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INTEGRATED OPTIMIZATION AND SIMULATION MODELS FOR THE LOCOMOTIVE REFUELING SYSTEM CONFIGURATION PROBLEM

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ABSTRACT

This paper introduces the locomotive refueling system configuration problem, which arises when railroad companies aim to improve efficiency in refueling yards through new technologies or policies. Refueling speed is important to freight railroad operational efficiency; faster refueling can increase rail network capacity without the infrastructure cost associated with new terminals or tracks. We propose a method that integrates integer programming and discrete event simulation to inform these decisions, and we demonstrate the method on data derived from industry. Specifically, the models determine the best location (denoted the "strike line") to align trains at the refueling platform and measure the impact on refueling yard throughput associated with adopting the optimal strike lines in combination with new refueling equipment. Results using realistic parameters demonstrate a statistically significant improvement over intuitive policies.

1 INTRODUCTION

This paper introduces the locomotive refueling system configuration problem and describes an integrated optimization and simulation method for solving it. Railroads account for nearly 40 percent of freight movement ton-miles in the U.S., and total freight tonnage moved by rail is expected to increase 22 percent between 2010 and 2035 (U.S. Department of Transportation 2010). U.S. Class I railroads generated $67.6 billion in freight revenue in 2012, a value that more than doubled (in inflation-adjusted dollars) in comparison to 2000 (U.S. Department of Transportation 2015). Refueling speed is important to overall freight railroad operational efficiency, because it directly impacts the time trains spend in the rail yard. Decreasing refueling time for each train has the potential to increase the maximum number of trains that can pass through a yard each day, positively impacting the overall rail network capacity. New equipment is being developed that can refuel a locomotive more than twice as fast as the current industry standard refueling system. The challenge for a given rail yard is how to configure existing fuel platforms and locomotives with new equipment to maximize the associated benefits.

The paper is organized as follows. Section 2 describes the locomotive refueling system configuration problem and the motivating context, and we distinguish our contributions to the broader railway logistics literature. The optimization and simulation models are introduced in Section 3, and results for a group of test instances are presented in Section 4. We conclude with insights about the problem and opportunities for future research.

2 PROBLEM CONTEXT

This section describes the motivating context for the locomotive refueling system configuration problem and summarizes related literature.

2.1 Locomotive Refueling System Configuration Problem Description

Refueling yards are vital points on freight rail networks. U.S. Class I railroads used 3.687 billion gallons of fuel in 2014 to power 25,916 locomotives (U.S. Department of Transportation 2016). A typical yard may refuel more than 100 trains per day. At busy times, a refueling station may make concessions, such as slowing train arrivals. This is not sustainable if rail traffic increases, as it is projected to do. Adding infrastructure, including tracks and fueling platforms, can increase a yard's capacity at considerable expense. A recently-developed upgraded refueling system safely dispenses fuel more than twice as fast as the current system. Upgrading to a new system may represent a more economical option not only to increase an individual yard's capacity, but also to impact throughput across the network.

Refueling yards utilize fuel pumps on fixed platforms and direct-to-locomotive (DTL) fuel trucks. Locomotives at the front of a train (front-end power) are fueled at platforms situated alongside the tracks and equipped with multiple fuel pumps. Some large trains have distributed power, meaning there are locomotives at the rear and/or middle of the train in addition to those at the front. Distributed power locomotives are refueled with DTL trucks.

In addition to fueling, other processes, including inspection or maintenance, may happen at these rail yards. The typical processes followed upon a train's arrival to the yard are depicted in Figure 1. The inbound train first traverses to the fueling platform and stops at a designated "strike line". A flag indicates that it is safe for fueling to begin and an inspector to board the train. The fueling process is dependent upon the availability of fuel pumps whose functional radius can reach the train's front locomotives and DTLs that can be dispatched to distributed power, if applicable. Inspection can happen concurrently with fueling. Upon completion of these tasks, the train must wait for the crew to finalize preparations for departure and for appropriate track clearance before departing the yard.

