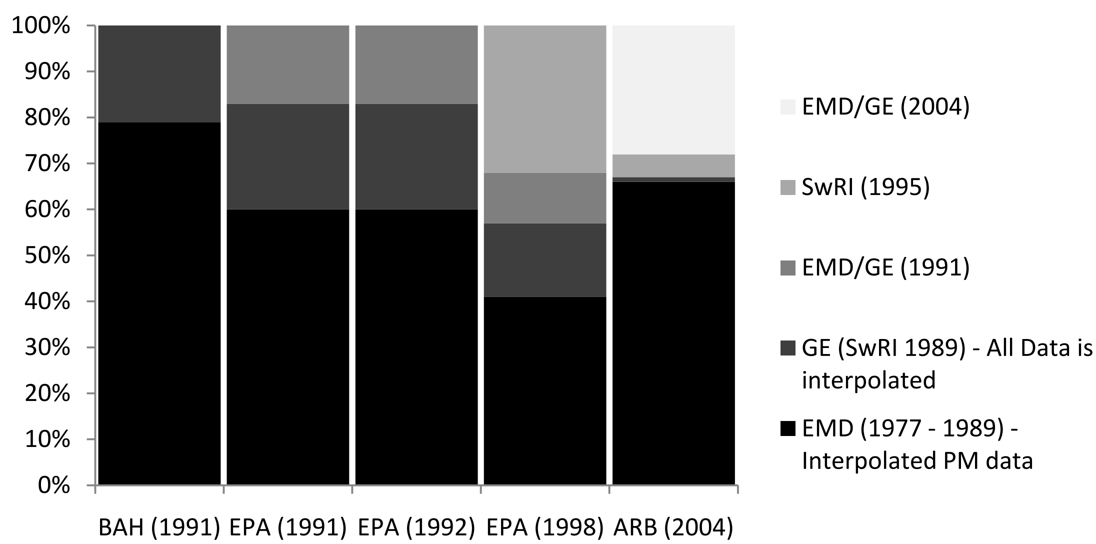


Figure 2-8 Sources of line-haul locomotive emission factors used in influential locomotive emission studies

The accuracy of locomotive emission factors is also affected by remanufacturing. Locomotives have long lifetimes and are remanufactured many times (EPA 1998). No studies have looked at the effects of recent re-manufacturing practices on locomotive emissions, but it would be difficult to believe that emission rates have not been affected. A study by the railroad industry in the early 1970's found only slight improvements in emission rates, and in one case an increase in emission rates due to regular maintenance (SP 1972). However, the locomotives from this study are no longer widely used and the test was carried out on only a single locomotive. The study recommended that the impact of maintenance on emission levels should be studied further. No studies have since been published.

The potential magnitude of errors caused by the use of out-dated emission factors is highlighted by considering CARB's 2004 study of PM emission from UP's Roseville, CA rail yard (Hand, Di et al. 2004). The study goal was to assess the public health risk posed by PM rail yard emissions, which are adjacent to the downtown business district and residential areas. The composition of the fleet of locomotives that pass through the yard and those used exclusively within the yard was provided by UP. Over 65% of the locomotive fleet was matched with emission factors from (BAH 1991b) as shown in Figure 6. However, the PM emission factors in (BAH 1991b) are derived from just two tests: a 1989 test at SwRI of a 2,500 hp EMD 12-645E3B engine and a 1989 test at SwRI of a 2,500 GE 12 cylinder 7FDL engine. The results of both tests at SwRI were extrapolated to other, more powerful and modern, locomotives using methods not specified in the available documentation. The 2004 CARB study relies on emission factors derived from 15 year old test data, for a locomotive model no longer used by UP, which does not account for subsequent remanufacturing or emissions during throttle changes. Additionally, CARB does not evaluate the accuracy of the emission factor data or acknowledge that an earlier CARB study is the source of these emission factors. There is potential for large errors in estimates of PM from the Roseville yard which stem from poorly documented sources of emission factor data and test procedures which assume steady state operation. Since no ambient measures of yard emissions have been made[14] and no updated emission tests have been performed on late model locomotives the magnitude of these errors is unknown, but likely large.

In addition to questionable accuracy, the precision of emission test data is largely unknown. Precision of locomotive emission factors can be evaluated by several metrics: the variability in repeated engine exhaust measurements, the variability of exhaust measurements between identical locomotive models and the variability of emission factors between similar types of locomotives (same EPA Tier certification, power, age, etc.).

Only one study has conducted repeated exhaust measurements on a single locomotive and across several identical locomotives (Fritz 2000), a summary of the repeated measurement data for an uncontrolled GE locomotive is shown in Figure 2-9. The data in Figure 2-9 were collected for a CARB study on the effect of differing diesel fuel sulfur levels on emission rates, and were not intended to lend insight to locomotive exhaust measurement precision. However, the repeated measurement data reveal several things: the variability of exhaust measurements varies across throttle notches, pollutant emission types and the difference in exhaust measurements between identical locomotives may be larger than the differences in repeated tests on a single locomotive. An identical set of measurements was also performed on a similar EMD locomotive with similar results.

In summary, few to no studies currently exist that correlate ambient concentrations with estimated emissions from a locomotive emissions model or measured laboratory data. Such studies have been conducted for on-road mobile sources, but not for rail sources. Projects underway now show great promise for increasing our understanding of emissions versus

PM measurements have been made at UP's Roseville yard; however, the study goal is to isolate and measure concentrations of locomotive PM emissions in ambient air samples. The study does not estimate emission inventories or validate emission models or test data. Roseville PM study available at http://www.placer.ca.gov/Departments/Air/railroad.aspx.

background. One obvious next step in these efforts would be to better correlate ambient concentrations with verification of laboratory emissions data.

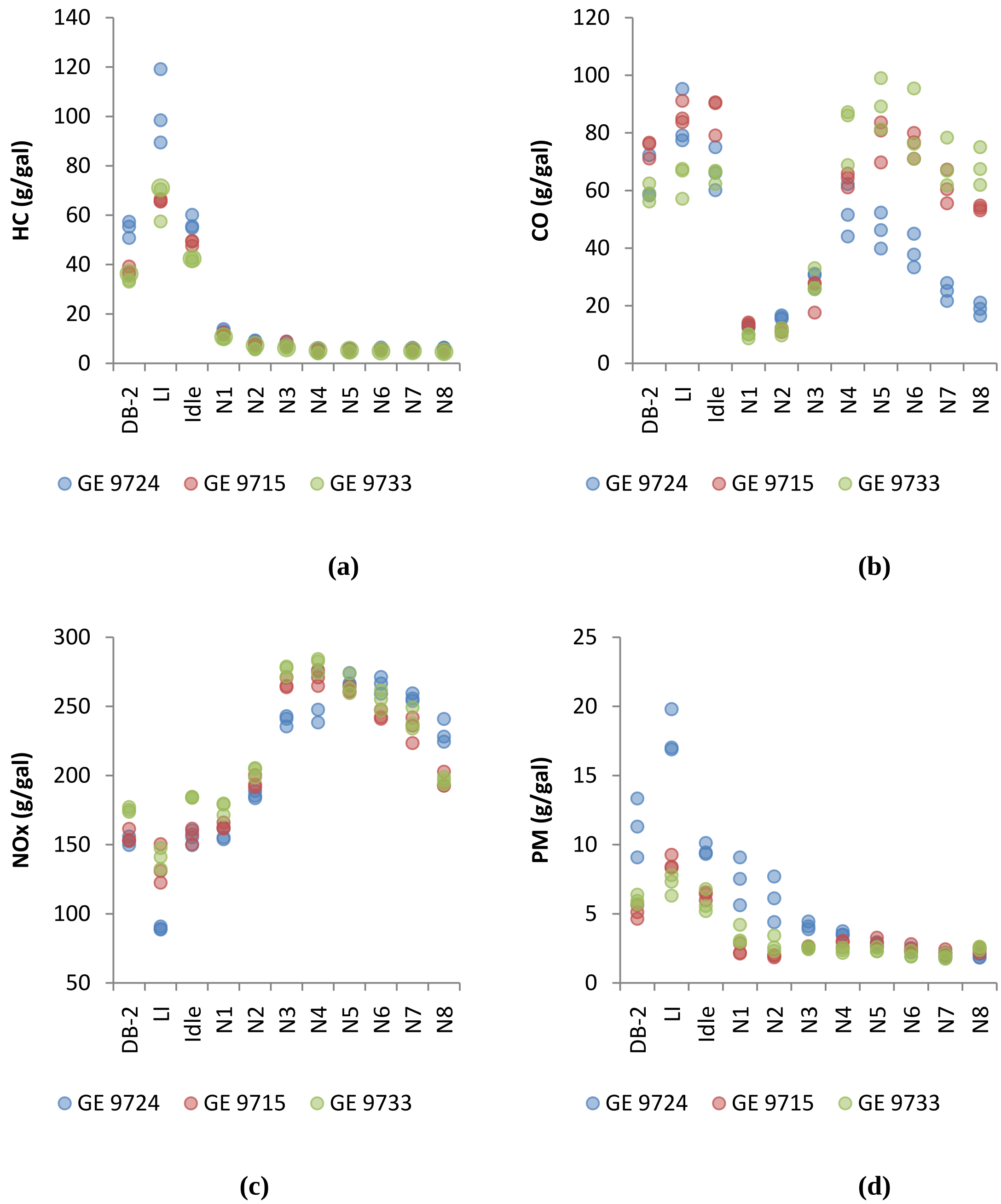


Figure 2-9 Variability of HC (a), CO (b), NO_x (c) and PM (d) emissions by throttle notch from three uncontrolled 3,400hp GE Dash9 locomotives

3 CREATING A NEW SPATIALLY RESOLVED LOCOMOTIVE EMISSION MODEL

3.1 Introduction

This section introduces the new model framework, with subsequent sections describing the mode structure, data collection and data analysis methods in more detail.

This report introduces a new locomotive emission model designed to provide increased spatial resolution and accuracy compared to current modeling techniques. The report begins with a brief review of locomotive emission modeling. This is followed by an outline of the model framework and a description of its improvements over current methods. The model development is provided in Section 3, and includes a comparison of results estimated for California with those using the California Air Resources Board (CARB) and the U.S. Environmental Protection Agency (EPA) guidance. The report concludes with a discussion on model use and additional aspects of the new approach that would benefit from more research.

The research described in this report was conducted in response to CARB's need for an updated and improved locomotive emission inventory.

3.1.1 Contributions of the Research

- There are significant issues with current rail modeling techniques. For example, CARB’s current inventory is based on forecasted changes in locomotive emissions from a 1987 inventory and EPA’s fuel based approach uses national average fuel efficiency values, thus obscuring changes in fuel use (and consequently, emissions) due to topography or differences in locomotive fleet. In this study, we describe a new approach that allows fuel efficiencies to vary depending on local conditions including topography, differing types of train traffic and varying locomotive fleets. By better reflecting local conditions the spatial resolution of emission estimates is greatly improved.

The new framework also improves how emission factors are estimated and applied to the fuel consumption estimates. The current EPA method relies on projecting estimates of base national fleet average emission rates based on historical locomotive replacement rates. The new framework can estimate spatially resolved emission factors that depend on the EPA certification level of locomotives currently in use by each of the railroads operating on a specific track segment. The emission inventory estimated in this report assumes a uniform locomotive fleet for California since railroads generally do not assign particular locomotives to particular routes. The ability to define different regional locomotive fleets allows the model to remain adaptable to future conditions or more detailed studies.

- The model system employs a new GIS modeling platform that facilitates the use of local data into the estimation. The GIS framework is built around a new statewide GIS layer which identifies all track alignments and their grades, and also rail yards. The GIS platform provides new capabilities in data management, scenario analysis and reporting of results. Data specific to an individual route or track segment can be located and adjusted through the GIS interface by selecting the link on map, the model can be run, and the results immediately displayed for that segment. Track specific emission estimates can also be easily aggregated to customized levels through the GIS interface. This contribution is also aligned with CARB's objective of moving all emission models to GIS based platforms. The use of a GIS platform is also important because it allows for the future development of an open source modeling system that tracks with the need for transparency in digital governance.

- As a result of this work, newly updated data and emission estimates have been synthesized and incorporated into the framework. We collected new data from

California's Class I railroads: Union Pacific (UP) and Burlington Northern Santa Fe (BNSF). This includes new traffic density data, train operation data and locomotive fleet information. New emission factors also have been collected from the literature and government testing programs while out of date or less reliable emission factors are abandoned. These data are available in the modeling platform and used to estimate new state wide emission inventories.

3.2 Model Framework

The model framework departs from the current CARB method based on Booz-Allen's time-in-notch approach (BAH 1991a) and extends EPA's fuel based method (EPA 1992) and similar methods (Caretto 2004a; Billings, Chang et al. 2006). Like EPA's method, fuel efficiency (gross ton-miles (GTM) per gallon of diesel fuel consumed) is applied to track segment level traffic density to estimate track segment level fuel consumption. However, the new framework provides a method to estimate track segment specific fuel efficiency values based on local factors which are known to impact fuel consumption rates: type of train (intermodal, bulk, manifest, etc.), track grade and locomotive fleet (Davis Jr. 1926; Hay 1982). EPA's method relies upon individual railroad company system-wide fuel efficiencies. Only seven railroads are responsible for moving most of the freight in the U.S. (AAR 2006), and each railroad's system typically spans more than half the country. System-level fuel efficiency values do not reflect regional conditions.

Emissions for each track segment are estimated by multiplying the track segment's fuel consumption estimate by a fuel based (gram per gallon) emission factor. Emission factors for each track segment are created by weighting EPA fuel based emission factors (EPA 2009) (available for each EPA locomotive tier standard[15]) by the proportion of locomotives using each

[15] EPA has published estimated in-use emission factors for locomotives meeting each certification level (tier standard) it has promulgated (see Table 6 for details).

track segment meeting each EPA tier standard[16]. EPA's method assumes a single national locomotive fleet (single national locomotive emission factor) and the CARB method uses locomotive make and model specific time based (gram per hour) emission factors. Locomotive make and model specific time based emission factors are especially problematic. As discussed in Section 2.2.2.3, emission tests have only been performed on a small sample of locomotives, often with no replications resulting in a high degree of uncertainty and emission factors being unavailable for some makes and models. Adding to the uncertainty in these estimates is the use of inferior analytical techniques for some tests and extrapolated data. Additional problems are encountered when using these locomotive make and model specific time based emission factors since most locomotives now used by Class I railroads are controlled[17]. Most of the available make and model specific emission test data (see Appendix E-2 for available test data) are derived from older, uncontrolled locomotives, which are no longer used or have been remanufactured to meet EPA standards. Emission rates from controlled locomotives are expected to be a function of their EPA certification level rather than their specific make and model[18].

The new framework stores the track specific fuel consumption estimates, emission factors and emission estimates in a database linked to a geographic information system (GIS). The GIS provides a spatial view of the model parameters and results, providing a more convenient format to view the spatially detailed data and facilitating additional spatial analysis. Current models apply differing methods to large and small railroads, for simplicity and consistency this model applies the same methods to all classes of railroads.

[16] A single locomotive fleet (proportion of locomotives by tier standard) was assumed for all UP and BNSF track segments respectively because it is assumed that particular locomotives are generally not assigned to particular routes. However, the model framework enables the user to specify track segment level detail to model potential policy outcomes (e.g. the 1998 South Coast MOU between CARB and the UP and BNSF railroads which requires the use of a cleaner locomotive fleet in the South Coast Nonattainment Area).

[17] Locomotives meeting EPA tier standards; locomotives manufactured prior to 1973 and locomotives currently owned by class III railroads are exempt from emission standards (40 CFR 1033.101 and 40 CFR 1033.610).

[18] It is assumed that locomotive manufactures produce locomotives that just meet EPA standards with a small compliance margin (emissions are slightly lower than the standards to accommodate variability and ensure certification). For more details see EPA's discussion for producing locomotive emission factors in [9].

The above methods are for line-haul operations (the movement of trains between origins and destinations), additional improvements also have been made for modeling rail yard operations. The new framework departs from current methods, which assume 24 hour operation and constant emission rates from all locomotives operating in every rail yard, by allowing these parameters to vary. Total annual switcher locomotive (a low powered locomotive used to organize rail cars into trains) operating hours are estimated for each yard and multiplied by a fuel consumption factor to estimate total fuel use. While a single baseline fuel consumption factor is estimated for application to all rail yards, a method is provided to adjust it based on more specific information about the efficiency of specific rail yard locomotive fleets. Similar to the method for line-haul operations, emission factors are developed for each rail yard based on the proportion of switchers that meet each EPA Tier certification level. The results of the yard inventories are also accessible through the GIS.

3.3 Detailed Model Development

The following two sections present a full development of the line-haul and yard emission models. The beginning of each section provides a detailed diagram of the modeling framework, depicting the input data, calculation steps and model results. The tables represent the actual MS Access® database tables used in the model. The calculations steps are performed using the open source statistical programming software R® (the model code is available from the authors upon request). And the database is linked to ESRI's ArcMap® for a spatial view of results and further analysis.

3.3.1 Line-Haul Method

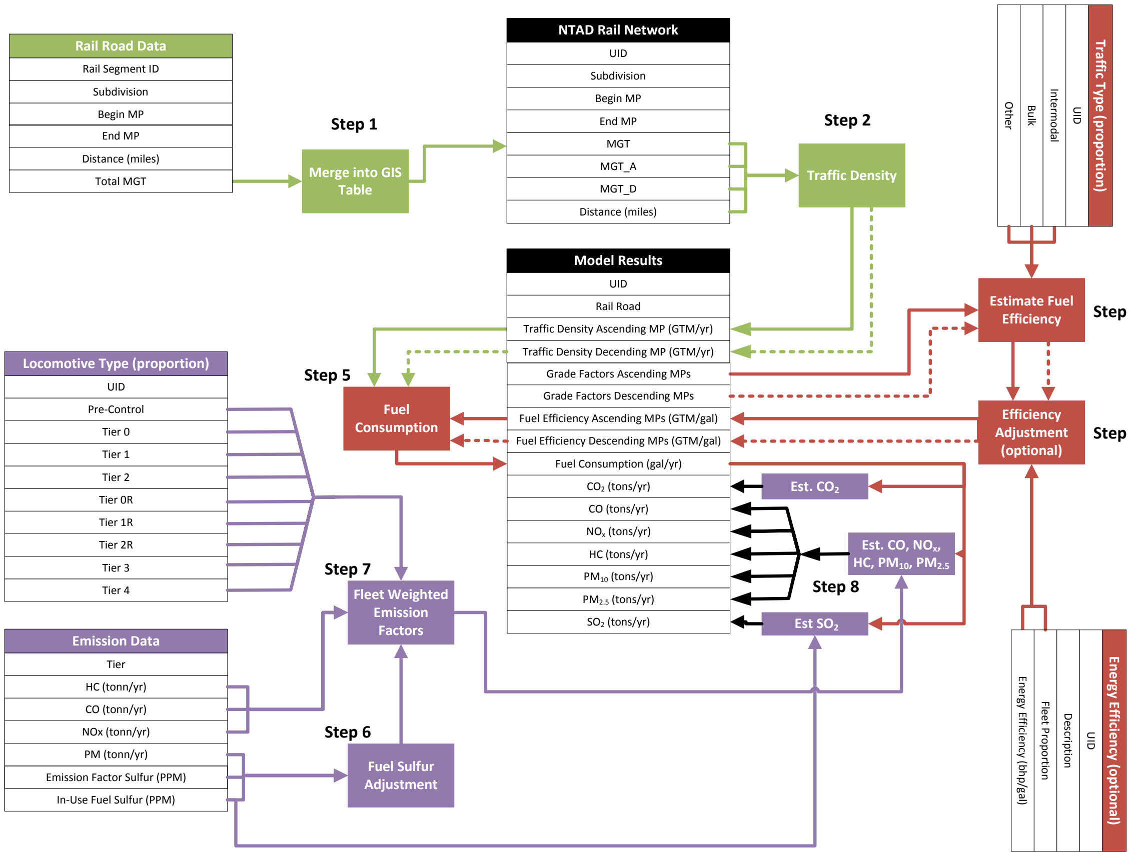


Figure 3-1 Detailed schematic of line-haul emission model: green, red and purple colored chart elements highlight activity, emission factor and fuel efficiency data, respectively; tables show the model input data; arrows indicate the flow of data and calculations; and boxes indicate model operations

Step 1: Populate Network Data

The first step in the process is to populate the rail network with rail traffic. Both of California's Class I railroads, the Union Pacific Railroad (UP) and Burlington Northern Santa Fe Railroad (BNSF) provided annual traffic data (gross tons per year) for each track segment in their systems. The data are generally the same, and include for each track segment mile post, subdivision, segment length and annual million gross tons (Appendix D-1 and D-2)[19]. Each data set also provides the gross ton data separate for each track direction[20].

These data are typically available from Class I railroads, but are not publically available and the railroads are not required to provide it as part of any federal or state reporting mechanisms. Gross ton data can also be obtained from Class II and III railroads; however, it may also be possible for these smaller, regional railroads to directly provide their annual fuel consumption, allowing the first four steps of the modeling process to be skipped. For small Class II and III railroads, the direct use of fuel consumption will not result in loss of much spatial detail (Gould and Niemeier 2009).

The model uses a rail network based on the 2008 National Transportation Atlas Database (NTAD) (2008); the network has been edited to include mile posts, re-classify parallel track segments (see Figure 3-2), add missing track segments and to correct track segments with missing or incorrectly labeled subdivision names. The beginning mile post for each subdivision is identified from a GIS file provided by Caltrans[21], subsequent mile posts are calculated by adding the length of each segment to the previous mile post calculation. The Caltrans GIS data were not used directly primarily because it would have required more editing, is not as widely available as the NTAD and would limit the possible geographic expansion of the model outside of California.

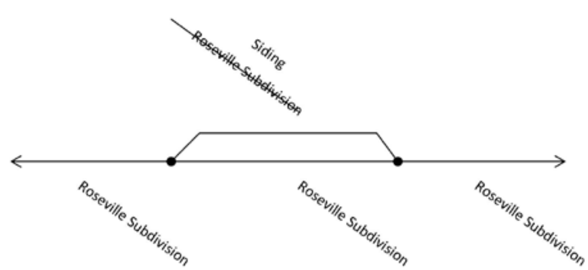


Figure 3-2 Editing parallel track segments

[19] For the original data files provided by UP and BNSF see Appendix C.
[20] The BNSF data includes tracks that oriented north/south. For these tracks, the directional labeling of "west" and "east" was unclear.
[21] Caltrans rail GIS file metadata and link to request form: http://www.dot.ca.gov/hq/tsip/gis/datalibrary/metadata/ff_rail.gdb.xml

The NTAD divides the rail network into track segments of different lengths than those represented in the annual traffic data provided by BNSF and UP. As a result, the traffic data (annual gross tons) cannot be directly linked to the rail network. Instead, the traffic data are *projected* onto the network using the process described in Figure 3-4 and explained below.

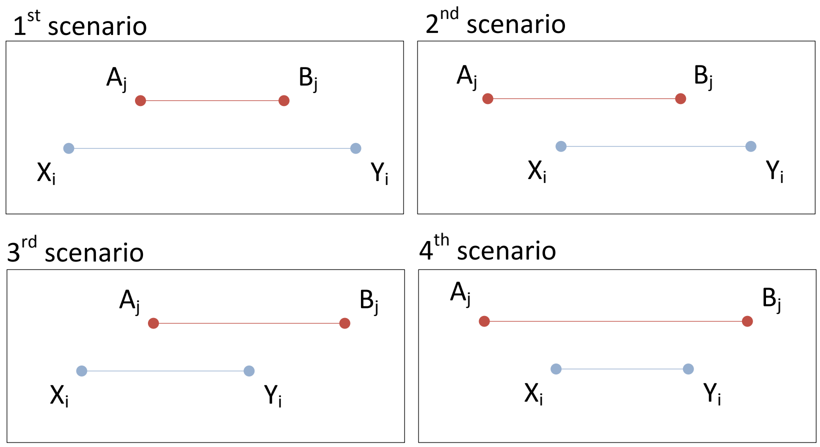
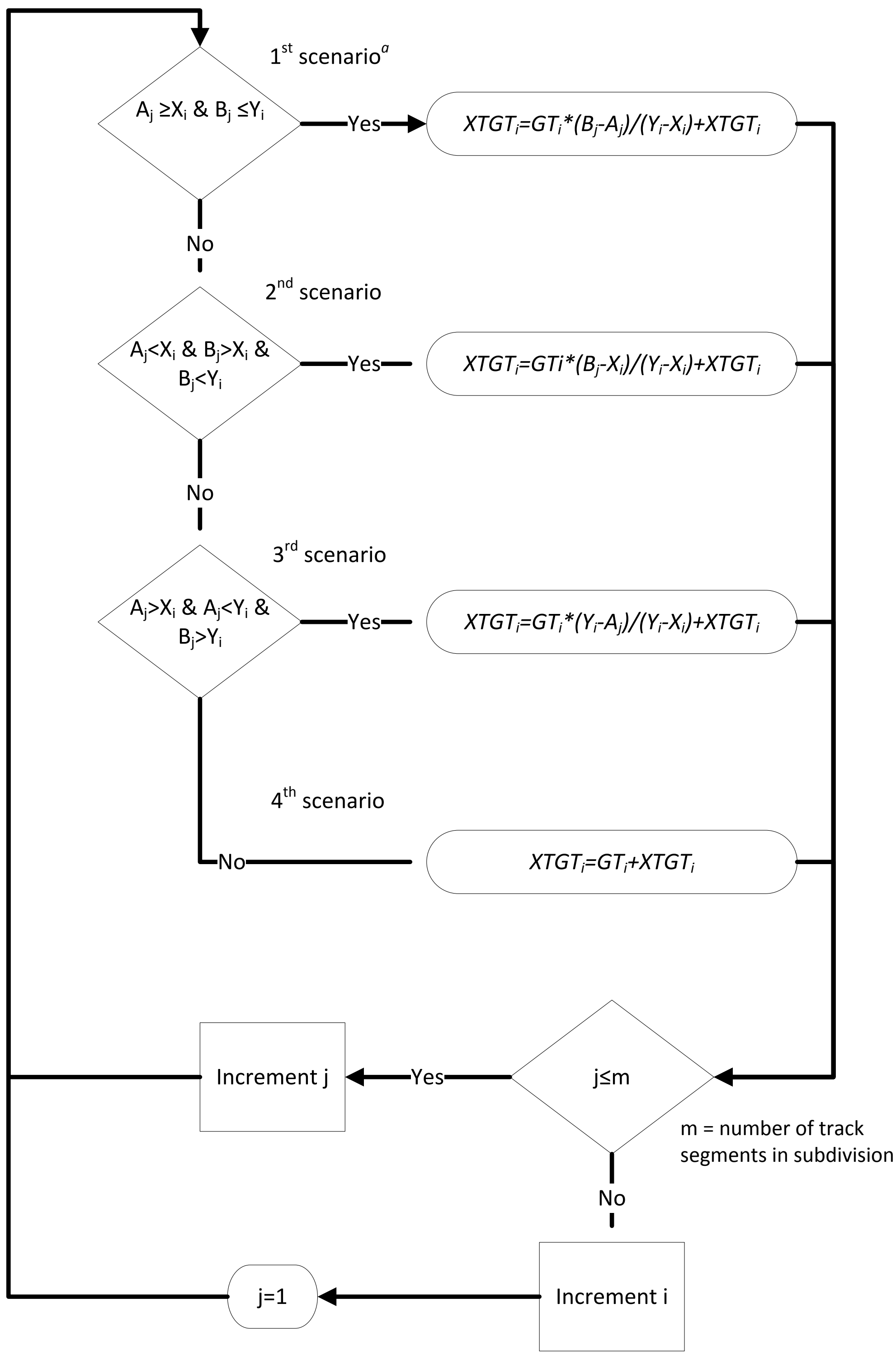


Figure 3-3 Railroad (red) and NTAD (blue) track segment overlap possibilities: the variables A_J and X_I are the milepost values at the beginning of each segment and B_J and Y_I are the milepost values at end of each segment

Figure 3-3 shows the four possible ways in which track segments defined by the railroads, *j* (blue), can overlap track segments defined in the NTAD, *i* (red). The variable A_j is the milepost value at the beginning of a railroad track segment and the variable X_i is the milepost value at the beginning of a NTAD track segment. Similarly, the variable B_j is the milepost value at the end of a railroad track segment and the variable Y_i is the milepost value at the end of a NTAD track segment. For each NTAD track segment, traffic data from overlapping railroad segments are added to the NTAD segment. Where only part of a segment overlaps, an amount of traffic proportional to the ratio of the over lapping track distance to the railroad track's length is added to the NTAD segment. The complete algorithm is shown by the block diagram in Figure 3-4.



[a]See Figure 3-3 for scenario definitions

Figure 3-4 Algorithm for Projecting traffic data for a subdivision onto the NTAD rail network: GT_j = annual gross tons traffic for each railroad track segment j, $XTGT_i$ = traffic projected onto each NTAD track segment i (the process is iterated for all subdivisions)

For the state's smaller railroads, no traffic density data are available or have been collected at this time. These railroads could be contacted and asked to report their traffic density or other available data (fuel consumption); however, the state does not have any legal authority to enforce the reporting of these data. In absence of these data, the NTAD (BTS 2006) can be used to obtain traffic density estimates. However, these data are only made available as six ranges of traffic density (to preserve the confidentiality of each railroad's data). If these data are used, the median values should be applied.

Step 2: Calculate Traffic Density

Traffic density by track segment and direction in the rail network, TD_{id} (gross ton-miles) for segment *i* and direction *d*, is calculated by equation eq 3-1,

$$\boldsymbol{TD_{id} = GT_i \cdot P_{id} \cdot D_i} \qquad \textbf{eq 3-1}$$

where;

GT_{id} = Tonnage moved over track segment *i* in direction *d* (gross tons)
P_{id} = Proportion of traffic moving in direction *d* over track segment *i*
D_i = Length of track segment *i* (miles)

The proportion of traffic moving in each direction for UP subdivisions is determined from the annual traffic data supplied by UP (Appendix D-3). The data provided by BNSF (Appendix D-4) classifies traffic as moving either "east" or "west", the direction of traffic moving over north/south routes is therefore ambiguous. Given this, the BNSF traffic is split evenly in each direction.

Step 3: Estimate Base Fuel Efficiency

Activity is measured by fuel consumption because it is highly correlated with locomotive emission rates (see Figure 2-2) (Gould and Niemeier 2009). However, regional or track specific fuel consumption estimates are not available, so fuel consumption is estimated from traffic density and an estimate of fuel efficiency.

To estimate the fuel consumption and fuel efficiency (gross ton-miles per gallon) of different types of trains traveling over various terrain, confidential operating data were provided by both UP and BNSF for a subset of the major routes in California (these data are provided in Appendix E)[22] . The data provided by the railroads consists of aggregate route specific throttle profiles (cumulative amount of time a locomotive operates in each throttle position) for each type of train (intermodal, unit/bulk, manifest, auto, other) along with the corresponding traffic density, average consist size (number of locomotives per train), annual number of train trips and locomotive fleet inventory . The throttle profiles can be combined with locomotive throttle notch fuel consumption data from existing, published locomotive exhaust tests (Fritz 1995; EPA 1998; Fritz 2000; Fritz 2004; Smith, Sneed et al. 2006) and the other operation data to estimate fuel consumption for each type of train over each route (eq 3-2).

$$\boldsymbol{FC_{jk} = N_{jk} \cdot C_{jk} \sum_l P_{jlk} \sum_n FC_{nl} \cdot T_{jnk}} \qquad \textbf{eq 3-2}$$

Where;

N_{jk} = annual number of trains traveling route *k of type j*
C_{jk} = average consist size for train type *j* traveling route *k*
P_{jlk} = fleet proportion of locomotive make and model *l* for route *k for train type j*
FC_{nl} = fuel consumption rate (gal/hr) for throttle position *n* for locomotive make and model *l*
T_{jnk} = average time (hr) in notch *n* for travel across route *k for train type j*

The fuel efficiency for each route and train type, FE_{jk}, is calculated by dividing the annual traffic density by the fuel consumption estimate derived from equation 3-3,

$$\boldsymbol{FE_{jk} = \frac{TD_{jk}}{FC_{jk}}} \qquad \textbf{eq 3-3}$$

Equations 3-2 and 3- 3 can provide relatively accurate fuel consumption and fuel efficiency estimates; however, the detailed, confidential data are not available for all track

[22] For the original data files provided by UP and BNSF see Appendix C.

segments, can be difficult and time consuming for railroads to collect and is not regularly updated. Because of these limitations, a more general method to estimate fuel consumption based on data that are available or observable is required.

Locomotive fuel consumption is proportional to the amount of work performed, and the amount of work performed is largely determined by the weight of the train being moved, the distance being covered, speed, track grade and the aerodynamic profile of the rail cars (Davis Jr. 1926; Hay 1982). The gross weight of all train traffic and the distance traveled is known (from step 1), track grade can be estimated with a GIS, and while train speed and the aerodynamic profile of rail cars are generally unknown or unavailable they are related to the type of train (intermodal, unit/bulk, manifest, etc.) (Hay 1982; AASHTO 2002). We can specify a regression model to capture the influences of these observable factors on fuel efficiency.

Fuel efficiency estimates for each route from equation 3-3 are regressed on the positive grade factor, negative grade factor, and train type by ordinary least squares (eq 3-4). Positive and negative grade factors are defined as the total route elevation gain or loss, respectively, divided by the total route distance. Grade factors are superior to regressing on grade because the influence of an elevation gain (or loss) is weighted by the route distance (e.g., the higher fuel consumption incurred when traveling over a mountain pass contributes relatively less to the calculation of average fuel consumption the longer a route is).

$$\boldsymbol{FI = \alpha + \beta_1 G_p + \beta_2 G_n + \beta_3 I + \beta_4 M + e} \qquad \textbf{eq 3-4}$$

where;

FI = Fuel intensity of route and train type combination (gal/GTM)
G_p = Positive grade factor for route and train type combination
G_n = Negative grade factor for route and train type combination
I = Dummy variable for intermodal and auto train types
M = Dummy variable for manifest and other train types
e = error term

To linearize the relationship to the independent variables, fuel intensity (gal/GTM, the inverse of fuel efficiency) is used as the dependant variable in equation eq 3-4. The constant term represents the fuel intensity of a bulk train over level tracks. Analysis indicated that auto trains[23] were similar in fuel intensity to intermodal trains, so auto trains were grouped with intermodal trains. Similarly, “other” trains[24] were found to have similar fuel intensity as manifest trains, so “other” trains were grouped with manifest trains. Local trains were excluded from the regression due to small sample size (less than 20 annual train trips).

