Operational Schedule Flexibility, Train Velocity and the Performance Reliability of Single-Track Railways

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ABSTRACT

Freight shippers and travelers demand a consistent level of service from transportation systems, including railways. Inventory and train connections are more efficiently managed when the total time for railways to move freight or passengers between origin and destination is predictable. One approach to achieve consistency is structured operations where trains are dispatched according to predetermined schedules. By precisely planning the meet and pass interactions to match available track infrastructure, train delay is minimized, train velocity is increased and total runtimes are highly predictable. In North America, the economics of transporting many freight commodities requires a certain amount of schedule flexibility that results in sub-optimal train conflicts and introduces additional train delay. Theoretically, the same total running time and train velocity can be achieved under these flexible operations by increasing the maximum allowable train speed on the line to compensate for the delays. To investigate the equivalency of structured operations at lower speeds versus flexible operations at higher speeds, a representative single-track route was simulated with Rail Traffic Controller. From a baseline minimum-delay schedule, the experiment design increased both maximum allowable speed and schedule flexibility to examine the interaction between these factors and the distribution of runtime and train velocity response for various traffic volumes. Simulation results suggest a slight shift from structured to flexible operations requires a substantial increase in operating speed to maintain runtime and velocity. Decreasing schedule flexibility to facilitate reduced maximum operating speed (and fuel and motive power savings) shows little return until operations become completely structured.

INTRODUCTION

Transportation systems, including railways, have a strong economic incentive to provide a high level of service to freight shippers and travelers. Short travel times corresponding to high train velocity minimize inventory holding costs and make passenger travel more competitive with other modes. However, the level of service provided by railways is not just a function of the travel time between origin and destination terminal but also its consistency and reliability. For both passengers and shippers, consistent travel times allow for more precise planning of connections between trains and to other modes. For freight shippers, inventory is more efficiently managed when the total time for railways to move freight between origin and destination is predictable. Inconsistent train running times and variation in train velocity requires shippers to maintain more "safety stock" and increases costs (*1*).

As shown be the relative average train velocity for different types of freight service on North American Class I railways (*2*), shipper demand for shorter and more consistent train running times can be directly related to the value of the goods being shipped. Lower-value bulk commodities tend to tolerate longer and more variable shipping times than higher-value and time-sensitive freight. This distinction is of current importance to the rail industry as recent rail traffic trends have seen a shift from lower-value bulk commodities to higher-value freight, often via containerized intermodal service. Coal traffic has declined by over 20 percent since North American freight rail traffic reached its peak in 2006, while intermodal and automotive traffic carloads are steadily increasing in volume *(3).* Domestic package delivery companies, driven by the upswing in online purchases, have contributed to the growth of premium domestic intermodal traffic that requires strict transit times to meet customer commitments. At the same time, led by Tesla Motors, there has been strong interest within the automotive industry to sell and deliver cars directly to the customer via contracts with rail carriers *(4)*. Chemical traffic can also be time sensitive and in 2016, U.S Class I railroads originated 2.1 million carloads of chemicals, yielding $9.9 billion in gross revenue, up from $6 billion in 2007 (*5*). Together, these recent railway traffic trends suggest that demand for faster and more consistent rail transit times and train velocity is intensifying.

Besides benefiting shippers, more consistent rail transit time and train velocity allows railways to improve operations planning. Consistency is central to the "precision railroading" concept as a way to reduce costs through improved efficiency and asset utilization (*6*). Developing and consistently executing an operating plan requires some contingency for inevitable delays and variation in train running time or precise methods to predict delays and proactively adjust the plan in real time. Thus several researchers have investigated techniques to predict the delay and train running times on single-track freight lines (*8-14*). Shih et al. developed a model that can accurately predict train delay up to the 70th percentile using the Bayesian Optimization approach (*15*). Davydov et al. created a stochastic model to estimate reliability of service while considering mainline disruptions and train handling (*16*). Sogin et al. considered the runtime impact of operating various combinations of passenger and freight traffic on single and double track. Depending on the track configuration, incremental upgrades in speed for passenger service increased freight train delay and variability in passenger train runtime (*17*). In addition, Sogin et al. revealed that efforts to enhance allowable track class and curvature to affect operating speed are valid alternatives to capital investments into additional rain lines (*18*). Recently researchers have begun to apply neural network and machine learning approaches to estimating train delays and running time (*19 - 20*).

Structured and Flexible Operations

One approach to achieve consistency in train running times is to dispatch trains according to predetermined schedules with a set timetable for passing each intermediate control point. Trains carefully adhere to planned meet locations, dwell times and routes from origin to destination. By precisely planning the train meets and overtakes to match available track infrastructure, train delay is minimized, train velocity is increased and total runtimes are highly predictable (outside of unplanned events such as equipment, track and signal failures). This type of operations has been termed “structured operations” (*21*).

For North American freight railroads, the business objective of maximizing the length of trains in carload freight service requires terminal operators and dispatchers to dynamically adjust predefined train plans. Additional departure time flexibility is required in the event of insufficient crew or locomotive availability, or train makeup requirements. After trains depart terminals, running time flexibility is necessary to accommodate random disruptions such as unanticipated meets or passes with other late trains, mechanical failures, signal failures, temporary slow orders, or track inspection delays. As a consequence, predefined train operating plans in North America are relatively imprecise compared to structured operations with fixed timetables. Meet and overtake times and locations are dynamic, arranged by dispatchers monitoring the progress of trains over a line. This operating style was named “improvised operation” by Martland (*21*) and is termed “flexible operation” in this study.

In North America, to meet different business objectives and shipper demands for consistent transit time, different types of freight trains operate at different points on a continuum between pure structured and completely flexible operations. Premium intermodal trains have published regular daily terminal departure times and guaranteed arrival times that place them towards structured operations. Bulk unit trains may depart at different times during a given week according to production schedules, placing them further towards completely flexible operations.

In this paper, the term “schedule flexibility” is used to describe the amount of variation in departure time relative to a baseline train operating plan with target departure times. A completely structured operation exhibits no schedule flexibility and all trains depart precisely at their scheduled time. Operations with low schedule flexibility are more structured and have all trains departing relatively close to set departure times. Operations with high schedule flexibility have train departures distributed over a wider range around the planned departure time. A completely flexible operation has trains departing randomly throughout each operating day.

Dick & Mussanov investigated the effect of varying amounts of schedule flexibility on train delay for fixed volumes of homogeneous rail traffic on representative North American single-track and partial-double-track lines (*22*). When starting from a fixed timetable with little train delay, introducing schedule flexibility in the form of random variation in scheduled departure times caused an increase in average train delay. Small amounts of schedule flexibility created rapid increases in train delay but beyond a certain level of schedule flexibility, further increases in train delay were not observed. Other researchers have investigated the relative delay performance of different combinations of scheduled and flexible trains operating on the same corridor across a range of schedule flexibility and volume (*23*, *24*). The results suggest it is difficult for scheduled trains to have a high level of service in the presence of flexible trains, and the effect is amplified as the line nears capacity. These previous studies of schedule flexibility were all performed for the same maximum allowable train speed (MAS) and largely considered average train delay as a measure of performance and capacity. This paper will expand upon this previous research to investigate the relationship between MAS, level of schedule flexibility, traffic volume and the distribution of both train running time and train velocity.

Running Time, Delay, Velocity and MAS

North American railroads monitor the performance and fluidity of their networks through various metrics including “train velocity”. Also termed “average train speed” or “network velocity’, train velocity is calculated by dividing the total distance traveled by the actual running time elapsed between origin and destination (*2*). The actual running time includes the time the train is in motion and the time the train is stopped waiting for other trains or other unexpected sources of delay once the train departs its origin terminal.

