Predicting the Cost and Operational Impacts of Slow Orders on Rail Lines in North America

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Abstract
Temporary speed restrictions, or slow orders, are a major concern to the largest North American railroads, but their effects on train operations and track maintenance costs do not appear to be sufficiently quantified. A new model is presented to estimate the operational impact of traffic disruptions, such as slow orders. The model considers the effects of cascading delays, relative speed reductions, overlapping slow order areas of influence, and the ability of a route to recover from a disruption. The sensitivity of the model to various input parameters, including slow order duration, capacity utilization, and normal and slow order operating speeds, is explored. The delay model was also used to compare the direct and delay costs of internal rail defects using a probabilistic rail defect model.

Keywords
Speed restriction, Track defects, Train delay, Operating costs

1 Introduction

Temporary speed restrictions are a substantial concern for major North American railroads. Commonly referred to as "slow orders," these restrictions are applied to a segment of track when it is deemed unsuitable for trains to operate at the posted maximum allowable speed. The main operating problem associated with slow orders is a reduction in average train speed, which is a metric of network fluidity reported by all major railroads in the United States (Association of American Railroads (AAR) (2016)). Decreasing average train speed increases railway operating costs at the network level by increasing the required number of railcars, locomotives, and crews for a given amount of traffic (Lovett et al. (2015a)). However, it is difficult to allocate these network cost increases to individual temporary speed restrictions on specific route segments and use the resulting costs to make track maintenance decisions. Previous research on railway maintenance planning indicated that slow orders do not have enough impact on railroad operations to materially influence track maintenance and operating decisions (Lovett et al. (2015b)). Since this finding is at odds with industry practice, further study is needed before definitive conclusions regarding the operational impact of slow orders can be reached. Factors that may affect slow order risk include the rate of occurrence, slow order length and duration, the cost of train delay, and potential compounding effects on subsequent trains and adjacent lines. In considering these factors, this paper attempts to improve upon previous research conducted by the authors on the cost and operational impact of slow orders.

As dictated by the Federal Railroad Administration Track Safety Standards or individual railroad track standards and recommended practices, slow orders are imposed when track defects are detected by vehicles equipped with various inspection technologies or visually by train crews and track inspectors (Federal Railroad Administration (FRA) (2014a)). Slow orders are also imposed after the track structure has been disturbed by certain track maintenance activities. Slow orders caused by track disturbance during maintenance typically require speeds to be reduced to 10-20 mph (16-32 km/h) for approximately 0.2 million gross tons (MGT) of traffic while the track structure stabilizes (Selig and Waters (1994)). This process is routine and can be included in the cost of maintenance, so it will not be explored in detail in this paper, although the model presented can be used for determining the associated train delay. Alternatively, slow orders prompted by track defects cannot be explicitly planned for and must be modeled to estimate how frequently they will occur. Due to the uncertainty of when defects will occur, it would be time and cost prohibitive to run simulations for every possible case. This is further complicated when considering slow orders in a maintenance planning optimization model that may not be able to access an external simulation. A complex slow order delay formulation may also substantially increase the optimization model solution time or make it difficult to solve exactly to a true optimum. To aid infrastructure owners in determining the operational impacts of slow orders and optimize associated maintenance plans, a new model was developed to help determine the expected slow order cost on a given rail line segment. These estimates can be used to aid in planning the timing and location of maintenance, including application in an optimization model.

2 Operational Impacts of Traffic Disruptions

Stopping rail traffic or otherwise decreasing average train speeds reduces the capacity of a particular line. If rail traffic is low enough, it is possible that headways between trains will be long enough that subsequent traffic will not be affected by delayed trains. However, this is not usually a good assumption for North American railroads where flexible operations do not have fixed headways and multiple trains can bunch together. In addition, the majority of the North American railway network is single track and capacity is less dependent on train headway than it is on the train running time on the single-track sections between passing sidings (passing loops). Under these conditions, a proper representation of slow order operational impacts needs to consider the effect of cascading train delays. When the location of a planned slow order is known, a rail traffic simulator can be used to determine the operational impacts. However, when dealing with defect-caused slow orders, the exact number and location of slow orders are unknown. Therefore, a general model is necessary to evaluate a wide range of possible scenarios and estimate the resulting operational impact.

For delays to vehicular traffic on roadways, the Webster uniform delay model can be used to simulate the impact of stopped traffic (Roess et al. (2004)). The basic theory behind this type of delay model is that the delay experienced by each train is the difference between when that train would be processed under normal operations and the time it is processed under the disrupted operations. This methodology is similar to the one Schafer and Barkan (2008) used for determining accumulated train delay after track outages, except their methodology used discrete trains rather than a continuous approximation. These methodologies must be modified to include a period of diminished operations during the time slow orders are in effect. Graphically, the delay model can be depicted by plotting the cumulative number of trains processed over time for both normal and disrupted operations and calculating the area between the curves (Figure 1). While this model is simple, it allows