Fuel efficiency estimates derived from equation 3-3 are of variable quality (i.e. reliability). Each estimate is computed using the mean train gross weight, consist size, time-in-notch (duty cycle) and proportions of locomotive types - which were provided by UP (see Appendix E). There are three main issues concerning these data. First, each mean value is computed from a sample of data which varies considerably with route and train type as shown in Table 3-1. Means estimated from larger samples of a population are more reliable that those estimated from smaller samples; reliability is typically measured using a confidence interval. However, estimating a confidence interval requires not only the sample size, but also the variance and ideally information about the distribution that produced the data (e.g. the normal distribution). This information was requested, but not provided. Second, no information was provided about the sampling method (e.g., do the data include every train trip that occurred over the year or a sub sample of trips from trains equipped with data recording devices?). The mean values provided by UP could be biased depending on how the data were sampled (i.e., are the sampled train trips representative of the population of train trips). An explanation of the data collection process was requested, but not provided. Third, the mean values provided by UP represent one year of train operations. Without providing greater temporal detail, or the individual

[23] Auto trains are a type of unit train that carries automobiles with specially designed rail cars for this purpose.
[24] The “other” trains category is specified by UP and BNSF, they have not provided a definition of what trains fall into this category.

data points, potential outliers (e.g., unusual events, such as the recent fire which destroyed a heavily used UP bridge in Northern California) and temporal trends (e.g., increased traffic during preholiday months) will not be detected and accounted for. These data too were requested, but not provided. The lack of basic summary statistics, knowledge of the data collection process and greater temporal detail limits the generalizability of the results and limits the options available to quantify model uncertainty.

Table 3-1 Sample sizes of UP route data

			Count of Train Trips		
RID[a]	**Subdivision**	**Route**	**Bulk**	**Intermodal**	**Manifest**
1	Mojave	Colton to Bakersfield	2	48	684
2	Mojave	Bakersfield to West Colton	0	83	872
3	Yuma	Yuma to West Colton	27	2,771	881
4	Yuma	West Colton to Yuma	13	2,876	765
5	Valley	Roseville to Dunsmuir	0	156	1,549
6	Valley	Dunsmuir to Roseville	6	31	1,306
7	Roseville	Sparks to Roseville	45	1	614
8	Roseville	Roseville to Sparks	319	25	615
9	Martinez	Roseville to Oakland	0	372	13
10	Martinez	Oakland to Roseville	0	340	253
11	Los Angeles	Yermo to West Riverside	26	265	579
12	Los Angeles	West Riverside to Yermo	30	21	597
13	Los Angeles	Riverside to Redondo	3	1,836	6
14	Los Angeles	Redondo to Riverside	0	1,402	155
15	Fresno	Sacramento to Fresno	174	105	1,207
16	Fresno	Fresno to Sacramento	20	149	1,021
17	Fresno	Fresno to Bakersfield	128	143	939
18	Fresno	Bakersfield to Fresno	25	166	745

[a]Unique route identification number that corresponds to RIDs in the Appendices

Without sufficient information on the underlying data used to estimate the means provided by UP, the only indication of data quality is that in general larger samples should result in means closer to the true population mean. Given this, we excluded means derived from samples with fewer than 20 observations (see Appendix I-1) from the regression on the estimated fuel intensities. Additionally, the data supplied by BNSF were not used in the regression because the data on bulk and manifest trains were grouped together and no data were provided on the makeup of the locomotive fleet[25]. Bulk and manifest trains are expected to have significantly different fuel intensities (as the results in Table 3-2 indicate), and variations in fuel intensity estimates across routes could be due to differing proportions of bulk and manifest train traffic, grades or both (or other unobserved factors).

The regression results shown in Table 3-2 indicate that the model specification explains about 86% of the variation in locomotive fuel intensity and, as expected, track grade and train type are significant factors. The residual plot in Figure 3-5 does not indicate any severe outliers or large bias, although the model may under predict fuel efficiency (over predict fuel consumption) for very fuel efficient trains (greater than 1,000 GTM/gallon). System wide fuel efficiencies of 757 GTM/gal and 793 GTM/gal reported by BNSF and UP respectively, fall around the median of fuel efficiency values produced by the model over the range of typical grades (200 GTM/gal to 2,000 GTM/gal), indicating the model produces plausible results. Specifically, the regression results indicate that on average in California, the estimated fuel efficiency for bulk trains is 1,061 GTM/gal, intermodal trains 700 GTM/gal and manifest trains 795 GTM/gal on level tracks. These results are consistent with what we might expect: bulk trains are most efficient, intermodal trains are least efficient and manifest trains fall somewhere in between (Gould and Niemeier 2009). The relationship between the grade factors and fuel efficiency are shown in Figure 3-6 for each train type. These results indicate for example, that a 0.005 positive grade factor (the median of observed positive grade factors) decreases the fuel efficiency of an intermodal train by 52% over level tracks (increases fuel consumption by 110%). Similarly, a 0.005 positive grade factor

[25] The most recent data file received from BNSF (which covers the time period 5/1/2007 to 4/30/2008) does not include information on the makes and models of locomotives used on each route. An earlier data file provided by BNSF (which covers the time period 5/1/2006 to 4/30/2007) does includes the makes and models of locomotives used on each route, but was determined to be unreliable - and the reason that the new data file was provided. The reliability of the older data file was discussed in a January 30, 2009 Memo sent from UC Davis to BNSF (a copy is attached in Appendix B).

decreases bulk and manifest train fuel efficiency by 62% and 55% respectively (a 166% and 125% increase in fuel consumption).

Table 3-2 Regression results

Variable		Coefficient	P-value
α	intercept	9.42E-04	< 0.001
G_p	positive grade factor	3.13E-01	< 0.001
G_n	negative grade factor	4.76E-02	0.02837
I	dummy for intermodal trains	4.85E-04	0.00262
M	dummy for manifest and other trains	3.15E-04	0.05509
Number of observations		47	
Adjusted R^2		0.8557	

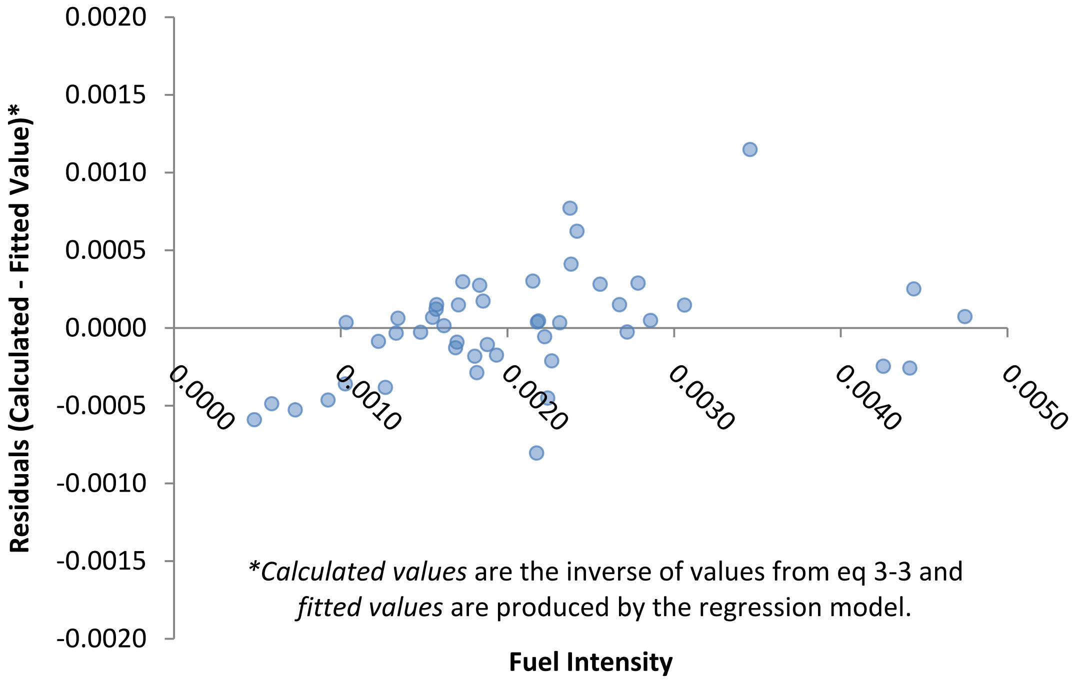
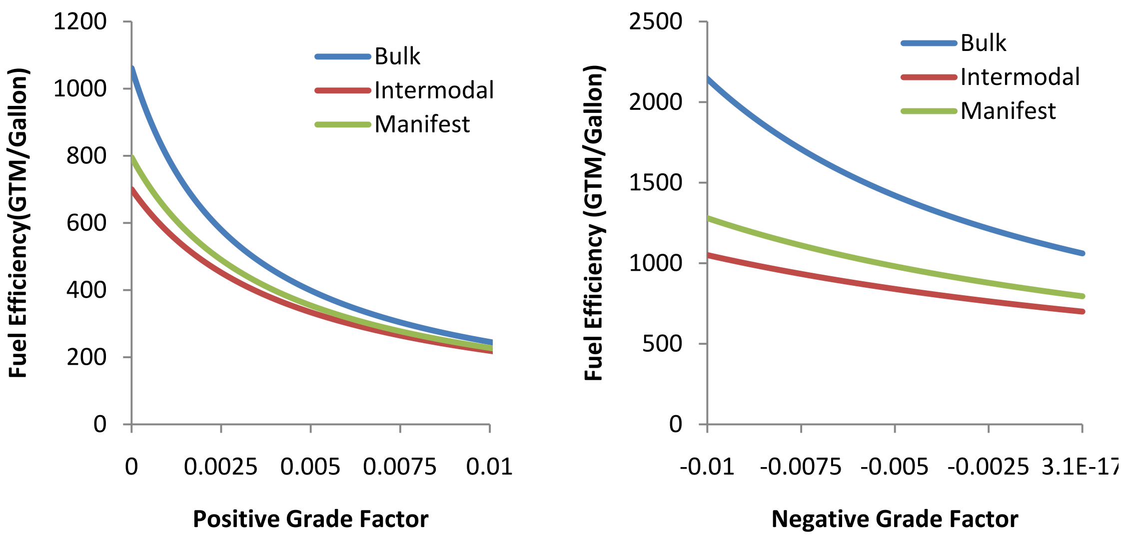


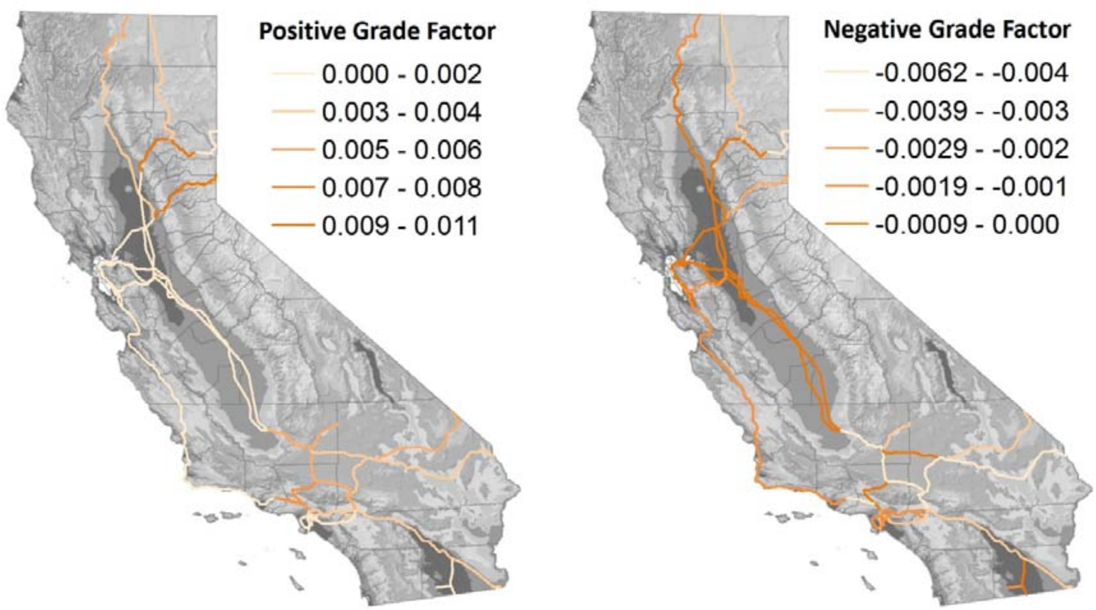
Figure 3-5 Plot of regression residuals



(a) (b)

Figure 3-6 Modeled relationships between positive grade factor (a) and negative grade factor (b) and fuel efficiency

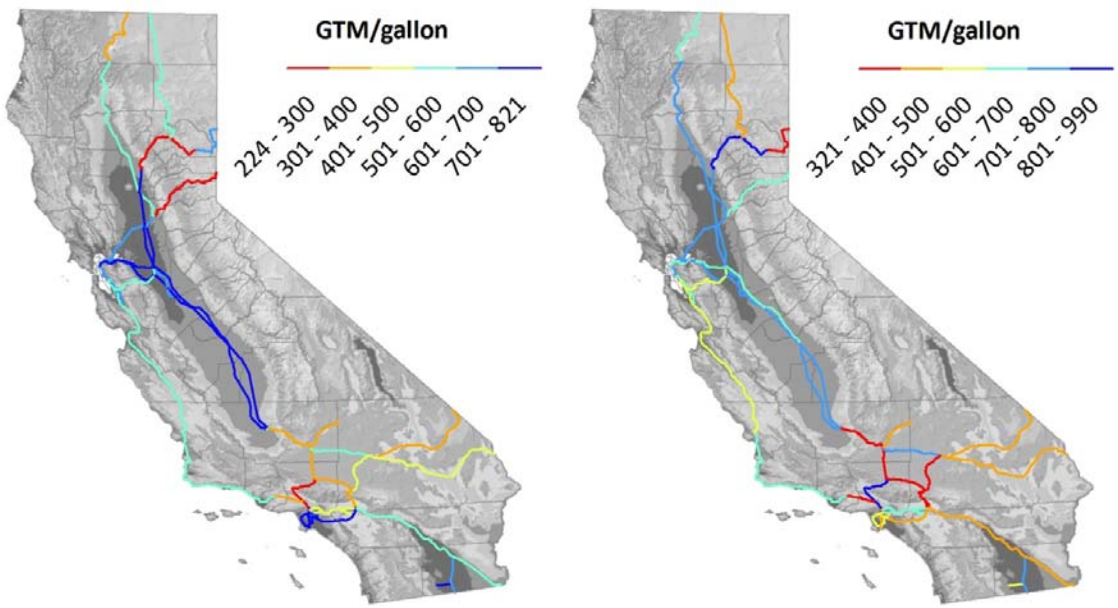
The regression results are used to determine unique fuel efficiency values for each track segment in the state. Grade factors are estimated from the NTAD rail network and digital elevation model data from the U.S. Geological Survey (USGS 2009) for travel in each track direction (Figure 3-7).



(a) (b)

Figure 3-7 Estimated positive grade factors (a) and negative grade factors (b) for travel in the direction of increasing mile posts

For each track segment, fuel efficiency is estimated for each train type and travel direction. A single fuel efficiency for each track segment and direction is then estimated by taking a weighted average of the fuel efficiencies with the weights representing the proportion of traffic density produced by each train type (Figure 3-8).



(a) (b)

Figure 3-8 Estimated fuel efficiency (GTM/gallon) for travel in the direction of ascending mile posts (a) and descending mile posts (b)

The proportion of train traffic by train type is generally not available on a route by route basis. The detailed route data from the railroads was used to estimate the proportion of traffic in each subdivision by train type (Table 3-3); for subdivisions where no detailed data were available the average proportions for either UP or BNSF were used. In the case of BNSF, where bulk and manifest trains are grouped together, these were disaggregated using the average proportions of UP bulk and manifest traffic. The discussion at the end of this report discusses other methods that could be developed to estimate these proportions.

Table 3-3 Proportion of traffic (gross ton-miles) by train type and subdivision (2007)

Subdivision	Bulk	Intermodal[b]	Manifest[c]
UP			
Mojave	0.08	0.34	0.58
Yuma	0.03	0.71	0.26
Valley	0.01	0.13	0.87
Roseville	0.22	0.16	0.62
Martinez	0.01	0.42	0.57
Los Angeles	0.11	0.62	0.28
Fresno	0.20	0.14	0.66
Average	*0.09*	*0.42*	*0.49*
BNSF			
Alameda Corridor[a]	0.02	0.74	0.24
Bakersfield	0.08	0.39	0.53
Cajon	0.02	0.56	0.41
Gateway	0.15	0.01	0.83
Harbor	0.02	0.46	0.53
Lucerne Valley	0.00	0.00	1.00
Mojave	0.09	0.36	0.55
Needles	0.03	0.59	0.38
Riverbank	0.00	0.00	1.00
San Bernardino	0.02	0.46	0.52
Stockton	0.08	0.31	0.61
Average	*0.05*	*0.48*	*0.47*

[a]Also applied to UP traffic on the Alameda Corridor
[b]Includes auto trains
[c]Includes all other trains

Step 4: Adjust FI for Efficiency (optional)

The fuel efficiency values estimated above may also be adjusted for various and evolving locomotive fleets; for example, the introduction of new technology such as hybrid locomotives[26]. A relatively simple method is provided where fuel efficiency is adjusted if additional locomotive fleet information is available (or needed for forecasting purposes). The approach requires knowledge of locomotive energy efficiency, EEF_s (bhp/gal), and corresponding fleet proportion,

[26] See GE’s website at http://ge.ecomagination.com/site/products/hybr.html.

P_s, of any additional locomotives, *s*, to estimate an adjustment factor, A_i (relative increase in efficiency), for each track segment, *i*, as shown in equation eq 3-5,

$$\boldsymbol{A_i = \frac{\left(\sum_s EEF_{is} \cdot P_{is} + EEFb \cdot (1 - \sum_s P_{is})\right) - EEFb}{EEFb}} \qquad \textbf{eq 3-5}$$

where;

EEF_{is} = locomotive energy efficiency of additional locomotives of type *s* on track segment *i* (bhp/gal)
P_{is} = fleet proportion of additional locomotives of type *s* on track segment *i*
EEFb = base locomotive fleet energy efficiency (bhp/gal)

Additional locomotives are defined here as locomotives that are not currently included in the base locomotive fleet used to develop the base fuel efficiency estimates in Step 3 (see Appendix F-1).

Fuel efficiency is then adjusted using equation eq 3-6,

$$\boldsymbol{FE^*_{id} = FE_{id}(1 + A_i)} \qquad \textbf{eq 3-6}$$

where;

FE_{id} = Base fuel efficiency (GTM/gallon) from e-q 3-4 specified with values shown in Table 3-2 for track segment *i* for travel in direction *d* (ascending or descending mile posts)
FE^*_{id} = Adjusted fuel efficiency (GTM/gallon)

Rail lubrication, improved aerodynamics, and optimized scheduling may also increase fuel efficiency. However little data are available to estimate the effect of these factors or predict future advances. Periodic updates of the base fuel efficiency could take account of these and other excluded factors over time, but the method does not allow for explicit modeling of these factors.

Step 6: Calculate Fuel Consumption

Fuel consumption, FC_i, is calculated for each track segment, *i*, using the railroad supplied traffic density, TD_{id} (eq 3-1), and the adjusted fuel efficiency, FE^*_{id} (eq 3-7).

$$\boldsymbol{FC_i = \sum_d \frac{TD_{id}}{FE^*_{id}}} \qquad \textbf{eq 3-7}$$

Step 7: Calculate Fleet Weighted Emission Factors

Fuel based emission factors (g/gal) for four criteria pollutants, hydrocarbons (HC), carbon monoxide (CO), NO_x and $PM_{10,}$ are developed for each EPA Tier emission standard and a pre-control locomotive category. Emission rates are likely to vary by locomotive make and model of the same Tier rating but the limited test data (often a single test on a single locomotive for each model as explained in the literature review) does not provide sufficient evidence to justify creating separate categories.

In absence of reliable locomotive test data, emission factors were derived from EPA's estimated emission factors for the national locomotive fleet (EPA 2009). These emission factors account for deterioration in emission control performance, variability among individual locomotives and manufacturer compliance margins (which typically result in emissions10% below EPA emission standards) (EPA 2008b). The PM_{10} emission factors also assume different diesel fuel sulfur concentrations. A sulfur concentration of 3,000ppm is assumed for Pre-Control, Tier 0, 1 and 2 PM_{10} emission factors and 15ppm for the remainder (EPA 2008b; Moulis 2009).

These emission factors are adjusted for the current sulfur concentration of in-use diesel fuel using a method for generic diesel engines from EPA (EPA 2004). The PM_{10} emission factors estimated by EPA are adjusted by the amount provided by equation 3-8, given EPA's assumed (base) fuel sulfur concentration (S_{base} = 3,000 ppm for Pre-Control, Tier 0, 1 and 2 emission factors in eq 3-8) and an estimate of actual (in-use) fuel sulfur concentration. California regulations (13 CCR 2299, 2281) and an agreement with UP and BNSF(CARB 2005) require the use of ultra low sulfur diesel (15ppm sulfur concentration) when locomotives are refueled in the state. These standards are stricter than current federal regulations which require railroads to use low sulfur diesel fuel (500ppm sulfur concentration), but not ultra low sulfur diesel until 2012 (40 CFR 80.510). In the draft rail yard toxic air contaminant mitigation plans prepared by Environ and BNSF for CARB (CARB 2009), the average sulfur concentration of diesel fuel used by

BNSF line-haul locomotives in California ahead of the federal ultra low sulfur standard is estimated at 340ppm[27]. This estimate is used to adjust all line-haul emission factors ($S_{in\text{-}use}$ = 340ppm in eq 3-8).

$$\boldsymbol{S_{PMadj} = BSFC \cdot M_{SO_4,S} \cdot M_{PM,S} \cdot 0.01 \cdot (S_{base} - S_{in-use})} \qquad \textbf{eq 3-8}$$

where;

S_{PMadj} = PM adjustment (g/bhp-hr)
BSFC = brake specific fuel consumption (gal/bhp-hr)15.2
$M_{SO4,S}$ = constant, sulfate fraction of total particulate sulfur (7.0 g PM SO_4/ g PM S)
$M_{PM,S}$ = constant, fraction of fuel sulfur converted to particulate sulfur (0.02247 g PM S/ g fuel S)
S_{base} = assumed diesel fuel sulfur concentration (w%)
$S_{in\text{-}use}$ = actual diesel fuel sulfur concentration (w%)

An alternative fuel sulfur correction method developed by EPA to adjust PM_{10} emission factors for its locomotive standards (40 CFR 92.12(i), 40 CFR 1033.101(f)(2)(iv) and 40 CFR 1033.150(k)) is not used (Moulis 2008)[28]. That method adjusts PM_{10} emission rates based on an equation derived from an ordinary least squares regression of PM_{10} emission rates from various locomotives tested with high, low and ultra low sulfur diesel fuels as shown in Figure 3-9.The regression data display a large amount of heteroskedasticity (non-constant variance); this probably contributes to an artificially high R^2 value (0.84, as shown in Figure 3-9). Additionally, the regression appears to be biased. The regression does not result in a good fit for low sulfur fuels (15ppm - 500ppm), which are currently required by California and federal regulations. Use of this EPA method would underestimate the benefit of lower sulfur fuels in reducing PM_{10} emissions. As shown in Figure 3-9, the regression line passes above all of the low sulfur data points (i.e., over estimates PM emissions) and intercepts the y-axis at a value above zero, implying that fuels with no sulfur still produce sulfate particulate emissions. This is probably caused by the observed heteroskedasticity and small sample size; data for high sulfur fuels have a

[27] This is the only estimate of in-use locomotive diesel fuel sulfur concentration that the authors are aware of.
[28] A copy of the entire memo is provided in Appendix B

disproportionately large influence on the regression fit due to their relatively larger variance. With a large enough sample, these large influences would tend to balance each other, reducing bias.

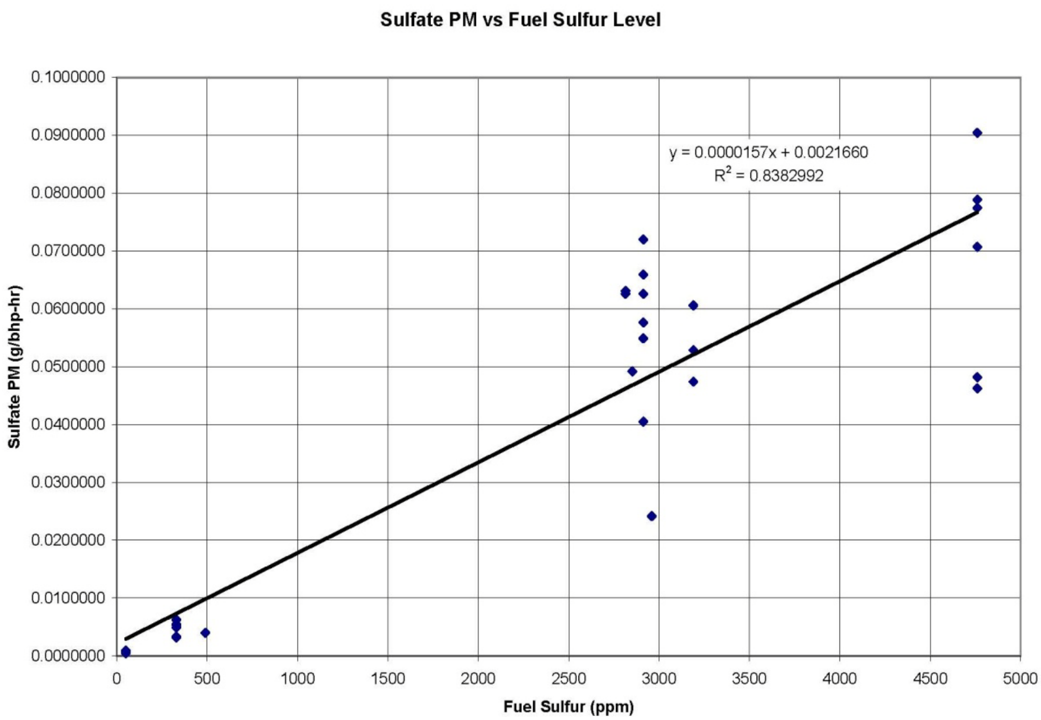


Figure 3-9 Relationship of fuel sulfur content and PM emissions reproduced from EPA memo (Moulis 2008)

Table 3-4 provides EPA's estimated emission factors for line-haul locomotives meeting each EPA locomotive emission (certification level) standard and the PM_{10} emission factors adjusted for current in-use fuel sulfur concentrations (340ppm).

Table 3-4 EPA Estimated emission factors for line-haul locomotives

Cert. Level	Effective Date	PM_{10} *g/bhp-hr*	Adj-PM_{10}[c] *g/bhp-hr*	HC *g/bhp-hr*	NOx *g/bhp-hr*	CO *g/bhp-hr*
Pre Control	current	0.32	0.255	0.48	13	1.28
Tier 0	current	0.32	0.255	0.48	8.6	1.28
Tier 1	current	0.32	0.255	0.47	6.7	1.28
Tier 2	current	0.18	0.115	0.26	4.95	1.28
Tier 0R[a]	2008/2010[b]	0.2	0.208	0.3	7.2	1.28
Tier 1R[a]	2008/2010[b]	0.2	0.208	0.29	6.7	1.28
Tier 2R[a]	2013	0.08	-	0.13	4.95	1.28
Tier 3	2012	0.08	-	0.13	4.95	1.28
Tier 4	2015	0.015	-	0.04	1	1.28

[a]R indicates revised EPA standards for remanufactured tier 0, 1 or 2 locomotives
[b]Standard effective in 2008 where retrofit kits are available, otherwise effective in 2010
[c]PM_{10} emission factors corrected for current in-use fuel sulfur concentration. Tier 2R, 3, and 4 are not shown since these standards do not take effect until after federal ultra low sulfur diesel standards become effective.

The brake specific emission factors, corrected for diesel fuel sulfur concentration are then converted to fuel based emission factors (g/gallon) using an estimate of the locomotive fleet's fuel efficiency (19.5 bhp-hr/gal). The fuel efficiency value is estimated from notch specific fuel consumption rate and power data, weighted by the EPA line-haul duty cycle[29], for the current in-use UP locomotive fleet shown in Appendix F-1. This fuel efficiency value is less than EPA's 20.8 bhp-hr/gal estimate, which has not changed for at least 12 years and is based on a national locomotive fleet (EPA 1997; EPA 2009).

Fleet average emission factors are then calculated by weighting the EPA emission factors for each tier standard by the proportion of in-use locomotives that meet each tier standard, and then taking the sum of the weighted emission factors. For the statewide inventory we have assumed a uniform locomotive fleet. The data supplied by UP and BNSF (shown in Appendix E-

[29] The EPA line-haul duty cycle is used in place of the actual duty cycle information provided by UP because the EPA emission factors assume the EPA duty cycle.

5 and E-6) provide the proportion of locomotives that meet each tier standard for major California routes; however, average state-wide fleet emission factors for each railroad are calculated (Table 3-5), not route specific emission factors, because individual locomotives are not usually assigned to a particular route.

Table 3-5 Proportion of locomotive fleet meeting each EPA emission standard

	Pre Control	Tier 0	Tier 1	Tier 2
UP	0.05	0.15	0.19	0.61
BNSF	0.07	0.62	0.20	0.11
Alameda Corridor[a]	0.06	0.40	0.20	0.35

[a]Gross ton-mile weighted average of UP and BNSF locomotive fleet

Class I railroads operating in the South Coast region of California are obligated to provide this information to track the compliance of a MOU between the railroads and CARB (CARB 1998). However, elsewhere, the railroads are not obligated to share this information, though some provide this information publicly on their websites. Information about most railroad locomotive fleets is also available from other, unofficial, published sources (Kerr 2008). In absence of specific information about a railroad's locomotive fleet, projected yearly fleet weighted emission factors from the EPA (EPA 2009) may also be used. The certification levels of locomotives used by Class II and III railroads are unknown at this time, but most are likely pre-control because these railroads typically do not purchase new locomotives and many have been exempt from EPA requirements to remanufacture existing locomotives to tier 0 standards under small businesses provisions of the EPA standards (40 CFR 1033.610)[30].

[30] Prior to 2008, class II and III railroads not owned by larger corporations were exempt from EPA regulations that required locomotives manufactured after 1973 to meet tier 0 standards when they are remanufactured. Current regulations no longer provide this exemption for class II railroads.

Step 8: Calculate Annual Emissions

Emission estimates, E_i, are made for each track segment by multiplying together fuel consumption estimates and emission factors (eq 3-9).

$$\boldsymbol{E_i = FC_i \cdot EF_i} \qquad \textbf{eq 3-9}$$

where;

EF_i = Emission factors (g/gallon) for track segment *i*

Carbon dioxide (CO_2) and sulfur dioxide (SO_2) emissions are estimated for each track segment based on fuel consumption only, not the certification level of the locomotives, using methods described by EPA (EPA 2009) (eq 3-10 and eq 3-11).

$$\boldsymbol{CO_2 = \frac{FC \cdot 10.1}{1000} \cdot 1.1023} \qquad \textbf{eq 3-10}$$

where;

FC	= annual fuel consumption by all locomotive tiers (gallons/year)
1000	= conversion factor (kg/tonne)
10.1	=carbon content of diesel fuel (kg/gallon)
1.1023	=conversion factor (ton/tonne)

$$\boldsymbol{SO_2 = (FC \cdot 3200 \cdot 0.978 \cdot 2 \cdot S) \cdot \frac{1.1023}{1{,}000{,}000}} \qquad \textbf{eq 3-11}$$

where;

3200	= density of fuel (g/gallon)
0.978	= sulfur conversion (to SO_2) factor
2	= constant (64 g SO_2/32 g S)
S	= sulfur content of fuel (PPM x 10^{-6})
1,000,000	= conversion factor (g/tonne)
1.1023	= conversion factor (ton/tonne)

$PM_{2.5}$ emissions are assumed to be 97% of PM_{10} emissions (EPA 2009).

3.3.2 Yard Method

Figure 3-10 provides a detailed description of the method to estimate emissions from rail yards. Like line-haul operations, emissions are estimated from fuel consumption, which we are unable to empirically derive. Operating hours are easily observed and have been reported; therefore operating hours are converted into fuel consumption. Once fuel consumption is estimated, emissions are calculated in the same way as for line-haul operations.

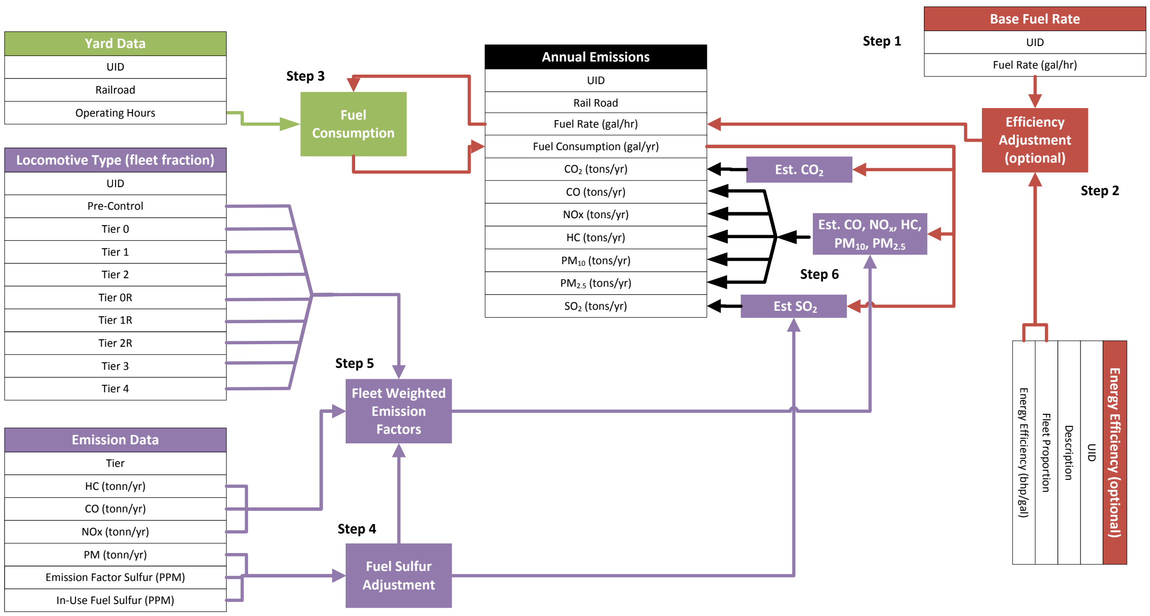


Figure 3-10 Detailed schematic of proposed rail yard emission model: green, red and purple colored chart elements highlight activity, emission factor and fuel efficiency data, respectively; tables show the model input data; arrows indicate the flow of data and calculations; and boxes indicate model operations

Step 1: Base Fuel Consumption Rate

Similar to line haul operations, fuel consumption rates for switching locomotive activity in rail yards are highly correlated with emission rates. In addition, fuel consumption data are likewise unavailable for rail yard locomotives but it can be estimated.