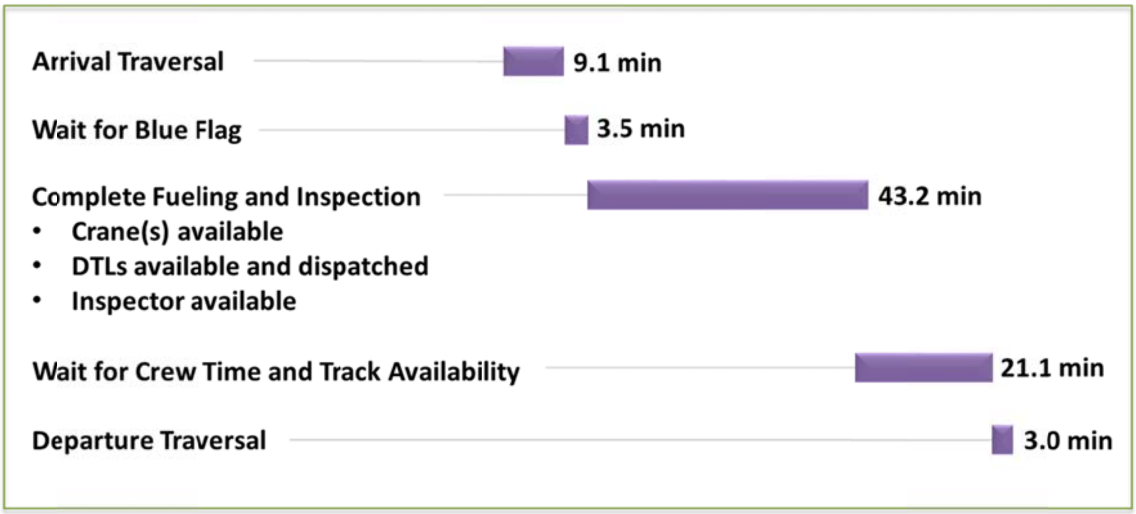

Figure 1: Processes completed for each train in the yard; times are representative of the current system.

The locomotive refueling system configuration problem arises when railroad companies aim to improve efficiency in refueling yards through new policies or technologies. Railroad operations personnel must determine where the strike lines should be placed. We propose an integer programming model, the objective of which is to maximize the weighted number of train combinations that can be filled without delay. The optimal strike lines from this model are inputs to a discrete event simulation model, which depicts the entire refueling process. The simulation produces two metrics: the average time each train spends in the yard and the average maximum number of trains waiting to enter the yard. We compare these metrics for multiple scenarios to gain insight about the impact of refueling system configuration on overall yard operations.

2.2 Relationship to the Literature

Strategic, tactical, and operational decisions arising in the railroad industry are complex, highly combinatorial, and frequently characterized by uncertainty. Researchers and practitioners have developed numerous models to support decision making; Cordeau, Toth, and Vigo (1998) and Assad (1980) provide reviews. Integer programming and simulation are among the most common methodologies.

Fundamentally, many decisions about railroad operations involve allocating resources. At the strategic level, this begins with scheduling trains (Dorfman and Medanic 2004; Sajedinejad et al. 2011). Solutions to this strategic problem may also consider operational guidance for handling disruptions to planned schedules (Barta et al. 2012; D'Ariano, Pacciarelli, and Pranzo 2007). At the strategic and tactical levels, researchers have introduced models for assigning locomotives to trains (Vaidyanathan, Ahuja, and Orlin 2008), crew planning (Chahar, Cheng, and Pranoto 2011), scheduling maintenance (Budai, Huisman, and Dekker 2006), and managing empty railcar movements (Sherali and Suharko 1998).

Solutions to one railroad management problem serve as inputs to other decision models. The locomotive fleet refueling problem considers a railroad company's decisions about when and where to refuel locomotives. Given a routing and scheduling plan for locomotives in a fleet, the company must decide at which sites to refuel each locomotive and on what schedule (Nourbakhsh and Ouyang 2010; Raviv and Kaspi 2012). This decision is impacted by site-specific fuel costs, contracting costs with fuel suppliers, and the costs for delays incurred while locomotives are being fueled.