The actual running time can be divided into two parts: the minimum running time and train delay. The minimum running time is the time required for a train to traverse the rail line segment of interest with no stops for meets or conflicts with other trains, while obeying all MAS and considering the acceleration and braking capabilities of the train. The minimum running time is inversely proportional to the MAS on the line.

In North America, under flexible freight operations, train delay for a particular train is defined as the difference between its minimum running time and its actual running time. Train delay includes the time a train is stopped waiting for other trains. This is different from other international definitions of train delay where scheduled time spent dwelling in stations or for planned train meets is not considered as delay. As described above, previous research has demonstrated that train delay is proportional to the amount of schedule flexibility present in the operation under study. These relationships are summarized in the equations below.

$$Train\ Velocity = \frac{Total\ Distance}{Actual\ Running\ Time} = \frac{Total\ Distance}{Minimum\ Running\ Time + Train\ Delay}$$

$$Minimum\ Running\ Time \propto \frac{1}{Maximum\ Allowable\ Speed}$$

$$Train\ Delay \propto Schedule\ Flexibility$$

Research Questions

In examining the above relationships, it is apparent that by increasing train delay, allowing for schedule flexibility decreases train velocity (and increases actual running time) compared to structured operations. Theoretically, the same total running time and train velocity can be achieved under flexible operations by increasing the MAS on the line. Increasing the MAS should effectively decrease the minimum running time to compensate for the additional delays created by flexible operations.

Competing against other railroads and highway transport, railroad operators must carefully control costs while fulfilling customer service commitments. Increasing MAS to compensate for schedule flexibility and maintain running times is not without its costs. Faster trains require higher horsepower-per-ton ratios, increasing fuel consumption and locomotive costs. Increased speeds may also require improvements to track infrastructure and increased maintenance. However, the alternative, building new track infrastructure to add capacity and directly mitigate the train delay due to schedule flexibility (*22*), may be more costly. Railroads should consider all infrastructure and operational alternatives when seeking to increase capacity and service reliability.

This paper seeks to investigate the equivalency of structured operations at lower speeds versus flexible operations at higher speeds. Through a better understanding of the interaction between schedule flexibility, MAS and traffic volume, railway practitioners can make more informed decisions involving trade-offs between these factors, desired train velocity and the distribution of running time on freight rail corridors.

To achieve this goal, this paper aims to address three specific research questions:

- How does the introduction of schedule flexibility alter the distribution of runtime and train velocity compared to structured operations?
- What increase in MAS is required to compensate for the additional delay introduced by flexible operations?
- Can decreasing schedule flexibility allow train velocity to be maintained while decreasing MAS?

To answer these questions, simulation experiments are conducted to determine the runtime and train velocity distribution for various combinations of traffic volume and MAS on a representative single-track rail corridor as it transitions from highly-structured to purely flexible operation. The remainder of the paper considers a baseline “return grid” structured operation and compares it to flexible operation at higher MAS to quantify the trade-off between MAS and schedule flexibility. The results of this study can streamline the decision-making process by establishing general guidelines for setting a combination of MAS, schedule flexibility and volume for a desired combination of reliability, train velocity and runtime.

RAIL TRAFFIC CONTROLLER

The train runtime response for each experiment scenario described in the methodology section is determined via Rail Traffic Controller (RTC) simulation software. RTC is a rail traffic simulation software widely used in the rail industry, including, but not limited to, Amtrak, Class I railroads and consultants. RTC simulates dispatcher decisions in guiding trains along the specific routes to resolve meet and pass conflicts. General RTC model inputs include track layout, signaling, curvature, grades, train characteristics etc.

To determine the runtime response, each unique combination of schedule flexibility, MAS and volume in the experiment design is simulated in RTC for five days of rail traffic. To allow for variation in train departure times according to the schedule flexibility factor, each simulation is replicated ten times, providing 50 days of train runtimes. Each replication represents a specific departure time set by a uniform distribution over the departure item window. Runtime accumulated by individual trains during this 50-day period produces a runtime distribution that is normalized to develop a train velocity response for that element of the experiment design matrix. The average or different percentile responses for a simulation scenario can be plotted as a single data point in the results where appropriate.

METHODOLOGY

The overall experimental approach is to first establish a baseline schedule for a given traffic volume of trains. Structured operations according to this schedule are simulated with zero schedule flexibility and a MAS of 30 miles per hour. Once the baseline structured operations are established, schedule flexibility and/or MAS are increased, alone and in combination, and total runtime is observed. This process is repeated for different traffic volumes. The resulting data allowed for quantification of the relationship between schedule flexibility, MAS and traffic volume for a given level of service (measured by the 95th percentile of total runtime).

The same baseline route infrastructure was used for all of the cases with route parameters selected to be representative of North American infrastructure and operating conditions. The route consists of 240 miles of single-track mainline with terminals at each end. Passing sidings were placed 10 miles apart (Table 1).

TABLE 1 Infrastructure and train parameters for all scenarios

Parameter	Characteristic
Length of the route	240 miles
Siding Length	2 miles
Siding Spacing	10 miles
Structured Departure Interval	2 hours
Traffic Composition	Homogeneous, Bulk Freight
Locomotive Type	SD70 4300hp, 3 locomotives per trainset
Train Consist	115 railcars at 138 tons each
Operating Protocol	CTC 2-block, 3-aspect

To avoid confounding the experiment results with the effects of train heterogeneity, the traffic on the route consists of identical freight trains. The trains have characteristics representative of typical North American bulk unit freight trains (Table 1).

Baseline Schedule

To create a baseline schedule that minimizes delay for the simulated traffic volumes, trains were set to depart each terminal at even intervals according to the single-track return-grid operating model. Under this schedule pattern, train departures are evenly distributed during each 24-hour period. The train speed, departure interval and siding spacing align such that all train meets naturally occur at a limited number of passing sidings with minimal delay. Since the return-grid model makes various simplifications, trial and error iteration through RTC software simulation was used to verify the feasibility of the schedule and its ability to minimize delay for the route infrastructure. Small adjustments in the schedule parameters were made to account for factors such as acceleration and braking characteristics of the trains and signal clearance time.

Experiment Design

The experiment design includes three variable factors: volume, schedule flexibility and MAS, schedule flexibility and daily traffic volume. Each factor was simulated over a range of values or "levels" (Table 2) in a full-factorial design. Simulating all factorial combinations of the experimental factors was necessary to capture the non-linear response of runtime and delay to each factor.

TABLE 2 Experiment design factor levels

Experiment Design Factor	Number of Levels	Level Specification
MAS (mph)	6	30, 35, 40, 50, 60, 70 mph
Schedule Flexibility (± minutes)	8	0, 10, 40, 60, 120, 240, 480, 720 min
Volume (trains per day)	7	24, 28, 32, 36, 40, 44, 48 tpd

The MAS factor is adjusted by changing the MAS of each track segment on the route within the RTC simulation. For higher speeds, the MAS may not be achievable by some trains due to traffic density or the design of the route infrastructure. For speeds under 60 mph, the MAS was achieved for each train on the mainline track.

The schedule flexibility factor establishes the range of departure times for each train relative to the baseline schedule. Schedule flexibility is measured in minutes and defines the window of time for each random departure. For example, with +/- 60 minutes of schedule flexibility, a train set to depart at 4 AM in the baseline schedule will randomly depart between 3 and 5 AM. The exact departure time within this window for each simulation trial was randomly set by the RTC software according to a uniform distribution. The schedule flexibility factor level of zero minutes corresponds to the structured baseline schedule, with no deviation in departure time. For higher factor levels, the actual departures are randomized over increasingly larger windows up to +/- 720 minutes (+/-12 hours) where trains depart each terminal randomly within a 24-hour period in totally unscheduled operations. By including these extremes, a whole spectrum of operations was considered, ranging from highly structured to completely flexible.