The main task of rail yard switching locomotives is to position rail cars to set up trains. This work is accomplished using low powered locomotives, often in their lowest throttle settings.

In this case, fuel consumption is not expected to vary considerably by the type and weight of the cars being moved, and can be approximated by the amount of time spent working. Operating hours for major rail yards in California have recently been reported in a series of rail yard toxic air contaminant emission inventories prepared by UP and BNSF for CARB (http://www.arb.ca.gov/railyard/hra/hra.htm). These inventories do not include smaller rail yards and will not be available in the future to update inventories; however, operating hours can be obtained by contacting each rail yard or by visiting each rail yard and observing their operations as suggested by the EPA (EPA 1992). The results reported here only include the major rail yards. A default fuel consumption rate (gal/hr) is estimated for calculating switching locomotive fuel consumption from operating hours. This method improves upon the current EPA method of assuming constant annual fuel consumption per yard locomotive (EPA 1992) and the CARB method which assumes 24 hour operation for each yard locomotive (BAH 1991a).

The fuel consumption rate of switching locomotives is determined from detailed switching locomotive operating data (locomotive fleet, operating hours and duty cycles) included in the rail yard toxic air contaminant studies. The reports prepared for UP rail yards do not contain enough detail about locomotive fleets to determine an accurate estimate of fuel consumption, so a subset of the reports, those prepared for BNSF rail yards, was used (Appendix G). The BNSF rail yards are assumed to be representative of typical rail yard operations.

The duty cycles developed for the BNSF rail yard studies were obtained from event recorder data collected from a portion of the switching locomotives at each yard over a couple of days. The EPA switcher duty cycle proportion of idle time was used instead of the idle time from the event recorders because the event recorders were unable to distinguish between when a locomotive was idling and turned off (this was not done for the Barstow, San Diego and San Bernardino rail yards, perhaps erroneously, as shown in Table 3-6). The proportion of time in the other notches was normalized to sum to 1 after adding the EPA idle time. As shown in Table 3-6, the duty cycles developed for BNSF are very similar to EPA's switcher duty cycle. Given this observation and the limitations of the BNSF duty cycle data[31], the EPA switcher duty cycle is used to estimate fuel consumption rates.

Table 3-6 Comparison of Environ/BNSF yard specific duty cycles to EPA switch duty cycle

	Proportion of Time-in-notch									
Rail Yard	**DB**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
Wilmington-Watson	0.00	0.60	0.13	0.10	0.06	0.03	0.02	0.02	0.01	0.04
Commerce Mechanical	0.00	0.60	0.13	0.15	0.07	0.04	0.01	0.00	0.00	0.00
Stockton	0.00	0.60	0.16	0.12	0.05	0.03	0.01	0.01	0.00	0.02
Commerce Eastern	0.00	0.60	0.13	0.15	0.07	0.04	0.01	0.00	0.00	0.00
Richmond	0.00	0.60	0.13	0.14	0.06	0.03	0.01	0.01	0.00	0.01
Los Angeles-Hobart	0.00	0.60	0.13	0.15	0.07	0.04	0.01	0.00	0.00	0.00
Barstow	0.00	0.78	0.06	0.04	0.05	0.03	0.02	0.01	0.00	0.01
San Diego	0.00	0.98	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
San Bernardino	0.02	0.87	0.04	0.03	0.02	0.01	0.01	0.00	0.00	0.01
EPA	0	0.60	0.12	0.12	0.06	0.04	0.04	0.02	0.00	0.01

The average fuel consumption rate of each rail yard is shown in Table 3-7. The estimates were made by weighting notch specific fuel consumption rate data by the EPA switch duty cycle (eq 3-12).

$$\boldsymbol{FR_k = \sum_j FR_{kj} \cdot DC_j} \qquad \textbf{eq 3-12}$$

where;

FR_k = fuel consumption rate of locomotive model k
FR_{kj} = fuel consumption rate of locomotive model k, throttle notch j
DC_j = EPA switch duty cycle proportion of time-in-notch j

Switching locomotive fuel consumption data are obtained from (EPA 1998); however, data are not available for every make and model of locomotive. In these cases, fuel consumption rates for locomotives without data were scaled from those with data based on the difference in power. The

[31] The rail yard studies completed for UP rail yards also assume the EPA switcher duty cycle.

duty cycle weighted fuel consumption rates were then weighted by the quantity of each type of locomotive in each yard (eq 3-13).

$$\boldsymbol{FR_l = \frac{\sum_k n_{lk}}{\sum_k \frac{n_{lk}}{FR_k}}} \qquad \textbf{eq 3-13}$$

where;

FR_l = fuel consumption rate of yard l
n_{lk} = quantity of model k locomotives in yard l

Finally, the base switch locomotive fuel consumption rate was estimated by averaging across all the rail yards and weighting by the total number of switch locomotives in each yard (eq 3-14 and Table 3-7). Switch locomotives are not captive to any particular yard, they are generally rotated in and out of yards based on their maintenance schedules. Therefore, use of a single switch locomotive fuel consumption rate based on an average off all in use (BNSF California) switch locomotives provides a reasonable simplification.

$$\boldsymbol{FR = \frac{\sum_l m_l}{\sum_l \frac{m_l}{FR_l}}} \qquad \textbf{eq 3-14}$$

where;

FR = weighted average fuel consumption rate of all BNSF rail yards (gallon/hr)
m_l = number of locomotives in yard l

Table 3-7 Estimated rail yard fuel consumption rates

Rail Yard	Fuel Consumption Rate *gal/hr*
Barstow	12.04
Commerce Eastern	13.01
Commerce Mechanical	13.01
Hobart	13.01
Richmond	12.56
San Bernardino	13.97
San Diego	13.94
Stockton	13.44
Wilmington-Watson	13.99
Weighted Average	12.87

Step 2: Locomotive Efficiency Adjustment

Similar to the methodology for line-haul locomotives, a method to adjust the base fuel consumption rate is developed to account for the introduction of new technology. This is a particularly important consideration for rail yards which have been replacing traditional diesel-electric locomotives with more efficient gen-set (a series of small, efficient diesel engines) and hybrid switching locomotives[32].

The locomotive efficiency adjustment factor is calculated as previously shown for line-haul locomotives (eq 3-5). However, the adjustment factor is applied to the inverse of the fuel rate (hr/gal) so that the adjustment response is linear (eq 3-15).

$$\boldsymbol{FR_i^*} = \frac{\mathbf{1}}{\frac{\mathbf{1}}{\boldsymbol{FR}}(\mathbf{1}+\boldsymbol{A_i})} \qquad \textbf{eq 3-15}$$

where;

FR^*_i = adjusted fuel consumption rate (gallons/hr) for locomotives in yard i
FR = base fuel consumption rate (gallons/hr) from eq 3-14
A_i = switching locomotive fuel efficiency adjustment factor for yard i

[32] CARB is currently considering options to accelerate the introduction of new switching locomotives to CA rail yards (http://www.arb.ca.gov/railyard/ted/ted.htm).

Step 3: Calculate Fuel Consumption

Fuel consumption for each yard is calculated by multiplying annual operating hours by the fuel consumption rate as shown in equation eq 3-16,

$$\boldsymbol{FC_i = FR_i^* \cdot OP_i} \qquad \textbf{eq 3-16}$$

where;

FC_i = Annual fuel consumption for yard i (gallons)
FR^*_i = Adjusted fuel consumption rate (gallons/hr) for yard i
OP_i = Annual operating hours for yard i

Step 4: Estimate Weighted Emission Factors

The procedure to estimate fleet weighted emission factors are similar to those described for line-haul locomotives. EPA estimated switcher locomotive emission factors (EPA 2009) are shown in Table 3-8.

Table 3-8 EPA estimated emission factors for switcher locomotives

Cert. Level	**Effective Date**	**PM_{10}** *g/bhp-hr*	**Adj-PM_{10}**[b] *g/bhp-hr*	**HC** *g/bhp-hr*	**NO_x** *g/bhp-hr*	**CO** *g/bhp-hr*
Pre Control	current	0.44	0.341	1.01	17.4	1.83
Tier 0	current	0.44	0.341	1.01	12.6	1.83
Tier 1	current	0.43	0.331	1.01	9.9	1.83
Tier 2	current	0.19	0.091	0.51	7.3	1.83
Tier 0R[a]	2008	0.23	-	0.57	10.62	1.83
Tier 1R	2008	0.23	-	0.57	9.9	1.83
Tier 2R	2013	0.11	-	0.26	7.3	1.83
Tier 3	2012	0.08	-	0.26	4.5	1.83
Tier 4	2015	0.015	-	0.08	1	1.83

[a]R indicates revised EPA standards for remanufactured tier 0, 1 or 2 locomotives
[b]PM_{10} emission factors adjusted for in-use diesel fuel concentration (15ppm in rail yards). Tier 0R, 1R, 2R, 3, and 4 are not shown since these emission factors assume a 15ppm diesel fuel sulfur concentration.

Similar to the case for line-haul emission factors, the switcher emission factors are adjusted for the sulfur content of in-use diesel fuel[33], converted to fuel based emission factors and then weighted by the proportion of yard locomotives meeting each tier standard and then summed. An average switcher locomotive fleet fuel efficiency of 15.9 bhp-hr/gal is used to convert the emission factors to a fuel basis (see Appendix G for calculation), which is slightly higher than EPA's estimate of 15.2 bhp-hr/gal (EPA 2009). Information about the tier standards of the switcher locomotive fleet is obtained from the rail yard toxic air contaminate inventories which indicate that in 2007 all yard locomotives were pre-control.

Step 5: Estimate Emissions

Once fuel consumption and weighted emission factors are estimated, the calculation of emissions is carried out using the same methods applied for line-haul emissions (see eq 3-9, eq 3-10 and eq 3-11).

3.4 Model Results and Inventory

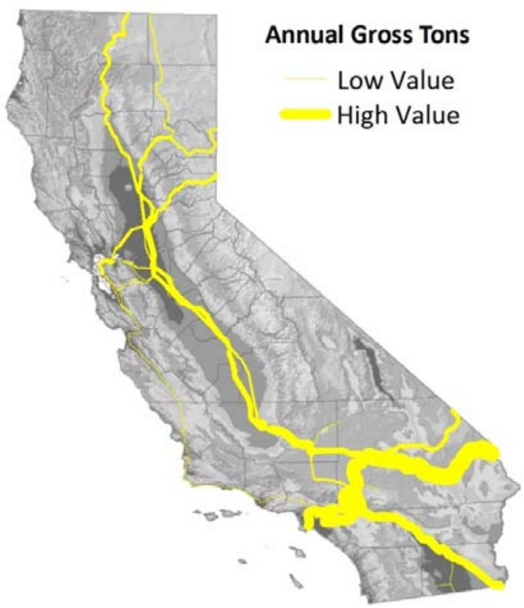
In this chapter, results derived using the new model for California's Class I railroads are discussed, including illustration of the geographic detail available by using this approach. We also compare results from this framework to the EPA and CARB methods. Note that Class II and III railroads are omitted at this time as CARB was unable to collect data for these railroads. All results shown below are for the year 2007.

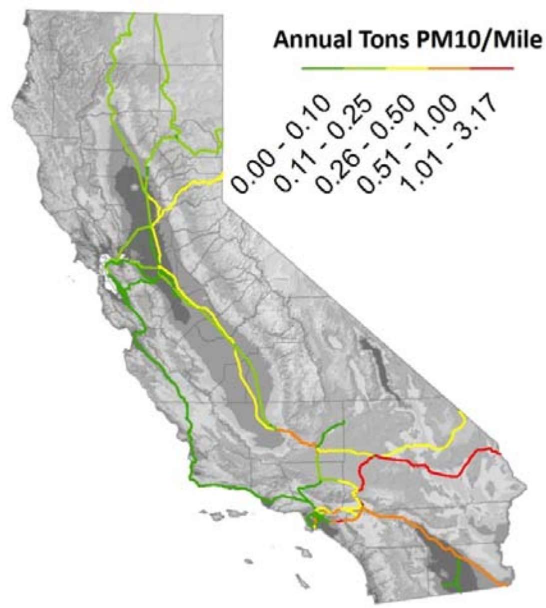
The fuel efficiency of each Class I route in California was shown previously in Figure 3-8. Those maps indicate, as expected that fuel efficiency is lowest (highest fuel consumption rate) in mountainous terrain. For example, fuel efficiency is 72% lower when traveling over Donner Pass in the Sierra Nevada Mountains east of Sacramento than traveling through the Central Valley (a 256% increase in the fuel consumption rate) and 53% lower traveling up the

[33] EPA's PM_{10} emission factors are reduced by the amount given by equation 3-8 where S_{base} = 3,000 ppm for Pre-Control, Tier 0, 1 and 2 emission factors and $S_{in\text{-}use}$ = 15 ppm .

Cajon Pass than traveling through the Los Angeles basin (a 114% increase in the fuel consumption rate).

Emission estimates are a function of the quantity of traffic and the type of traffic, grade and locomotive fleet. Figure 3-11(a) shows the annual quantity of Class I freight rail traffic and Figure 3-11(b) displays the estimated annual ton per mile PM_{10} emissions produced by this traffic. Maps of other emissions display similar trends since the emission factors are all fuel based.





(a) **(b)**

Figure 3-11 Class I line-haul annual traffic (line thickness is proportional to traffic volume) (a) and annual PM_{10} ton/mile emission rates (b)

A comparison of aggregate state-wide model results is shown in Table 3-9. The results vary between the three methods shown, and is expected given differences in methods and data underlying each approach.

Table 3-9 Comparison of UCD, EPA and CARB line-haul model results for California

Inventory Method	FI[a] *GTM/gal*	FC[b] *mgal*[c]	HC *tons/yr*	CO *tons/yr*	NO_x *tons/yr*	PM_{10} *tons/yr*	CO_2 *tons/yr*
UCD[d]	530	286	2,421	7,868	43,552	1,213	3,184,000
EPA[e]	777	180	1,843	5,429	34,675	1,248	2,024,000
CARB[f]	-[g]	261	3,227	11,652	44,510	1,439	2,945,039

[a] Average fuel efficiency
[b] Fuel consumption
[c]Million gallons
[d] The model developed at the University of California, Davis described in this paper (for year 2007).
[e] Results estimated following the procedures recommending in (EPA 1992) and with emission factors from (EPA 2009) for year 2007 (see Appendix H-6 for calculations).
[f] Results obtained from CARB (see Appendix H-5)
[g]No data available

Recall that the EPA method depends on a system-wide fuel efficiency that is much larger than the fuel efficiency estimated by the methods presented in this report (UC Davis method). The UC Davis approach accounts for grades, train types and the locomotive fleet. As a result of using the larger, system wide fuel efficiency, the EPA method appears to substantially underestimate fuel consumption (EPA fuel consumption is 37% less than the UC Davis estimate) and emissions (EPA emission estimates are 3% to 36% less than UC Davis estimates). The EPA method also assumes a nationally representative locomotive fleet with greater fuel efficiency than the UC Davis method; we applied a California specific locomotive fleet.

CARB estimated the inventory shown in Table 3-9 by projecting forward results of a detailed locomotive inventory originally completed in 1991 (BAH 1991a; Wong 2006). CARB's CO_2 estimate was calculated by UC Davis from fuel consumption data provided by CARB[34]. As shown in Table 3-9, the CARB estimates are generally larger than either the UC Davis or EPA estimates. However, the degree of the differences between the CARB and the UCD method varies by pollutant. CARB HC estimates are 33%, CO estimates 48% and PM_{10} estimates 19% greater than UC Davis estimates and CARB NO_x estimates are only 2% greater than UC Davis estimates.

[34] It is unclear how CARB estimated locomotive fuel consumption since their emission inventory is not fuel based (i.e., does not estimate fuel consumption or use fuel consumption data in any way) and regional locomotive fuel consumption data are typically unavailable as discussed in section 2.2.1.

Table 3-10 compares the three methods for 10 counties with the most freight rail traffic. Whereas in Table 3-9 the EPA estimates were less than, and CARB estimates greater than, the UC Davis estimates, the results in Table 3-10 show that these trends do not hold at the county level. The degree of the differences between the three methods varies by county. In some cases the EPA estimates are larger than UC Davis estimates and CARB estimates are less. Differences between the EPA and UC Davis results are due to the different topography of each county as well as the differing mix of rail traffic which is accounted for by the UC Davis method but not the EPA method.

Figure 3-12 shows a spatial comparison of the CARB and UC Davis county level inventories (State-wide emission inventories by county, air district and air basin are provided in Appendix H-1, H-2 and H-3).The maps show several trends. The gray hatched regions are counties where CARB estimates emissions from class I railroads. Data provided by UP and BNSF (Appendix D -1 and D-2) do not indicate any traffic in these counties.[35]

[35] Freight traffic has not operated for a fairly long time in the north coast region. The BNSF railroad does operate in San Diego County. The tracks are owned by the San Diego transit authority with BNSF retaining historical track rights. This is probably the reason these data were not provided by BNSF. Similar situations could exist on other publicly owned rail segments. However, in at least one case, the Alameda Corridor which is publicly owned, UP and BNSF did report their traffic.

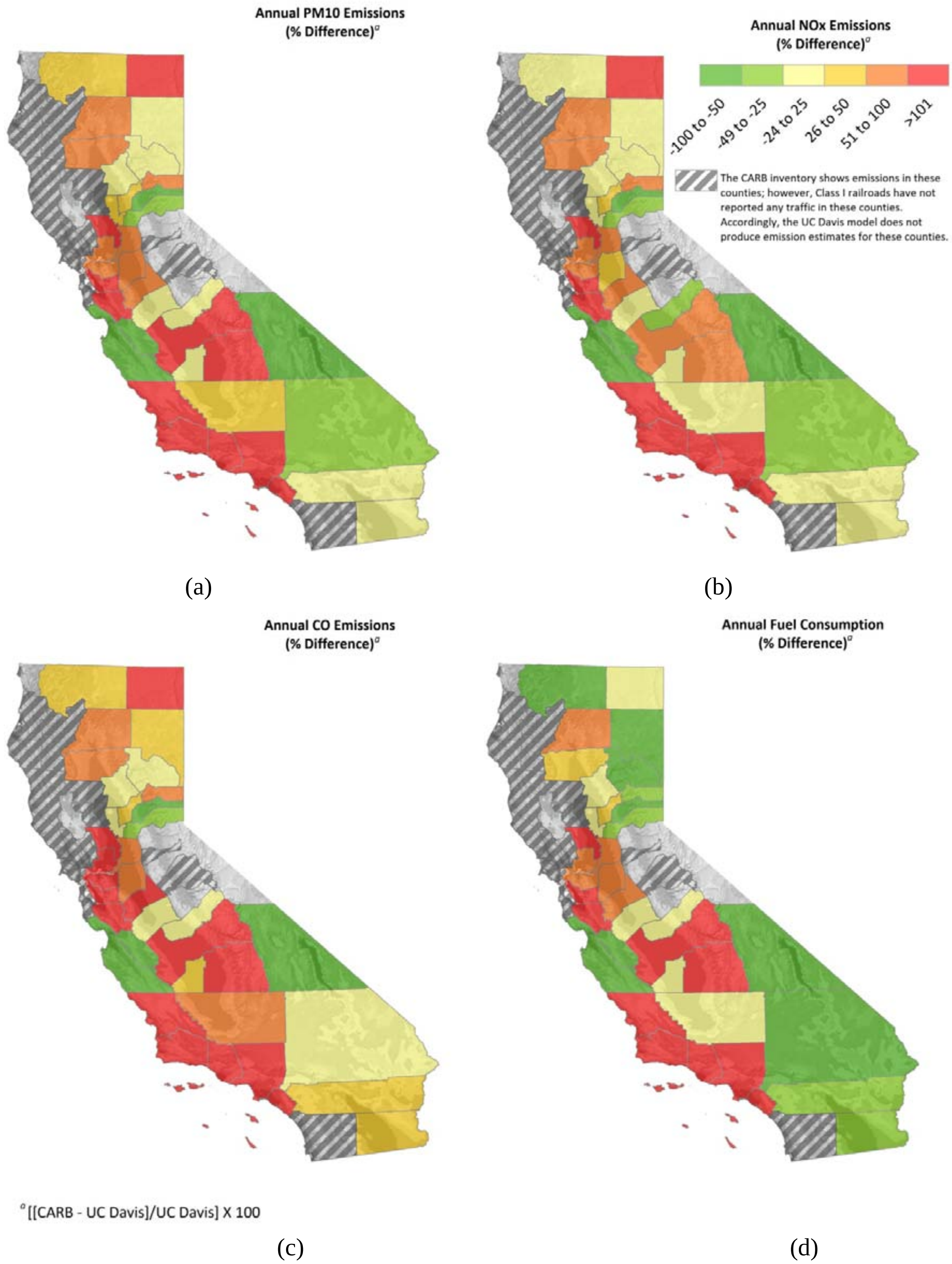
Table 3-10 Comparison of UCD, EPA and CARB line-haul fuel consumption, NO_x and PM_{10} estimates for 10 counties with the greatest amount of freight rail traffic

	Fuel Consumption			NO_x Emissions			PM_{10} Emissions		
	UCD[a]	**EPA**[b]	**CARB**[c]	**UCD**	**EPA**	**CARB**	**UCD**	**EPA**	**CARB**
County	***mgal***[d]***/yr***	***mgal/yr***	***mgal/yr***	***tons/yr***	***tons/yr***	***tons/yr***	***tons/yr***	***tons/yr***	***tons/yr***
San Bernardino	119	66	50	19,859	12,694	10,154	568	457	344
Riverside	23	14	16	3,250	2,793	2,917	88	101	98
Kern	23	14	19	3,345	2,689	3,497	91	97	115
Imperial	15	10	8	2,063	1,834	1,928	55	66	66
Los Angeles	15	11	33	2,033	2,175	4,766	55	78	155
San Joaquin	6	5	9	850	1,029	1,264	23	37	39
Placer	10	5	5	1,300	887	866	35	32	26
Sacramento	5	4	8	605	809	1,098	16	29	32
Plumas	6	4	3	859	773	762	23	28	23
Merced	4	4	4	684	782	604	19	28	18

[a] The model developed at the University of California, Davis described in this paper.
[b] Results estimated following the procedures recommending in (EPA 1992) and with emission factors from (EPA 2009).
[c] Results obtained from CARB emission inventory (See Appendix H-5)
[d] Million gallons

Some differences in the inventories in Table 11 can be attributed to projected emissions from Class I rail routes which are no longer in use, or to data not provided by the railroads. The maps also show that CARB's emission and fuel consumption estimates are much higher than UC Davis's in flatter regions (i.e., the Bay Area, Central Valley and Los Angeles) and lower in mountainous regions (in particular the Sierra Nevada Mountains). These trends are expected since the UC Davis model explicitly considers track grades in making all of its estimates. CARB's inventory, as discussed previously in section 2.2.1.1, is based on an inventory produced by Booz-Allen, in which detailed calculations of emissions were produced for regions of the state that at the time had poor air quality (BAH 1991a). In a follow up report (BAH 1992), Booz-Allen produced a statewide county by county inventory by using average locomotive emission rates from the original study to estimate emissions for the remaining routes in the state. Routes where average emission rates were used, which include many of the more remote mountain regions of the state, did not account for differences in topography. Other differences between CARB's and

UC Davis's inventory are probably due to errors and uncertainty related to the forecasting in the original Booz-Allen inventory. As discussed in section 2.2.1.1, these include applying growth factors based on national economic growth indicators and correction factors to account for new locomotive regulations and efficiency gains. In addition to the large uncertainty that is expected from such long term forecasts, the forecasting method cannot account for changes in traffic routing, traffic types and other changes in railroad operations that may have occurred over the past 20 years.



(a) (b) (c) (d)

Figure 3-12 Spatial comparison of CARB and UC Davis PM_{10} (a), NO_x (b), CO (c) and Fuel consumption estimates (d) for 2007

The rail yard switcher locomotive emissions also vary depending on the method used to estimate them (Table 3-11). The differences in the results vary across the yards, but are generally comparable. The differences between the UC Davis and EPA estimates are largely the result of EPA's assumption of a constant 228 gallons of fuel consumption per switcher locomotive per day and emission factors representative of a national locomotive fleet using diesel fuel with higher sulfur content. The UC Davis method accounts for the varying operating schedules across yards as well as differing locomotive fleets and diesel sulfur content. The difference between the UC Davis and HRA estimates is likely due to the use of a "time-in-notch" approach used by the HRA method and the fuel based approach used by the UC Davis method. The time-in-notch approach is not fuel based, but depends on the hourly emission rates of each throttle position of the yard locomotives and an estimate of the amount of time spent in each throttle position. This is similar to the method used to estimate the switcher locomotive fuel consumption factors applied in the UC Davis method, and should produce reasonable estimates. The generalization of the UC Davis method (use of a single fuel consumption factor) is likely the cause of some of the differences between the two estimates. The method used in the HRA's; however, is not suitable for larger scale modeling purposes given the yard and locomotive specific data requirements. A complete emission inventory of all major Class I rail yards is available in Appendix H-4.

Table 3-11 Comparison of UCD, EPA and CARB yard switcher locomotive fuel consumption, NO_x and PM_{10} estimates for several rail yards

Rail Yard	UCD[a] FC[b] *gal/yr*	EPA[c] FC *gal/yr*	HRA[d] FC *gal/yr*	UCD PM_{10} *tons/yr*	EPA PM_{10} *tons/yr*	HRA PM_{10} *tons/yr*	UCD NO_x *tons/yr*	EPA NO_x *tons/yr*
Wilmington	54,054	83,220	68,963	0.33	0.60	0.43	16.5	22.9
Stockton (BNSF)	252,406	249,660	254,004	1.53	1.79	1.55	77.0	68.8
Richmond	225,482	166,440	118,188	1.36	1.19	1.16	68.8	45.9
Hobart	387,541	416,100	358,371	2.34	2.98	2.22	118.2	114.6
Commerce	300,643	249,660	244,150	1.82	1.79	1.90	91.7	68.8
LATC	526,126	499,320	569,683	3.18	3.58	2.46	160.4	137.6
Mira Loma	206,692	166,440	223,804	1.25	1.19	2.38	63.0	45.9
Oakland	380,502	332,880	488,300	2.30	2.38	1.88	116.0	91.7
Stockton (UP)	714,028	665,760	773,142	4.32	4.77	3.58	217.8	183.4

[a] The model developed at the University of California, Davis described in this paper.
[b] Fuel consumption
[c] Results estimated following the procedures recommended in (EPA 1992) and with emission factors from (EPA 2009).
[d] Results obtained from rail yard toxic air contaminant inventories prepared for CARB: http://www.arb.ca.gov/railyard/hra/hra.htm

3.5 Summary and Conclusions

The model developed in this research provides a method to estimate diesel-electric locomotive emission inventories with a higher degree of robustness and greater spatial refinement than current methods. Unlike methods currently recommended by EPA for line-haul operations, the UC-Davis model accounts for differences in track grade, types of train traffic and locomotive fleet – factors known to affect fuel consumption and emission rates. While the increased accuracy and spatial detail comes at the cost of increased data requirements, they are less onerous than the data needs of the current methods used by CARB. The data required to run the model are typically available to government agencies through the railroads, observation or estimation. The model also improves upon current yard switcher locomotive methods by providing a method to account for the differing working schedules and locomotive fleets of each yard.

Understanding the source of air quality problems is especially important in California where large populations are exposed to air that regularly fails to meet federal air quality standards. A more accurate and spatially resolved emission inventory can help determine the contribution from railroads and the effectiveness of specific policy actions. Changes in locomotive emissions can be estimated for policies which introduce newer locomotive fleets and cleaner fuels to certain regions, and more train traffic along specific routes. Additionally, the spatially resolved emissions can be used as input for air dispersion models, estimating the concentration of air pollutants along railways. This would be a very useful tool for analyzing impacts on environmental justice communities.

Besides improving the accuracy and spatial resolution of emission inventories, the new modeling method provides for analysis of rail energy intensity. The model can be used to compute the energy intensity, fuel consumption and carbon emissions of each train route under various assumptions of in-use and future locomotive fleets, efficiency and traffic type. This is an important capability given the recent focus on improving the flow of goods movement and reducing its environmental and climate impacts, potentially by encouraging greater use of freight rail over trucking. Similar analysis of criteria air pollutant emissions can also be made. The impacts of shifting freight from road to rail can then be analyzed in terms of potential benefits of reduced energy consumption, carbon emission and criteria emissions for a region at the expense of increased levels of local criteria emissions from increased rail traffic.

While the methods presented are a substantial improvement over current methods, they could benefit from additional research. Future work on the development of a method to estimate the proportion of traffic type based on data that are publicly available (or at least available to government agencies) would be useful. This is not a simple task and will require testing possibly several different approaches. Relating information from the Carload Waybill Sample (STB 2009) to train types is a promising possibility. Perhaps one of the greatest areas for which additional research would be beneficial is more and better locomotive engine test data. Most of the available data are out-dated, performed using test procedures unlikely to achieve real world emission rates (Yanowitz and Cameron-Cole 2003) and have never been validated with any sort of in-use testing, as has been the case with on-road vehicles.

Additionally, methods to forecast freight traffic and future locomotive fleets could also be improved. This research developed a new framework for modeling locomotive emissions and energy use that takes traffic data (gross ton-miles) as the basic model input. We did not investigate methods to forecast the future train traffic which is the main factor in determining future emission levels. Generally, rail traffic should be expected to follow economic growth indicators such as gross domestic product, although this may not hold in the future. Changes in trade imbalances and energy sources (coal currently accounts for the majority of freight rail ton-miles nationally) can have large effects that will not be explained by these economic indicators. Emissions will also depend on changing types of rail traffic, the general trend being towards more intermodal traffic which is more fuel intensive. In the same way that MPOs use travel demand models to generate input for vehicle emission models, such as the CARB's EMFAC and the EPA's MOBILE6 model, MPOs could develop goods movement demand models that provide forecasts of freight rail traffic which feed into our locomotive emission model. The introduction of new locomotive technologies, such as hybrid locomotives which reduce fuel consumption and new locomotives that meet stricter EPA emission standards will also influence emissions in the future.

Under this study, we did not collect information for Class II and III railroads. However, the methods presented here and the model developed can (and should) be used for these railroads when appropriate data are available. An estimate of annual traffic (or fuel consumption) by route and the proportion of locomotives which meet each EPA tier certification level are required for each Class II and III railroad.

4 GOODS MOVEMENT DATA CONSTRAINTS ON PUBLIC POLICY AND PLANNING: A CASE STUDY OF CALIFORNIA'S TRADE CORRIDORS IMPROVEMENT FUND

4.1 Introduction

In this study, we argue that the recent push to expand freight rail capacity as a way of mitigating increasing congestion and air pollutant emissions from a growing goods movement demand may have outpaced our ability to adequately evaluate the merits of such projects. Specifically, we examine the decision processes and data used to select projects for inclusion in California's Trade Corridors Improvement Fund (TCIF) which allocated over $500 million in state funds to freight rail infrastructure projects in 2009. We conduct detailed evaluations of the 11 TCIF funding proposals to expand freight rail capacity that were ultimately selected for funding. These projects were submitted by local, regional and state transportation planning agencies, and all claimed significant public benefits. Our results suggest that public agencies may not have sufficient data, models or expertise to ensure that efficient freight rail funding decisions are made.

The heightened public interest in goods movement is driven by expectations of growing demand. The Federal Highway Administration estimates that by 2035 the volume of goods moved through the U.S. transportation system will increase by 75% over 2007 levels (FHWA 2008). This large increase in demand for goods movement has the potential to significantly increase road- and port congestion, as well as local air pollution and greenhouse gas emissions. Moving a greater share of goods by freight rail is seen as an important part of the solution by public policymakers and planners (AASHTO 2002; State of California 2005; GAO 2008), and there is evidence to suggest that this perspective is warranted.

Freight rail offers one of the most energy efficient and least polluting means for transporting goods. The Federal Rail Administration (FRA) compared the energy efficiency between trucking and rail on 23 different routes (FRA 2009) finding that rail was always the most energy efficient mode. The comparison considered shipments of commodities which are commonly transported by either mode, between origins and destinations served by both and included the energy consumption of intermodal container handling equipment and drayage. Rail's greater energy efficiency means less fuel consumption and less carbon dioxide (CO_2) emissions when compared to trucking. These results are consistent with earlier studies (Abacus Technology Corporation 1991) as well aw with more recent comparisons using life cycle emissions (Facanha and Horvath 2007) and when looking at freight alternatives producing the lowest social costs (Forkenbrock 2001).

While the emissions advantages to freight rail are fairly clear, the ability of the U.S. freight rail system to actually move more goods is less obvious. A recent report from the Government Accountability Office (GAO 2008) expressed concern that growth in highway and rail capacity was lagging goods movement demand. The American Association of State Highway and Transportation Officials (AASHTO), a non-profit organization representing state highway and transportation departments, concluded that $23 to $83 billion in public financing would be required for freight rail to even maintain its current market share (AASHTO 2002). This range was largely consistent with a similar study conducted for the Association of American Railroads (AAR) at the request of the National Surface Transportation Policy and Revenue Study Commission[36] which estimated a $39 billion shortfall in the rail revenue required to maintain reliable freight rail service (Cambridge Systematics 2007). The state of California also recently concluded that freight rail capacity was in short supply, a situation expected to worsen with increasing goods movement demand, and required an infusion of public funding for increasing capacity to mitigate congestion and worsening air quality (State of California 2005).

Concerns over freight rail capacity have also been expressed in the academic literature. In particular, a study by Gorman (2008) concluded that investing in freight rail rather than highways

[36] The commission was created by congress as part of the Safe, Accountable, Flexible, Efficient Transportation Equity Act – A Legacy for Users (SAFETEA-LU).

could save the public 58% in infrastructure and 80% in external costs per ton-mile. Similarly, Resor and Blaze (2004) argue that public investment is required to develop short-haul rail solutions to compete with trucks. The challenge for public planners is knowing when and where to provide support. In response to growing interest in freight rail as a solution for highway congestion, the Transportation Research Board (TRB) sponsored a study to provide guidance in selecting worthwhile projects (Bryan, Weisbrod et al. 2007).