Many processes necessary for freight railroad operations occur in rail yards. An important tactical decision is blocking, the process of grouping shipments (and their corresponding cars) together so that shipments need not be sorted in every yard they visit (Ahuja, Jha, and Liu 2007; Daganzo 1986; Newton, Barnhart, and Vance 1998). Given a blocking plan and a train schedule, the block-to-train assignment problem determines which trains will transport each block (Jha, Ahuja, and Şahin 2008). Additional rail yard activities include maintenance, inspection, and refueling. The complex operational processes are very important in railroads' overall efficiency. Detailed simulation models depicting rail yard operations have been proposed (Lin and Cheng 2009; Lin and Cheng 2011), enabling decision makers to evaluate changes in infrastructure, resource allocation, and operating policies. Similarly, He, Song, and Chaudhry (2003) propose an integer programming model that optimizes yard operations. Others have considered specific components within the framework of yard operations, such as optimal container transfer between trains in a yard where freight moves by container-on-flatcar (Bostel and Dejax 1998).

The locomotive refueling system configuration problem concerns operations within a single rail yard. However, unlike models previously described in the literature, the approach we propose models the refueling process in detail and specifically supports decisions that occur in the transition between fueling systems. This paper makes two contributions to the existing literature on operations research applications to railroad operations. First, it introduces the locomotive refueling system configuration problem. Second, it proposes a modeling approach that combines integer programming with discrete event simulation to generate solutions to this problem. The models are demonstrated using data derived from a Class I railroad, illustrating the capability to use this approach to support decision making about yard operations.

3 METHODS

The integer program, the simulation, and their integration are described in this section.

3.1 Mixed Integer Programming Optimization Model

Formally, the locomotive refueling system configuration problem has as input a set of fuel pumps $P=\{p_1, \ldots, p_q\}$, a set of trains $T=\{t_1, ..., t_n\}$, and a fixed number of tracks. The p_l fuel pump has an associated fixed location $d_l \in$ and functional radius $r_l \in {}_+$ for all $l \in \{1, \ldots, q\}$. Train t_i has m_i front locomotives that should be filled at the platform for all $i \in \{1, \ldots, n\}$. Each locomotive of train t_i has an f_{ik}, which represents the distance from the front of the first locomotive to the fuel port on the k^{th} locomotive for all $i \in \{1, \ldots, n\}$ and $k \in \{1, \ldots, m_i\}$.

For both brevity and real world applicability, the number of tracks is limited to two with the fuel platform located between them. Thus, there are $n^2 + 2n$ potential train combinations that could simultaneously be at each platform. The train combinations are n different trains on track 1 and n trains on track 2 (n^2) along with n different trains on track 1 with track 2 empty and the n trains on track 2 with track 1 empty.

Define a_r to be the probability that the refueling yard is in the r^{th} train combination for all $r \in \{1,\ldots, (n^2+2n)\}$. Let $E_r = \{1,\ldots, r'\}$ represent the r' locomotives on the r^{th} train combination for all $r \in \{1, \ldots, (n^2+2n)\}$. Obviously, E_r is partitioned into E_r^1 and E_r^2, which represents the locomotives on track one and two, respectively. Thus, if the r^{th} train combination has t_i and t_j on tracks one and two, respectively, then $r' = m_i+m_j$ and $E_r^1 = \{1, \ldots, m_i\}$ and $E_r^2 = \{m_i+1, \ldots, m_i + m_j\}$.

The train refueling integer program (TRIP) seeks to obtain a strike line for each track such that the maximum weighted (according to the a_r) number of train combinations can be refueled on the platform without delay. For a given train combination, refueling without delay occurs if every front-end locomotive on each train can be assigned a fuel pump, where each fuel pump can fill only one locomotive.

