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RESEARCH PAPER

Scheduling of the Shuttle Freight Train Services for Dry Ports Using Multimethod Simulation–Optimization Approach

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Abstract

This paper introduces a simulation–optimization method for addressing scheduling problems for shuttle freight trains (SFTs) in a shared railway corridor between a seaport and dry port. We use dispatching delays for scheduling the SFT trips so as to not disturb the existing scheduled regular train (SRT) paths. The method employs a multi-method microscopic simulation model and an optimization framework. A swarm-based optimization algorithm is used for finding the best dispatching delays to preserve SRT paths. The method is demonstrated for a railway corridor between the Alsancak seaport and a close-distance dry port. The railway corridor is modeled using a simulation model considering single and double railway tracks, stations, and schedules. By running the simulation–optimization, the SFT freight transport capacity and the quality of the SFT and SRT operations were compared using key performance indicators (number of completed trips and station stops, average trip delay, and average station delay) addressing the throughput and punctuality after the application of dispatching delays. The results show that, by preserving the existing SRT paths, freight transport capacity decreased by 11.1% (from 18 to 16 completed SFT trips) and 13.8% (from 36 to 31 completed SFT trips) for single and couple SFT scenarios, respectively. The methodology also decreased the average SFT station delays by 45.2% and 45.6% for the single and couple SFT scenarios comparing with the unoptimized SFT trips. However, the number of SFT station stops increased by 12.5% and 57.1% for the single and couple SFT scenarios for prioritizing the SRTs. Also after the optimization, the average SFT trip delays decreased by 30.7% and 0.58% for the single and couple SFT scenarios. This study successfully demonstrates that the proposed method can be used for scheduling the SFT trips inside a congested railway corridor and can be implemented as a capacity assessment tool for cyclic SFT service using a series of key performance indicators addressing throughput and punctuality.

Keywords Railway capacity · Corridor analysis · Shuttle train · Simulation optimization · Dry port

1 Introduction

Seaports are important commerce centers and drive significant commodities due to globalization and the growth of trade volume. Today, the freight movement generated from marine trade causes congestion problems at seaports and in transport infrastructure. These problems severely reduce the operational efficiency and economic competitiveness of seaports. Seaport-induced truck traffic is responsible for urban traffic jams in those cities hosting a seaport. While rail freight transport can be utilized for reducing truck traffic, scheduling freight trains in the railway network is a problematic task, due to existing train traffic and prevailing infrastructural constraints. The mixed (freight and passenger) train traffic is responsible for

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congestion and delays. In particular, more than 70% of the passenger train delays in USA are caused either by inferior freight train performance or infrastructure failure [1].

The railway capacity utilization problem for freight trains is prominent in developing countries such as Turkey. In the last decade, the continuous growth of the Turkish economy has triggered a solid boost in seaport throughput, leading to traffic congestion problems. The seaports of Turkey are often in the historical Mediterranean port cities and located around the populated city centers. The third most populated city, Izmir, hosts the Alsancak seaport. The seaport remained in the city center as it evolved from the historic Smyrna port and shares its transport network with the Izmir. The seaport has increased its trade throughput from 24 million tons to 31.6 million tons between 2010 and 2018 [2]. Also, with the emergence of the nearby rival seaports, the freight traffic in Izmir has significantly increased. In the last decade, the Turkish authorities tried to cope with this issue by developing dry ports used as freight accommodation and regulation centers. In Izmir, new dry ports were also planned, with the aim of increasing the utilization of rail freight transport using shuttle freight trains (SFTs) and thereby decreasing the use of road freight transport. Currently, a single SFT operates between the Alsancak seaport and a logistics center in Manisa. The SFT makes a single round trip each day and additional SFT trips will be planned in the future with the opening of a fully functional dry port. In the light of the above-mentioned issues, this paper addresses scheduling problems for the SFT trains between the Alsancak seaport and a close-distance dry port using a shared railway corridor with existing train traffic. The main purposes of the study are to develop a simulation–optimization framework for optimizing cyclic SFT trips without disturbing the regular train service and evaluate the SFT freight transport capacity by means of the train throughput and the punctuality considering the prevailing operational and infrastructural constraints. The study also contributes to the seaport-dry port integration and proposes a solution to the congestion problem of Izmir addressing the growing seaport freight traffic.