Drawing on 9 case studies, Bryan, Weisbrod et al. (2007) describe how public agencies at all levels of government are turning to freight rail as a means of addressing highway congestion. Seven of the studies describe how public financing was used to expand railroad capacity by upgrading mainline tracks, removing rail-rail at grade crossings, improving access to the rail network and creating inland ports. The remaining 2 studies similarly describe plans to use public financing to expand freight rail capacity, but these plans had not yet received funding. The projects are a mix of large corridor improvement projects and more isolated infrastructure projects. Based on these efforts, direction is provided on how public agencies can select cost effective freight rail infrastructure projects that are the most likely to reduce highway congestion.

While Bryan, Weisbrod et al. (2007) provide comprehensive guidance for prioritizing and selecting freight rail infrastructure projects, they say little about how to contrast the efficiency of those projects when comparing modal alternatives. Expanding freight rail capacity is just one approach for shifting more goods to rail, particularly if the goal is reducing highway congestion and air pollutant emissions. Conceptually, adding additional freight rail capacity is treating a symptom rather than the problem. In a perfectly competitive goods movement market without externalities the railroads would be expected to provide an efficient amount of capacity and level of service. There would be little reason to suspect a shortage of rail capacity. However, several market failures exist in the goods movement sector and correcting these problems may be more advantageous from a social welfare perspective than simply increasing rail capacity using public financing.

Despite the rush for public financing options, correcting market failures has been widely recognized as the preferred approach to reducing congestion and air pollutant emissions from goods movement. Correcting at least some of the externalities would involve ensuring that trucks pay the true costs of infrastructure provision and that increased goods movement efficiency is achieved through greater competition. What remains an open question, however, is the role of public financing in reducing the externalities.

It is generally argued that the main role of government in goods movement is ensuring economic efficiency (TRB 2003). That is, that government involvement becomes justified where markets are not providing efficient outcomes because of monopolies and externalities. When considering public financing options (e.g., grants), proponents argue from several perspectives: that providing grants to pay for rail expansion may be less expensive than providing equivalent highway expansion; that the scale and complexity requires government management; that there are large positive externalities, that it may not be possible to internalize external costs and finally, that public passenger trains use the freight tracks too. Opponents argue that fixing the subsidy to trucks with a subsidy to rail leads to excess rail and highway capacity; that user fees and taxes can correct for many externalities; that providing grants to physically expand rail capacity does not provide incentives for expanding capacity through improved management and technology and finally, that government does not have the data or tools to determine those projects that would have been built without grants or that are the most cost effective.

Two earlier goods movement studies, one on finance (TRB 1996) and the other on federal intermodal policy options (TRB 1998), also argued that imposing user fees that account for the costs of using highways and externalities should be the primary method to ensure an efficient goods movement system. However, they argue that in some cases government assistance may be required, mainly to organize complex projects, obtain rights of way or to provide loans for expensive capital projects, but grants are not automatically justified. In general, all funding provided by the government should be recovered by requiring private firms to pay back government loans or by collecting user fees. Requiring cost recovery creates an incentive for the railroads to suggest truly worthwhile projects and helps prevent an oversupply of infrastructure.

Regulatory standards offer an additional approach for correcting market failures where user fees may not be practical or necessarily efficient (Parry, Walls et al. 2007). Requiring a vehicle operator to pay a tax for the marginal damage caused by emissions from their vehicle will not be efficient if the operator does not correctly perceive the net present value of an investment in cleaner technology. This has been the argument in favor of fuel economy standards for passenger vehicles. In other situations it may be difficult to estimate the marginal cost of damages in order to determine appropriate user fees or taxes and relatively easier to adopt fuel and emission standards which guarantee some level of abatement.

Generally, any of these approaches, either funding infrastructure expansion, charging user fees and taxes to internalize external costs or adopting regulatory standards can lead to an efficient outcome. The preferred alternative should ideally be based on the approach that has the best chance for success. The main question we ask here is do transportation planning agencies know enough about the optimal level of goods movement infrastructure, the costs of externalities produced by trucks and train or the acceptable level of externalities produced by trucks and trains to select the optimal alternative? The consequences of miscalculating the supply side of infrastructure, the setting of tax and fee levels or the determining of standards are all important considerations. For example, are the costs posed by the risk of over supplying infrastructure larger than setting a tax too low? The ability to provide infrastructure, charge taxes and fees or enforce standards are parallel considerations.

We hypothesize that public planning and transportation agencies currently know much more about the cost of externalities and acceptable levels of externalities than they do about the optimal level of goods movement infrastructure. We also observe that infrastructure projects are more or less permanent while in theory taxes, fees and regulations can be adjusted over time until the desired results are achieved. Accordingly, we suggest that funding freight rail infrastructure projects may be relatively inefficient, potentially wasting limited public funds on projects which are unlikely to produce the expected public benefits. This is based partly on our experience working with the railroads to develop a new freight rail emission model (see chapter 3), where, we found that the railroads were extremely guarded about releasing any data about their traffic, which they considered confidential business information. Our difficulty in obtaining basic railroad operating data is not unique (Caretto 2004a; Billings, Chang et al. 2006). The lack of useful freight data and the difficulty in using what are available has also been noted by many state transportation agencies (TRB 2005). Weatherford, Willis et al. (2008) argue that more publicly available freight data are needed to support public policies, pointing out that many more data are available for highways than freight railroads. Bryan, Weisbrod et al. (2007) also describe the difficulty in obtaining railroad capacity data in their guidance for selecting beneficial freight rail projects.

Data availability and transparency may not be the only problem. Several studies have questioned the ability of public planners and MPO's to make informed goods movement decisions. This concern stems from a long history of planning almost exclusively for passenger travel (Weiner 1999; Woudsma 2001). Studies based on surveys of MPO's (Blonn, Guo et al. 2007; Schank, Hirschman et al. 2008) have found that most lack methods for evaluating goods movement projects and few rigorously consider air quality impacts. Other studies have also noted that public planners and MPOs have little goods movement expertise and may apply inappropriate project evaluation tools (TRB 2007; GAO 2008).

To test our hypothesis, this study examines the inputs/outputs and methods used to prioritize projects within California's TCIF program. The funding is expected to satisfy several different objectives, including, creating improvements in air quality and congestion relief – both key externalities. However, as we show, the calculations used to underpin project estimates of reductions in criteria air pollutants and carbon emissions and estimates of congestion relief vary widely from project to project, producing results that are at best questionable, and in some cases simply wrong. Based on our review, we argue that public planners and transportation agencies currently lack the required information or expertise to justify broadly granting significant public funds to expand private rail infrastructure over alternative policy options.

In this first study to conduct an in-depth post-hoc analysis of California's public financing option for goods movement, we point to evidence that identifying apparent market failures and working to correct them directly appears to offer a relatively simple and more effective course of action. For example, we note that vehicle emission standards have been highly successful at reducing air pollutant emissions and that as more stringent regulations come into force, the criteria pollutant emission rates from trucks and trains are expected to harmonize. Numerous cost allocation studies have also provided data on the subsidy that heavy trucks receive on public highways. Increasing truck specific fees (e.g. registration fees) or tolls could easily remove or diminish the subsidy. Lastly, a carbon cap and trade system or fuel taxes are widely proposed as the most efficient methods to reduce carbon emissions (Ellerman 2000; Stavins 2003; Tietenberg 2003).

4.2 TCIF Case Study

The TCIF program was included as part of the Highway Safety, Traffic Reduction, Air Quality, and Port Security Bond Act of 2006 (Proposition 1B) approved by California voters in 2006. The California Transportation Commission (CTC) was charged by Proposition 1B with the responsibility of programming the TCIF. The CTC adopted guidelines for project selection and solicited proposals from state, regional and local government agencies in the fall of 2007. The CTC project selection guidelines included provisions [37] requiring that funding decisions "[place] emphasis on projects which increase corridor mobility while reducing diesel particulate and other emissions" (CTC TCIF Guidelines, p. 2). Specific project evaluation criteria included in the CTC guidelines weighed such freight system factors as throughput, velocity and reliability;

[37] Available from the California Transportation Commission website at: http://www.catc.ca.gov/programs/TCIF/TCIF_Guidelines_112707.pdf

transportation system factors: safety, congestion reduction, bottleneck relief, multi-modal strategy and interregional benefits as well as; three community impact factors: air quality impacts, community impact mitigation and economic/job growth. Additionally, projects financing private infrastructure must "show that the share of public benefits is commensurate with the share of public funding" (CTC TCIF Guidelines, p. 4); specific methods to show attainment with this criteria were not provided. The TCIF evaluation criteria, project documentation requirements and variety of project proposals provide a unique opportunity to examine the underlying modeling methods used to justify a very important public policy decision on infrastructure expenditures.

The TCIF selection process ultimately awarded $680 million in public funding to 11 rail projects[38]. These projects directly benefit private railroads by either funding expansion of their existing infrastructure or by expanding publicly owned infrastructure over which they operate. The TCIF funding allocated to the projects represents 47% of the estimated total project costs; the remainder is derived from other public sources, such as local sale taxes and federal transportation funds, and from private investment from the respective ports, railroads and developers. Seven projects expand the capacity of mainlines owned or used by Class I railroads; two projects develop new inland ports in California's Central Valley, both are designed to provide intermodal rail service to and from the Port of Oakland. One project expands the capacity of an existing rail yard, and the ports of Los Angeles and Long Beach and Oakland each requested funding for the construction of new port intermodal rail facilities. A brief description of each project is provided in Table 4-1.

[38] Excluding grade separation projects, 16 rail projects were submitted as part of the process. In total, the TCIF awarded $3 billion to 70 projects (30 were rail/highway grade separations, 3 involved non-rail port projects and the remainder were highway related) out of 84 submitted, covering 36% of the total costs. See http://www.catc.ca.gov/programs/tcif.htm for more information.

Table 4-1 TCIF rail project descriptions

ID	Name	Description
1	Martinez Subdivision Rail Improvements	Expands the capacity of Union Pacific's Martinez Subdivision by building two additional mainline tracks extending 6.5 miles from the Port of Oakland.
2	Outer Harbor Intermodal Terminals	Expands the intermodal capacity of the Port of Oakland from 1 million TEU to 3 million TEU by building two new rail yards at the port.
3	Sacramento Intermodal Track Relocation	Expands the capacity of Union Pacific's Martinez Subdivision in Sacramento by realigning a 3,300 foot section of mainline track; separating passenger loading tracks from the freight mainline and removing two sharp turns. The project also reduces locomotive idling and improves access to land that the city is interested in developing.
4	Tehachapi Trade Corridor Rail Improvement	Expands the capacity of Union Pacific's Mojave Subdivision in the Tehachapi Mountains by extending sidings and adding additional double track segments.
5	LOSSAN N. Rail Corridor Improvements	Expands the capacity of the publicly owned LOSSAN N. rail corridor from four to eight daily freight trains. BNSF maintains track rights and operates the freight trains.
6	Ports Rail System (Tier 1)	Expands the on-dock rail capacity of the Ports of Long Beach and Los Angeles by adding additional tracks into the ports and expanding on-dock rail yards.
7	Colton Crossing Flyover	Expands the capacity of the UP’s and BNSF's Los Angeles area systems by grade separating two intersecting mainlines. Currently, trains take turns crossing the intersection. The project also reduces delays at highway grade crossings.
8	Southline Rail/San Ysidro Yard Improvements	Expands the capacity of the publicly owned South Line Rail Corridor and San Ysidro Rail Yard. Freight service is contracted to the San Diego and Imperial Valley Railroad. Mainline capacity is increased from two to four daily freight trains by adding new train control technologies. The rail yard is expanded from 10,000 to 19,600 annual car loads by adding two additional storage tracks.
9	San Joaquin Valley Short Haul Rail/Inland Port	Provides funding for the San Joaquin Regional Rail Commission to acquire control over 65 miles of Union Pacific's Oakland Subdivision between the San Francisco Bay Area and the Central Valley and operate 2 daily intermodal trains.
10	Shafter Intermodal Rail Facility	Provides funding to build a new intermodal rail yard in the City of Shafter and connect it to BNSF's Bakersfield Subdivision.
11	New Antelope Valley Siding	Expands the capacity of the Los Angeles County Metropolitan Transportation Authority's single track Antelope Valley Line by building a new 7,000 ft siding. Union Pacific currently operates 5 daily freight trains over the line, the new siding will reduce idling and allow Union Pacific to operate additional freight trains.

Each of these TCIF projects is expected to provide several public benefits (Table 4-2), including reductions in truck volumes and corresponding air pollutant emissions. Economic and job growth benefits are also expected since shipment by rail is assumed to be less expensive than trucking and temporary construction jobs will be created to complete the projects. The magnitudes of the benefits that were estimated for each project were highly dependent on estimates of reductions in truck travel. The only exception to this is the portion of benefits derived from reduced freight rail congestion, such as the benefits from project 1 (locomotive idling reduction), which depend only on the ability of the TCIF projects to expand freight rail capacity.

Table 4-2 Estimates of truck volume and air pollutant emission reductions from TCIF rail project applications and supporting material

	Truck Volume Reductions		**Net Emission Reductions**		
	Truck Travel	**Truck Trips**	**NO_X**	**PM10**	**CO_2**
Project ID	***million VMT/yr***	***million trips/yr***	***tons/yr***	***tons/yr***	***tons/yr***
1	0[a]	0	9.8	0.2	1,285
2	123	1.44	218	16.4	334,158
3	166[b]	0.67	5,343	220[c]	-[d]
4	132	1.12	116	3.4	170,000
5	6	0.05	47.5	3.65	18
6	24	9.90	2,061	33.5	-
7	365	4.30	-	-	-
8	4	0.03	-	-	5,789[e]
9	16	0.88	33.7	3.91	5,994
10	69[f]	0.22	1,684	104	172,801
11	23	0.33	43.7	1.8	18,898

[a] Project reduces locomotive idling, no reduction in truck travel expected.
[b] Inferred by authors from emissions calculation data provided in project documentation.
[c] Converted from PM2.5 estimate to PM10 by the authors: $PM10 = PM2.5/0.92$ (EPA 2003)
[d] Information not available from TCIF project documentation.
[e] CO_2 estimated by authors from an estimate of fuel consumption reduction provided in the TCIF application materials using a conversion factor of 22.2 lbs of CO_2 per gallon of diesel fuel (EPA 2005).
[f] VMT calculated by the authors from the reported number of daily truck trips (600 trips) and the reported truck trip distance from Oakland to Shafter (315 miles).

Together, the 11 TCIF projects in Table 4-2 claim to reduce statewide truck travel by 1,011 million VMT per year, NO_X emissions by 9,553 million tons per year and PM10 emissions by 371 tons per year. Most of these benefits are estimated for the year 2030; exceptions are projects 3 and 4 which do not provide a time frame for reductions and project 6 which made estimates for 2008. These are relatively large reductions considering the small number of projects. To put these reductions in perspective we compared them to the California Air Resource Board's estimated statewide heavy-heavy duty truck VMT and heavy-heavy duty truck and train emission forecasts for 2020, the most distant year for which forecasts are available[39]. The TCIF project truck VMT reductions represent 5.4% of the statewide 2020 truck VMT forecast and the TCIF project NO_X and PM10 reductions are 5.8% and 5.3% of the 2020 combined truck and rail NO_X and PM10 emission forecasts, respectively. The relative reductions would be smaller by 2030 since goods movement is expected to continue to increase.

4.2.1 Framework for quantifying project benefits

As part of the TCIF project proposal, project sponsors were asked to estimate the expected truck traffic and air pollutant emissions reductions. No instructions were provided on the methods to be used in these calculations; however, the methods used by the different project sponsors were similar. Each approach compares a do-nothing baseline scenario to a single TCIF project alternative that invariably results in the shifting of truck traffic to freight rail. The approaches diverge for different assumptions about the baseline scenario: either the existing rail facilities are at capacity (projects 1-8), or there is a latent demand (existing, but unmet) for freight rail (projects 9-11). Each approach is described in greater detail below.

4.2.1.1 Expanding Capacity for Growth

For projects 1-8, the baseline scenario assumes that all forecasted rail demand above current levels will move by truck (Figure 4-1). That is, there is no additional rail capacity

[39] Forecasts are available at the California Air Resource Board's website: http://www.arb.ca.gov/ei/emissiondata.htm

currently available to accommodate future growth. For the TCIF project alternative, it is assumed that all forecasted rail demand will continue to move by rail because the respective proposed alternatives increase rail capacity. From this standpoint, these projects do not promote a mode shift to rail, but rather prevent a shift to trucking. Reductions in truck VMT are thus calculated as the avoided increase in trucking that was posited to result if rail capacity was not expanded. Emission reductions are calculated as the quantity of emissions that would occur from future rail traffic, above current levels, moving by truck minus the amount of emissions that occur from moving this traffic by rail. In essence, this represents an all or nothing scenario: all forecasted rail growth moves to truck if capacity is not expanded and all marginal emissions are counted as a social benefit.

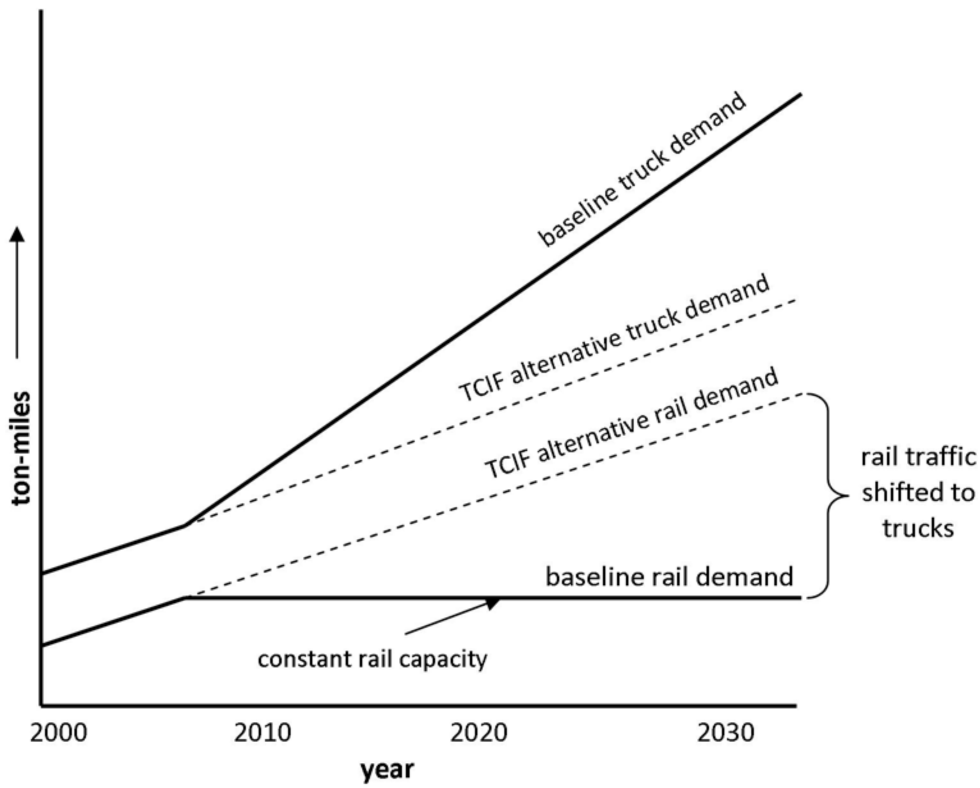


Figure 4-1 Expanding rail capacity for growth: truck and rail demand scenarios (projects 1-8)

4.2.1.2 Expanding Capacity for Latent Demand

For projects 9-11, the baseline scenario assumes that there is latent demand for rail that currently moves by truck (Figure 4-2). The TCIF project alternative assumes that the latent rail demand is met by expanding the capacity of existing infrastructure or by adding new rail infrastructure; this results in a mode shift from truck to rail. Reductions in truck VMT are calculated as the amount of truck traffic shifted to rail based on estimates of the latent demand. Emission reductions are calculated by estimating emissions that would occur if the diverted truck traffic continued to move by truck minus the emissions that occur when that traffic moves by rail.

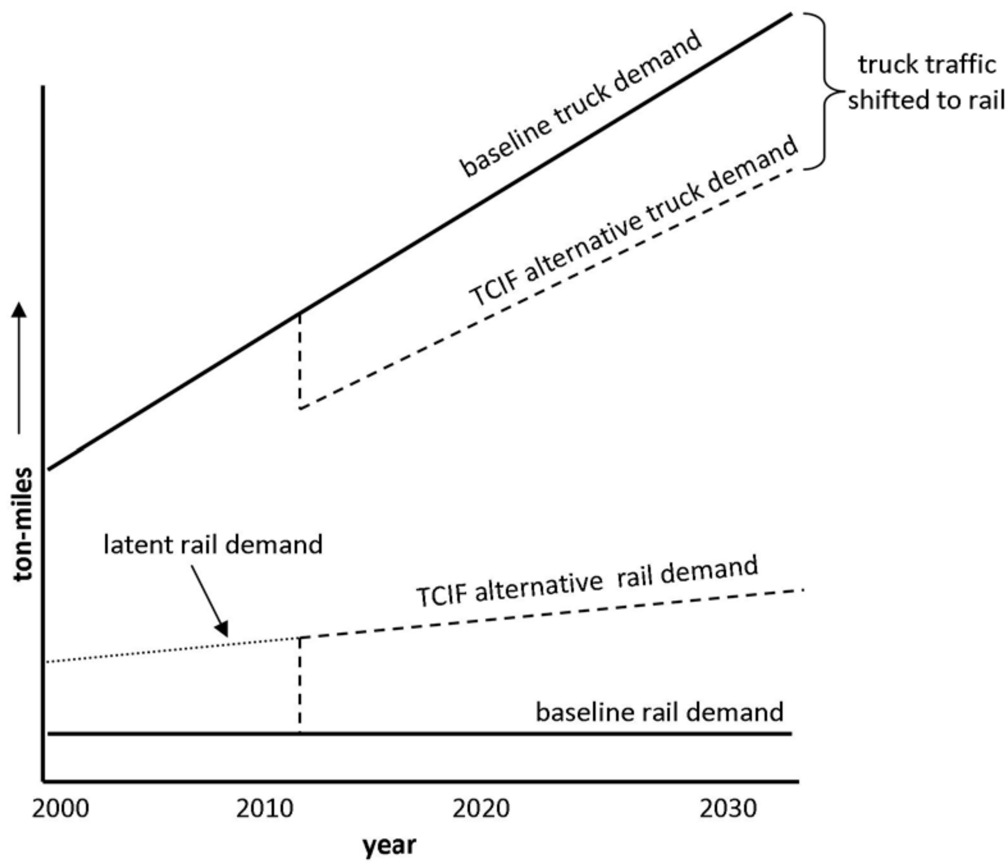


Figure 4-2 Expanding rail capacity for latent demand: truck and rail demand scenarios (projects 9-11)

The baseline and project scenarios and their assumptions reveal those factors that affect the estimates of public benefits (i.e., reductions in truck volume and air pollutant emissions). For the group of projects in which rail capacity is expanded for growth the benefit estimates depend on rail demand forecasts and rail capacity estimates. If rail *demand* forecasts are over-estimated, the project benefits will be as well. Similarly, if rail *capacity* is under estimated, the project benefits will be over-estimated. For the second group of projects (5, 6, and 11), the benefit estimates depend on the existence and size of a latent demand for rail capacity. If all current shippers are satisfied with their modal choices (i.e., any shipper that wants to send something by rail can do so within a reasonable timeframe and for a fair rate), then adding rail capacity will not shift truck traffic to rail. No benefits will occur. If the amount of latent demand is smaller than estimated, the project benefits will be over-estimated.

Thus, there are three key working variables critical to estimating the public benefits produced by each investment: rail demand, rail capacity and latent rail demand. These key variables are the basic inputs to the various models used to estimate the reductions in truck traffic and air pollutant emissions expected from each TCIF project.

4.3 Case Study Findings

The public benefits of reduced truck traffic and air pollutant emissions expected under the TCIF project alternative for each proposal depends on how much larger current and future rail demand (or latent demand) is than current and future rail capacity. We review how rail demand and capacity are estimated based on the case study. We then show how these estimates were used to calculate truck traffic and emission reductions and examine the underlying consistency of the estimates.

4.3.1 Rail Demand

Rail demand forecasts were used to support projects 1-8 and are based on estimates of port growth, cross-border trade with Mexico and regional economic growth (Table 4-3). The forecasts are generally made by either simple projections of historical growth trends or by more detailed economic analysis. A few proposals provided growth estimates without identifying what demand (e.g., sector) is expected to drive growth.

4-3 Estimated growth in rail demand and underlying growth assumptions

Project ID	Rail Demand Growth	Assumptions
1	22 train trips per day by 2020	100% to 140% increase in Oakland port activity, increase in intermodal cargo share from 31% to 50%
2	2 million TEU by 2025	100% to 140% increase in Oakland port activity, increase in intermodal cargo share from 31% to 50%
3	40 million gross tons by 2020	Growth in Oakland port activity
4	n/a	n/a
5	4 train trips per day by 2030	2% regional economic growth, 3% increase in trade with Mexico, doubling of San Diego port activity
6	9 million TEU by 2030	170% increase in LALB port activity, rail share of port goods movement remains at 52%
7	75 trains per day by 2033	2% annual growth in rail demand (consultant's assumption)
8	2 train trips per day by 2030	2% regional economic growth, 3% increase in trade with Mexico, doubling of San Diego port activity

4.3.1.1 Projects Using Port Container Throughput Forecasts

Rail demand forecasts for projects 1 through 3 depend on a container throughput forecast for the Port of Oakland and the rail demand forecast for project 6 depends on a container throughput forecast for the Port of LALB. In each case, rail demand is derived from the container throughput forecasts by estimating what share moves by rail versus truck.

Several different methods are available to forecast container throughput. In general, container throughput forecasts may be either constrained or unconstrained by port capacity. For example, forecasts 1, 3 and 4 for the ports of Los Angeles and Long Beach (LALB) (Figure 4-3) and both forecasts for the port of Oakland (Figure 4-4) are unconstrained by port capacity. Alternatively, forecast 2 for the port of LALB (Figure 4-3) assumes that the ports have a physical capacity limit. As throughput nears the port’s capacity, growth in demand slows as a result of congestion. The general forecasting approach applied to each port’s forecast also varies. All of the forecasts for the port of LALB are based on detailed assumptions about national and regional economic growth and international trade. In comparison, the Port of Oakland’s forecast was derived from an exponential curve fit to historical annual throughput data, and an extrapolation of that curve into the future.

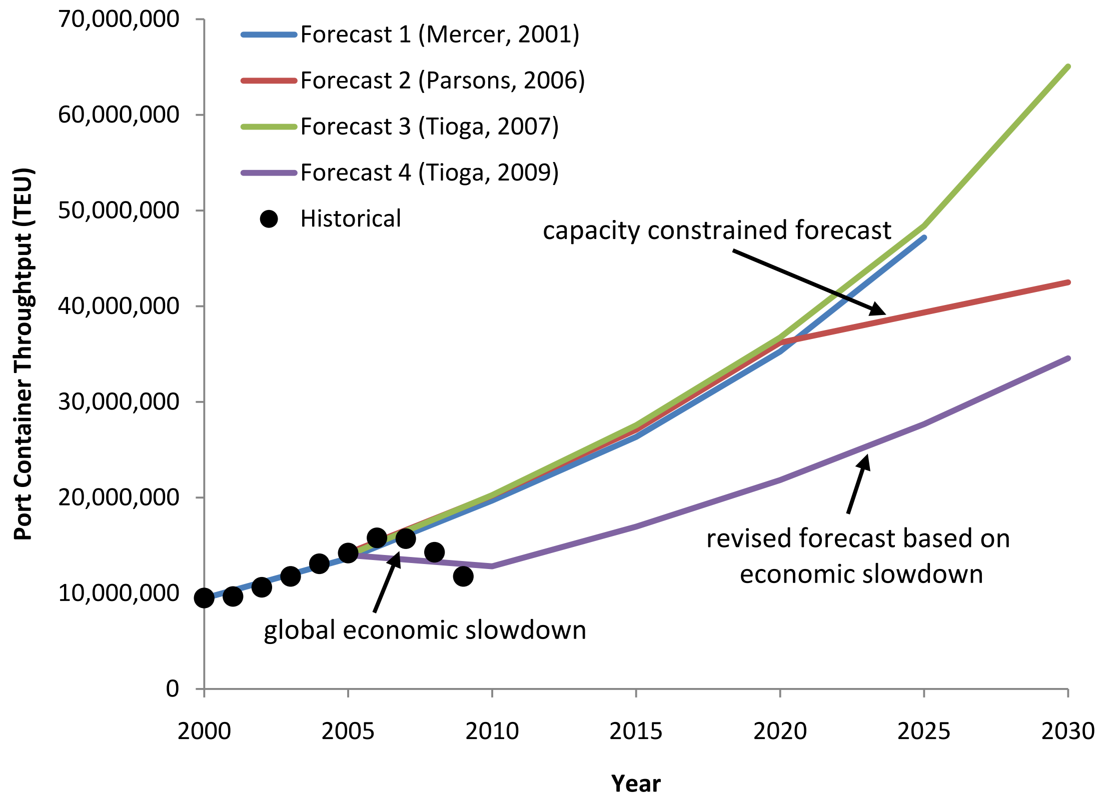


Figure 4-3 Comparison of historical and forecasted container throughput at the ports of Los Angeles and Long Beach

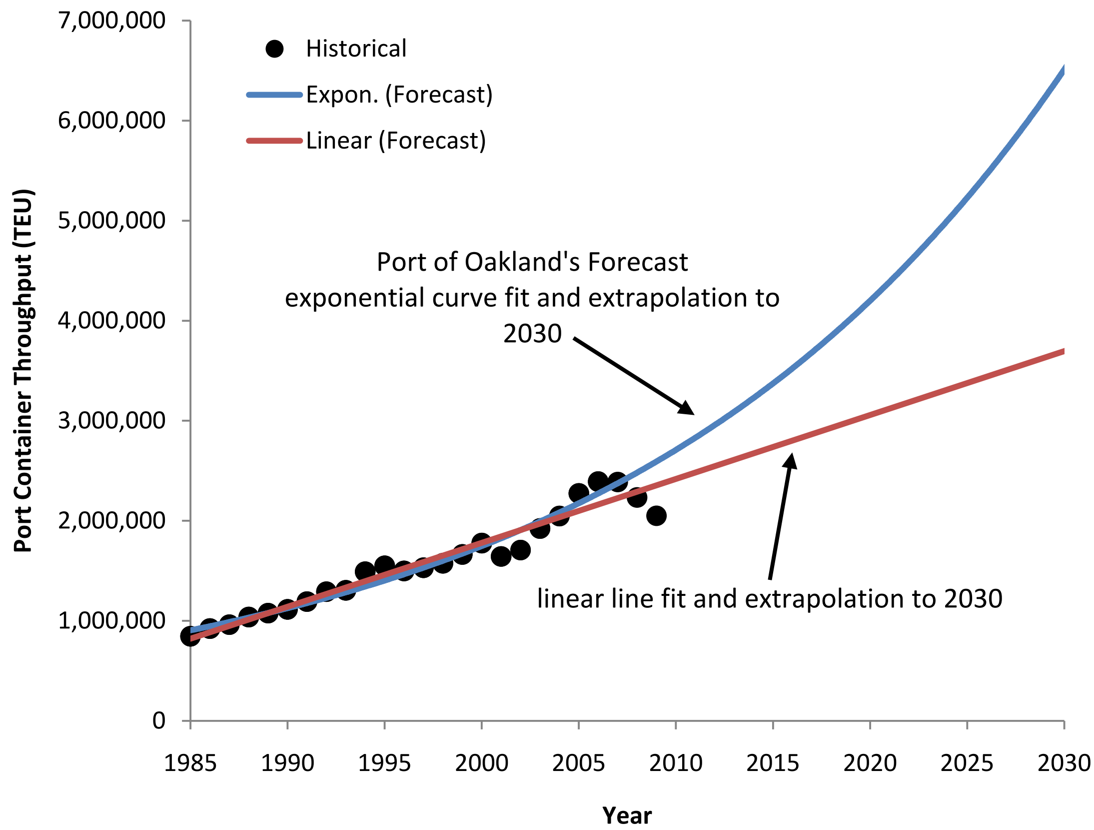


Figure 4-4 Comparison of historical and forecasted container throughput at the port of Oakland

In assessing the port container forecasts that were included in the TCIF project proposals, the exponential curve fit for the Port of Oakland and the 2006 Parsons forecast for the ports of LALB (Figure 4-3 and Figure 4-4), it’s clear that the forecasts are very uncertain and that they potentially over estimate demand. As might be expected given the uncertainty associated in forecasting, none of the original throughput forecasts predicted the economic slowdown that began in 2007 and resulted in a large drop in container throughput. Tioga subsequently revised their original throughput forecast for the ports of LALB to reflect the economic slowdown; the revised forecast predicts 47% lower throughput in 2030. The constrained throughput forecast for the ports of LALB made by Parsons, which is used in the port's TCIF proposal, is 35% is lower than Tioga's original forecast and 23% larger than Tioga's revised forecast. The Port of Oakland’s forecast in Figure 4-4, which is referenced by projects 1-3, assumes an exponential trend in port growth; however, a linear trend appears to offer equally as good a fit[40]. By 2030 the linear trend forecasts 43% less throughput than the port's exponential trend.

The size of the differences between the various forecasts is large. The difference between Tioga's original and revised forecast in 2030 for the ports of LALB, 30.5 million TEU, is almost 3 times the level of current throughput at the ports. The difference in the Port of Oakland's 2030 forecast and a linear growth trend, 2.8 million TEU, is more than 3 times the port's current throughput. Surprisingly, only a single container throughput estimate is carried on to estimate rail demand.

Freight rail demand is estimated as a share of the forecasted port container throughput at the ports of LALB and Oakland. The ports of LALB estimate this share will remain at the current level of 52%. The underlying assumption, not stated in the proposal, is that regional (served by truck) and national (served by rail) markets will grow at the same rate and the distance at which intermodal rail becomes competitive with trucking remains constant. The port of Oakland’s current freight rail share is about 31% and the port expects that this may increase to 50%. No evidence is provided to support the expectation of a growing rail share, even though the 50% rail share is used to estimate the benefits provided by the port’s TCIF proposal to build a new intermodal terminal (project 2).