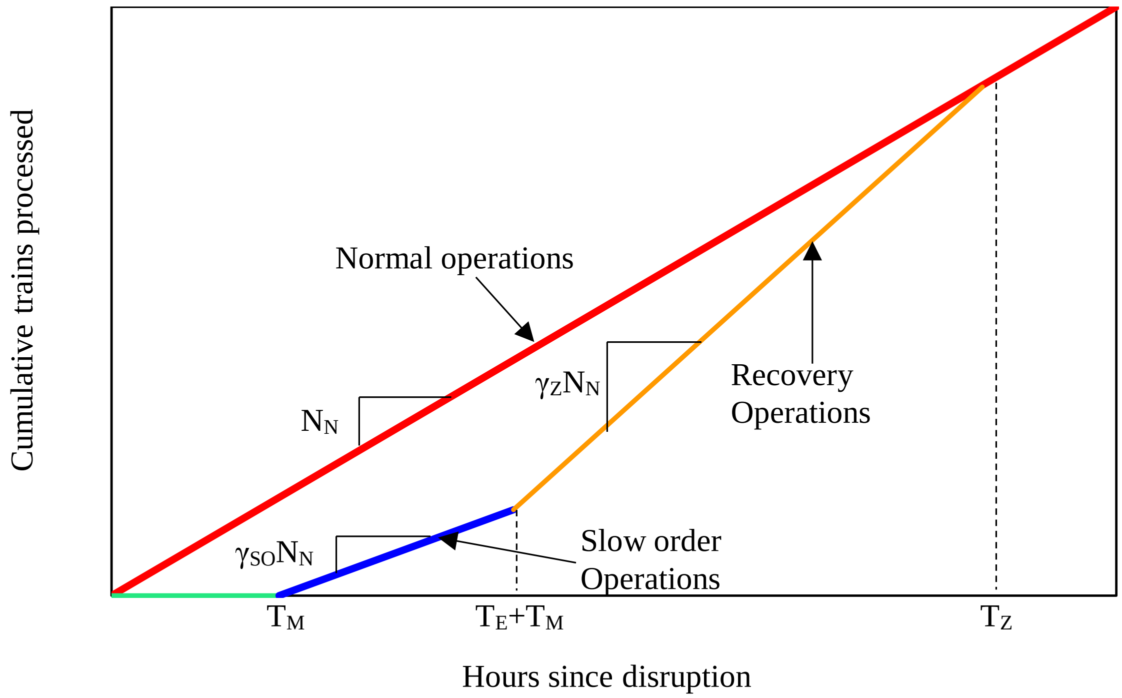

Figure 1: Slow order operations

for quick calculations to be made by infrastructure owners either directly or within a larger maintenance optimization model application framework.

Although slow orders resulting from track defects may not result in stopped trains, slow orders may be implemented after rail traffic is completely stopped for maintenance or repair. Accordingly, the model accounts for an initial period where the line is completely closed to rail traffic. The number of trains processed during and after a traffic disruption and the total time from the start of the disruption to the point where normal operations resume can be represented mathematically by

$$q = \begin{cases} 0, & 0 \leq t \leq T_M \\ \gamma_{SO} N_N (t - T_M), & T_M < t \leq T_M + T_E \\ N_N(\gamma_Z(t - T_E - T_M) + \gamma_{SO} T_E), & T_M + T_E < t \leq T_Z \\ N_N t, & else \end{cases}, \qquad (1)$$

$$T_Z = \frac{\gamma_{SO} T_E - \gamma_Z (T_M + T_E)}{1 - \gamma_Z}. \qquad (2)$$

Where:

q = number of trains processed after a disruption begins
t = time since a traffic disruption began
T_M = time after the disruption begins that the track is returned to service
γ_{SO} = slow order train throughput adjustment factor
N_N = number of trains processed per hour under normal operations
T_E = slow order duration
γ_Z = recovery operations train throughput adjustment factor
T_Z = time between disruption and resumption of normal operations

During the slow order, reduced train speed decreases capacity and the track segment has a reduced train processing rate. For specific applications, operational experience should guide the adjustment factor calibration to obtain a realistic train processing rate for specific maintenance circumstances. In the absence of a specific operating area, this analysis assumes that the reduction factor will be

$$\gamma_{SO} = \frac{T_N}{T_{SO}}, \tag{3}$$

$$T_N = \frac{L_R}{V_N}, \tag{4}$$

$$T_{SO} = L_R \, min\left(\frac{1}{V_N} + R_{SO} T_E \left((L_{SO} + L_T) \left(\frac{1}{V_{SO}} - \frac{1}{V_N}\right) + T_{AD} \right), \frac{1}{V_{SO}}\right). \tag{5}$$

Where:
T_N = time to traverse the route under normal operating conditions
T_{SO} = time to traverse the route with an average number of slow orders in place
L_R = length of the route
V_N = normal average train speed
R_{SO} = average annual number of slow orders per mile
L_{SO} = slow order length
L_T = average train length
V_{SO} = slow order speed
T_{AD} = additional time to accelerate and decelerate from and to the slow order speed
Other variables as previously defined

This method considers the condition where, as the slow order rate increases, trains leaving one slow ordered section are unable to accelerate to the normal operating speed before having to slow down for the next slow order. Under this condition, the entire line is effectively subject to a slow order, although additional defects may develop without further operational impact. Since trains must operate at the lowest maximum allowable speed for any part of the train, the slow order area of influence includes the length of both the slow order and an average train. In North America, where trains are regularly over one mile (1.6 km) in length, this means the amount of track affected by a slow order is much longer than just the slow ordered section.