This problem is easily generalized to an arbitrary number of tracks or fuel ports. In fact, most locomotives have a front and back fuel port, but only one port will be converted to the new technology. Thus, this paper assumes only one fuel port per locomotive.

The decision variables for TRIP are given below.

$$w_r = \begin{cases} 1 & \text{if train combination } r \text{ is filled without delay} \\ 0 & \text{otherwise} \end{cases} \quad \text{for all } r \in \{1,...,n^2+2n\}$$

$$x_{rkl} = \begin{cases} 1 & \text{if engine } k \text{ of } E_r \text{ is filled by pump } l \\ 0 & \text{otherwise} \end{cases} \quad \text{for all } r \in \{1,...,n^2+2n\},\ k\text{ò}E_r \text{ and } l\text{ò}P$$

$$y_{rkl} = \begin{cases} 1 & \text{if engine } k \text{ of } E_r \text{ could be filled by pump } l \\ 0 & \text{otherwise} \end{cases} \quad \text{for all } r \in \{1,...,n^2+2n\},\ k\text{ò}E_r \text{ and } l\text{ò}P$$

$s_1, s_2 \in$, the strike lines for tracks 1 and 2, respectively

TRIP is formally defined as follows.

Maximize $\sum_{r=1}^{n^2+2n} a_r w_r$

Subject to:

$$-s_1 - f_{ik} + d_l - r_l \le M(1-y_{rkl}) \text{ for all } r \in \{1,...,n^2+2n\},\ k \in E_r^1,\ l \in P \quad (1)$$

$$s_1 + f_{ik} - d_l - r_l \le M(1-y_{rkl}) \text{ for all } r \in \{1,...,n^2+2n\},\ k \in E_r^1,\ l \in P \quad (2)$$

$$-s_2 - f_{jk-m_i} + d_l - r_l \le M(1-y_{rkl}) \text{ for all } r \in \{1,...,n^2+2n\},\ k \in E_r^2,\ l \in P \quad (3)$$

$$s_2 + f_{jk-m_i} - d_l - r_l \le M(1-y_{rkl}) \text{ for all } r \in \{1,...,n^2+2n\},\ k \in E_r^2,\ l \in P \quad (4)$$

$$x_{rkl} \le y_{rkl} \text{ for all } r \in \{1,...,n^2+2n\},\ k \in E_r,\ l \in P \quad (5)$$

$$\sum_{k \in E_r} x_{rkl} \le 1 \text{ for all } r \in \{1,...,n^2+2n\},\ l \in P \quad (6)$$

$$w_r \le \sum_{l \in P} x_{rkl} \text{ for all } r \in \{1,...,n^2+2n\},\ k \in E_r \quad (7)$$

$$x_{rkl} \in \{0,1\} \text{ for all } r \in \{1,...,n^2+2n\},\ k \in E_r,\ l \in P$$

$$\mathrm{y}_{rkl} \in \{0,1\} \text{ for all } r \in \{1,...,n^2+2n\},\ k \in E_r,\ l \in P$$

$$w_r \in \{0,1\} \text{ for all } r \in \{1,...,n^2+2n\}$$

The objective function maximizes the weighted number of train combinations that can be filled without delay. The first constraints force y_{rkl} to be zero when $-s_1$-f_{ik}+d_l-$r_l > 0$. In other words, if d_l-r_l > s_1+f_{ik}, then the fuel port on the k^{th} locomotive of train combination r is too far away (on the negative side) from pump l to be fueled by that pump. Observe that $k \in E_r^1$, which forces this constraint to be implemented only on the locomotives on track 1. Similarly, the second set of constraints requires $y_{rkl} = 0$ whenever s_1+f_{ik}>d_l+r_l. Thus, pump l cannot reach on the positive side to fill the k^{th} locomotive on train combination r. Extending this logic to model the strike line for track 2 is straightforward and shown in constraints (3) and (4). The only change is to restrict the fuel port locations to be on the j^{th} train and the $k - m_i^{\text{th}}$ engine where $k \in E_r^2$.