To vary the traffic volume, trains were added or removed from the initial baseline schedules of 36 or 24 train departures. Trains were removed and added in pairs to maintain directional balance. Removing four trains from the ideal schedule of 36 trains provides the initial departure times for the scenarios with 32 trains per day. The remaining trains are not reorganized into even intervals, but remain in their original departure slots to preserve the ideal "return-grid" schedule. To increase traffic volume from 36 to 40 trains per day, four trains were dispatched in two time slots used for two trains in the base-line schedule. For 44 trains per day, the extra trains required doubling up traffic in four of the original time slots.

Analysis

To analyze the effects of the experimental factors on train performance, and the tradeoffs therein, different analytical methods are used. To observe the range of train performance for a given scenario, cumulative runtime and train velocity curves are compared. To track the influence of the experimental factors, a regression of runtimes at the 95th percentile is created, and arc elasticity is observed. In addition to the 95th percentile, 18 iterative regressions (5th –95th) are performed to demonstrate how the influence of the experimental factors varies at different levels of performance. The arc elasticity of the 5th percentile is compared to the 95th percentile.

Use of Runtime and Train Velocity to Measure Performance

Although train delay is a common metric for North American railroad performance, for the purposes of this study, runtime and train velocity are more appropriate. Delay can measure congestion but railway service is related to network velocity, and therefore runtime. When MAS varies, it is difficult to assess the service performance among the different cases using delay alone. For example, a higher-speed train can incur more delay than a lower-speed train but still have a higher network velocity and a shorter overall runtime. Therefore, for this experiment, total runtime and train velocity are the preferred metrics for evaluating train performance, not delay. Since some scenarios show great variation in train runtime performance, a 95th percentile runtime was analyzed instead of a mean value. Analyzing the 95th percentile provides a better measure of the reliability and consistent level of service desired by railway customers.

RESULTS

Consistency of Train Velocity and Runtime Performance

Cumulative distributions of train velocity and runtime for different MAS can be compared to determine the relative performance penalty for operating with various levels of schedule flexibility at different traffic volumes (Figure 1a-d). Each data series represents the speed–

schedule flexibility combination for a given traffic volume. It had previously been observed that runtime is most sensitive to schedule flexibility values between 0 and 240 minutes (*22*) so that range is displayed. The four groupings of cumulative curves denoted by different colors correspond to 30, 35, 40 and 50 mph MAS. For 30 mph MAS, structured operations with zero minutes of schedule flexibility is represented by the dotted black curve; all other curves are a permutation of flexible operations.

The negative cumulative distributions of train velocity (Figure 1a and 1b) indicate the fraction of trains in a particular scenario that achieve a train velocity greater than the value on the horizontal axis. As expected on single track, for all scenarios, the highest train velocity is well below the MAS and very few trains achieve this velocity. The velocity of these best-performing trains shows little sensitivity to schedule flexibility. The velocity of worse-performing trains is negatively impacted by the introduction of schedule flexibility. At the higher traffic volume of 36 trains per day, the worst-performing trains can achieve higher velocity through more structured operations compared to flexible operations at slightly higher MAS.

Comparing the cumulative runtime distributions (Figure 1c and 1d) highlights intersections that indicate equivalent performance from different combinations of MAS and schedule flexibility for a given traffic volume. Data sets with different MAS do not intersect until the 80th percentile. Train runtime performance is largely dictated by MAS rather than schedule flexibility. This is especially relevant in under-capacity situations (lower traffic volume of 24 trains per day) where there is excess track infrastructure to resolve the additional traffic conflicts induced by schedule flexibility, resulting in a lesser effect on runtime (Figure 1c).

In the scenario with 36 trains per day, higher MAS but more flexible operations may have similar runtime performance to slower trains with more structured operations (Figure 1d). As indicated by the black circles in the figure, this tradeoff is observed exclusively in cumulative percentages exceeding 80 percent; those below this threshold do not display this tradeoff. For instance, structured operations with a MAS of 30 mph intersect with operations running at 35 mph at 240 min of schedule flexibility. Both scenarios have 90-95 percent of trains with less than 11.5 hours of runtime.

An increase in traffic volume leads to a wider runtime distribution and lower reliability. For both volume data series, higher MAS leads to a narrower runtime distribution. With a faster MAS, trains can resolve conflicts more quickly due to decreased travel times between sidings. Railway practitioners aiming to push for more reliable service should be opting for lower volumes and higher speeds or more structured operation. The narrowest runtime distribution is achieved by structured operations with no schedule flexibility. Structured operations with 36 trains per day at 30 mph MAS surpasses the reliability of flexible operations with 24 trains per day at 50 mph MAS. Even though structured operations has some variation in runtime, the individual train symbols within the daily schedule do not have different runtimes each operating day; the variation only occurs between different train symbols based on the number of train meets they encounter. Thus, the service provided to individual shippers under scheduled operations is highly consistent.