2 Literature Review

In the last decade, railway studies have attracted many researchers from diverse fields because of the challenges encountered at the planning and operational levels. Among them, timetable scheduling and railway capacity analysis are two important research areas. Train scheduling or timetabling aims to achieve a timetable that satisfies operational constraints and utilizes idle infrastructure capacity. In literature, the most relevant approaches for railway capacity analysis and timetable scheduling are simulation techniques, analytical methods, and optimization, or the combination of the three [3].

2.1 Simulation Techniques

Event-based simulation is used mainly to address transport problems for seaport logistics: dealing with the Berth Allocation Problem [4] and planning regulations for cargo movement between a seaport and the hinterland [5]. In railway planning, many studies use simulations for evaluating timetables and train routing plans, and combine simulation with analytical models and optimizations. The analytical model provides a candidate timetable followed by a detailed assessment using a simulation tool. Solinen et al. [6] used the robustness in critical points indicator to increase timetable robustness using a macroscopic Mixed Integer Linear Programming (MILP) model. The optimized timetable was evaluated using a commercial microscopic railway simulation tool. The MILP model was also used for macroscopic timetable rescheduling for managing traffic disruptions [7]. Högdahl et al. [8] combined an MILP model for timetable rescheduling with a microscopic railway simulation tool to estimate the expected train delays. This method reschedules timetables to minimize the sum of the scheduled travel time and the expected delay, and improves timetable punctuality. Potti and Marinov [9] developed an event-based simulation model replicating the timetable-based train movements in a subway network, and evaluated passenger waiting time and utilization levels. They use queues to model network resources, stations, and line sections, using a system decomposition. Goverde and Besinovic [10] proposed a methodology for transformation between microscopic and macroscopic models to improve the analysis of the macroscopic timetables at the microscopic level. The study emphasized the reliability of microscopic models for computing minimum headway times. Schlechte et al. [11] proposed an integrated microscopic and macroscopic simulation approach for planning optimal long-term timetables. A macroscopic timetable was first obtained by minimizing a cost function and then its feasibility was validated at a microscopic level using a dispatching simulation software. Burggraeve and Vansteenwegen [12] proposed an iterative approach to construct a timetable with optimized train buffer times and passenger numbers using a mathematical optimization model and heuristics. A stochastic macroscopic event-based simulation model was used to evaluate the timetable and make assignments for the next iteration. The stochastic programming model was used for timetabling to minimize both passenger waiting times and a penalty function regarding capacity violation for crowding [13]. Pouryousef et al. [14] proposed a hybrid simulation technique using a non-timetable-based microscopic simulation model to generate candidate timetables for a timetable-based simulation model and applying the compression technique based on UIC 406 [15]. The new timetable was evaluated to analyze the trade-off between level of service (LoS) and capacity utilization. Shakibayifar et al. [16] proposed an event-based simulation model and a multi-objective simulation framework to solve train conflicts resulting from traffic disturbances. Not only was the simulation technique used for train operations, but also for simulating the yard operations and stations. Dessouky and Leachman [17] used event-based simulation and system decomposition for isolating railway network components into sub-systems, and analyzed the railway freight transport capacity of a seaport and railway network. The system decomposition with event-based simulation was also used by Rizzoli and Fornara [18] for separating the railway network and yard areas into sub-models. They implemented a railway corridor simulation to evaluate intermodal freight transport. Marinov and Viegas [19] studied yard operations and constructed a mesoscopic event-based simulation model with system decomposition for evaluating the use of flat-shunted yards for freight trains. Gambardella et al. [20] introduced an event-based model for simulating intermodal transport chains and transport of containers between inland intermodal terminals.

2.2 Analytical Methods and Optimization

In recent years, analytical methods, soft computing, optimization, decision-making techniques, and artificial intelligence systems were applied to solve the planning and decision-making problems in many areas of transportation. This includes multi-criteria decision analysis [21] and fuzzy logic for optimizing delays in road cross-sections [22] and road infrastructure performance assessment [23]. Analytical methods are widely used for railway capacity assessment, train scheduling, and timetable management. The International Union of Railways published the UIC 406 compression method for calculating railway line capacity, locating bottlenecks, and evaluating service quality [15]. The railway capacity problem can also be solved using analytical methods integrated with optimization and soft-computing approaches for generating optimized timetables and train paths. Several techniques were used for timetable optimization, such as Iterative Lagrangian methods [24], Stochastic optimization [25], or Multi-Objective optimization [26].