For the period of recovery operations after the slow order is removed, it is assumed that rail traffic will operate at maximum capacity until normal operations can resume. Since this maximum capacity will typically be somewhat higher than the normal operating traffic volume, the recovery adjustment factor is calculated by

$$\gamma_Z = \frac{1}{C_N}. \tag{6}$$

Where:
C_N = proportion of the operating capacity in use under normal operations
Other variables as previously defined

As with the slow order adjustment factor defined in equation (3), the factor in equation (6) should be adjusted to correspond with experience and local operating practices.

Similar to the Webster uniform delay model, train delay can be computed from the area between the curves using geometry. However, in this case, to account for the period of diminished train processing rate during the slow order, the train delay is the difference in the area of triangles O-Z-T_B and T_M-S-T_B on the plot of cumulative trains processed over time (Figure 2). The resulting area O-Z-S-T_M is a measure of cumulative train delay during the disruption and can be calculated by

$$T_D = \frac{1}{2}(T_B Q_Z - (T_B - T_M)Q_S), \tag{7}$$

$$T_B = T_M + T_E\left(1 - \frac{\gamma_{SO}}{\gamma_Z}\right), \tag{8}$$

$$Q_Z = N_N \frac{\gamma_{SO} T_E - \gamma_Z (T_M + T_E)}{1 - \gamma_Z}, \tag{9}$$

$$Q_S = \gamma_{SO} N_N T_E. \tag{10}$$

Where:
T_D = cumulative train delay
T_B = intercept of the recovery operations line with the x-axis
Q_Z = number of trains processed between the disruption and resumption of normal operations
Q_S = number of trains processed during the slow order
Other variables as previously defined

This approach for estimating train delay due to a disruption of rail traffic on a line segment will enable planners to approximate train delay without developing detailed scenarios for a rail traffic simulator. Although this model is designed for predominantly single-track sections, it can also be used to consider other types of traffic disruptions, such as removal of a parallel main line for maintenance or accident recovery. To be used in this

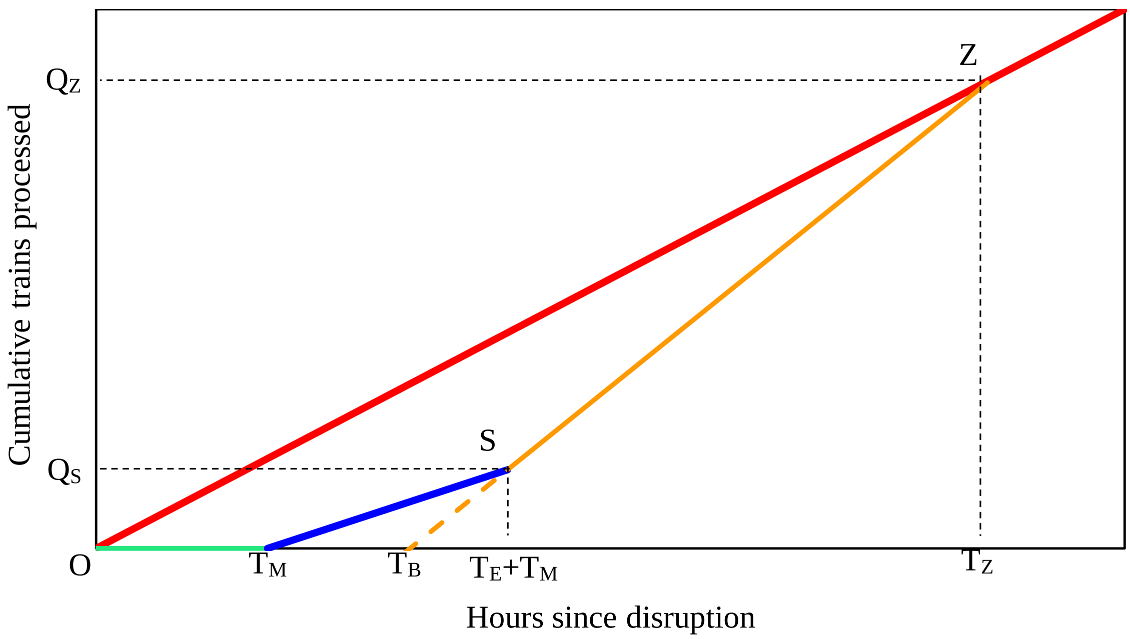

Figure 2: Slow order delay area

manner, equations (3) – (6) need to be altered since the adjustment factors for the reduced service and recovery operations will be more dependent on the type of infrastructure in place. Initial simulations may be necessary to determine the appropriate adjustment factors for use in multiple-track territory. If the route has large sections with multiple tracks, the model may become less applicable since there may be sufficient infrastructure to handle the traffic even if sections of track are removed from service.