4.3.1.2 Projects Using Other Sources to Forecast Rail Demand

A large portion of California’s rail demand is related to intermodal container traffic generated by the ports of LALB and Oakland but other factors also drive rail demand. Two rail capacity expansion projects in San Diego (projects 5 and 8) are proposed to accommodate growing rail traffic from increasing auto imports, trade with Mexico and regional economic growth. Rail traffic generated from the Port of San Diego is expected to double in throughput

[40] The Port of Oakland fit an exponential curve to historical data from 1985 – 2006. The linear fit, by the authors, is also fit to the 1985 – 2006 data.

from 10,000 car loads (about 150,000 vehicles) during 2006 to 20,000 car loads (or 300,000 vehicles) by 2030 due to the proposed expansion of the port's of auto storage facility which is also seeking TCIF funding. However, it is unclear if the auto storage facility will be built since it was denied TCIF funding.[41] It is also unclear how the auto facility expansion relates to the expected large increase in rail demand. The auto facility expansion would add capacity for 131,400 additional vehicles per year of which only half are typically moved by rail.[42] This suggests that the rail share is expected to increase and that the expanded auto facility will be 100% utilized by 2030. Growth in cross boarder rail traffic with Mexico is expected to increase by 3% while regional economic growth is expected to increase regional rail traffic by 2% annually. No evidence or references were provided to support these growth estimates; however, the 3% growth in cross boarder traffic appears to be based on the assumed rate of U.S. economic growth.[43] The combined growth in rail demand from these three sources is forecasted to double rail throughput by 2030.

Acknowledging the general uncertainty in forecasting, most of the TCIF rail demand forecasts rely on estimating demand specific to certain generators such as ports or are pinned to regional, state or national economic growth. However, several forecasts were more opaque and often lacked supporting data or references. For example, the Colton Crossing Flyover project (project 7) assumes a 2% growth rate in freight rail traffic[44], but no explanation, supporting data or reference is provided to support the estimate. The 2% annual growth rate assumed by the Colton Crossing Flyover project is much lower than the growth rates projected for the ports of LALB (the source of most of the regions freight rail demand), which ranges from 3.7% to 6.3% depending on the forecast. Similarly, the Tehachapi Trade Corridor project (project 4) provides

[41] See list from the California Transportation Commission TCIF website: http://www.catc.ca.gov/programs/TCIF/Projects_NOT_included_in_TCIF_Program041008.pdf
[42] Port of San Diego National City Marine Terminal Improvements TCIF proposal, submitted to the California Transportation Commission on January 14, 2008.
[43] Multi-County Goods Movement Action Plan: Technical Memorandum 4a – Freight Demand, p1-7
[44] Assumption reported in the public benefit analysis completed by HDR Inc. for the project.

no estimates of increased rail traffic, though it does estimate the amount of truck traffic and emissions reduced[45].

4.3.2 Rail Capacity

In general, each TCIF proposal assumed that a shortage of rail capacity combined with increasing goods movement demand was expected to increase the share of goods moving by truck in the future. For example, project 1's proposal states that the Martinez subdivision is "currently at or near capacity" (TCIF funding nomination for the Martinez Subdivision and Rail Improvements, p. 5), project 6's proposal states that the port of LALB's rail capacity is "becoming constrained" (TCIF funding nomination for the Ports Rail System (Tier I), p. 2) and project 7's proposal states that the Colton Crossing is a "major choke point" (TCIF funding nomination for the Colton Crossing Rail Improvement Project, p. 3) . Because no standard definition of rail capacity exists (Kozan and Burdett 2005; Abril, Barber et al. 2008; Weatherford, Willis et al. 2008), direct comparisons of the capacities that are referred to in the various proposals are problematic.

For example, while every TCIF proposal cited a rail capacity constraint, only five proposals actually quantified rail capacity as a maximum volume of goods movement that can be handled by a specific rail segment (Table 4-4). Proposals for projects 5 and 8 state that the current capacity is limited to 4 and 2 trains per day, respectively, due to constraints posed by the current signaling system, lack of double track and conflicts with passenger trains which have priority. Under the TCIF project alternative, the capacity of the rail facilities is expected to double. Under the TCIF alternative for project 4, modeling by the BNSF railroad estimates that capacity will be increased by 70%. The capacity expansions allows for 15 more trains per day which are up to 2,000 feet longer than the current trains. The proposal for project 3 states that the current facility has a capacity of 40 million gross tons per year of freight rail traffic. The capacity could be

[45] Growth forecasts may be provided in the supporting HDR report; however, we were unable to acquire a copy of the report from Caltrans despite making numerous requests.

increased by 20 million gross tons per year if conflicts with passenger trains are eliminated with additional tracks and a 90 degree corner removed. The proposal for project 2 estimates the Port of Oakland's intermodal container throughput at 1,000,000 TEU per year. The proposed construction of a new intermodal facility would increase throughput capacity by 2,000,000 TEU. Finally, the proposal for project 6 states that under the TCIF project alternative the port of LALB's rail capacity would be increased by 7 million TEU; however no estimate of the port's current capacity was provided.

4-4 Estimated TCIF project freight rail capacity improvements and modeling assumptions

Project ID	Rail Capacity Improvement	Assumptions
1	reduce delay by 1 hr per train per day	none provided
2	increase port intermodal container throughput by 2 million TEU	based on designed capacity of new intermodal facility
3	20 million gross tons annual freight rail traffic	increase maximum speed from 20 mph to 30 mph, avoid stopping for passenger trains
4	70% increase in capacity	based on BNSF modeling
5	4 additional trains per day	none provided
6	7 million TEU	none provided
7	52% reduction in delay	based on BNSF modeling
8	2 additional trains per day	none provided
11	reduce delay by 15 minutes per train	none provided

The remaining proposals do not quantify capacity, but rather estimate various measures of service quality. One method uses a level of service (LOS) approach (Cambridge Systematics 2007) analogous to that used in the highway capacity manual (TRB 2000). Rather than measuring the actual capacity remaining the quality of the service is instead rated. LOS is divided into A through F (best to worst) based on a route's volume to capacity ratio. Volume to capacity ratios below 0.8 indicate the route is operating below capacity and generally has stable flows. As ratios approach one, traffic conditions become unstable and eventually break down at ratios at or above

1. Estimating LOS also requires estimating capacity. The Cambridge Systematics study used detailed data provided by the railroads to create a table that provides estimates of the maximum practical number of trains per day a rail corridor can accommodate as a function of the number of tracks, type of traffic control system and whether only a single type or multiple types of trains use the corridor. The study notes that the data used to create the table is not available and must be requested directly from the railroads, who consider it confidential business information. It would be difficult for public agencies to regularly replicate these methods.

A poor level of service (LOS E) is cited as a need for project 4 which adds numerous sidings and double track segments to a busy mountain rail pass. The LOS rating applied to the track segment was taken from a national rail capacity study (Cambridge Systematics 2007). Proposals for projects 1, 7 and 11 estimate reductions in delay, but do not quantify LOS or capacity. For example, under the TCIF project alternative, proposal 1 will reduce delay by 1 hour per train, proposal 7 will reduce delay hours by 52% and proposal 11 will reduce wait times at sidings by 15 minutes per train. Projects 9 and 10 propose new rail services and do not anticipate any capacity issues.

Several issues regarding the capacity and service quality estimates are apparent. First is the lack of a general definition of capacity. Rail capacity is commonly defined in terms of the number of trains per day or amount of delay for a track segment (Kozan and Burdett 2005), although there is no universally accepted method for determining the upper bound for these values (Abril, Barber et al. 2008). While several TCIF project proposals did estimate capacity in terms of trains per day or delay, other TCIF projects used gross tons, TEUs and LOS. By mixing different metrics of rail capacity, especially with those that are best described as service quality measures, it becomes difficult, if not impossible, to determine if and to what extent rail capacity fails to meet rail demand. Rail demand was generally expressed in the more or less standard units of TEUs or carloads, while capacity was expressed in a range of (generally non-comparable) terms including number of trains, gross tons or service quality measures such as LOS and delay. Additionally, while a rail capacity constraint combined with increasing goods movement demand would result in either more goods moving by truck or not moving at all, this is not necessarily true for a reduction in service quality.

The LOS or amount of delay will increase as traffic volumes rise, but according to standard traffic theory, flow rate will also continue to rise until capacity has been reached. For example, although LOS C indicates a greater flow rate than LOS A, it is not until LOS F that capacity is reached. A lower quality of rail service should be expected to shift some goods movement to trucking, but the magnitude of the shift depends on the attributes of the shipments and each shippers preferences. A number of previous studies have explored shipper mode choice using stated preference methods (McGinnis 1989; Abdelwahab 1998; Oum, II et al. 2002; Norojono and Young 2003; Danielis, Marcucci et al. 2005; Witlox and Vandaele 2005; Fowkes 2007) and cost minimization models (Beuthe, Jourquin et al. 2001; Ham, Kim et al. 2005; Hancock and Xu 2005). The mode choice studies generally find that speed and reliability are two of the most important factors while safety and cost are relatively less important. The specific type of commodity and geographic location also play an important role. The proposals which rely on advocating for the project using increase service quality did not conduct any mode choice modeling or reference the large body of literature on this topic to support claims that a poor quality of service would divert *all* future rail demand to trucking.

The TCIF proposals lacked sufficient documentation to support capacity and service quality estimates. Proposals for projects 2-5 and 8 quantified capacity (as the number of trains per day, gross tons per year and TEU per year), but provided little to no detail on how capacity was estimated. In one case, project 4, the capacity estimates were provided directly by the railroad, but lacked any detailed calculations. Railroad capacity, like highway capacity, is a function of many factors including the size of the infrastructure (road or number of tracks), traffic signaling system, mix of vehicle speeds, hills and curves and speeds limits. In some sense, railroad capacity is more complex than highway capacity because it also depends on the location and number of sidings and crossovers which allow traffic to pass each other on the fixed guide-way, the efficiency of each railroad's dispatching and management and the availability of enough locomotive power to move trains at an adequate speed (Kozan and Burdett 2005; Abril, Barber et al. 2008; Weatherford, Willis et al. 2008; Dingler, Lai et al. 2009; Lai and Barkan 2009). Thus, the estimation of railroad capacity is not trivial and is in fact considered a very complex problem (Kozan and Burdett 2005; Abril, Barber et al. 2008; Weatherford, Willis et al. 2008). Similarly, proposals that quantified improvements in service quality were not supported with a description of calculation methods or data. Given the complexity of estimating railroad capacity and the general lack of even basic railroad operating data (Weatherford, Willis et al. 2008), combined with the seemingly ad-hoc approach applied by each TCIF project proposal, the estimates of rail capacity are doubtful and could easily lead to funding unnecessary rail capacity expansions projects. While we argue that the TCIF proposals lacked convincing analysis of rail capacity, the main problem is not necessarily a lack of good judgment but rather the inability of public planners to access better data and modeling tools. Typically, the data and models used to estimate a railroad's capacity are considered confidential business data.

As discussed previously and shown in Figure 4-1, rail capacity is also assumed to remain constant throughout the TCIF project analysis period (generally out to the year 2030). That is, under a no-build scenario rail capacity will remain at today's level indefinitely. While simplifying the analysis, assuming that no new rail capacity will be built over the next 20 years is a very weak if not completely incorrect assumption. The railroads have continuously upgraded their networks to current levels and it is unlikely they will simply stop investing in this development or in maintaining their networks. A recent study commissioned by the American Association of Railroads on railroad capacity and investment needs indicates that U.S. Class I railroads expect to generate $96 billion in revenue to invest in an estimated $135 billion in capital improvements to maintain and improve LOS by 2035 (Cambridge Systematics 2007). One important note is that physically expanding rail infrastructure is not the only way to expand capacity. Improvements in train control and network management driven by advancements in operations research and communications technology can optimize trains to operate more efficiently over the network (Assad 1980; Petersen and Taylor 1982; Kraay, Harker et al. 1991) and potentially provide a more cost effective alternative to infrastructure expansion (McClellan 2006; Abril, Barber et al. 2008). Increases in capacity due to advances in technology should be expected to continue. Positive Train Control (PTC) is one such technology that is expected to increase rail capacity over the next 30 years (Weatherford, Willis et al. 2008).

In short, missing methods and details on capacity and level of service calculations raise the question as to why the railroads would allow demand to exceed capacity where the railroads own the infrastructure or why the railroads are not willing to invest in expansion of public infrastructure to meet their business needs. Railroad revenue does not appear to be a limiting factor. For example, the Union Pacific railroad elected to move forward with a project to increase tunnel clearances allowing double stacked intermodal trains to travel over a shorter route[46] even though TCIF funding was denied. As mentioned above, the railroad industry is expecting to spend $96 billion on infrastructure improvements over the next 20 years. A report by the Congressional Budget Office (CBO 2006) on freight rail capacity issues also finds that U.S. railroads appear to be earning adequate returns on capital investments, though the health of the industry could be further improved though regulatory reform. As discussed in the introduction, there are numerous reasons why the railroads may not invest in the socially optimal level of rail capacity such as unfair subsidies, externalities and market power. However, none of these market failures were

[46] See Union Pacific's press release:
http://www.uprr.com/newsinfo/releases/service/2009/1123_donnerpass.shtml

identified by project proposals. If no serious market failures exist, there would be little reason to believe that a shortage of rail capacity exists now or will in the future.

4.3.3 Latent Demand

Three TCIF proposals argue that the current demand for freight rail is not being met. In other words, there is a latent demand. Increasing port activity is assumed to further increase the latent demand. Two of the proposals are for new inland ports where currently no rail service exists (projects 9 and 10) and the remaining proposal is to expand the capacity of an existing rail corridor by extending a siding (project 11). These projects propose to divert a portion of current truck traffic to freight rail.

The San Joaquin Valley short haul rail proposal (project 9) estimates that there is sufficient demand to start new rail service with one or two trains per day between the Port of Oakland and the inland port at Crow's Landing. The demand projections are based on a market study that considered the amount of containers being shipped between the Port of Oakland and the Central valley and a survey of 60 large shippers asking about their willingness to use the rail service if it offered cost savings. The- survey of shippers found some interest in the proposed rail service provided it could offer service similar to current truck options. However, one of Crow's Landing's consultants[47] cautioned that the survey results are not conclusive. While the survey indicates interest in having the rail option available, this does not necessarily signal a commitment to use it. The survey along with a cost model developed by the project developer and updated by Global Insight indicated that rail rates would have to be subsidized to attract shippers. It is unclear how long and how large of a subsidy would be required. Global Insight's cost model indicates subsidies ranging from a few hundred thousand dollars per year to over $2 million per year for the first 10 years. A previous study of the short haul rail market potential for the Central Valley, also referenced in the proposal, found that subsidies of several million dollars a year

[47] Global Insight reviewed the Crow's Landing short haul rail market study. The report is available at the Crows Landing website: http://www.crowsbizpark.biz/Short%20Haul%20Rail%20and%20Analysis.pdf

would be required indefinitely (Tioga 2003). The proposal calls for initial service starting with 1 train per day increasing to 6 trains per day by 2020.

The Shafter Intermodal proposal (project 6) appears to simply assume that due to highway and port congestion, particularly at the ports of LALB, and forecasts of increasing trade, there will be demand for its short haul rail service. The proposal involves diverting containership traffic from the port of LALB to the Port of Oakland, then moving the containers 315 miles from Oakland to Shafter using a new short haul rail service. Once in Shafter, the containers will be placed back on trucks and shipped 93 miles to Los Angeles (Figure 4-5). The proposal also notes that a significant volume of traffic from the Port of Oakland currently passes through the valley by truck for destinations in Los Angeles. Only a cursory market analysis appears to have been conducted. No cost estimates have been made, nor have shipper preferences been surveyed. Additionally, a report that describes the market potential of the proposal notes that operating subsidies of an unspecified amount will be required initially until a sufficient market is developed based on analysis completed for similar proposals (LECG 2004). The proposal calls for diverting 600 truck trips per day to 2 train trips; there are no estimates of growth potential.

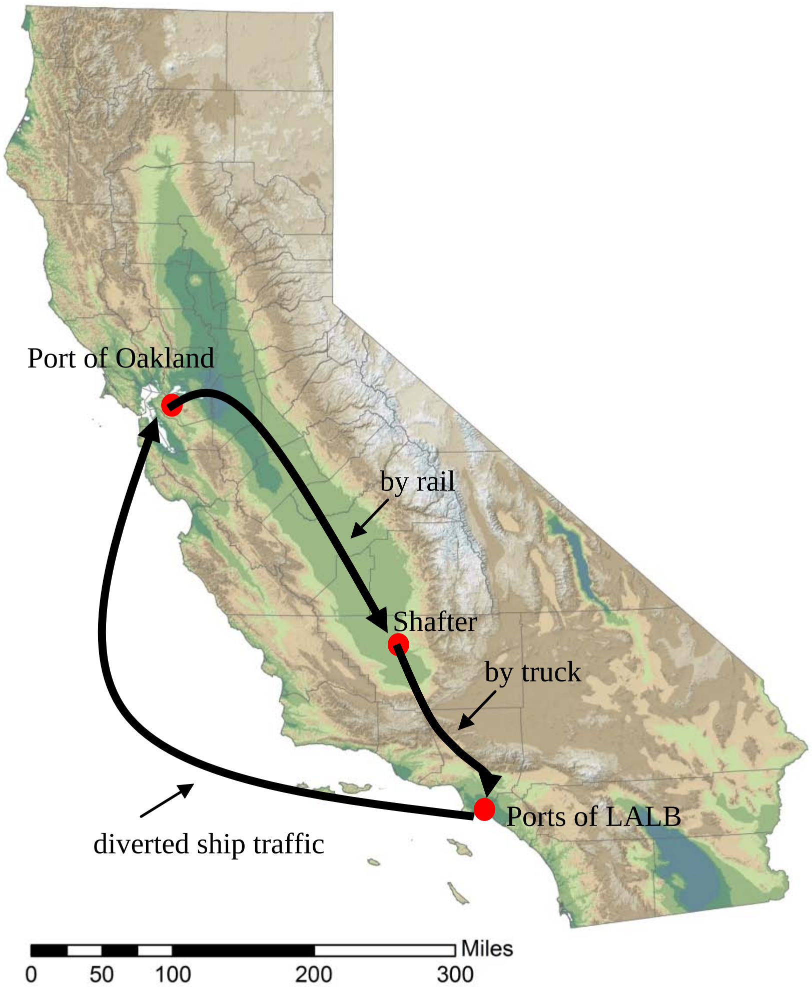


Figure 4-5 Schematic of Shafter short haul rail proposal

Finally, project 11 proposes expanding the capacity of an existing and currently in-use rail corridor to accommodate an existing demand for 5 more freight trains per day. Capacity is expanded by extending a siding to allow passenger trains which have priority to pass slower moving freight trains. No details are provided about how the latent freight rail demand was estimated.

It is difficult to determine the actual modal diversion that could be expected from these projects. For the two projects that propose to shift truck traffic to rail by starting new short haul rail services, a convincing market analysis that identifies shipper preferences and then models the mode choice decision is lacking. A rigorous analysis is especially important given the expected need for operating subsidies on top of the TCIF infrastructure subsidies which challenges the claim of unmet demand. Absolutely no information was provided about the estimated additional demand of 5 trains per day in the proposal for project 11. Similar to the other TCIF proposals, market failures that would explain why private firms or railroads are not willing to expand capacity or offer similar services to those proposed are not identified. Identifying the existence of any market failures would strengthen the case for subsidies.

4.3.4 Estimating Public Benefits

As we noted earlier, two of the main public benefits expected by the project sponsors from these TCIF projects are reductions in highway congestion and improvements in air quality. Reductions in highway congestion were not directly estimated by the TCIF proposals, rather reductions in truck trips and VMT resulting from a mode shift to rail were considered. Air quality improvements were generally quantified as the difference in emissions of air pollutants between the TCIF project alternative and the no-build scenario. Under the no-build scenario all emissions were produced by trucks. Under the TCIF project alternative emission reductions were calculated as the difference between the no-build truck emissions and the emissions produced by additional train trips.

4.3.4.1 Highway Congestion Relief

Diverting truck trips to rail is expected to reduce the number of truck trips and truck VMT, providing some highway congestion relief. The TCIF proposals did not calculate the magnitude of congestion relief, for example improvements in LOS or reduced delay, even though these are the standard metrics by which the benefits of highway projects are typically evaluated (TRB 2000). Truck trip reductions reported by the proposal were derived from the previously discussed demand forecasts. All future rail demand was assumed to travel by truck under the no-build scenario for all proposals. Under the TCIF project alternative, the reduction in truck trips was estimated by converting the forecasted rail demand into truck trips using various conversion factors. There is no standard method for making these conversions and as a result each proposal appears to have taken a different approach (a few proposals did not discuss how these conversion were made) (Table 4-5).

4-5 Estimated TCIF project truck trip reductions and truck to rail conversion assumptions

Project ID	Truck trip reduction *million trips/yr*	Truck to rail conversion assumptions
1	0	increasing congestion does not result in mode shift to trucks
2	1.44	520 containers are moved by either 750 trucks or 1 train
3	0.67	15 gross tons freight rail per TEU, 2 TEU per truck trip
4	1.12	none provided
5	0.05	none provided
6	9.9	none provided
7	4.3	none provided
8	0.03	3.3 truck trips per mixed carload, 2 truck trips per intermodal carload, no information on carloads per train
9	0.88	115 containers per train trip, no information on truck trips per container
10	0.22	300 trucks per train trip
11	0.33	2 TEU per truck trip, no information on TEU per train

For example, the proposal for project 2 converted the Port of Oakland's container throughput forecast of 2 million containers per year to 2.9 million truck trips by assuming 1 train carries 520 containers and 750 trucks carry the containers moved by 1 train. The ratio of truck trips to containers is greater than one to account for extra trips required to reposition truck trailer chassis and complete empty back hauls. These conversion factors were obtained from a report detailing the design of the new intermodal terminal (Parsons/JWD 2007); however, that report does not discuss how the conversions were estimated. The same conversion factors were also used in a study for the ports of LALB (PARSONS 2006), suggesting that they are not specific to any particular project. The proposal for project 3 converts a freight rail demand forecast of 20,000,000 additional gross tons per year to 1,333,000TEU, then assuming 2TEU per truck, 666,555 truck trips are estimated. No data or references are provided to support these conversions. The proposal for project 8 converts the expected demand for 2 additional trains per day to rail carloads and then converts the carloads to truck trips. The conversion from rail carloads to trucks is based on the ratio of the average net weight of cargo carried by one truck to one rail car. Based on data obtained from a study of rail transportation in the state of Washington[48] and the rail way bill sample, a ratio of 3.3 truck trips per rail carload was found; for intermodal containers a ratio of 2 truck trips per carload was assumed. No information is provided about how many rail cars make up the 2 additional trains. The proposal for project 11 converts a forecast of 5 additional intermodal trains per day to truck trips by assuming 2TEU per truck; however, the proposal does not state how many TEU the 5 additional trains are expected to carry.

The proposals for projects 9 and 10, which add new infrastructure to meet a latent demand, estimated the number of truck trips that could be shifted to rail based on market studies as previously discussed. Proposals 9 and 10 estimate that 2,400 and 600 truck trips per day could be shifted to rail respectively. Lastly, the proposals for projects 4 and 7 do not describe how reductions in truck trips were calculated; noting only that estimates were made by a consultant.

The reduction in truck VMT is estimated by multiplying the average truck trip distance by the number of truck trips shifted to rail. For projects 2, 5, 6, 8, and 11, the truck trip distance was estimated based on the shortest truck route between the origin and destinations (ports, border crossings and intermodal facilities). The method used for project 4 was more detailed. Truck VMT was estimated by running a truck travel demand model with and without the diverted truck trips. The method used for project 10 was the most simple, assuming that truck and train distances were equivalent. It is unclear how the distances were estimated. Finally, no information was available about how VMT was estimated for projects 3, 4 and 7.

[48] No reference was provided

The various methods used by each proposal for estimating rail demand, rail capacity, the equivalency of a truck trip to rail trip and comparable truck and rail route distances add to the uncertainty of each proposal's estimates of reduced truck trips and VMT. For example, different methods of converting rail demand to truck trips will lead to different values. Many conversions did not account for extra truck trips that may be required to reposition equipment and account for empty backhauls. It is unclear how many extra trips should be expected; to some extent, freight rail faces similar issues of equipment positioning and imbalances in the flow of goods. Different methods for determining truck VMT will also lead to different results. However, the different methods used to forecast freight rail demand are likely the largest source of uncertainty.

Estimating the truck trips and corresponding truck VMT diverted to rail may also be a poor proxy for highway congestion improvement. There is some evidence that truck traffic tends to avoid morning and even peak hour congestion (Woudsma 2001). If truck traffic reductions occur during off-peak times, then there will be little congestion relief. Taking the additional step of running a travel demand model that has the ability to model truck trips would provide more useful congestion metrics such as LOS and delay by time of day. However, removing truck trips from the highway also effectively increases highway capacity and reduces travel time, therefore inducing additional vehicle trips (Goodwin 1996; Hansen and Huang 1997; Noland 2001; Cervero 2002). The magnitude of induced demand is uncertain (Mokhtarian, Samaniego et al. 2002; Cervero 2003), but should be expected to offset some capacity gains.

4.3.4.2 Air Pollutant Emission Reduction

Mobile source air pollutant emissions are generally modeled by multiplying a measure of vehicle activity by an emission factor. The method for trucks is fairly standard; every proposal used the California Air Resource Board’s EMFAC model[49] which provides gram per mile emission factors. The EMFAC model requires the user to select an analysis year, geographic

[49] EMFAC is freely available from CARB’s website: http://www.arb.ca.gov/msei/onroad/latest_version.htm

region and season at a minimum. Users may also enter more detailed information depending on data availability such as custom vehicle speed distributions. However, none of the TCIF proposals provided a complete description of which parameters were input or selected to run EMFAC. Emission estimates are produced by multiplying the EMFAC emission factors by the truck VMT estimates previously discussed.

In comparison, no standard method or modeling software exists for locomotives though several reports are available that provide guidance (Ireson, Germer et al. ; Battele 1973; BAH 1991a; BAH 1992; EPA 1992; CARB 2004; Caretto 2004a; ERG 2005; Billings, Chang et al. 2006). Not surprisingly, a variety of methods were used to estimate locomotive emissions. Table 4-3 describes how activity was calculated and the source of the corresponding emission factors for the TCIF proposals that provided this information.

Table 4-6 Locomotive air pollutant emission calculation methods

TCIF Project	Activity Measure	Calculation
2	$fuel\ consumption\left(\frac{gal}{yr}\right)$	$= rail\ traffic\left(\frac{containers}{yr}\right) \times distance(mi) \times weight\left(\frac{ton}{container}\right) \times fuel\ intensity\left(\frac{gal}{revenue\ ton-mile}\right)$
3	$container\ traffic\left(\frac{TEU-miles}{yr}\right)$	$= rail\ traffic\left(\frac{gross\ ton}{yr}\right) \times \left(\frac{TEU}{gross\ ton}\right) \times distance(mi)$
9	$power\left(\frac{hp}{yr}\right)$	$= rail\ traffic\ \left(\frac{train\ trips}{yr}\right) \times travel\ time\left(\frac{hr}{trip}\right) \times ave.power\left(\frac{hp}{hr}\right)$
10	$freight\ traffic\left(\frac{ton-miles}{yr}\right)$	*unspecified*
5	$fuel\ consumption\left(\frac{gal}{yr}\right)$	$= rail\ traffic\ \left(\frac{train\ trips}{yr}\right) \times \left(\frac{loco.}{train}\right) \times distance(mi) \times speed\left(\frac{mi}{hr}\right) \times fuel\ rate\left(\frac{gal}{hr}\right)$
	Emission Factor	**Source**
2	$time\ based\left(\frac{g}{hr}\right)$	*locomotive test data, test data source unspecified*
3	net rail advantage $\left(\frac{\left(\frac{g}{mi}\right)}{TEU}\right)$	*unspecified*
9	$power\ based\left(\frac{g}{bhp-hr}\right)$	*EPA Tier 4 Locomotive Emission Standards*
10	*Unspecified*	*OFFROAD 2007*
5	$fuel\ based\left(\frac{g}{gal}\right)$	*EPA 2020 in-use estimated locomotive emission rates (EPA, 1997)*

The main challenge in estimating locomotive emissions appears to be converting train activity into a form that can be used with the available emission factors. Locomotive emission factors are generally available in terms of fuel consumption, locomotive operating hours or locomotive power consumption while train activity was forecasted as the annual number of train trips or amount of gross tons or TEUs transported. In making the required conversions, the calculations in each proposal depend on various assumptions.

For example, in project 2, the conversion of shipping containers to fuel consumption requires estimates of the average weight of a shipping container and intermodal train fuel intensity, assumed to be 11.79 tons and 2.41 gallons per 1,000 ton-miles respectively. No reference or supporting information was provided for the average weight of a shipping container. The fuel intensity is the system-wide average for the BNSF and UP railroads. Project 3 converts gross tons to containers, implying that some conversion rate was assumed; however, no information was provided about the conversion. The conversion of train trips to power consumption for project 9 requires estimates of average train travel time and hourly power consumption, estimated to be 3.3 hours and 1,206 hp-hr respectively. These values were derived from train energy modeling, no further details were provided. No information was provided to support the conversion of train trips to ton-miles in project 10. Finally, the conversion from train trips to fuel consumption in project 5 requires assumptions about the number of locomotives per train, train speed and the locomotive hourly fuel consumption rate, assumed to be 4 locomotives, 50 mph and 110 gallons per hour respectively. The number of locomotives per train appear to have been provided by the BNSF railroad while the estimate of train speed and fuel consumption were provided by Caltrans.

The approaches used by each proposal in Table 4-3 are reasonable in that given the correct parameter values the calculations would result in an accurate conversion. In contrast to highway and traffic studies, however, there are no standard reference sources or calculation procedures for most of the required parameter values. Generally, each proposal made different assumptions, and many of these were unsupported by either data or reference to a reputable source. In at least one case the analysis notes that the parameters may be inaccurate; the analysis for project 5[50] states that estimates of train speed and hourly fuel consumption were not verified

[50] Details about the locomotive emission calculations are provided in appendix 3.3-A of the project's EIR completed in September 2007.

with the railroad that operates those trains. It is unclear how train speed or fuel consumption were estimated or if the values were borrowed from elsewhere.

The system-wide average fuel intensity used in the analysis of project 2 is also a concern. Approximately 50% of the BNSF's and UP's rail activity measured as ton-miles is moving coal in unit trains while just 10% is due to intermodal trains (AAR 2001). Unit coal trains are generally extremely fuel efficient while intermodal trains are the least efficient (see chapters 2 and 3). The system-wide average likely under estimates intermodal train fuel consumption.

The next step in estimating locomotive emissions is determining which emission factors to use. There are two main sources of emission factors: either estimates developed by EPA that are designed to represent the national locomotive fleet and account for EPA locomotive emission standards (EPA 2009), or emission test data that are available for some specific makes and models of locomotives (SwRI 1972; BAH 1991a; Fritz and Cataldi 1991; Fritz 1995; Fritz 2000; Smith, Sneed et al. 2006).

Each project proposal took a different approach to selecting emission factors. For project 2, locomotive test data were used with information provided by the railroads to develop emission factors tailored to the specific fleet of locomotives operating to and from the Port of Oakland. The sources of these emission test data were not specified, but they appear to be from the sources referenced above. No information was provided about the gram per mile per TEU "net rail advantage" emission factors used by project 3. Project 9 used EPA tier 4 locomotive emission standards, rather than EPA's emission factors. Project 10 claims to have used emission factors from CARB's OFFROAD 2007 emission factor; however, OFFROAD 2007 does not provide locomotive emission factors. Project 5 uses EPA's average locomotive emission factors.

The concerns about emission factors are in many ways similar to those discussed for the activity conversions. Mainly, there was a lack of supporting information describing how emission factors were chosen or where emission factor data were obtained. This is particularly concerning with regards to projects 3 and 10. A search of the rail literature and recent modeling studies did not reveal any previous estimates of a “net rail advantage” per TEU and it is completely unclear which emission factors were obtained from the OFFROAD 2007 model since OFFROAD does not contain any locomotive emission factors.

There are also two flaws in the approach used by project 9. The underlying assumption in the analysis is that the entire fleet of locomotives will meet EPA tier 4 locomotive emission standards by 2016. This is very unlikely since the standard only affects new locomotives manufactured after 2015, implying that the railroad will upgrade its entire fleet of locomotives in just one year. Locomotives have long lifetimes (over 30 years) and are fairly expensive; therefore, it is much more likely that the railroad will continue to use its current fleet of locomotive in 2016 and gradually replace fleet over time. The analysis for project 9 also suffers from using regulatory emission standards as emission factors. The EPA estimates that manufacturers generally design locomotives with a 10% compliance margin (EPA 2008b). Using the regulatory standards will therefore over estimate emissions. A final concern involves the use of individual locomotive test data. Individual locomotive test data are attractive since project specific emission factors can be developed; however, they are potentially subject to a large degree of error. Much of the currently available locomotive test data has been derived from just a single test on a single locomotive (see section 2.2.2.3). The small number of tests performed on each locomotive and limited population of locomotives tested almost certainly result in large errors and significant uncertainty.

Table 4-4 compares the emission factors for the three proposals that provided them. The emission factors vary because of the differences in data sources and assumptions as was explained. The values in the table show that the different assumptions can have a large affect on the emission factors, which will in turn have a large affect on the calculation of locomotive emissions. For example, the emission factors used for project 9 are just 1/6th and 1/8th the value of those estimated by EPA for NO_X and PM10, respectively, which were used in project 5. The emission factors derived from individual locomotive test data used in project 2 are also significantly smaller than EPA's.

Table 4-7 Comparison of locomotive emission factors

Project ID	**NO_X** ***g/gal***	**PM_{10}** ***g/gal***	**CO_2** ***g/gal***
2	104	1.36	10,268
9	23[a]	0.62[a]	10,070[b]
5	136.9	4.8	10,115[b]

[a]NO_X and PM_{10} emission factors converted from g/bhp-hr to g/gal using EPA's recommended conversion factor of 20.8 bhp-hr/gal (EPA 1997).
[b]CO_2 emission factor converted from lb/gal to g/gal

It is also interesting to note that although the differences in the estimated CO_2 emission rates for locomotives are relatively small, they should actually not vary at all since they are not impacted by the particular locomotive fleet or operating conditions, but are a function of fuel properties. According to EPA[51] a gallon of diesel fuel produces 10,084 grams of CO_2.