Timetable scheduling has also been handled using heuristic algorithms, mathematical programming techniques, or the combination of both. Fischetti et al. [27] combined Linear Programming, Stochastic Programming, and robust optimization techniques to improve train timetables. Higgins et al. [28] used Mathematical Programming to develop a planning framework for evaluating influences of infrastructural and schedule modifications on train paths. Li et al. [29] addressed the train scheduling problem and demonstrated a methodology for determining satisfactory route schemes with delay information using MILP and the Tabu-Search algorithm. Quaglietta [30] proposed a stochastic simulation-based approach with a black-box optimization loop to identify cost-effective signaling layouts for railway networks. Goverde and Bešinović [31] proposed a performance-based railway timetabling framework using linear programming. They integrated a microscopic timetable construction with running time calculation and performed macroscopic network optimization using the microscopic data. Altazin et al. [32] presented an integrated MILP with an objective function that minimized both the recovery time and the waiting time of passengers. Additional criteria related to the weighted number of stations that are skipped were included in the objective function. Zhang et al. [33] used integer programming and developed an integrated model to optimize the rail operation planning by maximizing the operator profit and reducing passenger waiting time.

2.3 Studies Involving Freight Trains and Dry Ports

Several studies have addressed freight trains and transport capacity using analytical and simulation techniques. The principal element of these studies is the problem of scheduling freight trains taking into account the priority of passenger trains. Among these studies, Singhania and Marinov [34] developed an event-based microscopic simulation model for railway corridor analysis. The impact of freight trains on the scheduled passenger trains was evaluated by considering track utilization. The study did not involve schedule optimization for the freight trains, so they were added using a schedule sheet to avoid the train conflicts. Meirich and Nießen [35] illustrated an analytical approach for a generic railway network to maximize the number of operating freight trains while considering fixed passenger train paths. They achieved the best train path arrangement using analytical optimization. Zhang and Lin [36] developed a bi-level mathematical model for maximizing the railway operational profit for rail freight transport by integrating the railway planning and transport pricing.

Hampaeyan et al. [37] presented a linear programming model that chose the best schedule for movement of passenger trains and SFTs with the least environmental pollution on a single-line route on a railway network. They used delays and the number of unplanned station stops as key performance indicators. Murali et al. [38] used integer programming witha genetic algorithm and proposed a methodology for scheduling freight trains while taking into account daily time horizons. Dingler et al. [39] investigated the influence of freight train traffic heterogeneity using a train dispatching simulator for a hypothetical signalized single-track line. They identified the key factors influencing delays. Despite the recent advances in the transport sector and seaport logistics, seaport-induced traffic congestion is an increasing problem worldwide. In recent years, the role of dry ports as a solution to seaport congestion has been emphasized in the literature. Roso et al. [40] were among the first to highlight nearby dry ports as a tool for solving seaport congestion problems. They demonstrated the usefulness of nearby dry ports for expanding the capacity of seaports. Recent studies have also addressed conceptual dry port development models [41], location selection, and capacity optimization based on costs and environmental footprints [42].

2.4 Railway Capacity Analysis and Level of Service Concept

We define railway capacity as the ability to transport a specific number of trains through a railway corridor within a specific time with a given set of resources and LoS [43]. In current practices, railway capacity cannot be considered merely as hourly traffic or transported cargo without addressing service quality and LoS criteria. In fact, practical capacity is a trade-off between railway train throughput and the LoS given to the customers. One approach for assessment of railway corridor capacity is to implement performance metrics or key performance indicators (KPIs). These KPIs can be classified as throughput (train traffic or transported cargo quantity), level of service (station dwell time, travel time, punctuality, and delays), and resource utilization (utilization ratio of the railway line sections). A widely used KPI for capacity assessment using LoS is delay, which is defined as the total difference between the planned and the realized arrival time of a train to a station. A capacity limit is reached when delay statistics exceed acceptable limits for each type of traffic. Operations may still be feasible with more trains, but delays will prevent the railroad from meeting customer expectations and ultimately damage the business and/or increase costs [44]. In practice, European rail operators frequently use the number of trains per day or hour and delay as the throughput and punctuality KPIs, respectively [3]. For the rail freight industry, the LoS is also evaluated by total transit times, reliability of arrival [45], or derivatives of delay (delay percentage, station, and trip delays) and is used as a performance metric in planning and decision-making. Also, the punctuality or "on-time" criteria are also used if the actual arrival time of a train and the scheduled arrival time differ by less than a specific amount [46].