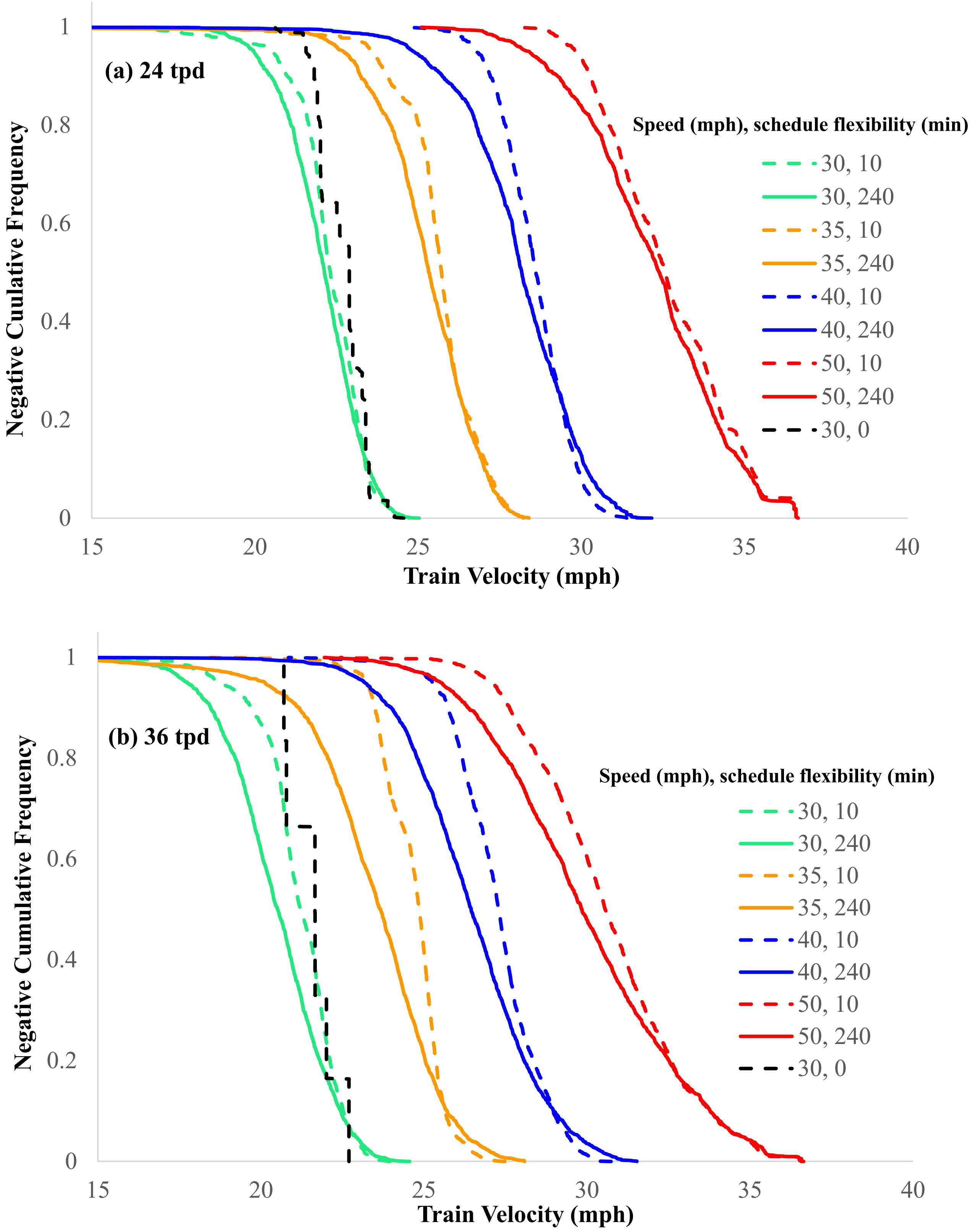
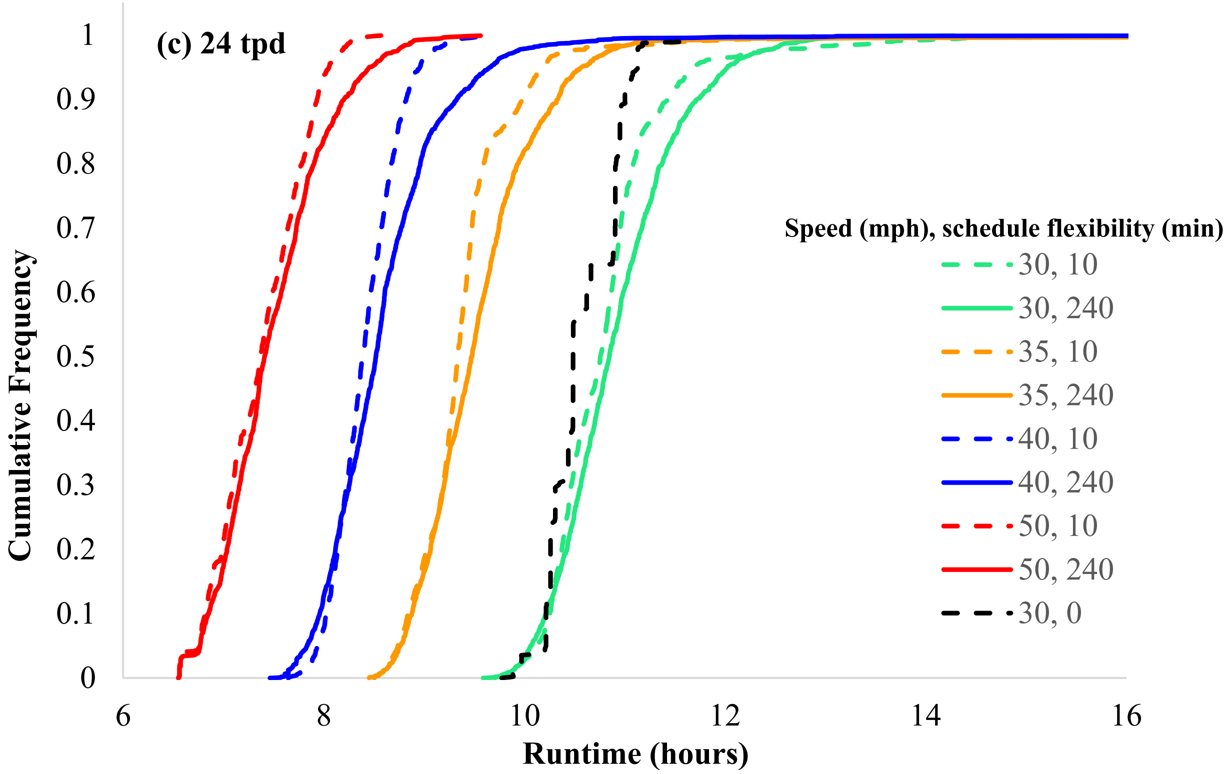


FIGURE 1 Negative cumulative frequency distribution of train velocity (a-b) and cumulative frequency distribution of runtimes (c-d) for 24 and 36 trains per day



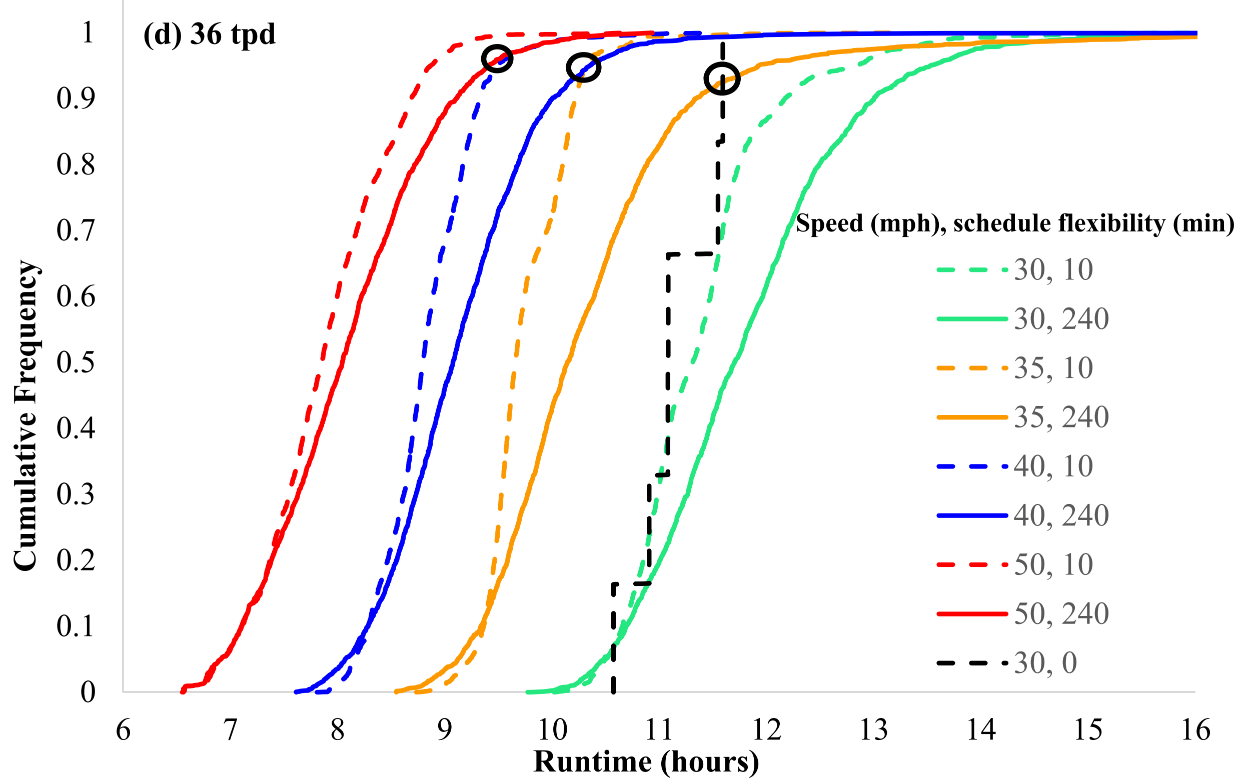


FIGURE 1 (continued) Negative cumulative frequency distribution of train velocity (a-b) and cumulative frequency distribution of runtimes (c-d) for 24 and 36 trains per day

The 95th percentile train velocity was plotted for each combination of MAS and schedule flexibility for both 24 and 36 trains per day (Figure 2a and 2b). Both graphs display a linear function with similar slopes for all levels of schedule flexibility and a steeper slope for structured operation. As MAS is increased, structured operation sees a greater increase in train velocity compared to the scenarios with schedule flexibility. The greater the schedule flexibility, the less train velocity benefit is obtained from increases in MAS. A slight shift from structured to flexible operation (black 0 minutes to blue 10 minutes line) leads to a steep penalty in 95th percentile train velocity. For both traffic volumes, approximately the same (or faster) 95th-percentile train velocity can be achieved with a lower 35 mph MAS and structure operations and a higher 50 mph MAS and 240 minutes of schedule flexibility. Achieving the same train velocity with lower MAS could allow for less stringent maintenance standards and potential fuel savings. The maintenance and fuel costs of higher MAS to maintain a baseline train velocity represent another potential cost of introducing schedule flexibility.