4.3.5 Analysis of Air Pollutant Emission Reductions

Section 4.3.4 described how truck trip, truck VMT and air pollutant emissions were calculated to support the TCIF proposals. About half of the proposals and their supporting documents did not contain enough detail to determine how these calculations were made. For the projects that did provide some details, a number of concerns were raised about the use of unsupported assumptions, modeling and data provided by consultants and the railroads, the details of which were not provided, and flawed methodologies. The result is that many estimates of reduced truck travel and reduced air pollutant emissions are at best unreliable and at worst clearly wrong. The accuracy of these estimates is analyzed further by comparing the emissions reductions reported in the TCIF proposals to an estimated range of plausible emission reductions based on the best available data.

[51] http://www.epa.gov/oms/climate/420f05001.htm

One of the main difficulties in quantifying the air pollutant benefits of a modal shift from trucks to rail or evaluating the plausibility of such estimates, is that emission rates for each mode are often expressed in units that are not directly comparable. This is why so many conversions were required in each TCIF proposal. To help evaluate the emission reductions claimed by the TCIF proposals, truck and locomotive emission factors are converted to a common basis so that they can be directly compared and the relative benefit of replacing truck trips with trains can be estimated.

Truck and locomotive emission factors are typically expressed in terms of grams per mile, gallon or brake horsepower hours. To make a fair comparison requires accounting for the differing fuel efficiency of each mode, we converted the emission factors to a grams per ton-miles basis as shown by equations 4-1 and 4-2,

$$EF_{truck}\left(\frac{g}{ton-mile}\right) = EF_{EMFAC}\left(\frac{g}{mi}\right) \times FE_{truck}\left(\frac{mi}{gal}\right) \times \frac{1}{Eff_{truck}\left(\frac{ton-mile}{gal}\right)} \qquad \textbf{eq 4-1}$$

where;
EF_{truck} = calculated average heavy-duty diesel truck gram per ton-mile emission factor
EF_{EMFAC} = California state-wide average heavy-duty diesel truck gram per mile emission factor from EMFAC 2007
FE_{truck} = California state-wide average heavy-duty diesel truck miles per gallon fuel economy from EMFAC 2007
Eff_{truck} = average heavy-duty truck ton-mile per gallon fuel efficiency

$$EF_{train}\left(\frac{g}{ton-mile}\right) = EF_{EPA}\left(\frac{g}{gal}\right) \times \frac{1}{Eff_{train}\left(\frac{ton-mile}{gal}\right)} \qquad \textbf{eq 4-2}$$

where;
EF_{train} = calculated average intermodal train gram per ton-mile emission factor
EF_{EPA} = EPA U.S. average locomotive gram per gallon emission factor
Eff_{train} = average train ton-mile per gallon fuel efficiency

Using equation 4-1, we converted the heavy-duty diesel truck emission factors from EMFAC for the years 2010 (16.2 g/mi NO_X and 0.66 g/mi PM10) and 2030 (3.6 g/mi NO_X and 0.11 g/mi PM10) to a ton-mile basis. We assumed heavy-duty diesel truck fuel economy, EF_{truck}, is 5.3 mi/gal based on output from EMFAC 2007. Heavy-duty truck fuel efficiency, Eff_{truck}, was obtained from a recent FRA study which compared the fuel efficiency of moving freight by trucks and rail over 23 competitive routes (FRA 2009). The FRA study found that trucks achieved 68 to 133 ton-miles/gal over the routes.

Similarly, using equation 4-2, we also converted locomotive emission factors from EPA (EPA 2009) for the year 2010 (157 g/gal NO_X and 4.7 g/gal PM10) and 2030 (53 g/gal NO_X and 1 g/gal PM) to a ton-mile basis. Locomotive fuel efficiency, Eff_{train}, was also obtained from the FRA study, which found a range of values from 156 to 512 ton-miles/gal. Our standardized emission factors for trucks and trains are shown in Figure 4-6.

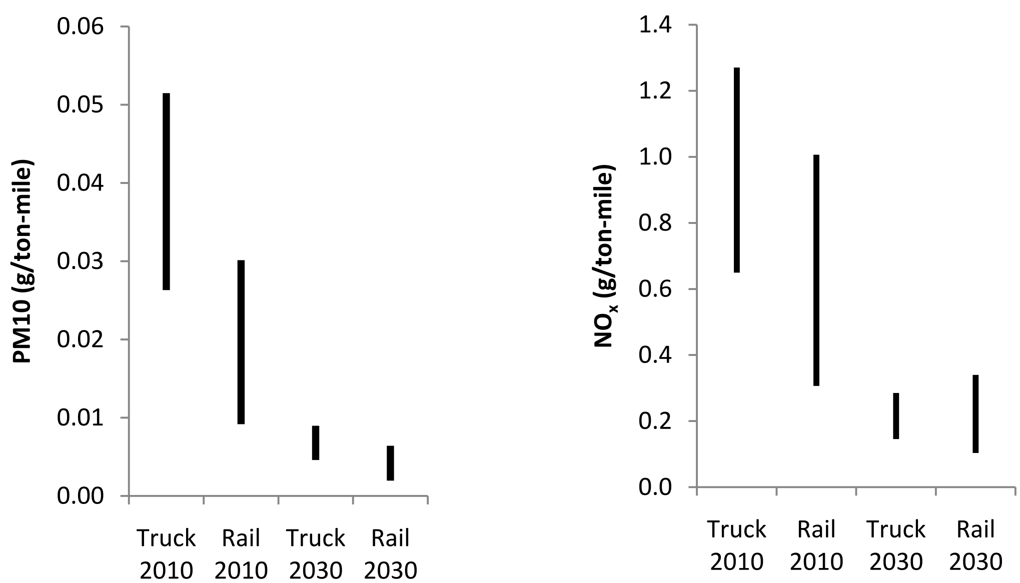


Figure 4-6 Comparison of the range of EPA U.S. average line-haul locomotive emission factors and EMFAC California average heavy duty diesel truck emission factors on a ton-mile basis for the years 2010 and 2030

The comparisons in Figure 4-6 challenge the common perception that freight trains offer a cleaner alternative to trucking in the forecasted build year. While this may be generally true for PM10 emissions, it is not for NO_X emissions. Where trucking does offer a cleaner alternative, the margins are not necessarily large. For PM10 emissions, the most efficient truck movements produce similar emission rates as the least efficient train movements. For NO_X, a large range of truck and rail movements produce similar emission rates. By 2030, the penetration of new trucks into the in-use fleet, which must meet relatively more stringent emission standards than locomotives, results in goods movement by trucks and trains achieving similar emission rates. Comparing the difference in emission rates on a route by route basis for all 23 routes in the FRA study, using equations 4-1 and 4-2 and the year 2030 emission factors cited above, reveals that trucks emit 1.2 to 3.3 times more PM10 emissions than trains when traveling the same routes and carry the same type and amount of cargo. For NO_X emissions the results are more varied; the range extends from trains emitting 1.4 times more NO_X than trucks to trucks emitting 2 times more NO_X than trains, depending on the route and commodities. While criteria emission rates are somewhat similar between trucks and trains, the FRA study does indicate that trains are always more fuel efficient than trucks and therefore are expected to emit relatively less CO_2 emissions.

The maximum emission reduction possible from diverting truck trips to train trips is the amount emissions that would have been produced by the trucks had they not been diverted. In other words, the emission reductions gained by replacing truck travel with rail can never be greater than those from just eliminating truck travel. Actual emission reductions will be less because truck trips are replaced by train trips which also produce emissions. In Figure 4-7 the net emission reductions from diverting truck traffic to rail as reported by each TCIF proposal for the year 2030 is plotted against the reported reduction in truck VMT (these values are provided in Table 4-2). Also shown are three lines. The dashed line labeled “max” represents an estimate of the maximum emission reduction possible from replacing truck trips with train trips. The line is produced by equation 4-3,

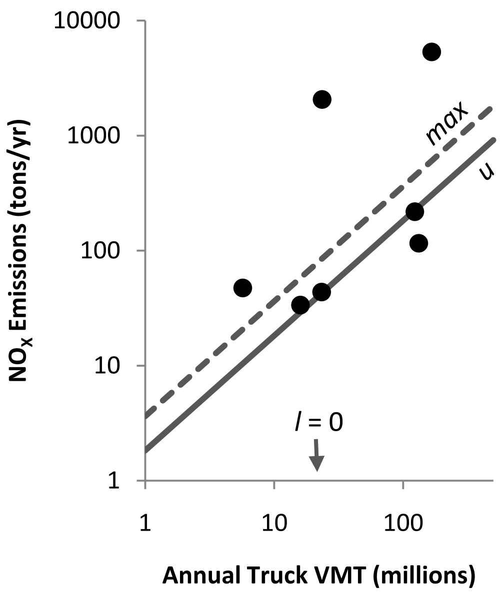
$$max\left(\frac{tons}{yr}\right) = truck\ VMT\left(\frac{mi}{yr}\right) \times truck\ emission\ factor\left(\frac{g}{mi}\right) \times \frac{1}{1.1023\times10^{-6}} \qquad \textbf{eq 4-3}$$

where, truck VMT is truck travel diverted to rail, the truck emission factor is the state-wide average heavy-duty diesel truck emission rate for the year 2030 from EMFAC 2007 and the last value is the conversion from grams to tons. The two solid lines, produced by equations 4-4 and 4-5, enclose the area where the plotted data points are expected to be located,

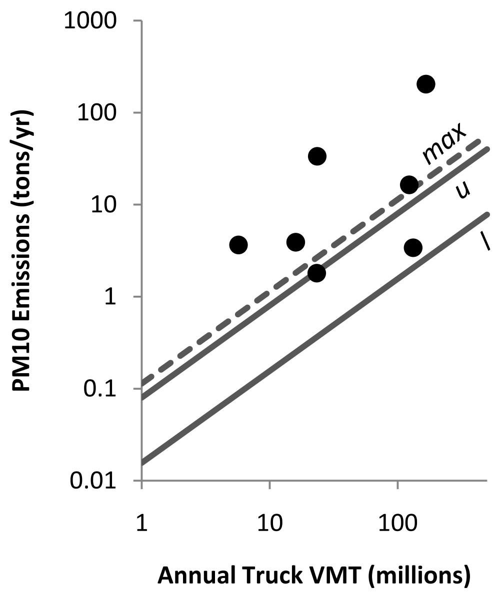
$$upper\ bound\left(\frac{tons}{yr}\right) = \frac{max\left(\frac{tons}{yr}\right)}{R_{max}} \qquad \textbf{eq 4-4}$$

$$lower\ bound\left(\frac{tons}{yr}\right) = \frac{max\left(\frac{tons}{yr}\right)}{R_{min}} \qquad \textbf{eq 4-5}$$

where; *max* is the value from eq 4-3, R_{max} is the maximum ratio of truck emissions to rail emissions as reported above (2 for NO_X and 3.3 for PM10) and similarly R_{min} is the minimum ratio of truck emission to rail emissions (0 for NO_X and 1.2 for PM10). The region between these two lines provides the expected emission reduction from diverting a given amount of truck VMT to freight rail based on FRA's analysis of truck and train fuel efficiency, EPA's locomotive emission factors and California average heavy-duty diesel truck emission factors from the EMFAC 2007 model.



(a)



(b)

Figure 4-7 Plots of reported TCIF project annual truck VMT replaced with freight rail by annual (a) NO_X emission reductions and (b) PM10 emission reductions where *u* = upper bound and *l* = lower bound.

The plots in Figure 4-7 suggest that many the TCIF proposals have likely overestimated emission reductions. We would expect the data points to fall between the two solid lines and certainly not above the max line. The data points should also form a relatively straight line since the marginal effect of replacing one mile of truck travel with rail should be roughly equal across projects. As Figure 4-7 indicates, several of the estimates are suspiciously large, falling above the predicted maximum, and even 10 times the predicted maximum, and there is wide range of marginal impacts since the points are scattered. Note that the axes are on a log scale.

Some of this variation is expected. Different distances between truck and rail routes could move the estimates up or down, but no estimate should ever appear above the max line in Figure 4-7. Rail and highway distances should be similar for each of these projects since the major rail corridors parallel most of the major highway routes in California. Additionally, truck emission factors vary between regions due to differences in truck fleets, congestion and climate;

locomotive emission factors should also be expected to vary depending on local factors. However, regional difference in emission factors should not result in such large over predictions. Comparing the statewide EMFAC emission factors to those estimated for the San Joaquin Valley, San Francisco Bay Area and South Coast shows small variations. NO_X emission factors vary by no more than ± 1% of the statewide value and PM10 emission factors vary from -16% to +12% of the statewide value.

These apparent errors could be caused by errors in the conversion of rail activity to truck activity, the conversion of rail activity to a form useful for estimating emissions or in the selection of particular locomotive emission factors as previously discussed. The results in Figure 4-7 are likely a combination of all these factors.

4.1 Summary and Conclusions

Proposals to expand freight rail capacity as a means to reduce truck traffic have seen significant gains in popularity with public planners and policymakers. At least one study (Bryan, Weisbrod et al. 2007) has provided examples and guidance for selecting the types of freight rail infrastructure projects where public involvement could provide public benefits. Additional studies have advocated for a greater public role in expanding freight rail infrastructure (Resor and Blaze 2004; Gorman 2008). However, some have questioned this approach (TRB 1996; TRB 1998; TRB 2003), suggesting that correcting market failures by instituting more rational pricing policies and adopting taxes, fees or standards for reducing pollutant externalities offers the best solution.

While there is general consensus that a more rational approach to pricing transportation would solve many transportation related problems, the main argument against this is that it is considered politically difficult if not completely infeasible. While funding new projects may be relatively easier than rationalizing pricing, there are serious concerns about the ability of public planners and policymakers to select beneficial and cost effective freight rail projects. Due to a long history of planning almost exclusively for passenger transportation, and the fact that many goods movement data are confidential, public planners and policymakers may simply lack the requisite technical information, skills, and modeling tools to effectively plan for goods movement. While Bryan, Weisbrod et al (2007) provide useful guidance on strategies to select beneficial freight rail projects, they do not consider whether or not public planning and transportation agencies have the technical ability or sufficient access to data to carry out the recommended analyses.

To fill this gap, this case study retrospectively examined California's TCIF program which has the objective of reducing highway congestion and air pollutant emissions from increasing levels of goods movement though infrastructure investments. Eleven TCIF projects were submitted for review, all proposing to expand freight rail infrastructure owned or used by private railroads. The main findings of this study are that the analysis and calculations performed to support the need for each project and the expected magnitude of public benefits, in this case reductions in highway congestion and air pollutant emissions, are questionable and in some cases plainly incorrect (Table 4-8). These findings support our hypothesis that public planning and transportation agencies may not have the necessary data, tools and expertise to select beneficial and cost effective private goods movement infrastructure projects.

4-8 Summary of the main TCIF project public benefit analysis flaws

Analysis steps	Main Problems	Magnitude
Rail demand forecast	- forecast uncertainty	serious
	- unsupported growth rate assumptions	serious
Rail capacity forecast	- baseline assumes no expansion through 2035	very serious
	- calculation methods are not provided	moderate
	- calculations are performed by the railroad, methods not provided	minor
	- no standard definition of rail capacity	moderate
Mode shift	- lack of documentation for truck trip to rail trip conversions	moderate
	- different methods for comparing route distances	minor
Air quality benefits	- use of inappropriate locomotive emission factors	serious
	- unsupported assumptions in rail activity calculations	moderate

Specifically, we show that goods movement demand growth estimates proposed by the submitters were highly uncertain; results were unacceptably influenced by methods and underlying assumptions used to complete the calculations. Many of the forecasts were nothing more than a continuation of past trends or were simply unsupported by any analysis or data. We also showed that the demand forecasts are crucial to the argument that the project is needed and for estimating the projects expected benefits: reductions in truck traffic and air pollutant emissions. The general assumption made by the proposers was that growing demand combined with a freight rail capacity shortage would lead to more goods moving by truck. In some cases proposers argued that too many goods are currently moving by truck due to the lack of freight rail infrastructure. In either case, rail capacity was assumed to remain constant under the no-build scenario while demand continued to rise. The assumption of constant rail capacity under the no-build scenario is clearly flawed, and no justification for this assumption was provided by any of the proposals. Railroads have been continuously investing in their infrastructure so rail capacity should be expected to increase over time. It was also shown that at least one project denied TCIF funding has been privately built.

A more plausible argument is that demand for rail capacity is growing faster than supply. To support this argument rail demand and capacity should be modeled in similar terms (i.e., ton-miles or containers) so that the two can be directly compared. Since the demand and supply forecasts are likely very uncertain, care should also be taken to express the uncertainty in the analysis. This can be accomplished by considering several plausible growth scenarios; for example, using each of the growth projections available for the ports of LALB or considering both linear and exponential growth trends for the Port of Oakland. If the argument holds up under each scenario that demand will exceed capacity, there will be greater confidence that something needs to be done. The analysis should also identify the root cause of any current or projected capacity shortfall. If a case can be made that a particular market failure exists, the main reason for a shortage of rail capacity, this provides additional support to the argument that demand may exceed capacity, but more importantly also provides additional options for solutions.

Given the difficulties and uncertainties in forecasting freight rail supply and demand, public planners and transportation agencies may be better off considering alternatives other than directly subsidizing freight rail infrastructure. If the cause of the expected shortage in rail capacity can be identified, which it should be in order to support the expenditure of public funds, the planner or agency may be able to correct the problem. For example, in many TCIF proposals it was claimed that trucks disproportionately add to highway congestion and maintenance costs considering the amount of taxes and fees they pay. However, a number of cost allocation studies (Balducci and Stowers 2008) have been conducted that estimate the implied subsidy that different classes of vehicles receive. It therefore seems relatively simple to eliminate the subsidy to trucks by increasing fees rather than attempting to counter the subsidy by building more freight rail infrastructure. Another reason given for subsidizing freight rail is that it is generally less polluting than trucking. However, it was shown that increasingly stringent vehicle emission standards are closing the gap between emissions of air pollutants from trucks and rail making this argument less relevant.

Vehicle emission standards also offer a much more certain environmental benefit than building more rail infrastructure. If we assume compliance, we know that emissions will be reduced below a scenario where no standards are adopted. By comparison, this case study has suggested that we know very little about the emission reductions expected from expanding freight rail capacity. Freight rail does offer a clear environmental benefit when considering CO_2 emissions; however, alternative policy solutions such as carbon cap and trade or carbon taxes would likely be much more efficient (Ellerman 2000; Stavins 2003; Tietenberg 2003) and may be available very soon. California has adopted climate change legislation (AB32, which became law in 2006) which sets a target of reducing greenhouse gas emissions to 1990 levels by 2020 and 80% below 1990 levels by 2050. A carbon cap and trade program is being considered to help achieve these reductions. If the cap and trade system is applied to transportation fuels, they should begin to internalize the cost of CO_2 emissions, resulting in a more optimal distribution and level of goods movement by truck and freight rail. The monopoly position of most railroads could also cause a shortage of rail capacity; however, this does not seem to be the case for the TCIF projects. In most cases both the UP and BNSF railroads provide service to each region or port and are engaged in direct competition with trucking firms for the movement of containerized merchandise. Finally, every option except for expanding infrastructure offers the option to adjust the policy over time or eliminate it altogether. While it may be difficult in practice to continually adjust taxes, fees and standards to achieve the desired public policy goals, it offers a degree of safety in the event that serious errors were made in adopting the policies.

Regardless of the policy solution adopted, there is likely a need to calculate the relative benefits of more goods moving by rail. The case study found that a variety of ad-hoc approaches, some which were clearly flawed, were used to estimate the equivalency of truck trips to train trips and calculate locomotive emissions. It was also shown that most of the estimated emission reductions from the assumed diversion of truck trips to freight rail were inconsistent with our best estimates. The errors are not necessarily a result of poor judgment or biased agendas. Many of the problems result from the lack of data available to local and regional planning agencies and absence widely recognized methods for making the calculations. These findings point to the need for development of a standardized approach to evaluate the benefits of modal shifts from truck to freight rail.

Adopting a standard locomotive emission modeling framework, such as that developed in chapter 3, would streamline the locomotive emission modeling process much in the way EPA's MOBILE6 model and CARB's EMFAC model have for highway vehicles. The challenge will be adopting standards for reporting rail activity. For example, highway vehicle activity is almost always reported as VMT. Gram per mile emission factors and mile per gallon fuel efficiency estimates are widely available for making calculations. Similar standards do not exist for rail. The TCIF projects reported activity as the number of containers transported, gross tons of train traffic, train trips, TEUs or carloads. None of these are very useful for estimating emissions or fuel consumption which are generally available in terms of grams per gallon, brake horse-power hours per gallon and ton-miles per gallon. The general lack of data and inconsistent use of metrics is probably a result of federal laws which pre-empt states or other regional agencies from regulating railroads, therefore limiting their ability to request data. Adopting a standard locomotive modeling framework should lead to more standardized rail activity data. Converting truck and rail emission factors to a comparable basis, as described previously, offers a useful method for screening the relative air quality benefits of replacing trucks with trains.

5 SUMMARY AND CONCLUSIONS

This dissertation has filled some important gaps in transportation planning and modeling. A new spatially detailed locomotive emission model was developed for California. The new model is based on a new framework which allows modelers to produce much more detailed locomotive emission estimates compared to the options currently available. The new model also incorporates updated rail activity data and can account for important factors which are known to affect locomotive emissions, such as route grade, the specific locomotive fleet and different types of trains. A case study of the TCIF program revealed that many public planning and transportation agencies appear to currently lack the required data, models or expertise to evaluate the merits of publicly funded freight rail projects. Accordingly, better data, models and training must be provided or alternative policy options considered. Alternative policy options such as taxes and fees to internalize external highway congestion and road damage costs, vehicle emission standards to control air pollutant emissions and economy wide carbon tax or cap and trade systems to account for GHG emissions seem to offer more certain and cost effective approaches to ensuring a socially optimal level of freight rail service given the current constraints on public planning and transportation agencies. The new locomotive model developed in this dissertation should also help provide a more standardized approach to modeling locomotive emissions.

Data, which were generally lacking, was a theme carried throughout the dissertation. Data constraints presented challenges to the development of the new locomotive emission model, to the many agencies who submitted TCIF proposals and to the evaluation of the estimates in the submitted TCIF proposals. Data collection is a challenge for goods movement, and particularly in the case of freight rail, for several reasons. Many passenger transportation data are collected through surveys, vehicle registration records and highway traffic sensors (Richardson, Ampt et al. 1995; Ortuzar and Willumsen 2001). For the most part, passenger vehicle trips also are predictable. Most people go to work in the mornings and return in the afternoon. People use their vehicles to go shopping, visit friends and travel on the weekends. A large amount of data has been collected on passenger vehicle emission rates and energy use to enforce compliance with tail pipe emission standards and fuel economy standards. Goods movement is a different story. Goods movement demand and mode choice are driven by extremely complex global supply chains and the very different needs of different industries (Ogden 1992; Woudsma 2001; Rodrigue 2006). Goods movement trips can range from a few miles to thousands of miles. Generally, surveys offer little help since most freight data are considered confidential business information which firms are unwilling to report. What is available though observation of the highway system is also limited; while trucks can be counted it is difficult to know what is in them and where they are going. Since the freight railroad system is privately owned and operated, even less data are available. Information about truck and locomotive emission rates and energy efficiency are also limited due to a shorter history of regulation (heavy duty truck emission standards were adopted 15 years and locomotive emission standards were adopted 22 years, respectively after those for light-duty vehicles)[52] and the absence of fuel economy standards.

Some standard data sources are available such as the commodity flow survey for trucks[53] and the rail waybill sample for freight rail[54]. However, standard approaches available to state, regional and local planning and transportation agencies to translate these data in to actual trips and those trips in to estimates of air pollutant emissions are not readily available. The full rail waybill sample is not available to agencies below the state level[55]. Progress is being made to improve data collection and dissemination. The Federal Highway Administration has developed

[52] Light-duty vehicle standards were adopted under the 1970 Clean Air Act Amendments; heavy-duty truck standards were required by the 1977 Clean Air Act Amendments and adopted in 1985; and locomotive emission standards were required by the 1990 Clean Air Act Amendments and adopted in 1997.
[53] Data are available from the Bureau of Transportation Statistics website: http://www.bts.gov/publications/commodity_flow_survey/
[54] Further information about access to this data is available from the Surface Transportation Board: http://www.stb.dot.gov/stb/industry/econ_waybill.html
[55] A public version of the waybill sample is available, but it provides very little geographic detail in order to maintain railroad data confidentiality.

the Freight Analysis Framework (FAF)[56], a website which provides some analysis of data from the commodity flow survey and rail waybill sample and provides links to modeling and reports from other agencies and researchers. Much more work is need to provide up to date and user friendly goods movement data.

In addition to continuing to develop new and more reliable freight data resources, research should continue to develop models and policy solutions which are workable given the data constraints. This dissertation provides some good examples. The new locomotive model made use of a limited amount of confidential railroad data, which was very difficult to obtain, to create a modeling framework which requires only minimal data for periodic updates and which can incorporate more detailed data when they are available. The TCIF case study concluded that different policy options, which require less knowledge of railroad operations, future goods movement demand or shipper modal preferences, are available to satisfy a common policy goal.

Finally, given that confidential data and modeling undertaken by private firms are likely to continue to be used to support public policy decisions regarding goods movement, and given the highly questionable analysis performed by public agencies described in this dissertation, an independent review system could offer substantial benefits. Ideally, an independent panel of expert reviewers could be assembled to review projects which grant public funds to the benefit of private firms based on the analysis of confidential data or modeling. Expert reviewers may not be able to access confidential data, but may be able to recognize inconsistent or implausible results or flawed analysis approaches based on their experience. This would essentially be similar to the analysis undertaken for the case study conducted in Chapter 4.

[56] http://ops.fhwa.dot.gov/freight/freight_analysis/perform_meas/index.htm

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APPENDICES

Appendix A: Estimating Mobile Source Emission Factors

Appendix B: Copies of difficult to obtain public documents

Appendix C*: Original data files provided by UP and BNSF

Appendix D*: Annual UP and BNSF California line-haul traffic

Appendix E*: Detailed operational data supplied by UP and BNSF

Appendix F-1*: Notch specific fuel consumption estimates for the UP locomotive fleet

Appendix F-2**: MS Access database of all available locomotive test data

Appendix G: Rail yard inventory data and fuel consumption rate calculations

Appendix H: UC Davis emission inventories and CARB 2008 inventory

Appendix I*: Regression Data and Results

*Appendices C to E and I are in electronic form as MS Excel files and contain information deemed confidential business information by the UP and BNSF railroads. They may be available upon request from the California Air Resources Board.

**Appendix F-2 is in electronic form and available upon request from the author.

Appendix A – Estimating Mobile Source Emission Factors

There are two general methods to estimate mobile source emission factors: laboratory engine exhaust measurements and in-use exhaust measurements.

Engine exhaust measurements performed in a laboratory setting provide a relatively straightforward approach. A test vehicle (or sometimes just its engine) is operated over a representative duty cycle, simulating real world acceleration and speed profiles. A dynamometer is used to provide resistance to the wheels or engine and enables measurement of engine torque and speed, from which the amount of work can be calculated. A variety of analytical equipment is used to measure the concentration of pollutants in the engine exhaust stream during the test. Most emission measurements are continuous with the exception of PM which is captured by a filter and weighed at the end of the test. Pollutant concentration measurements combined with measurements of the exhaust flow rate are used to estimate mass emission rates (mass/unit time). Typically fuel consumption, work and distance traveled are also measured which enable the emission rates to be converted to a more useful fuel, work or distance basis. The procedure for locomotives is similar expect that the locomotive's dynamic brake is used to provide resistance to the engine. Locomotives without dynamic breaks are connected to a large resistor which absorbs the power generated by the locomotive similar to a dynamic brake.

Potentially large errors in on-road vehicle emission models prompted calls for in-use measurement of emissions (Seinfeld 1989; NRC 2000) and as a result, many in-use measurements have now been made. For example, in-use, on-road measurements are being used to develop EPA's next generation on-road mobile emission model (MOVES)(Younglove, Scora et al. 2005). In-use measurements provide an opportunity to measure actual in-use vehicle drive cycles and the actual in-use vehicle fleet, a major limitation to laboratory studies. Two common methods are road-side and tunnel studies.

Road-side studies instantaneously measure exhaust pollutants as a vehicle passes by a detector which measures the absorption of a beam of light by the exhaust plume (Bishop and Stedman 1996). This method can determine the ratios of HC, CO and NO to CO_2 in the exhaust, though not the concentration or mass of the pollutants directly. The concentration of emissions and mass emission rates per quantity of fuel use are estimated by solving a carbon mass balance. Simultaneous to the exhaust measurement, a camera records the passing vehicles. Vehicle attributes observed from the camera or from looking up vehicle registration records by license plate number allows the recorded emission measurements to be aggregated by vehicle class. The accuracy of road-side measurements has been found to be relatively good: CO, HC and NO are found to fall within ± 5%, ± 10%, and ± 5% of actual values, respectively (Lawson, Stedman et al. 1990; Popp, Bishop et al. 1999).

Tunnel studies provide another measure of in-use emissions. Air pollutant concentrations are measured in the air flowing into and out of a highway tunnel, the difference in pollutant concentration being the contribution from vehicle exhaust (Pierson, Gertler et al. 1996). By measuring the air flow rate thought the tunnel, the tunnel distance and the number of vehicles traveling though tunnel, pollutant concentrations can be converted to a mass per unit distance emission factor. Using a carbon mass balance similar to road-side studies provides fuel based emission factors(McGaughey, Desai et al. 2004). Tunnel studies measure emissions generated by vehicles traveling a certain distance, offering a more realistic measure of actual vehicle operation as compared to the instant of vehicle operation captured by road-side methods. However, tunnels studies are opportunistic – a suitable tunnel must be present – making this approach unsuitable for developing emission factors for use in other locations. Tunnel studies are best suited for validation of emission models.

More recent studies have begun to develop additional methods to measure in-use emissions. Given the right atmospheric and topographical conditions, a gentle breeze perpendicular to a flat roadway and no physical obstacles between the road and metrology equipment, it is possible to measure the concentration of pollutants from vehicle traffic alongside a roadway (Corsmeier, Imhof et al. 2005). Analogous to a tunnel study, the concentration of pollutants is measured upwind and downwind of a roadway, the difference being the contribution from vehicles. This method may be more representative of vehicle operation (travel in tunnels not being the norm); however, it is prone to error when conditions are not ideal. The introduction of more compact and portable analytical equipment now allows for onboard emission measurements(Younglove, Scora et al. 2005). Onboard emission measurement allows for laboratory type analytics to be used in the field, measuring emissions produced from actual vehicle operation rather than duty cycles on a dynamometer. Onboard methods are being used to develop EPA’s next generation mobile emission model (MOVES). Onboard emission measurement can be made by specifying a particular route for an instrumented vehicle to travel, specifying that the instrumented vehicle make certain maneuvers (such as hard accelerations) or simply instrumenting a large sample of vehicles in a number of different regions to develop representative measurements(Younglove, Scora et al. 2005).

In-use measurements provide a valuable check on models based largely, if not entirely, on laboratory measurements and assumptions of typical driving conditions and vehicle fleets. But in use measurements of locomotive emission have not been made, or at least have not be published. Given the absence of in-use measurements to check the accuracy of locomotive emission models, this report critically examines the laboratory based exhaust emission measurements that have been made.

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Appendix B – Copies of Difficult to Obtain Documents

1) EPA (1991a). Locomotive Emission Factors for Inventory Guidance Document, U.S. Environmental Protection Agency, National Fuel and Vehicle Emission Laboratory.

2) Moulis, C. (2008). Memorandum: Analysis of Fuel Sulfur Conversion Rates in Locomotives. Ann Arbor, MI, U.S. Environmental Protection Agency National Vehicle and Fuel Emissions Laboratory.