The railway capacity assessment and scheduling problems were considered vastly with analytical models such as linear programming, MILP, stochastic programming, and heuristics. Especially, the analytical models were used for macroscopic train timetabling. Scheduling of freight trains in an existing timetable has been studied using integer programming and macroscopic simulation models without detailed system definitions. Additionally, simulation techniques have been employed to solve transport problems regarding seaports, yard operations, intermodal transport chains, and railways. Rather than an individual application, simulation models are used for evaluation of timetable and schedules generated by an analytical optimization model. It must be emphasized that microscopic simulation models are an efficient tool for simulating the complex train traffic in railway corridors and are more effective than macroscopic models. Simulation techniques can use either specialized railway simulation software or general-purpose simulation languages. In the latter case, event-based simulation techniques are mostly addressed using a system decomposition approach.

Several studies have also touched upon the scheduling problem for freight trains. The timetabling of the freight trains has been studied using integer programming, linear programming, and macroscopic simulation models without detailed system definition and without a simulation–optimization framework. Location selection, development, and integration problems for dry ports have been addressed in recent years based on contributions to the literature. Although the positive effects of dry ports on seaport congestion have been emphasized and demonstrated, this functionality requires a high capacity transport corridor. There have been very few studies on the regulation of freight transport between a seaport and a dry port. In particular, the assessment of operational capacity of SFTs and cyclic trip scheduling of SFTs were yet untouched.

As a novel contribution to the literature, this study proposes a multi-method microscopic simulation model for simulating both timetable-based and non-timetable-based passenger train and SFT operations in a railway corridor for a dry port. This study also introduces a simulation–optimization framework using a swarm-based heuristic to schedule cyclic SFT trips in the railway corridor without disturbing the regular train services. The methodology is also demonstrated using freight transport capacity assessment for the SFT service, while taking into account train throughput and LoS criteria (trip delays and the number of stops).

3 Methods

3.1 Multimethod Simulation Modeling

Event-based simulation modeling relies on the composition of numerous synchronized discrete events changing model states or attributes at a certain time. During the simulation execution, the model continuously evolves through distinct time points at which system state and attributes are modified. For each time point, a discrete event triggers an interaction, a change in agent state, or the next event. Simulation modeling of the railway operations is a complex task, involving various interactions between trains and railway infrastructural elements. Modeling can be simplified using system decomposition, which divides the railway network into functional parts and establishes a detailed system representation. Railway infrastructure and operational elements can be classified using Agent-Based Simulation (ABS), which makes use of system decomposition without detailed abstractions. ABS modeling relies on the individual active components of a system and handles individual objects, behaviors, and interactions. In the ABS methodology, agent states modify agent behaviors and attributes. Transition events are scheduled between agent states. ABS can be coupled with event-based simulation; this is known as multi-method simulation. For the present study, the Shuttle Train Simulation Model (STSM) was developed to simulate train operations in a railway corridor using a multi-method simulation methodology. The STSM was developed using *AnyLogic 7* and *Java* programming. The ABS methodology was used for decomposing the system into smart and interacting agents: stationary agents (railway track resources, sidetrack resources, seaport, and dry port marshaling yards), moving agents (SFT cars, SFT locomotives, and SRTs), and container agents (main and station agents). The container agents were used as living spaces for the moving and stationary agents. The hierarchical structure of the model agents is shown in Fig. 1.

In Fig. 1, the boundaries of the station agents are shown as rectangular blocks. $S_1,\ldots, S_6$ are sidetracks, T_1 and T_2 are waiting and moving SFT cars, L_1 and L_2 are SFT locomotives, and $\underline{R}_1, \ldots, R_3$ are railway track agents. The main agent M_1 contains the rest of the agents. STSM can draw train paths to illustrate capacity problems and delay locations along with the line segments. A graphical user interface can be used for modifying the model parameters, as shown in Fig. 3a.