The fifth set of constraints only allows a locomotive to be fueled at pump k if the pump could reach (y_{rkl} can be set to 1). Each pump can only fuel one locomotive per train combination as shown in (6). The final constraint allows w_r=1 only if every locomotive from the r^{th} train combination is fueled by some pump. Observe that the strike lines are unrestricted variables and a negative strike line implies that the front of the train stopped beyond the beginning of the platform

TRIP can be large. Currently, the vast majority of trains passing through the yard in our study have at most five front-end locomotives. If one restricts the problem to a single locomotive model and seven pumps, then there are only five train types. In this case, TRIP has over 2,500 variables and 4,000 constraints and is solved in less than one second using CPLEX 12.6.2 on a desktop computer. If one allows two different locomotive models, the number of train types expands to 64 and TRIP has over 450,000 variables and over 750,000 constraints. Unfortunately, this instance of TRIP did not solve in two days. Solving large TRIP instances requires additional research, such as implementing cutting planes or advanced branching strategies.

3.2 Simulation Model

The optimal strike lines identified by TRIP serve as input to a simulation of the refueling yard processes described in Section 2.1. These processes include arrival traverse time, pre-fueling crew time, time to setup and pump fuel at the platforms and with DTLs, inspection time, post-fueling delays for crew, track clearance, and departure traverse time. The simulation model's purpose is to measure the impact of the strike lines and fueling technology choices on two rail yard performance measures: the average time in yard for a train and the maximum number of trains waiting to be assigned a platform during the day. The latter measure captures the brief part of the day when the system is busiest. This is reported as the average maximum queue length. The simulation model is built in Simio®, which is well-equipped to run numerous scenarios with ease and to handle all the intricacies of modeling this system. This section describes the model logic.

3.2.1 Model Overview

The simulation model depicts a refueling yard with eight different tracks, four facing east and four facing west. Inbound trains come from both directions and require refueling at one of four platforms in the yard. Each refueling platform has seven pumps. A train continues along the inbound track until it reaches the refueling platform, where the train waits until all of its locomotives have been fully refueled. After refueling is complete, the train then waits until crew time and inspection processes are completed, after which it leaves the yard. Figure 2 depicts one platform in the simulation model.

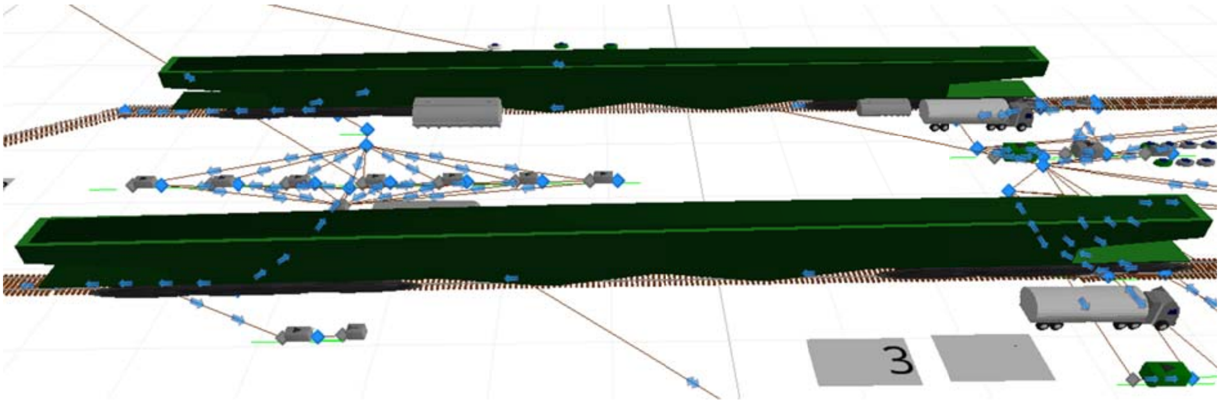

Figure 2: Simulation model visualization of one refueling platform.