3 Train Delay Sensitivity

In the discussion of the model formulation, it was noted that several parameters related to capacity utilization and train processing rate during the slow order may need to be set based on experience. The sensitivity of the model to these parameters will determine how important it is to obtain precise estimates of their values so as not to introduce excess uncertainty into the calculated train delay. Since the presented model consists of several levels of equations, it is not immediately obvious what the effect of changing a single variable will be. To determine which variables have the greatest influence on the model output and how train delay varies based on the selected inputs, both single- and two-variable sensitivity analyses were performed.

3.1 Single-Variable Sensitivity

The sensitivity of the model to each individual factor was examined over a range of typical input values (Table 1). The arc elasticity, which controls for the relative magnitude of each input (Allen and Lerner (1934)), was calculated for each factor (Figure 3), using the upper and lower bounds in Table 1. For each factor, the average of the upper and lower bounds was taken as the base case condition.

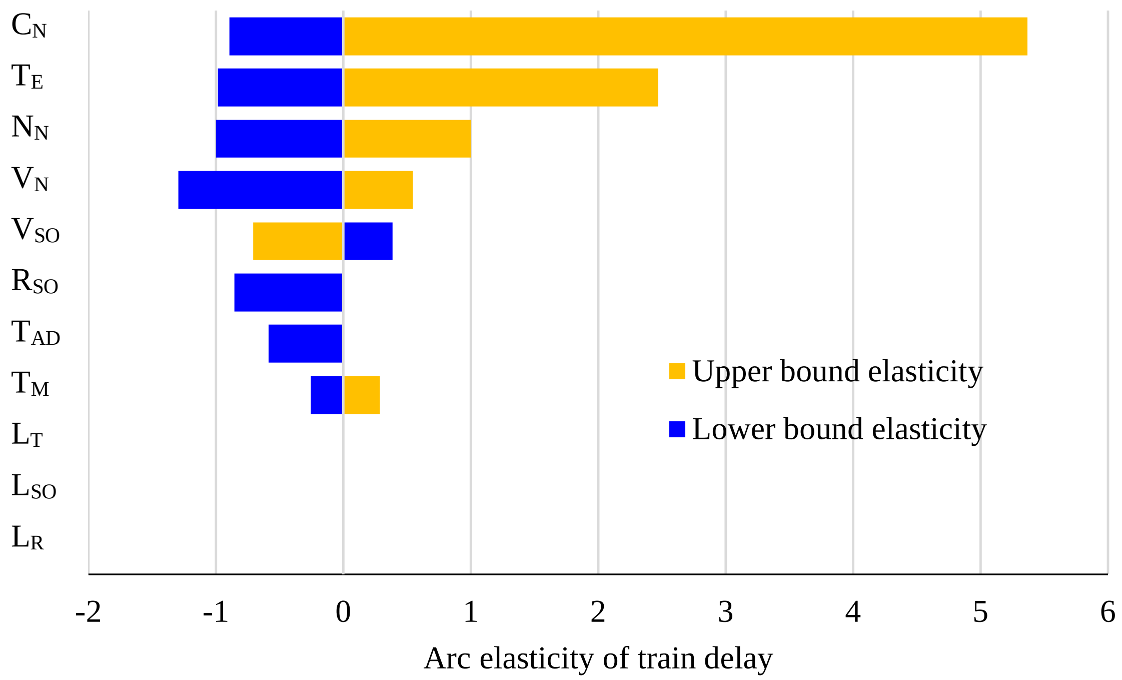

Figure 3: Arc elasticity of the delay model

Table 1: Arc elasticity bounds

Variable	Lower bound	Upper bound
T_M (hours)	0	24
T_E (hours)	0	240
L_R (mile [km])	2 [3]	200 [322]
L_{SO} (mile [km])	0.01 [0.02]	1 [1.6]
L_T (mile [km])	0.5 [0.8]	1.5 [2.4]
V_N (mph [km/h])	25 [40]	80 [129]
V_{SO} (mph [km/h])	10 [16]	30 [48]
R_{SO} (defects per year)	0.5	5
T_{AD} (hours)	0.1	1
N_N (trains per hour)	0.1	4
C_N	0.4	0.9