Regression Analysis of Train Runtime

After the scenarios were simulated, a multivariable regression model was constructed to predict 95th percent runtime performance based on MAS, schedule flexibility, and volume as inputs (Equation 1).

$$\begin{gathered} R = 29.2 + 0.12V - 0.96S + 0.0045F + 0.00062V^2 + 0.01S^2 \\ -4 \times 10^{-6}F^2 - 0.002VS + 0.00008VF - 0.000084SF \end{gathered} \tag{1}$$

where,
R is the 95th percentile runtime (minutes);
V = volume (trains per day);
S = MAS (mph)
F = schedule flexibility (minutes)

The model has an R-squared of 0.97 and significant interactions with p-values below 0.01. Thus, the model should be a good predictor of the runtime for the range of simulated factor levels. By examining the combinations of schedule flexibility and MAS that correspond to a given 95% runtime, the data can be transformed to illustrate the relationship between schedule flexibility and MAS required to provide a particular 95th percentile runtime for a given traffic volume (Figure 3a and 3b).

Starting from structured operations (zero minutes of schedule flexibility), initial increases in schedule flexibility require an increase in MAS to maintain runtime. At a certain MAS the operation is unaffected by further increases in schedule flexibility. To maintain the desired runtime, a railway operator may not need to further increase MAS once schedule flexibility approaches 480 minutes.

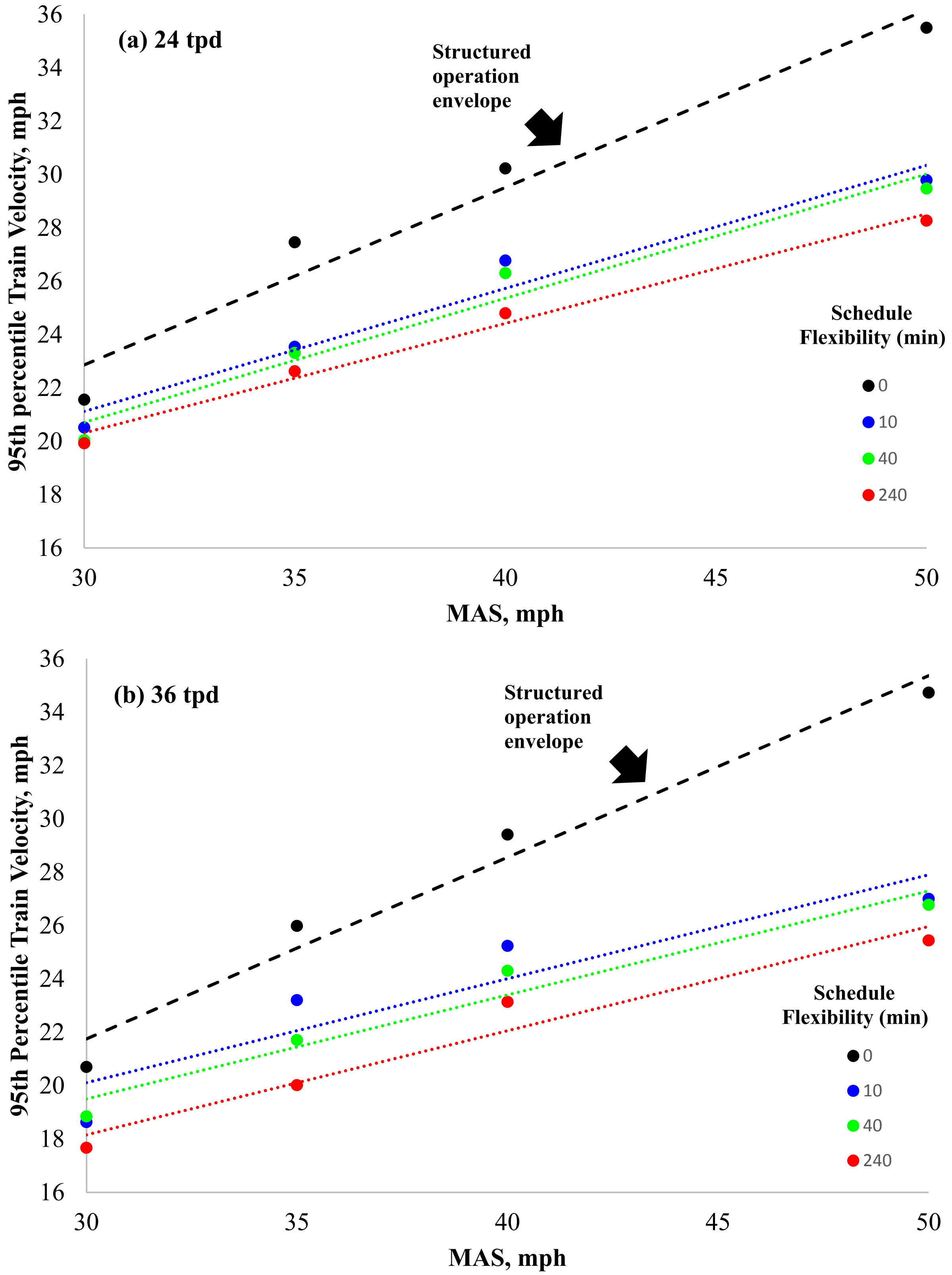


FIGURE 2 95th percentile train velocity for combinations of schedule flexibility and MAS with a) 24 and b) 36 trains per day