A key part of this system that is not covered by the optimization portion of this paper is the DTL refueling. This process is modeled with seven different trucks that travel to the rear of each train while it waits at the platform. A truck refuels one rear locomotive and then returns to its base to refuel its tank before moving on to dispense fuel to another rear locomotive on the same or another train. DTL processes are the same, regardless of the strike line chosen for front-end refueling. Changes to DTL operations are outside the scope of this analysis, which focuses on the refueling platforms.

3.2.2 Platform Modeling

Modeling this platform is not straightforward. A primary reason is that the system does not immediately seize a pump resource or join a queue. Instead, it must determine which pump resource to seize upon arrival to the system, delay additional time due to a failure to seize a resource, and have resources seized by two independent sets of objects. These features and the required model logic provide some insight into the interesting pieces of this problem and its impact on real world applications.

As mentioned previously, each platform consists of seven pumps, which are created as single servers so that each pump can fill at most one locomotive at a time. Unlike most simulations, no locomotives are waiting on a pump to finish. Rather, the next train does not begin approaching the platform until the track is free. Once a train is at the platform, the track becomes free after all of the train's locomotives are filled with fuel, the inspection has taken place, and the train has had sufficient time to start and move forward. Thus, trains are queued off of the track and the fuel dispensing pumps never have a queue.

When a train reaches the platform, an entity is created for each of the front locomotives and each "locomotive" travels to a node where the train and locomotive dimensions are set. This entity calculates f_{ik} for each locomotive. Based upon this distance and the track's strike line, the simulation assigns each locomotive to a pump. This assignment is fairly complex and incorporates 28 different decisions as well as various other assignments through Simio®'s add-on processes. This assignment begins with the first locomotive and sequentially assigns locomotives to the first available pump. A pump is available if it is not filling a locomotive and the pump can reach the locomotive's fuel port. This logic follows identically for the second track with the obvious adjustments for the second strike line.

If a locomotive cannot immediately be filled by any of the pumps at its platform, the locomotive is considered infeasible. This scenario calls a process that increases the delay at the next location (the inspection and crew time) to account for 10 minutes plus refueling time. This time accounts for either waiting for the pump to become available or moving the train to a location where the infeasible locomotive can be fueled by an open pump. Then, the process delays the additional time period for actually refueling that locomotive. In other words, if a locomotive is considered infeasible, the time the train spends at the platform refueling nearly doubles. This highlights the importance of optimizing the strike lines to refuel the maximum number of trains and decrease the number of infeasible locomotives.

The simulation model is fairly large. The model has over 1,300 Simio® blocks, which are spread across 234 separate processes. An individual replication for a 24-hour period required less than 10 seconds. Thus, the model is computationally tractable and experiments with multiple replications can be performed easily.

4 RESULTS

The simulation model is demonstrated on a single rail yard using data derived from industry sources and literature. We compare the optimal strike lines generated by TRIP against intuitive policies to determine the impact on refueling yard performance measures.

4.1 Parameters

Input parameters for the model are summarized in Table 1. In addition, the model was built under the following assumptions. Incoming trains are assumed to be equally distributed between east- and west-bound arrivals. All locomotives are refueled to capacity starting from a current fuel volume, which is generated randomly for each locomotive based on a probability distribution derived from historical data. We assume that setup times for upgraded and conventional fueling systems are the same, and that adapters can be fitted to upgraded nozzles, if needed, to deliver fuel to conventional receivers. Each simulation replication is one day, and each scenario has 100 replications.

Prior to conducting experiments with the strike lines and refueling technologies, the simulation model was validated. Using parameter values for the current system, the simulation results indicate that the average refueling time for a train is 68.87 minutes. The corresponding value from historical data is 70.05 minutes. The simulation suggests that the refueling yard begins to experience delays when there are 95 – 105 trains arriving per day. Personnel familiar with the operation confirmed that it is necessary to adjust arrival rates when more than 100 trains are scheduled to arrive in a day. Consequently, this simulation model accurately represents the existing system.