All the variables tested had the expected elasticity directionality, meaning an increase in the variable had the expected effect on the level of train delay. For example, increasing the normal capacity utilization, C_N, which the model is most sensitive to, results in an increased level of train delay. However, the amount of elasticity is not the same for the upper and lower bounds. This is intuitively correct because if a route is being operated near capacity, there will be less flexibility to recover from a disruption. However, high levels of excess capacity, indicating low utilization, may not result in substantial levels of cascading delay, so the recovery may be relatively quick and not influence many subsequent trains. The average slow order duration, T_E, has a similar effect because the longer the slow order is in place, the more trains will be affected and the more time is required for recovery. The slow order speed, V_{SO}, is the one variable where an increase results in a lower train delay. This is because higher slow order speeds result in a smaller impact to the train processing rate, so fewer trains will be affected. The normal train processing rate, N_N, is another anomaly since increasing or decreasing the processing rate yields an arc elasticity of one. This is because the train delay is linearly related to the processing rate as shown in (9) and (10). The annual slow order rate, R_{SO}, and the acceleration and deceleration time, T_{AD}, do not appear to have upper bound elasticities because the base case results in the entire line being slow ordered. In this case, increasing those variables will not affect the train delay. The effects of L_T, L_{SO}, and L_R have a similar result, but their elasticity is so small as to not show up on the plot.

3.2 Two-Variable Interactions

Since many of the variables interact, it is beneficial to see how changing two variables affects the amount of train delay. In the following illustrative cases, the factors that are not varied remain at the base values from the single-variable sensitivity analysis.

Since the model was most sensitive to track capacity utilization and slow order duration, they were varied first (Figure 4). For a given capacity utilization, the train delay increases disproportionately to increases in slow order duration. As the slow order duration increases, the additional train delay between C_N curves also increases, showing the necessity of keeping slow order durations low on highly utilized routes (where C_N will be highest). While this result is expected based on intuition and equations (6)-(9), quantifying the effects allow for an objective comparison of the costs to operate track at different utilization levels.

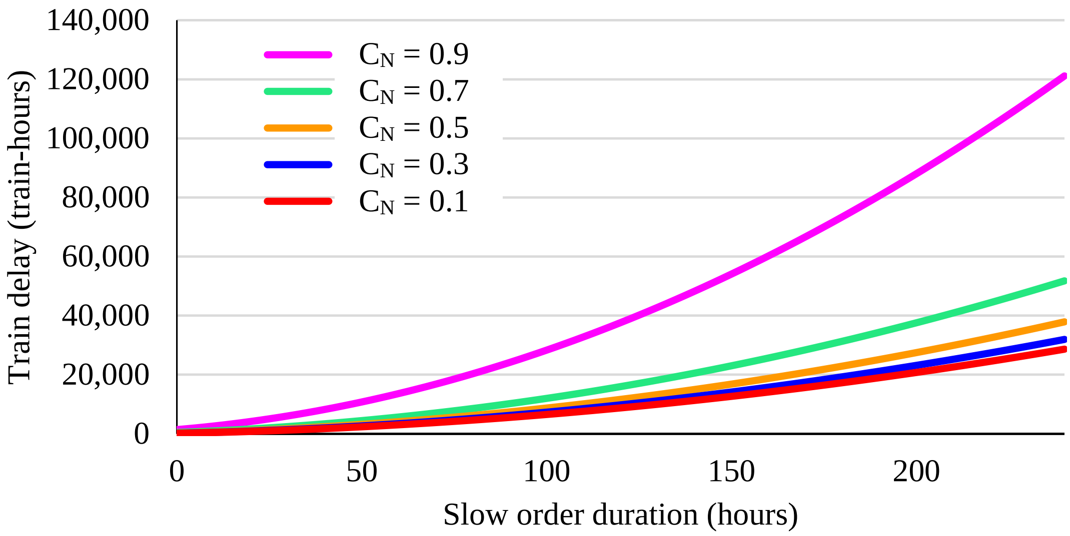

Figure 4: Effect of operating capacity and slow order duration on train delay

Since the normal operating speed, V_N, was the next most sensitive variable and has direct interactions with the slow order speed, V_{SO}, they were also varied (Figure 5). For the 10 mph (16 km/h) slow order curve, there is a discontinuity around 19 mph (31 km/h) normal operating speed, which is where the entire line is effectively slow ordered. For the other two normal operating speeds, the base conditions result in the entire line being slow ordered, so there is no discontinuity. Once the entire line is slow ordered, the ratio of the normal to slow order speeds drives the delay. This can be seen by looking at the constant 20,000 train-hour level, which intersects each of the slow order speed curves at double their value on the x-axis. For example, the 10, 25 and 40 mph (16, 40, 64 km/h) slow order speed curves have approximately 20,000 train hours of delay for 20, 50, and 80 mph (32, 80, 128 km/h) normal operating speed respectively.