Appendix F-1

Appendix F-1 Table of Contents

Worksheet	Description	Source
Power	Brake horse power (bhp) by throttle notch for each locomotive model group	Various sources, see Appendix F-2
Fuel Consumption Factors	Fuel consumption rate (lb/hr of diesel fuel) by throttle notch for each locomotive model group	Various sources, see Appendix F-2
C60	Fuel consumption data and estimates for GE C60 Locomotives	Various sources, see Appendix F-2
Dash9	Fuel consumption data and estimates for GE Dash-9 Locomotives	Various sources, see Appendix F-2
Dash8	Fuel consumption data and estimates for GE Dash-8 Locomotives	Various sources, see Appendix F-2
Dash7	Fuel consumption data and estimates for GE Dash-7 Locomotives	Various sources, see Appendix F-2
SD90	Fuel consumption data and estimates for EMD SD90 Locomotives	Various sources, see Appendix F-2
SD70	Fuel consumption data and estimates for EMD SD70 Locomotives	Various sources, see Appendix F-2
GP60	Fuel consumption data and estimates for EMD GP60 Locomotives	Various sources, see Appendix F-2
GP50	Fuel consumption data and estimates for EMD GP50 Locomotives	Various sources, see Appendix F-2
GP4x	Fuel consumption data and estimates for EMD GP4x Locomotives	Various sources, see Appendix F-2
GP3x	Fuel consumption data and estimates for EMD GP3x Locomotives	Various sources, see Appendix F-2
Switch	Fuel consumption data and estimates for low powered switcher locomotives	Various sources, see Appendix F-2
UP National Roster	UP 2008 Locomotive roster by make and model and model group	UP website: http://www.uprr.com/aboutup/reference/locorost.shtml

Locomotive power by throttle notch (see individual worksheets for calculation details)

UID	Model Group	DB bhp	LI *bhp*	I *bhp*	N1 *bhp*	N2 *bhp*	N3 *bhp*	N4 *bhp*	N5 *bhp*	N6 *bhp*	N7 *bhp*	N8 *bhp*
1	Switch N	70	15	15	72	233	440	669	885	1,109	1,372	1,586
2	Switch 0	70	15	15	72	233	440	669	885	1,109	1,372	1,586
3	Switch 1	70	15	15	72	233	440	669	885	1,109	1,372	1,586
4	Switch 2	70	15	15	72	233	440	669	885	1,109	1,372	1,586
5	GP3x N	49	13	14	91	328	574	919	1,210	1,492	1,862	2,135
6	GP3x 0	49	13	14	91	328	574	919	1,210	1,492	1,862	2,135
7	GP3x 1	49	13	14	91	328	574	919	1,210	1,492	1,862	2,135
8	GP3x 2	49	13	14	91	328	574	919	1,210	1,492	1,862	2,135
9	GP4x N	69	17	17	105	395	686	1,034	1,461	1,971	2,661	3,159
10	GP4x 0	69	17	17	105	395	686	1,034	1,461	1,971	2,661	3,159
11	GP4x 1	69	17	17	105	395	686	1,034	1,461	1,971	2,661	3,159
12	GP4x 2	69	17	17	105	395	686	1,034	1,461	1,971	2,661	3,159
13	GP50 N	55	12	12	228	460	865	1,242	1,756	2,489	3,318	3,774
14	GP50 0	55	12	12	228	460	865	1,242	1,756	2,489	3,318	3,774
15	GP50 1	55	12	12	228	460	865	1,242	1,756	2,489	3,318	3,774
16	GP50 2	55	12	12	228	460	865	1,242	1,756	2,489	3,318	3,774
17	GP60 N	18	7	7	198	430	974	1,349	1,784	2,415	3,500	4,051
18	GP60 0	18	7	7	198	430	974	1,349	1,784	2,415	3,500	4,051
19	GP60 1	18	7	7	198	430	974	1,349	1,784	2,415	3,500	4,051
20	GP60 2	18	7	7	198	430	974	1,349	1,784	2,415	3,500	4,051
21	SD7x N	18	14	18	205	438	980	1,517	2,000	2,882	3,652	4,205
22	SD7x 0	18	14	18	205	438	980	1,517	2,000	2,882	3,652	4,205
23	SD7x 1	15	13	14	216	432	975	1,437	1,981	2,855	3,626	4,178
24	SD7x 2	325	21	40	266	625	1,144	1,564	2,036	3,046	3,743	4,498
25	SD90 N	20	20	18	382	781	1,544	2,232	2,831	4,027	5,560	6,444
26	SD90 0	20	20	18	382	781	1,544	2,232	2,831	4,027	5,560	6,444
27	SD90 1	20	20	18	382	781	1,544	2,232	2,831	4,027	5,560	6,444
28	SD90 2	20	20	18	382	781	1,544	2,232	2,831	4,027	5,560	6,444
29	Dash7 N	128	20	20	143	311	714	1,058	1,550	2,058	2,604	3,000
30	Dash7 0	128	20	20	143	311	714	1,058	1,550	2,058	2,604	3,000
31	Dash7 1	128	20	20	143	311	714	1,058	1,550	2,058	2,604	3,000
32	Dash7 2	128	20	20	143	311	714	1,058	1,550	2,058	2,604	3,000
33	Dash8 N	170	27	27	170	370	850	1,260	1,845	2,450	3,100	3,600
34	Dash8 0	170	27	27	170	370	850	1,260	1,845	2,450	3,100	3,600
35	Dash8 1	170	27	27	170	370	850	1,260	1,845	2,450	3,100	3,600
36	Dash8 2	170	27	27	170	370	850	1,260	1,845	2,450	3,100	3,600
37	Dash9 N	25	12	11	195	498	1,036	1,550	2,223	2,941	3,664	4,481

UID	Model Group	DB bhp	LI *bhp*	I *bhp*	N1 *bhp*	N2 *bhp*	N3 *bhp*	N4 *bhp*	N5 *bhp*	N6 *bhp*	N7 *bhp*	N8 *bhp*
38	Dash9 0	27	13	12	209	489	1,021	1,541	2,211	2,916	3,345	4,487
39	Dash9 1	35	5	5	191	503	994	1,516	2,071	2,735	3,422	4,219
40	Dash9 2	28	10	17	268	587	1,187	1,683	2,296	3,046	3,773	4,454
41	C60 N	36	17	16	276	708	1,471	2,202	3,158	4,178	5,204	6,365
42	C60 0	36	17	16	276	708	1,471	2,202	3,158	4,178	5,204	6,365
43	C60 1	36	17	16	276	708	1,471	2,202	3,158	4,178	5,204	6,365
44	C60 2	36	17	16	276	708	1,471	2,202	3,158	4,178	5,204	6,365

Locomotive fuel consumption rates by throttle notch (see individual worksheets for calculation details)

UID	Model Group	DB *lb/hr*	LI *lb/hr*	I *lb/hr*	N1 *lb/hr*	N2 *lb/hr*	N3 *lb/hr*	N4 *lb/hr*	N5 *lb/hr*	N6 *lb/hr*	N7 *lb/hr*	N8 *lb/hr*
1	Switch N	80	26	26	41	95	167	249	332	419	529	630
2	Switch 0	80	26	26	41	95	167	249	332	419	529	630
3	Switch 1	80	26	26	41	95	167	249	332	419	529	630
4	Switch 2	80	26	26	41	95	167	249	332	419	529	630
5	GP3x N	70	27	30	52	134	223	347	456	572	727	861
6	GP3x 0	70	27	30	52	134	223	347	456	572	727	861
7	GP3x 1	70	27	30	52	134	223	347	456	572	727	861
8	GP3x 2	70	27	30	52	134	223	347	456	572	727	861
9	GP4x N	114	40	40	64	167	275	404	556	740	994	1,177
10	GP4x 0	114	40	40	64	167	275	404	556	740	994	1,177
11	GP4x 1	114	40	40	64	167	275	404	556	740	994	1,177
12	GP4x 2	114	40	40	64	167	275	404	556	740	994	1,177
13	GP50 N	93	44	44	115	191	334	463	634	868	1,143	1,313
14	GP50 0	93	44	44	115	191	334	463	634	868	1,143	1,313
15	GP50 1	93	44	44	115	191	334	463	634	868	1,143	1,313
16	GP50 2	93	44	44	115	191	334	463	634	868	1,143	1,313
17	GP60 N	87	22	25	88	166	354	482	634	842	1,175	1,361
18	GP60 0	87	22	25	88	166	354	482	634	842	1,175	1,361
19	GP60 1	87	22	25	88	166	354	482	634	842	1,175	1,361
20	GP60 2	87	22	25	88	166	354	482	634	842	1,175	1,361
21	SD7x N	46	26	77	91	170	355	536	697	973	1,195	1,375
22	SD7x 0	46	26	77	91	170	355	536	697	973	1,195	1,375
23	SD7x 1	43	23	32	91	167	357	517	701	988	1,203	1,367
24	SD7x 2	134	24	54	107	234	432	600	760	1,093	1,305	1,525
25	SD90 N	50	32	32	156	288	548	566	961	1,343	1,780	2,079
26	SD90 0	50	32	32	156	288	548	566	961	1,343	1,780	2,079
27	SD90 1	50	32	32	156	288	548	566	961	1,343	1,780	2,079
28	SD90 2	50	32	32	156	288	548	566	961	1,343	1,780	2,079
29	Dash7 N	228	31	39	61	118	267	385	547	695	857	986
30	Dash7 0	228	31	39	61	118	267	385	547	695	857	986
31	Dash7 1	228	31	39	61	118	267	385	547	695	857	986
32	Dash7 2	228	31	39	61	118	267	385	547	695	857	986
33	Dash8 N	299	43	66	76	141	320	455	647	819	1,004	1,154
34	Dash8 0	299	43	66	76	141	320	455	647	819	1,004	1,154
35	Dash8 1	299	43	66	76	141	320	455	647	819	1,004	1,154
36	Dash8 2	299	43	66	76	141	320	455	647	819	1,004	1,154
37	Dash9 N	43	20	25	81	188	392	571	795	1,009	1,236	1,521
38	Dash9 0	43	20	28	81	183	381	553	830	1,026	1,275	1,597
39	Dash9 1	55	20	20	86	185	373	512	725	945	1,169	1,470

UID	Model Group	DB *lb/hr*	LI *lb/hr*	I *lb/hr*	N1 *lb/hr*	N2 *lb/hr*	N3 *lb/hr*	N4 *lb/hr*	N5 *lb/hr*	N6 *lb/hr*	N7 *lb/hr*	N8 *lb/hr*
40	Dash9 2	44	17	20	102	210	449	615	830	1,067	1,319	1,609
41	C60 N	61	28	36	115	266	557	812	1,129	1,433	1,756	2,161
42	C60 0	61	28	36	115	266	557	812	1,129	1,433	1,756	2,161
43	C60 1	61	28	36	115	266	557	812	1,129	1,433	1,756	2,161
44	C60 2	61	28	36	115	266	557	812	1,129	1,433	1,756	2,161

Fuel consumption data and estimates for GE C60 Locomotives

No test data available

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
			C60	6250		N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
			C60	6250		N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Estimated Values

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
			C60	6250		60.55	27.71	36.05	115.15	266	556.97	811.7	1129	1433	1756	2161.1

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
			C60	6250		35.51	16.79	16.01	276.34	708	1471.1	2202	3158.2	4178	5204	6365.3

Adjustment factor 1.42

Adjustment Factor: ((C60 HP - 44CW HP)/44CE HP)+1)

Fuel Consumption Estimate: Adjustment factor*44CW Fuel Consumption

Fuel Power Estimate: Adjustment factor*44CW Power

Fuel consumption data and estimates for GE Dash-9 Locomotives

Values from All Available Test Data																
									Fuel Consumption (lb/hr)							
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
4	9	0.033	Dash-9 40C	4000	Pre	40	16	26	57	159	358	505	720	914	1114	1315
4	4	0.033	Dash-9 40C	4000	Pre	41	16	22	59	160	359	506	719	913	1114	1315
14	53	0.033	Dash-9 44CW	4400	Pre	47	21	25	82	189	384	569	789	1003	1221	1514
14	54	0.033	Dash-9 44CW	4400	Pre	42	22	27	83	188	393	568	785	994	1216	1505
14	55	0.033	Dash-9 44CW	4400	Pre	44	22	26	81	188	392	569	784	994	1220	1509
13	56	0.033	Dash-9 44CW	4400	Pre	44	20	25	80	186	394	574	799	1020	1258	1553
13	57	0.033	Dash-9 44CW	4400	Pre	41	16	27	81	184	393	575	807	1022	1256	1554
13	58	0.033	Dash-9 44CW	4400	Pre	41	17	22	79	185	388	563	794	1009	1240	1518
15	59	0.033	Dash-9 44CW	4400	Pre	41	20	27	83	188	392	578	797	1016	1241	1554
15	60	0.033	Dash-9 44CW	4400	Pre	45	22	26	80	188	393	573	795	1011	1241	1547
15	61	0.033	Dash-9 44CW	4400	Pre	43	19	25	80	191	399	577	808	1024	1260	1508
1	1	0.033	Dash-9 44CW	4400	Pre	42	18	25	82	188	395	570	794	1003	1233	1493
1	6	0.033	Dash-9 44CW	4400	Pre	40	18	25	80	187	391	570	792	1003	1214	1481
10	23	0.2857	Dash-9 44CW	4400	0	43	20	28	81	183	381	553	830	1026	1275	1597
11	24	0.2857	GE AC4400	4400	1	55	20	20	86	185	373	512	725	945	1169	1470
12	25	0.2857	GE GEVO	4400	2	44	17	20	102	210	449	615	830	1067	1319	1609

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
4	9	0.033	Dash-9 40C	4000	Pre	23	10	10	125	418	952	1399	2054	2734	3442	4101
4	4	0.033	Dash-9 40C	4000	Pre	23	10	10	133	419	948	1400	2051	2734	3438	4105
14	53	0.033	Dash-9 44CW	4400	Pre	26	14	14	196	500	1041	1550	2223	2941	3660	4499
14	54	0.033	Dash-9 44CW	4400	Pre	23	12	12	197	495	1032	1549	2223	2942	3663	4490
14	55	0.033	Dash-9 44CW	4400	Pre	33	16	16	196	496	1034	1555	2224	2946	3662	4498
13	56	0.033	Dash-9 44CW	4400	Pre	25	11	11	197	497	1035	1551	2223	2941	3667	4495
13	57	0.033	Dash-9 44CW	4400	Pre	25	11	11	179	507	1034	1549	2225	2942	3665	4478
13	58	0.033	Dash-9 44CW	4400	Pre	22	10	10	196	499	1039	1550	2222	2939	3665	4495
15	59	0.033	Dash-9 44CW	4400	Pre	22	16	10	201	497	1035	1552	2223	2942	3664	4504
15	60	0.033	Dash-9 44CW	4400	Pre	23	10	10	190	497	1038	1549	2224	2941	3665	4506
15	61	0.033	Dash-9 44CW	4400	Pre	30	10	10	194	497	1035	1549	2222	2938	3664	4325
1	1	0.033	Dash-9 44CW	4400	Pre	23	10	10	197	498	1035	1548	2223	2941	3661	4499
1	6	0.033	Dash-9 44CW	4400	Pre	23	10	10	197	499	1034	1550	2225	2941	3665	4504
10	23	0.2857	Dash-9 44CW	4400	0	27	13	12	209	489	1021	1541	2211	2916	3345	4487
11	24	0.2857	GE AC4400	4400	1	35	5	5	191	503	994	1516	2071	2735	3422	4219
12	25	0.2857	GE GEVO	4400	2	28	10	17	268	587	1187	1683	2296	3046	3773	4454

Average Values

Model	HP	Tier	Fuel Consumption (lb/hr)										
			DB	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
40C	4000	Pre	40	16	24	58	159	358	505	719	914	1114	1315
44CW	4400	Pre	43	20	25	81	188	392	571	795	1009	1236	1521
44CW	4400	0	43	20	28	81	183	381	553	830	1026	1275	1597
GE AC4400	4400	1	55	20	20	86	185	373	512	725	945	1169	1470
GE GEVO	4400	2	44	17	20	102	210	449	615	830	1067	1319	1609

Model	**HP**	**Tier**	**Power (bhp)**										
			DB	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
40C	4000	Pre	23	10	10	129	419	950	1400	2053	2734	3440	4103
44CW	4400	Pre	25	12	11	195	498	1036	1550	2223	2941	3664	4481
44CW	4400	0	27	13	12	209	489	1021	1541	2211	2916	3345	4487
GE AC4400	4400	1	35	5	5	191	503	994	1516	2071	2735	3422	4219
GE GEVO	4400	2	28	10	17	268	587	1187	1683	2296	3046	3773	4454

Fuel consumption data and estimates for GE Dash-8 Locomotives

Values from All Available Test Data

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
41	113		7FDL-16	3600	Pre	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
41	113		7FDL-16	3600	Pre	170	27	27	170	370	850	1260	1845	2450	3100	3600

Estimated Fuel Consumption Values

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
41	113		7FDL-16	3600	Pre	298.609	42.93	65.61	76.434	140.706	320.3605	454.842	646.5815	818.6083	1004.031	1153.97

Estimated method: ((Dash8 HP - Dash9 HP)/Dash9 HP)+1)*Dash 9 Fuel Consumption

Fuel consumption data and estimates for GE Dash-7 Locomotives

Values from All Available Test Data

Loco	Test	Sulfur	Model	HP	Tier	Fuel Consumption (lb/hr) DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
42	114		7FDL-16	3000	Pre	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Loco	Test	Sulfur	Model	HP	Tier	Power (bhp) DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
42	114		7FDL-16	3000	Pre	128	20	20	143	311	714	1058	1550	2058	2604	3000

Estimated Fuel Consumption Values

Loco	Test	Sulfur	Model	HP	Tier	Fuel Consumption (lb/hr) DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
42	114		7FDL-16	3000	Pre	228.049	30.91667	39.16667	61.28571	118.0379	266.5385	385.4706	546.7431	694.8968	856.6272	986.4714

Estimated method: ((Dash7 HP - Dash9 HP)/Dash9 HP)+1)*Dash 9 Fuel Consumption

Fuel consumption data and estimates for EMD SD90 Locomotives

No test data available

Fuel Consumption (lb/hr)

Loco	Test	Sulfur	Model	HP	Tier	DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
			SD90	6250		N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Power (bhp)

Loco	Test	Sulfur	Model	HP	Tier	DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
			SD90	6250		N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Estimated Values

Fuel Consumption (lb/hr)

Loco	Test	Sulfur	Model	HP	Tier	DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
			SD90	6250		49.7093	32.12209	32.12209	155.6686	287.5	547.7471	565.5523	960.6105	1343.023	1779.506	2079.07

Power (bhp)

Loco	Test	Sulfur	Model	HP	Tier	DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
			SD90	6250		20.49419	20.49419	18.31395	382.2674	781.25	1543.605	2231.831	2830.669	4026.89	5560.32	6444.041

Adjustment factor 1.453488

Adjustment Factor: ((SD90 HP - SD75 HP)/SD75 HP)+1)

Fuel Consumption Estimate: Adjustment factor*SD75 Fuel Consumption

Fuel Power Estimate: Adjustment factor*SD75 Power

Fuel consumption data and estimates for EMD SD70 Locomotives

Values from All Available Test Data																		
						Fuel Consumption (lb/hr)												
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
16	44	0.033	EMD SD70MAC	4000	Pre	46.6	26.5	46.6	92.4	170.9	354.5	538.5	706.8	993.6	1214.4	1393.2
16	45	0.033	EMD SD70MAC	4000	Pre	45.5	24.8	455.5	90	171.6	356	544	705.6	1002.8	1220.4	1396.8
16	46	0.033	EMD SD70MAC	4000	Pre	48	26	48	91.8	172.3	358.5	542.6	711.3	1007.1	1225.5	1403.1
17	47	0.033	EMD SD70MAC	4000	Pre	47.4	28.2	47.4	94.2	171	353	528.9	690	962.4	1182	1353.6
17	48	0.033	EMD SD70MAC	4000	Pre	46	26.6	46	92.4	171.6	352.8	531.6	692.4	974	1189.2	1365.6
17	49	0.033	EMD SD70MAC	4000	Pre	47.6	27.2	47.6	92.7	171	353.4	530.5	691.8	967.7	1190	1361
17	62	0.033	EMD SD70MAC	4000	Pre	47.3	25.3	47.3	91.3	171.4	354	532.5	696	979.7	1196	1369.2
18	50	0.033	EMD SD70MAC	4000	Pre	47	25.2	47	88	169.2	357.6	541.2	699.6	957.6	1182	1370.4
18	51	0.033	EMD SD70MAC	4000	Pre	46.2	26.5	46.2	92	170	358	540	698	958	1184	1370
18	52	0.033	EMD SD70MAC	4000	Pre	48.6	26	48.6	91	172	358	545	693	963	1194	1375
2	2	0.033	EMD SD70MAC	4000	Pre	42.6	23.1	23.1	88.9	166.2	350.2	529	691.5	956.4	1183.8	1373.1
2	7	0.033	EMD SD70MAC	4000	Pre	43.8	22.3	22.3	87.6	167.4	348.6	528	689.4	957	1184.2	1372
8	21	0.2875	EMD SD70MAC	4000	1	43	23	32	91	167	357	517.2	700.8	987.6	1203	1366.8
3	3	0.033	EMD SD75	4300	Pre	33.6	21.4	21.4	108	199.2	376.8	525.6	660	924	1224.6	1430.4
3	8	0.033	EMD SD75	4300	Pre	34.8	22.8	22.8	106.2	196.4	376.9	252.6	661.8	924	1224	1430.4
9	22	0.2875	EMD SD70ACe	4300	2	133.8	24	54.4	106.8	234	432	600	760	1093.4	1305	1525

Loco	Test	Sulfur	Model	HP	Tier	Power (bhp) DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
16	44	0.033	EMD SD70MAC	4000	Pre	19	14	19	205	437	980	1519	2005	2881	3655	4210
16	45	0.033	EMD SD70MAC	4000	Pre	19	14	19	205	439	980	1519	2005	2881	3654	4206
16	46	0.033	EMD SD70MAC	4000	Pre	19	14	19	205	439	980	1520	2008	2891	3652	4208
17	47	0.033	EMD SD70MAC	4000	Pre	19	14	19	205	438	980	1515	2005	2883	3655	4210
17	48	0.033	EMD SD70MAC	4000	Pre	19	14	19	205	439	980	1514	2004	2883	3657	4211
17	49	0.033	EMD SD70MAC	4000	Pre	19	14	19	205	438	980	1515	2004	2883	3657	4211
17	62	0.033	EMD SD70MAC	4000	Pre	19	14	19	205	439	980	1513	2005	2883	3654	4208
18	50	0.033	EMD SD70MAC	4000	Pre	19	13	19	205	438	980	1519	1996	2883	3656	4210
18	51	0.033	EMD SD70MAC	4000	Pre	18.9	13	18.9	205	438	980	1519	1995	2883	3656	4209
18	52	0.033	EMD SD70MAC	4000	Pre	19	13	19	205	438	980	1519	1965	2881	3652	4197
2	2	0.033	EMD SD70MAC	4000	Pre	13.9	13.9	10.8	202	435	979	1514	2003	2874	3640	4185
2	7	0.033	EMD SD70MAC	4000	Pre	13.9	13.9	10.8	202	436	978	1514	2003	2879	3641	4189
8	21	0.2875	EMD SD70MAC	4000	1	15.4	12.6	13.7	216	432	974.9	1437.4	1981.3	2854.8	3625.9	4177.9
3	3	0.033	EMD SD75	4300	Pre	14.2	14.2	12.6	263	539	1062	1531	1940	2767	3824	4433
3	8	0.033	EMD SD75	4300	Pre	14	14	12.6	263	536	1062	1540	1955	2774	3827	4434
9	22	0.2875	EMD SD70ACe	4300	2	325	21	40	266	625	1144	1564	2036	3046	3743	4498

Average Values

Loco	Test	Sulfur	Model	HP	Tier	Fuel Consumption (lb/hr) DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
			SD70MAC	4000	Pre	46.4	25.6	77.1	91.0	170.4	354.6	536.0	697.1	973.3	1195.5	1375.3
			SD75	4300	Pre	34.2	22.1	22.1	107.1	197.8	376.9	389.1	660.9	924.0	1224.3	1430.4
			SD70MAC	4000	1	43.0	23.0	32.0	91.0	167.0	357.0	517.2	700.8	987.6	1203.0	1366.8
			SD70ACe	4300	2	133.8	24.0	54.4	106.8	234.0	432.0	600.0	760.0	1093.4	1305.0	1525.0

Loco	Test	Sulfur	Model	HP	Tier	**Power (bhp)** DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
			SD70MAC	4000	Pre	18.1	13.7	17.6	204.5	437.8	979.8	1516.7	1999.8	2882.1	3652.4	4204.5
			SD75	4300	Pre	14.1	14.1	12.6	263.0	537.5	1062.0	1535.5	1947.5	2770.5	3825.5	4433.5
			SD70MAC	4000	1	15.4	12.6	13.7	216.0	432.0	974.9	1437.4	1981.3	2854.8	3625.9	4177.9
			SD70ACe	4300	2	325.0	21.0	40.0	266.0	625.0	1144.0	1564.0	2036.0	3046.0	3743.0	4498.0

Fuel consumption data and estimates for EMD GP60 Locomotives

Values from All Available Test Data

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
29	101	0.27	16-710G3A	3600	Pre	134	23	23	88	167	351	478	635	888	1147	1328
7	20	0.2857	16-710G3A	3800	0	39	20	26	87	165	356	486	632	795	1202	1394

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
29	101	0.27	16-710G3A	3600	Pre	23	5	5	198	430	975	1351	1817	2637	3496	4035
7	20	0.2857	16-710G3A	3800	0	12.8	8	9.8	198.6	430.4	973.6	1347.3	1750.7	2192.6	3504.2	4067.7

Average Values

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
			16-710G3A		pre/0	86.5	21.5	24.5	87.5	166	353.5	482	633.5	841.5	1174.5	1361

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
			16-710G3A		pre/0	17.9	6.5	7.4	198.3	430.2	974.3	1349.15	1783.85	2414.8	3500.1	4051.35

Fuel consumption data and estimates for EMD GP50 Locomotives

Values from All Available Test Data

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
23	98	0.28	16-645F3	3500	Pre	94	66	66	137	203	305	445	615	816	1150	1345
25	99	0.23	16-645F3B	3600	Pre	91	22	22	92	179	363	480	652	919	1136	1281

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
23	98	0.28	16-645F3	3500	Pre	74	15	15	250	444	725	1131	1635	2212	3182	3681
25	99	0.23	16-645F3B	3600	Pre	36	9	9	205	475	1005	1353	1876	2766	3454	3866

Average Values

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
average						92.5	44	44	114.5	191	334	462.5	633.5	867.5	1143	1313

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
average						55	12	12	227.5	459.5	865	1242	1755.5	2489	3318	3773.5

Fuel consumption data and estimates for EMD GP4x Locomotives

Values from All Available Test Data

						Fuel Consumption (lb/hr)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
19	96	0.24	16-645E3 (SD40)	3000	Pre	114	40	40	64	167	275	404	556	740	994	1177
20	102	0.26	20-645E3 (SD45)	3800	Pre	157	47	47	68	187	310	468	665	865	1227	1432

						Power (bhp)										
Loco	**Test**	**Sulfur**	**Model**	**HP**	**Tier**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
19	96	0.24	16-645E3 (SD40)	3000	Pre	69	17	17	105	395	686	1034	1461	1971	2661	3159
20	102	0.26	20-645E3 (SD45)	3800	Pre	95	17	17	111	435	781	1219	1741	2299	3344	3819

Fuel consumption data and estimates for EMD GP3x Locomotives

Values from All Available Test Data

Loco	Test	Sulfur	Model	HP	Tier	DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
						Fuel Consumption (lb/hr)										
6	19	0.2857	16-645E (GP38)	2000	0	36	21	27.7	48.9	128.4	219.5	364.8	475.2	579.6	741.6	867.6
38	110	0.29	16-645E (GP38)	2000	Pre	103	32	32	55	137	226	331	442	567	710	854
21	92	0.33	12-645E3B (GP39-2)	2500	Pre	76	28	28	54	159	223	324	404	549	749	872

Loco	Test	Sulfur	Model	HP	Tier	DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
						Power (bhp)										
6	19	0.2857	16-645E (GP38)	2000	0	17.6	10.3	13.4	82.9	314.7	557.1	970.3	1269.4	1516.6	1890.9	2115.4
38	110	0.29	16-645E (GP38)	2000	Pre	82	15	15	98	333	589	871	1161	1465	1810	2124
21	92	0.33	12-645E3B (GP39-2)	2500	Pre	36	11	11	111	417	594	878	1105	1517	2103	2451

UP Roster Weighted Average

Loco	Test	Sulfur	Model	HP	Tier	DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
						Fuel Consumption (lb/hr)										
			UP GP3x			69.80794	26.57106	29.76236	52.04712	133.946	222.7618	346.7677	456.0133	572.1488	726.8991	861.3306

Loco	Test	Sulfur	Model	HP	Tier	DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
						Power(bhp)										
			UP GP3x			49.14622	12.57183	14.0484	91.42356	328.263	574.0425	918.6294	1209.979	1492.041	1862.415	2135.395

Fuel consumption data and estimates for low powered switcher locomotives

Values from All Available Test Data

Loco	Test	Sulfur	Model	HP	Tier	Fuel Consumption (lb/hr) DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
37	91	0.22	12-645E	1500 (GP15)	Pre	80	26	26	41	95	167	249	332	419	529	630

Loco	Test	Sulfur	Model	HP	Tier	Power (bhp) DB	LI	I	N1	N2	N3	N4	N5	N6	N7	N8
37	91	0.22	12-645E	1500 (GP15)	Pre	70	15	15	72	233	440	669	885	1109	1372	1586

UP 2008 Roster

Model Group	**Count**	**Proportion**
Dash8 4000	392	0.046
Dash8 4100	199	0.023
Dash9 4400	376	0.044
GE C44AC	1488	0.173
GEVO 4400	506	0.059
GE AC60	80	0.009
Other	362	0.042
GP15	210	0.024
GP20	40	0.005
GP-38	5	0.001
GP38-2	671	0.078
GP39-2	37	0.004
GP40	5	0.001
GP40-2	196	0.023
GP50	11	0.001
GP60	186	0.022
MP15	195	0.023
SD38-2	68	0.008
SD40	1	0.000
SD40-2	996	0.116
SD60	375	0.044
SD70ACE	315	0.037
SD70M	1755	0.204
SD90	21	0.002
SW1500	105	0.012
Total	8595	

GP38x	744	0.953
GP39x	37	0.047
Total	781	

Appendix G

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Appendix G-1: Railyard Locomotive Inventory, Average Fuel Consumption Rates and Fuel

Efficiency

Yard Loco[a]	FC Loco[b]	HP	Major California BNSF Rail Yards - Locomotives per Rail Yard								
			Barstow	Commerce Eastern	Commerce Mechanical	Hobart	Richmond	San Bernadino	San Diego	Stockton	Willmington -Watson
GP25	EMD 12-645E3B	2500	1	1	1	1	1	2	2	0	0
GP30	EMD 12-645E3B	2500	6	3	3	3	0	2	1	0	1
GP35	EMD 12-645E3B	2500	12	4	4	4	1	4	0	2	3
GP38	EMD 16-645E	2000	0	0	0	0	0	1	0	0	0
GP38-2B	EMD 16-645E	2000	1	0	0		0	1	0	1	2
GP39-2	EMD 12-645E3B	2300	1	6	6	6	0	2	1	3	2
GP39E	EMD 12-645E3B	2300	1	1	1	1	0	0	0	0	0
GP39M	EMD 12-645E3B	2300	0	0	0	0	0	0	0	1	0
GP9	1.167x EMD 12-645E[d]	1750	1	0	0	0	1	0	0	0	0
SD39	EMD 12-645E3B	2500	8	1	1	1	0	2	0	0	0
SD9	1.167 x EMD 12-645E	1750	1	0	0	0	0	0	0	0	0
SW1000N	.67 x EMD 12-645E[d]	1000	4	0	0	0	0	0	0	0	0
SW1200	.8 x EMD 12-645E[d]	1200	2	0	0	0	0	0	0	0	0
SW1500	EMD 12-645E	1500	4	0	0	0	1	0	0	1	0
MK1200G	.8 x EMD 12-645E	1200	0	2	2	2	0	0	0	0	0
Total			*42*	*18*	*18*	*18*	*4*	*14*	*4*	*8*	*8*

Locomotive Groups for Fuel Consumption Calculation[c]										
EMD 12-645E3B	2500	29	16	16	16	2	12	4	6	6
EMD 16-645E	2000	1	0	0	0	0	2	0	1	2
EMD 12-645E	1500	4	0	0	0	1	0	0	1	0
.8 x EMD 12-645E	1200	2	2	2	2	0	0	0	0	0
.67 x EMD 12-645E	1000	4	0	0	0	0	0	0	0	0
1.167x EMD 12-645E	1750	2	0	0	0	1	0	0	0	0
Total		*42*	*18*	*18*	*18*	*4*	*14*	*4*	*8*	*8*
Yard Fuel Consumption Rates (gal/hr)										
		12.04	13.01	13.01	13.01	12.56	13.97	13.94	13.44	13.99
Yard Fuel Efficiency (bhp-hr/gal)										
		15.75	15.96	15.96	15.96	15.56	15.91	16.08	15.80	15.78
Average BNSF Rail yard fuel consumption Rate (gal/hr)										12.87
Average BNSF Rail yard fuel efficiency (bhp-hr/gal)										15.86

[a]Actual yard locomotives

[b]Most similar switcher locomotive with available fuel consumption data

[c]Locomotive group fuel consumption rates, for data and calcualtions see tab F-2

[d]Fuel rate from an EMD 12-645E multiplied by the ratio of the "yard locomotive" bhp to EMD 12-645E bhp; used to estimate fuel consumption rates for locomotive model with no available test data

Appendix G-2: Switcher locomotive fuel consumption and fuel efficiency data and estimates

Assumed specific gravity of diesel fuel	0.85
Assumed density of water (lb/gal)	8.345

					fuel consumption (lb/hr)										
LocoID	**Engine Model**	**Loco Model**	**Tier**	**Rated Power**	**DB**	**LI**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
37	EMD 12-645E	EMD 1500, MP15, GP15	P	1500	80	26	26	41	95	167	249	332	419	529	630
21	EMD 12-645E3B	EMD GP39-2	P	2500	76	28	28	54	159	223	324	404	549	749	872
24	EMD 12-645F3B	N/A	P	2850	33	18	18	95	134	274	364	484	615	841	991
6	EMD 16-645E	EMD GP38	0	2000	36	21	27.7	48.9	128.4	219.5	364.8	475.2	579.6	741.6	867.6
38	EMD 16-645E	EMD GP38, GP38-2	P	2000	103	32	32	55	137	226	331	442	567	710	854
					fuel consumption (gal/hr)										
37	EMD 12-645E	EMD 1500, MP15, GP15	P	1500	11.28	3.67	3.67	5.78	13.39	23.54	35.10	46.81	59.07	74.58	88.82
21	EMD 12-645E3B	EMD GP39-2	P	2500	10.71	3.95	3.95	7.61	22.42	31.44	45.68	56.96	77.40	105.59	122.93
24	EMD 12-645F3B	N/A	P	2850	4.65	2.54	2.54	13.39	18.89	38.63	51.32	68.23	86.70	118.56	139.71
6	EMD 16-645E	EMD GP38	0	2000	5.08	2.96	3.91	6.89	18.10	30.94	51.43	66.99	81.71	104.55	122.31
38	EMD 16-645E	EMD GP38, GP38-2	P	2000	14.52	4.51	4.51	7.75	19.31	31.86	46.66	62.31	79.94	100.10	120.40
					Power (bhp)										
37	EMD 12-645E	EMD 1500, MP15, GP15	P	1500	70	15	15	72	233	440	669	885	1109	1372	1586
21	EMD 12-645E3B	EMD GP39-2	P	2500	36	11	11	111	417	594	878	1105	1517	2103	2451
24	EMD 12-645F3B	N/A	P	2850	15	8	8	222	339	735	993	1322	1704	2389	2823
6	EMD 16-645E	EMD GP38	0	2000	17.6	10.3	13.4	82.9	314.7	557.1	970.3	1269.4	1516.6	1890.9	2115.4
38	EMD 16-645E	EMD GP38, GP38-2	P	2000	82	15	15	98	333	589	871	1161	1465	1810	2124
					Proportion Time-in-notch										
	EPA Switch Duty Cycle				0	0.30	0.30	0.12	0.12	0.06	0.04	0.04	0.02	0.00	0.01