To determine the strike lines to test within the simulation model, TRIP is solved with each train combination equally likely: $a_r = 1/(n^2+2n)$ for all $r \in \{1, \ldots, (n^2+2n)\}$. The optimal strike lines identified by TRIP are 10 and 66, which is to stagger the strike lines of the two tracks. However, the staggering is not the anticipated half staggering as a locomotive is about 72 feet long. Rather, the answer is to move the strike line on the second track so the front locomotives overlap by only a quarter. Furthermore, the starting point is adjusted slightly backwards and the second track can never have an engine use the first pump.

Table 1: Parameter values.

Parameter	Value
Fueling Rates	**gallons per minute**
Platform, Conventional System	220
Platform, Upgraded System	450
DTL, Conventional System	170
DTL, Upgraded System	450
DTL Refueling	280
Train Composition	**number of locomotives (fraction of trains)**
Front	1 (<1%), 2 (32%), 3 (53%), 4 (14%), 5 (<1%)
Middle	0 (94%), 1 (1%), 2 (5%)
Rear	0 (76%), 1 (4%), 2 (18%), 3 (2%)
Other Processes	
Inspection time (minutes)	40
Fraction of trains inspected	80%
Post-fueling delay (minutes)	24.25

Three sets of strike lines are examined for this model: 0 and 0, 0 and 150, and 10 and 66. The first two pairs represent intuitive policies. The first policy, denoted 0 and 0, corresponds to each train stopping at the beginning of the platform. The second set of strike lines are 0 and 150, which implies that trains on the first track stop at the first pump and those on the second track stop at the fourth pump. Under this configuration, no train with fewer than four locomotives will ever experience refueling delays. The third set of strike lines used are 10 and 66, which are the optimal strike lines from TRIP.

With these strike lines, we test three daily arrival rates: 100, 125, and 166 trains per day. The first is the current average arrival rate. The second is approximately the current capacity, and the third represents anticipated growth in freight volume.

4.2 Findings and Discussion

The simulation results for different strike lines in different scenarios can be seen in Tables 2 – 5. The first table shows the system at 100 trains per day and using the refueling system that is currently operational. As can be seen in Table 2, the average train time in the yard decreases from 68.87 to 68.16 minutes, or about 1.0%. A standard two-sample t-test for the 100 replications is used to compare the average train time in the yard for the optimized strike lines to results for intuitive strike lines. The p-value of each test is <0.0001, which shows that for any reasonably desired confidence level, the optimized strike lines decrease the average train time in the yard. It may seem surprising that a small difference yields such a small p-value, but this is due to the small variance between replications. Even though there is a statistically significant difference, the practical benefit is marginal at an arrival rate of 100 trains per day.

However, we note that the average number of infeasible trains throughout the 100 replications is substantially lower for the optimized strike lines versus the other two strike line configurations.

Table 3 shows the system at 125 trains per day and using the refueling system that is currently operational. In this case, the average train time in the yard decreases from 70.38 to 68.49 minutes, or about 2.7%. A standard two-sample *t*-test for the 100 replications is used to compare the average train time in the yard for the optimized strike lines to results for intuitive strike lines. The *p*-value of each test is <0.0001, which shows that for any reasonably desired confidence level, the optimized strike lines decrease the average train time in the yard. Additionally, it is clear that the average number of infeasible trains is substantially lower for the optimized strike lines versus the other two strike line configurations.

Table 2: Impact of strike line decisions on refueling yard performance measures using current refueling system at arrival rate of 100 trains per day.

Strike Lines (Track 1, Track 2)	Average Max Queue (trains)	Average Train Time in Yard (min)	Average Number of Infeasible Trains
0, 0	0.09	68.87	0.22
0, 150	0.22	69.99	0.49
10, 66 (TRIP optimal solution)	0.04	68.16	0.03

Table 3: Impact of strike line decisions on refueling yard performance measures using current refueling system at arrival rate of 125 trains per day.