Since routes with high utilization typically have higher speeds, V_N and C_N were also varied together (Figure 6). As the normal capacity utilization approaches one, the train delay

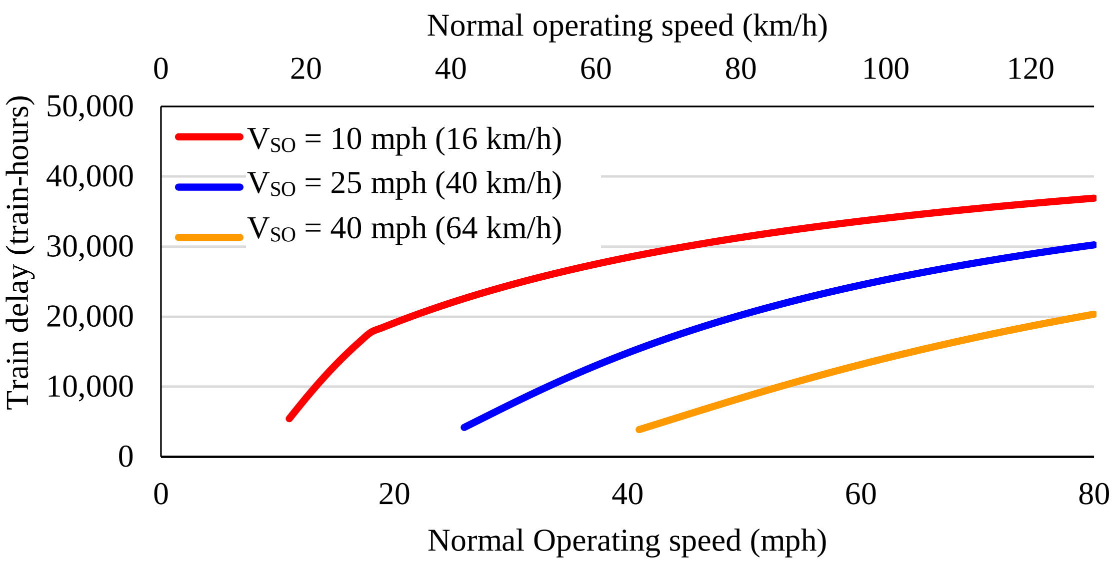

Figure 5: Effect of normal operating and slow order speeds on train delay

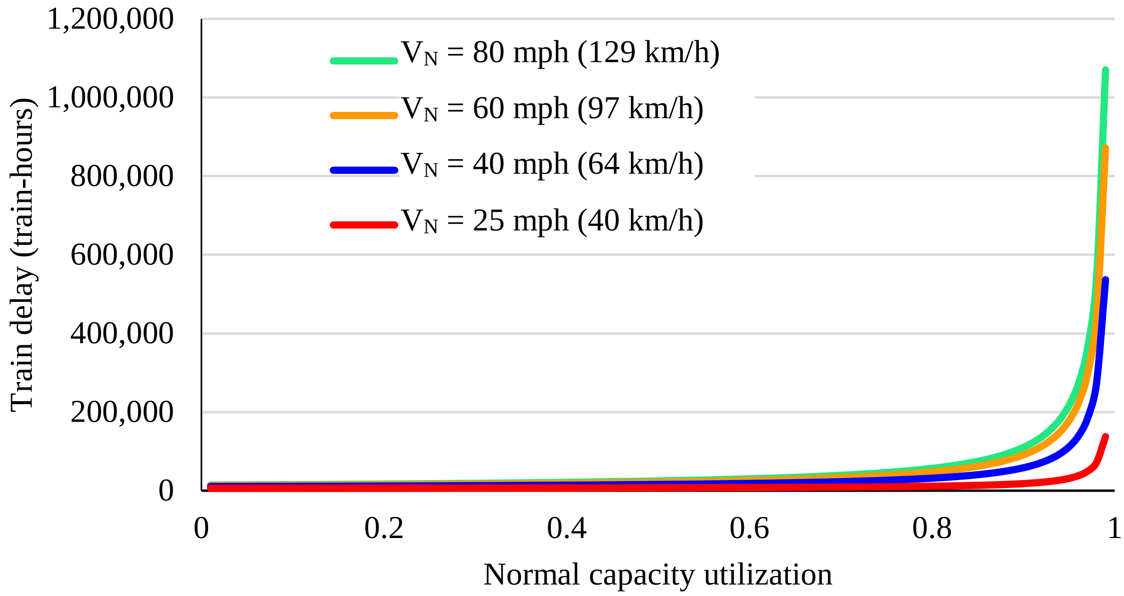

Figure 6: Effect of normal operating speed and capacity utilization

begins to asymptote. Using this delay model, if the route is already being operated at full capacity before a disruption, the route will not be able to recover to normal operations after a disruption without annulling and combining or rerouting trains on the route under consideration. At lower normal capacity utilization levels, the curves are almost linear until a C_N value of about 0.6 is reached. Above that level of capacity utilization, routes with higher normal operating speeds will begin to asymptote much quicker due to the difference in normal and slow order speeds. This and the results in Figure 4 validates the industry practice of keeping track utilization below 75-percent to ensure adequate recovery capacity (American Railway Engineering and Maintenance-of-Way Association (AREMA) (2012a)).

4 Application to Track Defects

Slow order cost is comprised of both likelihood and consequence (Ang and Tang (2007)). While Section 3 detailed a model of the train delay consequence of slow orders, this section discusses the likelihood of slow order occurrence. To predict the number of slow orders on a route in a given year, probabilistic models can be used to determine the average annual defect rate per mile. This paper focuses on slow orders caused by transverse fissures in rail as most internal rail defects are given this categorization until they are removed from service (Sperry Rail Service (1999)).