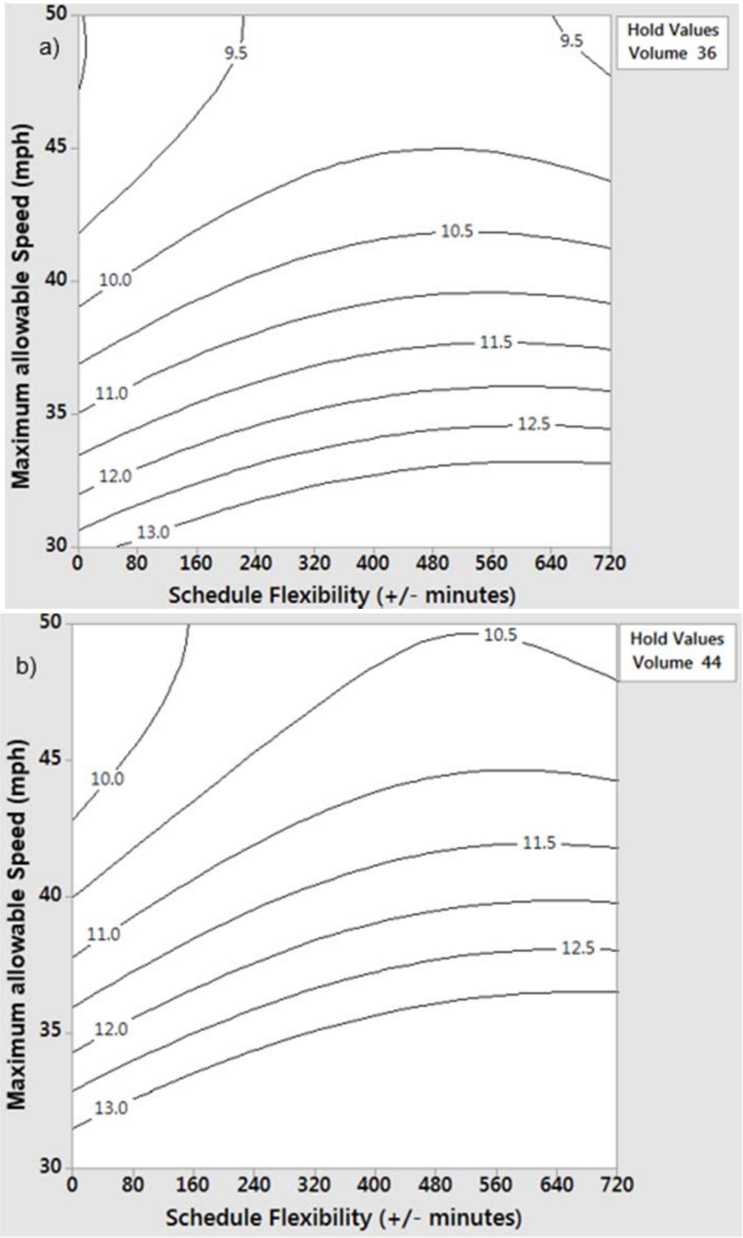


FIGURE 3 Relationship between schedule flexibility and MAS under contours of fixed runtime in hours for a) 36 trains per day and b) 44 trains per day

The tradeoff between schedule flexibility and MAS is more apparent at MAS above 40 mph. Speed must increase sharply to maintain a given runtime when schedule flexibility is initially increased. Higher volumes, such as 44 trains per day, are also more sensitive to the initial increase in schedule flexibility, and therefore require higher speeds to maintain runtime (Figure 3b). At 44 trains per day, structured operations must shift from 40 to 50 mph service to maintain a 10.5-hour runtime during a major disruption that introduces substantial schedule flexibility. To be immune to such disruptions, the MAS must be kept at 50 mph.

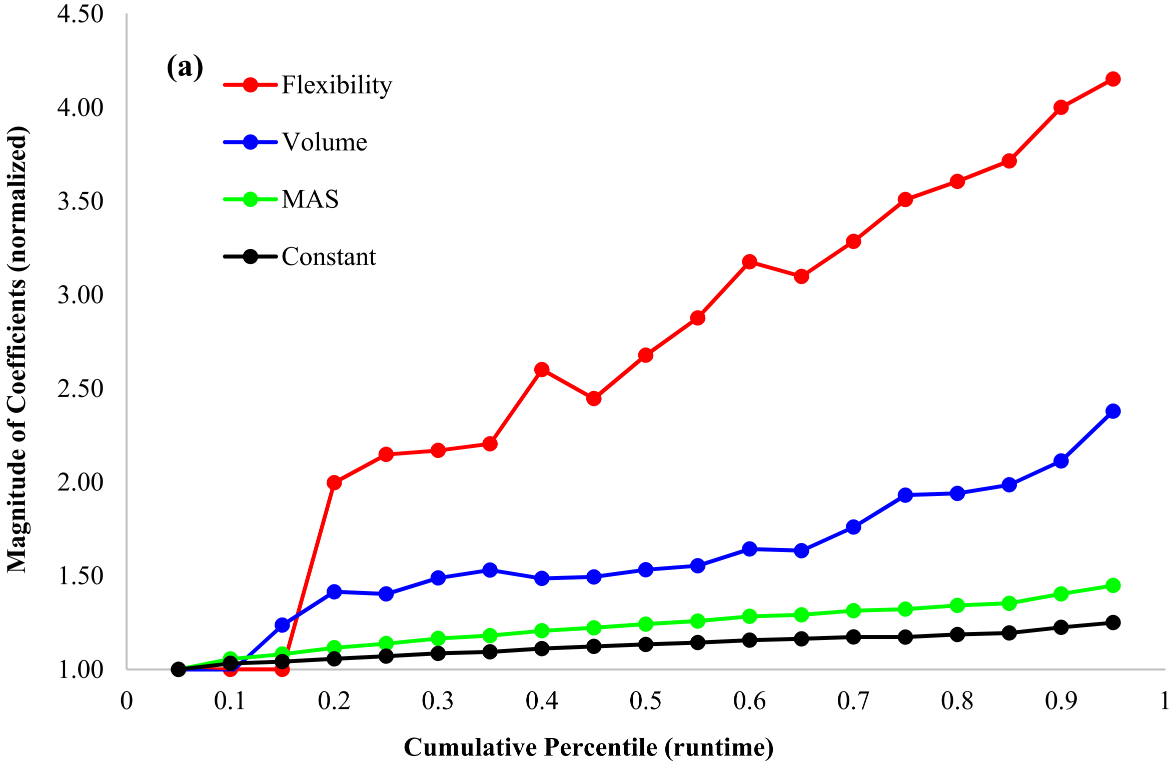
From the perspective of a capacity planner, these results suggest that when structured operations encounter small disruptions, speed increases may be necessary to maintain runtime performance. To ensure efficient operations, planners could opt for a faster MAS that ensures runtime regardless of schedule flexibility. Conversely, if a planner is confident in their ability to maintain structured operations, they have the ability to lower the MAS. Lower MAS has the benefit of reduced track maintenance, reduced fuel consumption and lower horsepower-per-ton ratios that may even reduce the number of locomotives required on some trains.

Runtime Curve Regression

Although the 95th percentile runtime is important, not all train operations can be dictated from one metric that does not fully capture reliability. All levels of train velocity and runtime performance may be relevant to railways. The entire distribution of train runtime performance must be assessed to properly quantify reliability.

Rather than fitting a Weibull curve or other distributions to the data, this research employed a different approach to quantify reliability and its relationship to different experimental factors. A set of 18 regressions were performed at intervals between the 5th and 95th percentile runtime in increments of five percent, using the regression methodology described previously. All the models have an R-squared of at least 0.97 and significant interactions with p-values below 0.01. The resulting set of expressions can be used to model the entire runtime distribution with volume, MAS and schedule flexibility as inputs, and percentiles of runtime as the output. Comparing the cumulative raw data with the cumulative curves developed through the regression process suggests these three experimental factors are together good predictors of runtime at all levels of performance.

From the perspective of the service planner, the method of constructing a model of runtime distribution curves from a series of regressions on raw data can provide additional insight on the changing relative impact of speed, volume and schedule flexibility parameters on different runtime percentiles. In comparing the regression equations used to predict the different percentiles of the runtime distribution, the relative influence of each factor changes across the percentiles. Since the magnitudes of each coefficient in the regression differ greatly, to illustrate the relative change of each coefficient across the percentiles, the coefficients for each term in model were normalized relative to their values in the regression equation for the 5th percentile and then plotted across all percentiles (Figure 4). For the first-order coefficients (Figure 4a), schedule flexibility shows the greatest relative change from the 5th percentile to the 95th percentile while volume also shows increasing importance beyond the 70th percentile. In contrast, MAS and the constant coefficient remain mostly stable even in the higher percentiles. For the second-order coefficients (Figure 4b), those with flexibility and/or volume show the greatest relative change with increasing percentile. For service planners, this relative magnitude comparison indicates that higher-percentile runtimes are increasingly sensitive to changes in volume and schedule flexibility while the influence of MAS remains relatively constant.