LocoID	Engine Model	Loco Model	Tier	Rated Power	Duty Cycle Weighted Fuel Consumption (gal/hr)	Duty Cycle weighted Power (bhp)	Fuel Efficiency (bhp-hr/gal)
37	EMD 12-645E	EMD 1500, MP15, GP15	P	1500	10.62	160.09	15.08
21	EMD 12-645E3B	EMD GP39-2	P	2500	13.94	224.04	16.08
24	EMD 12-645F3B	N/A	P	2850	14.70	252.90	17.20
6	EMD 16-645E	EMD GP38	0	2000	13.61	212.47	15.62
38	EMD 16-645E	EMD GP38, GP38-2	P	2000	14.17	211.98	14.96
	.8[a] x EMD 12-645E			1200	8.49	128.07	15.08
	.67[a] x EMD 12-645E			1000	7.11	107.26	15.08
	1.167[a] x EMD 12-645E			1750	12.39	186.82	15.08

[a]rated power/EMD 12-645E rated power; used to estimate fuel consumption rates and fuel efficiencies for locomotives types where no test data are avaiable

Appendix G-3: BNSF rail yard switcher locomotive duty cycles

	Proportion of Time-in-notch									
Rail Yard	**DB**	**I**	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
Wilmington-Watson	0.00	0.60	0.13	0.10	0.06	0.03	0.02	0.02	0.01	0.04
Commerce Mechanical	0.00	0.60	0.13	0.15	0.07	0.04	0.01	0.00	0.00	0.00
Stockton	0.00	0.60	0.16	0.12	0.05	0.03	0.01	0.01	0.00	0.02
Commerce Eastern	0.00	0.60	0.13	0.15	0.07	0.04	0.01	0.00	0.00	0.00
Richmond	0.00	0.60	0.13	0.14	0.06	0.03	0.01	0.01	0.00	0.01
Los Angeles-Hobart	0.00	0.60	0.13	0.15	0.07	0.04	0.01	0.00	0.00	0.00
Barstow	0.00	0.78	0.06	0.04	0.05	0.03	0.02	0.01	0.00	0.01
San Diego	0.00	0.98	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
San Bernardino	0.02	0.87	0.04	0.03	0.02	0.01	0.01	0.00	0.00	0.01
EPA Switch Duty Cycle	0	0.60	0.12	0.12	0.06	0.04	0.04	0.02	0.00	0.01

Appendix G-4: UP and BNSF rail yard annual operating hours

UID	Rail Yard	Rail Road	Annual Operating Hours (2007)
1	Wilmington-Watson	BNSF	4,200
2	Commerce Mechanical Facility	BNSF	730
3	Stockton	BNSF	19,612
4	Commerce Eastern	BNSF	2,808
5	Richmond	BNSF	17,520
6	Los Angeles-Hobart	BNSF	30,112
7	Barstow	BNSF	70,080
8	San Diego	BNSF	9,958
9	San Bernardino	BNSF	70,064
10	Oakland	UP	29,565
11	City of Industry	UP	31,390
12	Colton	UP	100,740
13	Dolores/ICTF	UP	66,430
14	Commerce	UP	23,360
15	LATC	UP	40,880
16	Mira Loma	UP	16,060
17	Stockton	UP	55,480

Appendix H

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Appendix H-1: UC Davis Class I Line-Haul Emission Inventory, Year 2007

County	FC (gal/yr)	HC (tons/yr)	CO (tons/yr)	NOx (tons/yr)	PM10 (tons/yr)	PM25 (tons/yr)	SO2 (tons/yr)	CO2 (tons/yr)
Alameda	1,687,550	12	46	225	6	6	4	18,788
Alpine								
Amador								
Butte	5,773,462	43	159	771	21	20	14	64,277
Calaveras								
Colusa								
Contra Costa	1,930,352	16	53	293	8	8	5	21,491
Del Norte								
El Dorado								
Fresno	3,305,973	29	91	528	15	14	8	36,806
Glenn								
Humboldt								
Imperial	15,461,735	114	425	2,063	55	53	36	172,139
Inyo	70,141	1	2	9	0	0	0	781
Kern	23,243,381	186	640	3,345	91	89	55	258,774
Kings	2,024,217	20	56	354	10	10	5	22,536
Lake								
Lassen	4,183,042	36	115	643	18	17	10	46,571
Los Angeles	14,761,211	113	406	2,033	55	53	35	164,340
Madera	3,113,003	27	86	489	14	13	7	34,658
Marin								
Mariposa								
Mendocino								
Merced	4,299,756	38	118	684	19	19	10	47,870
Mono								
Modoc	1,498,093	15	41	262	8	7	4	16,679
Monterey	1,540,702	11	42	206	5	5	4	17,153
Napa								
Nevada	3,003,634	22	83	401	11	10	7	33,440
Orange	2,847,543	28	78	497	14	14	7	31,702
Placer	9,741,675	72	268	1,300	35	34	23	108,456
Plumas	6,219,108	48	171	859	23	22	15	69,239
Riverside	22,923,033	180	631	3,250	88	86	54	255,207
Sacramento	4,531,114	33	125	605	16	16	11	50,446
San Benito	24,183	0	1	3	0	0	0	269
San Bernardino	118,793,016	1,107	3,268	19,859	568	551	279	1,322,550
San Diego								
San Francisco								
San Joaquin	5,804,523	47	160	850	23	23	14	64,623

San Luis Obispo	959,255	7	26	128	3	3	2	10,680
San Mateo								
Santa Barbara	1,382,542	10	38	185	5	5	3	15,392
Santa Clara	819,051	6	23	109	3	3	2	9,119
Santa Cruz	38,098	0	1	5	0	0	0	424
Shasta	4,304,917	32	118	575	15	15	10	47,928
Sierra	154,035	1	4	21	1	1	0	1,715
Siskiyou	5,918,610	44	163	790	21	20	14	65,893
Solano	1,612,451	12	44	215	6	6	4	17,952
Sonoma								
Stanislaus	2,746,615	24	76	424	12	11	6	30,579
Sutter	1,461,330	11	40	195	5	5	3	16,269
Tehama	2,473,954	18	68	330	9	9	6	27,543
Trinity								
Tulare	3,512,693	30	97	538	15	15	8	39,108
Tuolumne								
Ventura	948,368	7	26	127	3	3	2	10,558
Yolo	463,399	3	13	62	2	2	1	5,159
Yuba	2,406,356	18	66	321	9	8	6	26,791
Total	285,982,120	2,421	7,868	43,552	1,213	1,177	671	3,183,905

Appendix H-2: UC Davis Class I Line-Haul Emission Inventory by Air District, Year 2007

Air District	**Fuel Consumption** *gal/yr*	**HC** *tons/yr*	**CO** *tons/yr*	**NOx** *tons/yr*	**PM10** *tons/yr*	**PM25** *tons/yr*	**SO2** *tons/yr*	**CO2** *tons/yr*
	3,739	0	0	1	0	0	0	42
Amador	0	0	0	0	0	0	0	0
Antelope Valley	2,635,216	19	73	352	9	9	6	29,338
Bay Area	5,230,761	41	144	733	20	19	12	58,235
Butte	5,773,752	43	159	771	21	20	14	64,281
Calaveras	0	0	0	0	0	0	0	0
Colusa	0	0	0	0	0	0	0	0
El Dorado	0	0	0	0	0	0	0	0
Feather River	3,865,921	29	106	516	14	13	9	43,040
Glenn	0	0	0	0	0	0	0	0
Great Basin Unified	0	0	0	0	0	0	0	0
Imperial	15,528,229	115	427	2,072	55	54	36	172,879
Kern	12,974,516	103	357	1,852	51	49	30	144,448
Lassen	4,172,263	36	115	641	18	17	10	46,451
Mendocino	0	0	0	0	0	0	0	0
Modoc	1,500,527	15	41	262	8	7	4	16,706
Mojave Desert	101,636,917	955	2,796	17,124	491	476	238	1,131,547
Monterey Bay Unified	1,602,545	12	44	214	6	6	4	17,842
North Coast Unified	0	0	0	0	0	0	0	0
Northern Sierra	9,036,486	68	249	1,235	33	32	21	100,605
Northern Sonoma	0	0	0	0	0	0	0	0
Placer	10,093,538	75	278	1,347	36	35	24	112,374
Sacramento Metro	4,526,398	33	125	604	16	16	11	50,393
San Diego	0	0	0	0	0	0	0	0
San Joaquin Valley Unified	35,071,013	298	965	5,358	149	145	82	390,454
San Luis Obispo	959,537	7	26	128	3	3	2	10,683
Santa Barbara	1,381,988	10	38	184	5	5	3	15,386
Shasta	4,297,276	32	118	573	15	15	10	47,843
Siskiyou	5,925,927	44	163	791	21	20	14	65,975
South Coast	55,057,023	454	1,515	8,165	226	219	129	612,963
Tehama	2,472,927	18	68	330	9	9	6	27,532
Tuolumne	0	0	0	0	0	0	0	0
Ventura	948,729	7	26	127	3	3	2	10,562
Yolo-Solano	1,286,863	10	35	172	5	4	3	14,327
Total	285,982,090	2,421	7,868	43,552	1,213	1,177	671	3,183,904

Appendix H-3: UC Davis Class I Line-Haul Emission Inventory by Air Basin, Year 2007

Air Basin	**Fuel Consumption** *gal/yr*	**HC** *tons/yr*	**CO** *tons/yr*	**NOx** *tons/yr*	**PM10** *tons/yr*	**PM25** *tons/yr*	**SO2** *tons/yr*	**CO2** *tons/yr*
	3,739	0	0	1	0	0	0	42
GREAT BASIN VALLEYS	0	0	0	0	0	0	0	0
MOJAVE DESERT	117,246,650	1,077	3,226	19,328	551	534	275	1,305,334
MOUNTAIN COUNTIES	14,896,381	112	410	2,017	54	52	35	165,845
NORTH CENTRAL COAST	1,602,545	12	44	214	6	6	4	17,842
NORTH COAST	0	0	0	0	0	0	0	0
NORTHEAST PLATEAU	11,598,718	94	319	1,694	47	45	27	129,131
SACRAMENTO VALLEY	26,456,781	195	728	3,531	94	91	62	294,549
SALTON SEA	27,311,634	202	751	3,645	97	94	64	304,067
SAN DIEGO	0	0	0	0	0	0	0	0
SAN FRANCISCO BAY AREA	5,230,760	41	144	733	20	19	12	58,235
SAN JOAQUIN VALLEY	35,071,013	298	965	5,358	149	145	82	390,454
SOUTH CENTRAL COAST	3,290,254	24	91	439	12	11	8	36,631
SOUTH COAST	43,273,621	366	1,191	6,592	184	178	102	481,775
Total	285,982,094	2,421	7,868	43,552	1,213	1,177	671	3,183,904

Appendix H-4: Class I Rail Yard Switcher Locomotive Emission Inventory, Year 2007

YUID	Rail Yard	Rail Road	County	Fuel_Consumption (gal/yr)	HC (tons/yr)	CO (tons/yr)	NOx (tons/yr)	PM10 (tons/yr)	PM25 (tons/yr)	SO2 (tons/yr)	CO2 (tons/yr)
1	Wilmington-Watson	BNSF	Los Angeles	54,054	0.96	1.73	16.48	0.33	0.32	0.006	602
2	Commerce Mechanical Facility	BNSF	Los Angeles	9,395	0.17	0.30	2.87	0.06	0.06	0.001	105
3	Stockton	BNSF	San Joaquin	252,406	4.47	8.10	76.97	1.53	1.48	0.026	2,810
4	Commerce Eastern	BNSF	Los Angeles	36,139	0.64	1.16	11.02	0.22	0.21	0.004	402
5	Richmond	BNSF	Contra Costa	225,482	3.99	7.23	68.76	1.36	1.32	0.023	2,510
6	Los Angeles-Hobart	BNSF	Los Angeles	387,541	6.86	12.43	118.19	2.34	2.27	0.040	4,315
7	Barstow	BNSF	San Bernardino	901,930	15.97	28.93	275.05	5.45	5.29	0.093	10,041
8	San Diego	BNSF	San Diego	128,159	2.27	4.11	39.08	0.77	0.75	0.013	1,427
9	San Bernardino	BNSF	San Bernardino	901,724	15.96	28.92	274.99	5.45	5.29	0.093	10,039
10	Oakland	UP	Alameda	380,502	6.74	12.20	116.04	2.30	2.23	0.039	4,236
11	City of Industry	UP	Los Angeles	403,989	7.15	12.96	123.20	2.44	2.37	0.042	4,498
12	Colton	UP	San Bernardino	1,296,524	22.95	41.58	395.39	7.84	7.60	0.134	14,434
13	Dolores/ICTF	UP	Los Angeles	854,954	15.13	27.42	260.73	5.17	5.01	0.088	9,518
14	Commerce	UP	Los Angeles	300,643	5.32	9.64	91.68	1.82	1.76	0.031	3,347
15	LATC	UP	Los Angeles	526,126	9.31	16.87	160.45	3.18	3.08	0.054	5,857
16	Mira Loma	UP	Riverside	206,692	3.66	6.63	63.03	1.25	1.21	0.021	2,301
17	Stockton	UP	San Joaquin	714,028	12.64	22.90	217.75	4.32	4.19	0.074	7,949
18	Roseville	UP	Placer	1,127,412	19.96	36.16	343.82	6.82	6.61	0.117	12,552
	Total			8,707,700	154	279	2,656	53	51	0.90	96,945

Appendix H-5: CARB Clas I Line-Haul Emission Inventory, Year 2007

County	FUEL *gal/yr*	THC *tons/yr*	CO *tons/yr*	NOX *tons/yr*	PM *tons/yr*	SOX *tons/yr*	CO2 *tons/yr*
Alameda	5,041,272	50.87	181.40	708.68	20.75	2.34	56,776
Amador	306,428	5.73	21.81	90.48	2.72	0.50	3,451
Butte	6,078,508	47.59	177.51	846.85	24.63	5.69	68,457
Colusa	1,715,928	13.43	50.11	239.06	6.95	1.61	19,325
Contra Costa	3,835,738	38.70	138.02	539.21	15.78	1.78	43,199
Fresno	7,164,737	65.75	235.65	996.80	30.44	3.36	80,691
Glenn	2,213,751	17.33	64.65	308.42	8.97	2.07	24,932
Humboldt	1,097,268	10.78	36.80	151.24	15.43	0.07	12,358
Imperial	8,498,515	163.79	586.05	1,927.72	66.17	12.34	95,712
Kern	19,119,087	273.98	980.79	3,497.21	115.15	24.48	215,323
Kings	2,228,762	20.45	73.30	310.08	9.47	1.04	25,101
Lassen	1,545,551	40.36	154.81	720.02	21.82	6.01	17,406
Los Angeles	32,786,179	371.57	1,329.27	4,765.56	155.24	31.85	369,244
Madera	2,619,584	24.04	86.16	364.45	11.13	1.23	29,502
Marin	270,874	2.73	9.75	38.08	1.11	0.13	3,051
Mendicino	1,260,506	12.38	42.27	173.74	17.72	0.08	14,196
Merced	4,343,582	39.86	142.86	604.30	18.45	2.03	48,918
Modoc	1,378,799	36.01	138.10	642.34	19.47	5.36	15,528
Napa	999,186	10.08	35.95	140.46	4.11	0.46	11,253
Nevada	569,018	10.64	40.50	168.02	5.06	0.94	6,408
Orange	7,928,599	84.18	301.15	1,094.91	35.39	6.93	89,293
Placer	4,897,477	51.16	192.54	866.31	25.55	5.42	55,156
Plumas	2,581,821	48.26	183.76	762.37	22.95	4.24	29,077
Riverside	16,077,533	238.98	855.03	2,916.67	97.82	20.83	181,068
Sacramento	7,880,982	61.70	230.15	1,097.97	31.93	7.38	88,757
San Bernardino	50,266,808	850.41	3,042.70	10,153.55	344.46	86.82	566,115
San Diego	381,638	4.43	15.80	52.40	1.72	0.36	4,298
San Francisco	631,559	6.37	22.73	88.78	2.60	0.29	7,113
San Joaquin	9,084,820	83.37	298.80	1,263.93	38.59	4.25	102,315
San Luis Obispo	3,374,947	27.24	98.38	474.96	13.55	0.64	38,009
San Mateo	1,138,057	11.48	40.95	159.98	4.68	0.53	12,817
Santa Barbara	7,698,506	62.13	224.41	1,083.42	30.90	1.46	86,702
Santa Clara	3,658,975	36.92	131.66	514.36	15.06	1.70	41,208
Shasta	6,591,339	51.60	192.49	918.30	26.70	6.17	74,233
Sierra	111,922	2.09	7.97	33.05	0.99	0.18	1,260
Siskiyou	2,114,371	55.22	211.78	985.01	29.85	8.22	23,812
Solano	2,751,916	24.81	90.15	385.21	11.24	1.90	30,993
Sonoma	1,411,993	14.19	50.29	197.90	7.94	0.57	15,902
Stanislaus	4,785,680	43.92	157.40	665.81	20.33	2.24	53,897

Sutter	1,698,348	13.30	49.60	236.61	6.88	1.59	19,127
Tehama	3,593,566	28.13	104.94	500.65	14.56	3.37	40,471
Trinity	111,773	1.10	3.75	15.41	1.57	0.01	1,259
Tulare	7,499,728	68.82	246.66	1,043.40	31.86	3.51	84,463
Tuolumne	429,742	8.03	30.59	126.90	3.82	0.71	4,840
Ventura	4,364,702	35.22	127.23	614.25	17.52	0.83	49,156
Yolo	4,349,301	34.05	127.01	605.94	17.62	4.07	48,983
Yuba	3,008,353	23.55	87.85	419.12	12.19	2.82	33,881
Total	261,497,729	3,227	11,652	44,510	1,439	280	2,945,039

Appendix H-6: EPA Line-Haul Emission Inventory, Year 2007

County	Subdivision	RailRoad	GTM_A[a]	GTM_D[a]	System-wide Fuel Intentisty[b]	EPA Emission Factors for 2007[c] HC	CO	NO_x	PM_{10}	Estimates From Applying EPA Method Fuel Consumption	HC	CO	NO_x	PM_{10}	CO_2
					GTM/gal	*gram/gal*	*gram/gal*	*gram/gal*	*gram/gal*	*gallons*	*tons*	*tons*	*tons*	*tons*	*tons*
Los Angeles	ALAMEDA CORRIDOR	UP/BNSF	730	730	775	9.3	27.4	175	6.3	1,884,418	19.3	56.9	363.5	13.1	21,223
Los Angeles	ALAMEDA CORRIDOR	UP/BNSF	41	41	775	9.3	27.4	175	6.3	105,629	1.1	3.2	20.4	0.7	1,190
Los Angeles	ALAMEDA CORRIDOR	UP/BNSF	40	40	775	9.3	27.4	175	6.3	102,799	1.1	3.1	19.8	0.7	1,158
Riverside	YUMA	UP	4,324	3,834	793	9.3	27.4	175	6.3	10,287,017	105.5	310.7	1,984.4	71.4	115,854
Imperial	YUMA	UP	3,890	3,450	793	9.3	27.4	175	6.3	9,256,068	94.9	279.6	1,785.5	64.3	104,244
San Bernardino	YUMA	UP	533	473	793	9.3	27.4	175	6.3	1,268,052	13.0	38.3	244.6	8.8	14,281
Inyo	YUMA	UP	18	16	793	9.3	27.4	175	6.3	42,807	0.4	1.3	8.3	0.3	482
Lassen	WINNEMUCCA	UP	276	643	793	9.3	27.4	175	6.3	1,158,897	11.9	35.0	223.6	8.0	13,052
Plumas	WINNEMUCCA	UP	133	309	793	9.3	27.4	175	6.3	557,220	5.7	16.8	107.5	3.9	6,276
Los Angeles	WILMINGTON	UP	20	23	793	9.3	27.4	175	6.3	54,375	0.6	1.6	10.5	0.4	612
Santa Clara	WARM SPRINGS	UP	2	0	793	9.3	27.4	175	6.3	2,918	0.0	0.1	0.6	0.0	33
Alameda	WARM SPRINGS	UP	2	0	793	9.3	27.4	175	6.3	2,788	0.0	0.1	0.5	0.0	31
Ventura	VENTURA	UP	70	49	793	9.3	27.4	175	6.3	149,775	1.5	4.5	28.9	1.0	1,687
Los Angeles	VENTURA	UP	96	67	793	9.3	27.4	175	6.3	205,610	2.1	6.2	39.7	1.4	2,316
Los Angeles	VALLEY SUB	UP	20	37	793	9.3	27.4	175	6.3	71,959	0.7	2.2	13.9	0.5	810
Los Angeles	VALLEY SUB	UP	4	8	793	9.3	27.4	175	6.3	15,039	0.2	0.5	2.9	0.1	169
Shasta	VALLEY	UP	2,164	0	793	9.3	27.4	175	6.3	2,729,354	28.0	82.4	526.5	19.0	30,739
Butte	VALLEY	UP	1,490	0	793	9.3	27.4	175	6.3	1,878,862	19.3	56.7	362.4	13.0	21,160
Tehama	VALLEY	UP	1,244	0	793	9.3	27.4	175	6.3	1,568,508	16.1	47.4	302.6	10.9	17,665
Placer	VALLEY	UP	818	0	793	9.3	27.4	175	6.3	1,031,858	10.6	31.2	199.0	7.2	11,621
Yuba	VALLEY	UP	598	0	793	9.3	27.4	175	6.3	754,449	7.7	22.8	145.5	5.2	8,497

Sutter	VALLEY	UP	347	0	793	9.3	27.4	175	6.3	437,334	4.5	13.2	84.4	3.0	4,925
Siskiyou	VALLEY	UP	77	0	793	9.3	27.4	175	6.3	97,548	1.0	2.9	18.8	0.7	1,099
San Joaquin	TRACY	UP	30	32	793	9.3	27.4	175	6.3	77,684	0.8	2.3	15.0	0.5	875
Contra Costa	TRACY	UP	14	15	793	9.3	27.4	175	6.3	36,361	0.4	1.1	7.0	0.3	410
Alameda	TRACY	UP	1	1	793	9.3	27.4	175	6.3	1,464	0.0	0.0	0.3	0.0	16
Stanislaus	TIDEWATER	UP	22	10	793	9.3	27.4	175	6.3	40,181	0.4	1.2	7.8	0.3	453
Santa Barbara	SANTA BARBARA	UP	472	328	793	9.3	27.4	175	6.3	1,008,397	10.3	30.5	194.5	7.0	11,357
Ventura	SANTA BARBARA	UP	204	142	793	9.3	27.4	175	6.3	436,364	4.5	13.2	84.2	3.0	4,914
San Luis Obispo	SANTA BARBARA	UP	107	74	793	9.3	27.4	175	6.3	227,842	2.3	6.9	44.0	1.6	2,566
Los Angeles	SAN PEDRO	UP	60	62	793	9.3	27.4	175	6.3	153,318	1.6	4.6	29.6	1.1	1,727
Yuba	SACRAMENTO	UP	314	583	793	9.3	27.4	175	6.3	1,131,099	11.6	34.2	218.2	7.9	12,739
Sacramento	SACRAMENTO	UP	238	442	793	9.3	27.4	175	6.3	857,985	8.8	25.9	165.5	6.0	9,663
Sutter	SACRAMENTO	UP	199	370	793	9.3	27.4	175	6.3	717,440	7.4	21.7	138.4	5.0	8,080
Butte	SACRAMENTO	UP	110	205	793	9.3	27.4	175	6.3	397,345	4.1	12.0	76.6	2.8	4,475
San Joaquin	SACRAMENTO	UP	88	164	793	9.3	27.4	175	6.3	317,206	3.3	9.6	61.2	2.2	3,572
Placer	ROSEVILLE	UP	1,250	1,355	793	9.3	27.4	175	6.3	3,285,056	33.7	99.2	633.7	22.8	36,997
Nevada	ROSEVILLE	UP	482	522	793	9.3	27.4	175	6.3	1,266,697	13.0	38.3	244.3	8.8	14,266
Sierra	ROSEVILLE	UP	25	27	793	9.3	27.4	175	6.3	64,960	0.7	2.0	12.5	0.5	732
Los Angeles	RIVER EAST BANK LINE	UP	2	2	793	9.3	27.4	175	6.3	4,790	0.0	0.1	0.9	0.0	54
Alameda	OAKLAND	UP	175	298	793	9.3	27.4	175	6.3	595,558	6.1	18.0	114.9	4.1	6,707
San Joaquin	OAKLAND	UP	138	234	793	9.3	27.4	175	6.3	469,104	4.8	14.2	90.5	3.3	5,283
Alameda	NILES	UP	89	82	793	9.3	27.4	175	6.3	215,783	2.2	6.5	41.6	1.5	2,430
Kern	MOJAVE	UP	3,249	2,658	793	9.3	27.4	175	6.3	7,448,917	76.4	225.0	1,436.9	51.7	83,891
San Bernardino	MOJAVE	UP	742	607	793	9.3	27.4	175	6.3	1,700,713	17.4	51.4	328.1	11.8	19,154
Los Angeles	MOJAVE	UP	542	443	793	9.3	27.4	175	6.3	1,242,548	12.7	37.5	239.7	8.6	13,994
Solano	MARTINEZ	UP	523	590	793	9.3	27.4	175	6.3	1,403,461	14.4	42.4	270.7	9.7	15,806
Sacramento	MARTINEZ	UP	485	547	793	9.3	27.4	175	6.3	1,300,764	13.3	39.3	250.9	9.0	14,649

Contra Costa	MARTINEZ	UP	337	380	793	9.3	27.4	175	6.3	903,363	9.3	27.3	174.3	6.3	10,174
Yolo	MARTINEZ	UP	150	170	793	9.3	27.4	175	6.3	403,338	4.1	12.2	77.8	2.8	4,542
Placer	MARTINEZ	UP	105	119	793	9.3	27.4	175	6.3	282,467	2.9	8.5	54.5	2.0	3,181
Alameda	MARTINEZ	UP	67	75	793	9.3	27.4	175	6.3	178,635	1.8	5.4	34.5	1.2	2,012
Los Angeles	LOS NIETOS	UP	28	10	793	9.3	27.4	175	6.3	48,011	0.5	1.5	9.3	0.3	541
Los Angeles	LOS ANGELES	UP	1,811	814	793	9.3	27.4	175	6.3	3,309,458	33.9	100.0	638.4	23.0	37,272
Riverside	LOS ANGELES	UP	469	211	793	9.3	27.4	175	6.3	856,910	8.8	25.9	165.3	6.0	9,651
San Bernardino	LOS ANGELES	UP	326	147	793	9.3	27.4	175	6.3	596,516	6.1	18.0	115.1	4.1	6,718
Kern	LONE PINE	UP	86	70	793	9.3	27.4	175	6.3	196,326	2.0	5.9	37.9	1.4	2,211
San Bernardino	LONE PINE	UP	6	5	793	9.3	27.4	175	6.3	13,975	0.1	0.4	2.7	0.1	157
Los Angeles	LA HABRA	UP	8	2	793	9.3	27.4	175	6.3	12,750	0.1	0.4	2.5	0.1	144
San Joaquin	FRESNO	UP	1,323	882	793	9.3	27.4	175	6.3	2,781,268	28.5	84.0	536.5	19.3	31,323
Sacramento	FRESNO	UP	968	646	793	9.3	27.4	175	6.3	2,035,375	20.9	61.5	392.6	14.1	22,923
Tulare	FRESNO	UP	842	561	793	9.3	27.4	175	6.3	1,769,619	18.1	53.4	341.4	12.3	19,930
Merced	FRESNO	UP	750	500	793	9.3	27.4	175	6.3	1,576,718	16.2	47.6	304.2	10.9	17,757
Madera	FRESNO	UP	607	405	793	9.3	27.4	175	6.3	1,275,482	13.1	38.5	246.0	8.9	14,365
Stanislaus	FRESNO	UP	600	400	793	9.3	27.4	175	6.3	1,261,447	12.9	38.1	243.3	8.8	14,207
Fresno	FRESNO	UP	545	363	793	9.3	27.4	175	6.3	1,145,344	11.7	34.6	220.9	8.0	12,899
Kern	FRESNO	UP	529	353	793	9.3	27.4	175	6.3	1,111,316	11.4	33.6	214.4	7.7	12,516
Imperial	EL CENTRO	UP	9	3	793	9.3	27.4	175	6.3	15,493	0.2	0.5	3.0	0.1	174
Monterey	COAST	UP	514	388	793	9.3	27.4	175	6.3	1,138,188	11.7	34.4	219.6	7.9	12,818
Santa Clara	COAST	UP	251	190	793	9.3	27.4	175	6.3	556,224	5.7	16.8	107.3	3.9	6,264
San Luis Obispo	COAST	UP	216	163	793	9.3	27.4	175	6.3	477,877	4.9	14.4	92.2	3.3	5,382
Alameda	COAST	UP	119	90	793	9.3	27.4	175	6.3	264,147	2.7	8.0	51.0	1.8	2,975
Santa Cruz	COAST	UP	13	10	793	9.3	27.4	175	6.3	28,144	0.3	0.9	5.4	0.2	317
San Benito	COAST	UP	8	6	793	9.3	27.4	175	6.3	17,865	0.2	0.5	3.4	0.1	201
Santa Clara	COAST	UP	21	16	793	9.3	27.4	175	6.3	46,259	0.5	1.4	8.9	0.3	521
San	CIMA	UP	2,418	3,077	793	9.3	27.4	175	6.3	6,929,632	71.0	209.3	1,336.7	48.1	78,043

Bernardino															
Plumas	CANYON	UP	753	1,599	793	9.3	27.4	175	6.3	2,965,779	30.4	89.6	572.1	20.6	33,401
Butte	CANYON	UP	399	849	793	9.3	27.4	175	6.3	1,573,949	16.1	47.5	303.6	10.9	17,726
Imperial	CALEXICO	UP	114	73	793	9.3	27.4	175	6.3	235,598	2.4	7.1	45.4	1.6	2,653
Siskiyou	BLACK BUTTE	UP	989	1,685	793	9.3	27.4	175	6.3	3,372,351	34.6	101.9	650.5	23.4	37,980
Los Angeles	ALHAMBRA	UP	435	1,175	793	9.3	27.4	175	6.3	2,029,684	20.8	61.3	391.5	14.1	22,859
San Bernardino	ALHAMBRA	UP	281	760	793	9.3	27.4	175	6.3	1,312,755	13.5	39.6	253.2	9.1	14,785
Merced	STOCKTON	BNSF	939	939	758	9.3	27.4	175	6.3	2,479,553	25.4	74.9	478.3	17.2	27,925
San Joaquin	STOCKTON	BNSF	641	641	758	9.3	27.4	175	6.3	1,690,870	17.3	51.1	326.2	11.7	19,043
Madera	STOCKTON	BNSF	631	631	758	9.3	27.4	175	6.3	1,665,609	17.1	50.3	321.3	11.6	18,758
Stanislaus	STOCKTON	BNSF	490	490	758	9.3	27.4	175	6.3	1,294,680	13.3	39.1	249.7	9.0	14,581
Fresno	STOCKTON	BNSF	339	339	758	9.3	27.4	175	6.3	895,531	9.2	27.0	172.8	6.2	10,086
Contra Costa	STOCKTON	BNSF	301	301	758	9.3	27.4	175	6.3	793,374	8.1	24.0	153.0	5.5	8,935
Orange	SAN BERNARDINO	BNSF	11	11	758	9.3	27.4	175	6.3	28,080	0.3	0.8	5.4	0.2	316
Riverside	SAN BERNARDINO	BNSF	1,263	1,263	758	9.3	27.4	175	6.3	3,334,349	34.2	100.7	643.2	23.2	37,552
Orange	SAN BERNARDINO	BNSF	767	767	758	9.3	27.4	175	6.3	2,024,619	20.8	61.1	390.6	14.1	22,802
San Bernardino	SAN BERNARDINO	BNSF	405	405	758	9.3	27.4	175	6.3	1,069,186	11.0	32.3	206.2	7.4	12,041
Stanislaus	RIVERBANK	BNSF	1	1	758	9.3	27.4	175	6.3	2,325	0.0	0.1	0.4	0.0	26
San Bernardino	NEEDLES	BNSF	13,396	13,396	758	9.3	27.4	175	6.3	35,365,223	362.5	1,068.1	6,822.0	245.6	398,290
San Bernardino	MOJAVE (BNSF)	BNSF	946	946	758	9.3	27.4	175	6.3	2,498,572	25.6	75.5	482.0	17.4	28,139
Kern	MOJAVE (BNSF)	BNSF	932	932	758	9.3	27.4	175	6.3	2,460,168	25.2	74.3	474.6	17.1	27,707
San Bernardino	LUCERNE VALLEY	BNSF	10	10	758	9.3	27.4	175	6.3	26,738	0.3	0.8	5.2	0.2	301
Los Angeles	HARBOR	BNSF	10	10	758	9.3	27.4	175	6.3	27,315	0.3	0.8	5.3	0.2	308
Lassen	GATEWAY	BNSF	533	533	758	9.3	27.4	175	6.3	1,407,101	14.4	42.5	271.4	9.8	15,847
Modoc	GATEWAY	BNSF	389	389	758	9.3	27.4	175	6.3	1,028,065	10.5	31.1	198.3	7.1	11,578
Plumas	GATEWAY	BNSF	183	183	758	9.3	27.4	175	6.3	483,134	5.0	14.6	93.2	3.4	5,441

San Bernardino	CAJON	BNSF	5,691	5,691	758	9.3	27.4	175	6.3	15,023,495	154.0	453.8	2,898.1	104.3	169,198
Kern	BAKERSFIELD	BNSF	1,032	1,032	758	9.3	27.4	175	6.3	2,723,231	27.9	82.2	525.3	18.9	30,670
Kings	BAKERSFIELD	BNSF	734	734	758	9.3	27.4	175	6.3	1,937,066	19.9	58.5	373.7	13.5	21,816
Tulare	BAKERSFIELD	BNSF	607	607	758	9.3	27.4	175	6.3	1,602,636	16.4	48.4	309.2	11.1	18,049
Fresno	BAKERSFIELD	BNSF	419	419	758	9.3	27.4	175	6.3	1,105,197	11.3	33.4	213.2	7.7	12,447
Total					*777*[d]					179,752,700	1,843	5,429	34,675	1,248	2,024,411

[a]Annual million gross ton-mile data reported by the railroads for acending and decending mile post directions. This is the same data used by the UC Davis method

[b]System-wide fuel intensity factors (GTM/gallon) reported by UP (Detailed route data in Appendix C) and BNSF (Detailed route data in Appendix C)
[c]EPA estimated emission factors for 2007 (EPA (2009). Emission Factors for Locomotives, U.S. Environmental Protection Agency, Washington, D.C., EPA-420-F-09-025.)

Sum of BNSF GTM	61339.93
Sum of UP GTM	76678.13
[d]Weighted Average Fuel Intensity	777.267