The model developed by Orringer (1990) was adapted to determine the rate of slow orders caused by rail defects. This model predicts the expected number of detected defects per mile based on the accumulated tonnage on the rail, inspection interval, and historical ratio of service to detected defects. Service defects are those that cause the rail to break, while detected defects are found through rail flaw inspections, such as ultrasonic testing. Only detected defects will be addressed here because service defects require more extensive remedial actions (Federal Railroad Administration (FRA) (2014b)). Orringer's original formulation was modified to use the cumulative distribution function, rather than a probability density function, which makes the model more accurate and computationally simpler. It was also assumed that the defects will develop uniformly through the year rather than sum the defects that develop between each rail inspection. This simplification was made because Liu et al. (2014) showed that weighting the number of defects near the end of the year more heavily does not make a material difference in defect costs. The detected rail defect slow order rate is calculated by

$$R_{SO,R}(y) = N_{Rail}\left(e^{-\left(\frac{yN_A}{\beta_R}\right)^{\alpha_R}} - e^{-\left(\frac{(y+1)N_A}{\beta_R}\right)^{\alpha_R}}\right)\Big/\left(1+\lambda(\Delta N-\theta)\right). \qquad (11)$$

Where:

$R_{SO,R}$ = annual detected rail defect rate per mile
N_{Rail} = number of rail sections per mile
y = years since capital maintenance was performed
N_A = annual tonnage (MGT)
ΔN = average tonnage between rail inspections (MGT)
θ = minimum inspection interval (10 MGT (Orringer (1990)))
λ = proportionality factor (0.014 (Orringer (1990)))
α_R = Weibull shape factor (3.1 (Davis et al. (1987); Liu et al. (2014)))
β_R = Weibull scale factor (2150 (Davis et al. (1987); Liu et al. (2014)))

While the model is dated, it is still used by the FRA to recommend rail flaw detection intervals (Volpe Center (2014)), and the parameter values are the most recent that could be found in the literature. New models are in development that could be used for application here (Davis et al. (2016)).

The train delay model described in Section 2 and equation (11) were applied to a hypothetical route with length, L_R, of 100 miles (160 km), normal operating speed, V_N, of 40 mph (64 km/h), handling 60 MGT of freight traffic annually, N_A. This traffic level equates to approximately 24 freight trains per day, N_N (Association of American Railroads (AAR) (2015)), with train length, L_T, of 1 mile (1.6 km). The normal capacity utilization, C_N, is taken as 0.65, which provides sufficient excess capacity to recover from maintenance and other disruptions (Cambridge Systematics (2007)).

When a defect is detected, a slow order is implemented with speed, V_S, of 30 mph (48 km/h), length, L_{SO}, of 0.1 miles (0.16 km), and duration, T_E, of 24 hours. The speed reduction is a common FRA remedial action for moderate sized internal rail defects. The defects also have to be re-tested every 24 hours while the defect remains in place (Federal Railroad Administration (FRA) (2014a)), so it was assumed that on average, the slow orders would remain in place that long. Although it is common practice in North America to replace approximately 20-foot (6 m) sections of rail surrounding the defect (American Railway Engineering and Maintenance-of-Way Association (AREMA) (2012b)), temporary track condition information in North America is communicated in tenth-of-a-mile increments, so that is the smallest practical length of track a slow order can be applied over. The cost to repair a rail defect and the rail inspection interval, ΔN, were assumed to be \$859 and 20 MGT, respectively, based on Liu et al. (2014). The cost of train delay was based on an updated methodology of Lovett et al. (2015a) for manifest traffic where delay would not result in lost shipments and was taken as \$950 per train hour. For the parameters of this case study, it was assumed that all trains operate at the maximum speed, but average operating speeds could also be used.

Using the equations in Section 3 and (11), the expected direct and delay slow order costs can be calculated (Figure 7). Even though the defects are being repaired, each subsequent