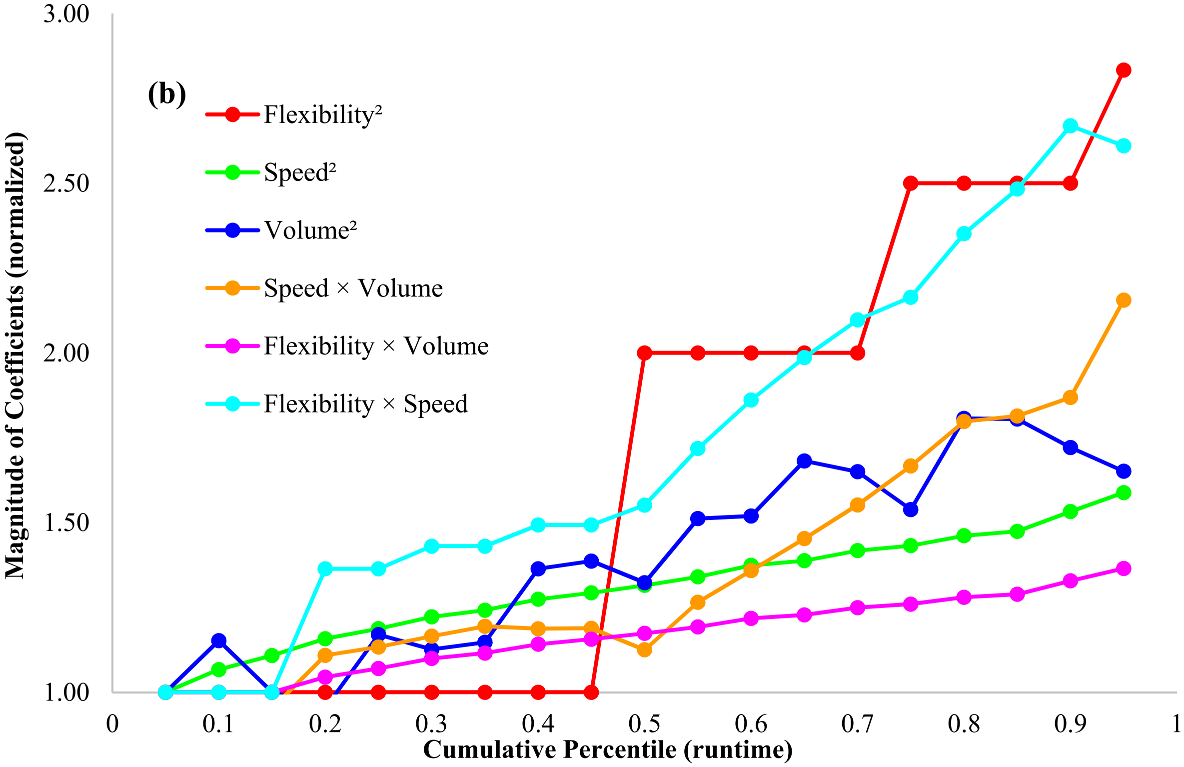


FIGURE 4 Magnitude of regression model coefficients for different percentiles of runtime normalized relative to 5th-percentile coefficients

Elasticity of Factors to Freight Train Runtime

To better quantify the relative influence of each parameter, arc elasticity was calculated for each factor (*25*). The elasticity index is used to demonstrate the relative influence of the factors considered in this study on train runtime. It is an appropriate index, since it considers the different magnitudes of each regression input to provide valid factor comparisons regardless of the original units and numeric ranges. The elasticity values are obtained using runtime values provided by the regression model and varying the three factors from baseline conditions. The positive and negative elasticities are related to maximum increase or decrease in the value of each respective factor.

According to elasticity values (Figure 5), runtime is most sensitive to changes in the MAS. This is not an unexpected result as MAS is obviously linked to runtime; it is the relative sensitivity of MAS and the other factors that is of interest. A one percent reduction in train speed leads to a 1.19% increase in runtime, whereas a one percent increase in train speed corresponds to 0.36% reduction in average train runtime. This runtime saving is equivalent to reducing the volume in the route. Faster trains operating at a higher volume will have greater conflict resolution than a slower train operating in a lower volume setting.

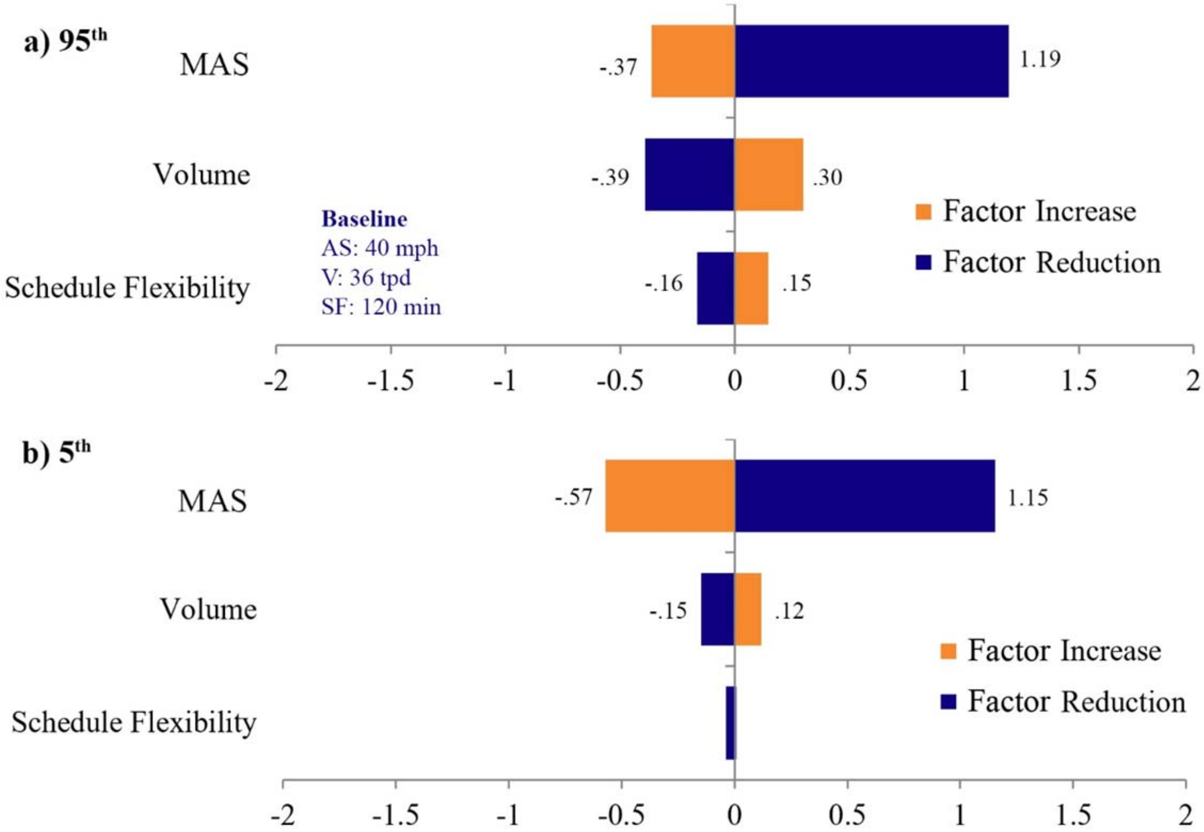


FIGURE 5 Elasticity of a) 95th percentile and b) 5th percentile runtime to factors AS = allowable speed, V = volume and SF = schedule flexibility.

Second to speed, traffic volume is the most significant factor with more traffic resulting in higher runtimes. The elasticity suggests that a reduction in volume has a bigger effect than an increase. Schedule flexibility had a very small effect on overall runtime in comparison to MAS and volume.

In addition to the elasticity index based on the 95th percentile, the elasticity at the 5th percentile demonstrates how the influence of the experimental factors varies at different levels of train performance. Compared to the 95th percentile, the 5th percentile is much less sensitive to changes in schedule flexibility and volume. At low percentiles, changes in schedule flexibility do not affect runtime to the same extent as trains with much longer runtimes. The 5th percentile trains operate relatively freely, and extra meet pass interactions due to increased schedule flexibility are less impactful to runtime performance. Similarly, volume increases have less influence on 5th percentile runtime performance because this percentile of trains tends to stay very close to ideal train paths.