Strike Lines (Track 1, Track 2)	Average Max Queue (trains)	Average Train Time in Yard (min)	Average Number of Infeasible Trains
0, 0	1.00	70.38	0.89
0, 150	1.11	71.10	0.98
10, 66 (TRIP optimal solution)	0.72	68.49	0.26

Table 4 demonstrates the impact of strike line choice when train arrival rates are elevated (166 trains per day) under the current refueling system. The average train time in the yard decreases from 79.21 to 73.24 minutes, or about 7.5%, with optimal strike lines. A standard two-sample *t*-test for the 100 replications is used to compare the average train time in the yard for the optimized strike lines versus intuitive strike lines. The *p*-value of each test is <0.0001, which shows that for any reasonably desired confidence level, the optimized strike lines decrease the average train time in the yard. The average number of infeasible trains is also notably smaller for the optimal strike lines when compared to the intuitive values.

Table 4: Impact of strike line decisions on refueling yard performance measures using current refueling system at arrival rate of 166 trains per day.

Strike Lines (Track 1, Track 2)	Average Max Queue (trains)	Average Train Time in Yard (min)	Average Number of Infeasible Trains
0, 0	5.66	79.21	2.98

0, 150	4.81	77.43	2.64
10, 66 (TRIP optimal solution)	3.36	73.24	0.50

Finally, Table 5 summarizes the combined impact of converting the pumping technology to the faster nozzles and optimizing strike lines when the arrival rate is 166 trains per day. The optimized strike lines provide measurable improvement compared to intuitive strike lines even when new refueling technology is adopted. Here, the average train time in the yard decreases from 76.05 to 67.89 minutes, or about 10.7%. A standard two-sample *t*-test for the 100 replications is used to compare the average train time in the yard for the optimized strike lines to results for intuitive strike lines. The *p*-value of each test is <0.0001, which shows that for any reasonably desired confidence level, the optimized strike lines decrease the average train time in the yard. Again, it is clear that the average number of infeasible trains is substantially lower for the optimized strike lines versus the other two strike line configurations.

Table 5: Impact of strike line decisions on refueling yard performance measures using upgraded refueling system at arrival rate of 166 trains per day.

Strike Lines (Track 1, Track 2)	**Average Max Queue (trains)**	**Average Train Time in Yard (min)**	**Average Number of Infeasible Trains**
0, 0	5.12	76.05	4.24
0, 150	4.42	73.98	3.46
10, 66 (TRIP optimal solution)	2.64	67.89	1.15

Based on the experimental results, solving TRIP and incorporating the optimal strike lines will improve the refueling yard operations regardless of whether or not a new refueling technology is adopted. This impact is statistically significant and allows more trains to be processed each day. Using a new refueling technology should enable railroad companies to dramatically escalate the number of trains through a refueling yard, which increases system capacity without the enormous expense of laying new track.

5 CONCLUSIONS

In this paper we propose a method that integrates integer programming and discrete event simulation to inform railroad companies how to align trains at refueling platforms to increase a refueling yard's capacity. An integer program determines the optimal strike lines for the tracks, which is where the front of the train should stop. A simulation model implements these strike lines to validate the results. Assigning optimal strike lines decreases the average train time in the yard by 1–10%. Furthermore, these results are statistically significant. Thus, the optimal strike lines improve the throughput capabilities of the rail yard. Railroad companies should implement these results as they are far cheaper than the cost of laying additional tracks and building additional fuel dispensing platforms.

Future work includes modeling two fuel ports on a given locomotive, allowing TRIP to account for the option to fill either the front or the rear fuel port. Capturing this flexibility at the pumps will make TRIP an even more accurate representation of the refueling system. Examining a larger number of train combinations by incorporating additional locomotive types will expand the applicability of the optimal strike lines. Also, adding weights to trains that appear more often in the real world application instead of putting equal weight on trains will increase the accuracy of the optimal strike lines. Further research may develop advanced techniques that solve larger TRIP instances. It may also be useful to incorporate TRIP directly into the simulation, allowing strike lines to vary based on train arrivals. Although both the integer programming and simulation models are presented for a particular yard layout, the proposed approach may be adapted to other platform configurations.

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