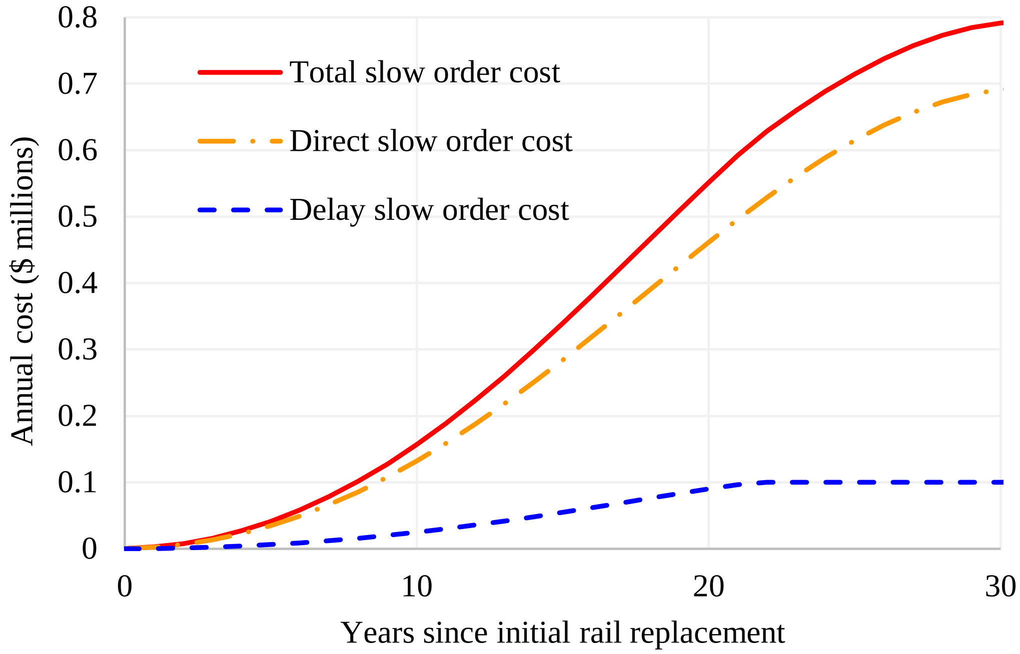

Figure 7: Annual cost of rail related slow orders vs. years since capital maintenance

year experiences more new defects than the year before, as indicated by the direct slow order cost curve. This is because the rail is getting older and defects have had more time to grow to a detectable size. The delay costs plateau around year 21 because the influence of individual slow orders begins to overlap. Besides the number of defects, average train length also influences the plateau location, since it increases the area of influence of a single slow order. Running shorter trains would reduce the distance trains must travel at the slow order speed but would require additional cost for crews and motive power, which may increase the overall cost of a slow order. Around year 15, the slope of the total cost curve begins to decrease because there is less of the original rail left to develop defects since it has been replaced by new rail when each defect is repaired. However, other rail-related defects, such as broken welds, will likely increase as more replacement rail is welded into place. In this case, the delay costs are about 15-percent of the total cost, but Figure 3 shows that changing certain variables can have a substantial effect on the amount of train delay, potentially making it the dominant cost component.

5 Conclusions and Future Work

This paper presented a new closed-form model for determining the train delay effects of traffic disruptions. This model is intended to be used by infrastructure managers for maintenance planning. The simplicity of the model will make it more accessible to planners and easier to apply within a larger maintenance planning optimization framework. The model also helps quantify the effects of how the route is operated before, during, and after a disruption. If the line is normally operated near capacity, it will take much longer to recover from a disruption and the train delay will be much higher than if there is ample excess capacity. Additionally, if the line is normally operated at capacity, then the line may not be able to recover without reducing the number of trains through annulments or rerouting. This is especially true if the slow order duration is long or the normal operating speeds are high. The relationship between the normal and slow order operating speeds can also be observed. The relationship is particularly evident after the entire line is effectively slow ordered, and their relative values have more impact than the individual speeds. Before that point, when each slow order can be treated independently, train delay is much more sensitive to changes in the normal operating speed for a constant slow order speed.

Quantifying the impact of train delay and the nature of the operational effects of slow orders provides insight on how to reduce the overall cost of the rail system by factoring these effects into a capital maintenance plan. Performing capital maintenance earlier will decrease the slow order costs but has its own drawbacks in terms of asset utilization. Infrastructure owners can balance the costs of disruptions over time with the cost to perform maintenance that will prevent slow orders and reactive defect repair, sometimes referred to as spot maintenance. If spot maintenance is made more efficient, effective, and timely, it can reduce the disruption caused train delay costs in addition to direct maintenance cost because they will not need to be performed as frequently. As was seen in the slow order case study, the train delay costs will plateau due to overlapping slow order areas of influence. Maintenance improvements will be most cost effective if they enable the route to avoid the plateau region, through either improved response time or reducing the number of defects. Cost analyses will help determine which routes would benefit from maintenance improvements, and determine cutoffs for where preventative maintenance should be performed based on risk tolerances. Another way to reduce the delay effects of service disruptions is to add capacity to the line. While many infrastructure owners treat capacity expansion as a last resort, quantification of train delay accumulation can help determine where that may be more cost-effective than investments in additional maintenance crews or equipment.

Future research will explore how train delay and defect probability can be incorporated into an optimization model for scheduling track maintenance over a network. This will require probabilistic models for approximating the failure rate associated with other track components such as crossties (sleepers) and ballast. Specifically with delay modeling, additional work can expand our understanding of the application of the slow order and recovery adjustment factors to make them more general and allow for their direct use on double track routes or in situations where the normal traffic can be rerouted or combined to mitigate the impact of a disruption.

Acknowledgements

Research supported by AAR and National University Rail (NURail) Center, a US DOT-OST Tier 1 University Transportation Center. Lead author also supported by the CN Research Fellowship in Railroad Engineering and Dwight David Eisenhower Transportation Fellowship Program.

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