The performance of the best 5 percent of trains is primarily driven by the MAS while the performance of the worth 5 percent of trains is more related to traffic volume and schedule flexibility. From the perspective of a capacity planner, these relative effects are of interest if only a portion of the traffic on a route is premium service that demands high train velocity and consistent runtimes under increasing schedule flexibility.

CONCLUSIONS AND FUTURE WORK

For a given track infrastructure and fixed volume, runtime increases and train velocity decreases as schedule flexibility increases. Consistent with previous research, runtime conditions became insensitive to further increases in schedule flexibility above 120 minutes. Reducing schedule flexibility with the desire to decrease MAS showed little return until operations became more structured.

Rail operators can mitigate increases in runtime due to increased schedule flexibility by increasing the MAS of trains, particularly at lower initial speeds. Conversely, by moving from flexible operations to structured operations, small decreases in MAS can be made while maintaining train velocity and total runtime. Although these decreases in MAS may decrease fuel consumption, for the tested conditions, the small decrease in MAS is unlikely to result in large savings from reduced track maintenance and fewer locomotives assigned to trains.

An increase in schedule flexibility or traffic volume leads to a wider runtime distribution and lower reliability while higher MAS leads to a narrower runtime distribution. The most consistent performance with a narrow runtime distribution is achieved by structured operations with no schedule flexibility. Structured operations with higher volumes and lower allowable speed can surpass the runtime reliability of flexible operations with fewer trains and higher speeds. An added benefit of the slower structured operations is that on a train-by-train basis, daily runtimes are more consistent potentially offering a more predictable level of service to railway customers.

The factors of volume and schedule flexibility showed significantly less effect on the best performing trains, while MAS remained dominant. The iterative regression model was able to predict the entire runtime distribution based on the three experimental factors. To create a more robust model, additional experimental factors could be introduced and added to the iterative regression to predict the runtime curve of more complex traffic. Introducing various random disruptions during scheduled operation and allowing increased velocity to return to scheduled path could be another take on the problem.

This study only considered the "line of road" performance of trains between terminals. Future work will consider the influence of schedule flexibility on the performance and reliability of yards and terminals and the resulting contribution to overall freight transit times. Through this future work there is potential to link the delay and speed-related costs of schedule flexibility to decisions to deviate from planned schedules to maximize the revenue of individual trains. This future work could influence railroad operating practices as they compete with highways for freight with increasing demand for highly-reliable and predictable service times.

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REFERENCES

1. Sussman, J. *Introduction to Transportation Systems.* Artech House, Boston, 2000.

2. Railroad Performance Measures. RPM. www.railroadpm.org. Accessed Jul. 5, 2017.

3. Railroads and Coal. *Association of American Railroads*, 2016. https://www.aar.org/BackgroundPapers/Railroads%20and%20Coal.pdf. Accessed Jul. 5, 2017.

4. Lao, M., D. Feinstein, and F. Lafontaine. *Direct-to-Consumer auto sales: It's not just about Tesla.* Federal Trade Commission. https://www.ftc.gov/news-events/blogs/competition-matters/2015/05/direct-consumer-auto-sales-its-not-just-about-tesla. Accessed Jul. 5, 2017

5. Railroads and Chemicals. *Association of American Railroads*, 2016. https://www.aar.org/BackgroundPapers/Railroads%20and%20Coal.pdf. Accessed Jul. 5, 2017.

6. Harrison, E. H. *CN – How We Work and Why: Running a Precision Railroad.* Canadian National Railway Company, Montreal, 2005.

7. American Railway Engineering and Maintenance-of-Way Association. *Manual for Railway Engineering* – Chapter 16, 2014 Edition, Lantham, MD, 2014.

8. Chen, B., and P.T. Harker. Two Moments Estimation of the Delay on Single-track Rail Lines with Schedule Traffic. *Transportation Science*, Vol. 24, Issue 4, 1990, pp. 261-275.

9. Gorman, M.F. Statistical estimation of railroad congestion delay, *Transportation Research Part E: Logistics and Transportation Review*, vol. 45, 2009, pp. 446-456.

10. Murali, P., M. Dessouky, F.Ordonez, K.Palmer. A delay estimation technique for single and double-track railroads, *Transportation Research Part E: Logistics and Transportation Review*, vol. 46, 2010, pp. 483-495.

11. Higgins, A., L. Ferreira and E. Kozan. Modeling Delay Risks Associated with train Scheduled. *Transportation Planning and Technology*, Vol. 19, No. 5, 1995, pp. 89-108.

12. Kraay, D.R.,and P.T. Harker. Real-time Scheduling of Freight Railroads. *Transportation Research part B: Methodological*, Vol. 29, 1995. pp. 213-229.

13. Hallowell, S.F., and P.T. Harker. Predicting on-time performance in scheduled railroad operations: methodology and application to train scheduling. *Transportation Research part A: Policy and Practice,* Vol. 32, 1998, pp. 279-295.

14. Estes, R.M., and L.R. Rilett. Advanced prediction of train arrival and crossing times at highway-railroad grade crossings. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1708, 2000, pp. 68-76.

15. Shih, M-C., C.T. Dick, D. Mussanov and C.P.L. Barkan. 2017. A Parametric Model of the Train Delay Distribution Based On Traffic Conflicts. P*roceedings of the International Association of Railway Operations Research (IAROR) 7th International Conference on Railway Operations Modelling and Analysis*, 2017.

16. Davydov, B., V. Chebotarev and K. Kablukova. Adaptive Stochastic Model for Train Rescheduling. *Proceedings of the International Association of Railway Operations Research (IAROR) 7th International Conference on Railway Operations Modelling and Analysis*, 2017.

17. Sogin, S., Y-C. Lai, C.T. Dick and C.P.L. Barkan. Comparison of capacity of single- and double-track rail lines. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2374, 2013, pp. 111-118.

18. Sogin, S.L., C.T. Dick, Y-C. Lai and C.P.L. Barkan. Analyzing the Incremental Transition from Single to Double Track Railway Lines. *Proceedings of the International Association of Railway Operations Research (IAROR) 5th International Conference on Railway Operations Modelling and Analysis*, 2013.

19. Wang, R. and D. Work. Data driven approaches for passenger train delay estimation. *Proceedings of the IEEE Conference on Intelligent Transportation Systems*, 2015.

20. Barbour, W., J. C. Martinez Mori, S. Kuppa, and D. Work. “Estimating arrival times for US freight rail traffic.” submitted to Transportation Research Part C: Emerging Technologies, 2017 (in review).

21. Martland, C.D. Improving on-time performance for long-distance passenger trains operating on freight routes. *Journal of the Transportation Research Forum*, Vol. 47, 2010, pp. 63-80.

22. Dick, C.T. and D. Mussanov. Operational schedule flexibility and infrastructure investment: capacity trade-off on single-track railways. *Transportation Research Record: Journal of the Transportation Research Board*, No.2546, 2016, pp. 1-8.

23. Mussanov, D., N. Nishio and C.T. Dick. Building Capacity through Structured Heavy Haul Operations on Single-Track Shared Corridors in North America. *Proceedings of the 11th International Heavy Haul Association Conference*, 2017.

24. Mussanov, D., N. Nishio and C.T. Dick. Delay Performance of Different Train Types Under Combinations of Structured and Flexible Operations on Single-Track Railway Lines in North America. *Proceedings of the International Association of Railway*

Operations Research (IAROR) 7th International Seminar on Railway Operations Modelling and Analysis, 2017.

25. Allen, R. G. D., and A. P. Lerner. The Concept of Arc Elasticity of Demand. *The Review of Economic Studies*, Vol 3, 1934, pp. 226-230.