SFT car agents are formed with coupled flat cars for transporting marine containers and can be coupled with SFT locomotives to form a rolling stock. Train cars are decoupled and handled at the seaport and dry port marshaling yards, with reach stackers or gantry cranes, and wait for an idle SFT locomotive for coupling. Coupled SFT cars occupy an idle sidetrack at the marshaling yard. SFT locomotives are initially dispatched from either the seaport or the dry port and operate a cyclic route between the seaport and dry port without a timetable. At the end of each daily operational period, SFT locomotives park at the marshaling yard and are kept idle until the next cycle.

SRT agents are passenger and freight trains operating on the railway tracks and are dispatched from an initial station and disposed at a final station. SRT routing is synchronized with a train timetable (the planned arrival and dispatch time for each station). Scheduled waiting times at intermediate stations for passenger boarding or train meeting are planned. Like SFTs, SRTs seize and release railway track/sidetrack resources, but have priority over SFTs when train meetings occur on single-track line segments. SRTs are operated with punctuality criteria, and no-delay criteria should be met for passenger satisfaction and service quality.

Railway and sidetrack agents are stationary agents that represent the railway track and node resources. Train agents systematically seize a railway track agent, travel, then release it. Railway track agents are categorized as single or double-track line agents. Single-track line agents can only be seized by a single train. Double-track line agents can be occupied by two trains heading in opposite directions. Sidetrack agents are bidirectional single-track line agents and are used for temporarily hosting trains at stations or at intermediate nodes.

Train agents contain attributes storing the initial and final stations, speed, type, train id, generation number, and train schedule. SRT agent attributes are assigned from a

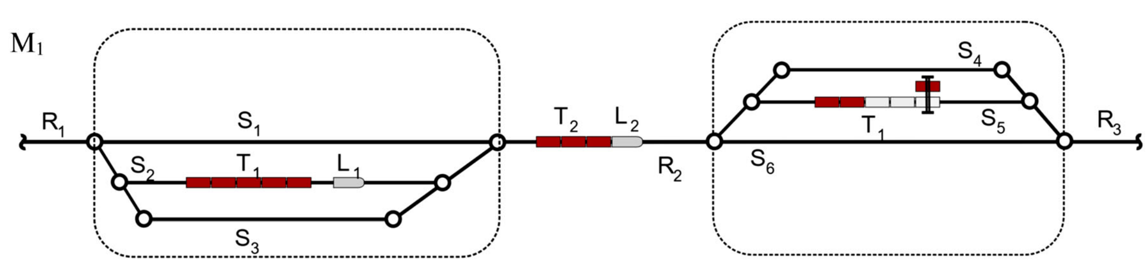

Fig. 1 Hierarchical structure of the STSM agents

train schedule database and dispatched according to the scheduled departure times. As the principal rule, a train seizes the next railway track before occupying it. Also, the train seizes a sidetrack at the next node or station to avoid a deadlock resulted from the trains coming from the opposite direction. The simulation algorithm can be viewed as connected transactions which seize/release a specific resource agent or alter agent states. Each transaction is represented by a delay in the STSM and a finished transaction triggers a new state or resource state. The hierarchical of the agent states, transactions, and resources of the STSM is depicted in Fig. 2.

After seizing the next track and sidetrack resources, a train's speed profile is calculated using the scheduled train paths. The train agent state is updated at this point. After the train reaches the end of a railway track segment with routing delay, a new system state is reached, and model attributes are updated. The railway track segments end either with a station or an autoblock node where the train agent releases the previous railway track and requests to seize the next track and node resource. If the request is accepted, the occupied sidetrack resource is released, and train routes to the next station or autoblock node. The SFT cars are initiated as a loaded state. SFT locomotive arrives in the marshaling yard and couples with the SFT cars to form a rolling stock. The SFT seizes the next railway track and the sidetrack before leaving the marshaling yard. If a railway track is requested by an SRT, the SFT waits at the sidetrack (Fig. 3).

3.2 Simulation–Optimization Methodology

The STSM is coupled with a simulation–optimization framework for minimizing total SRT delays. During minimization, a zero-delay goal is aimed for SRTs. During STSM execution, the total trip delay of an SFT for a single trip is calculated with Eq. (1):

$$D_T = D_{cdp} + D_{sw} + D_t + D_{dp} + D_{od}, \tag{1}$$

where D_T is the total delay, D_{cdp} is the coupling/decoupling delay of the SFT cars and locomotive, D_{sw} is the waiting delay for seizing the next railway track, D_{od} is the SFT dispatching delay, and D_t is the rooting delay. The simulation–optimization approach is mathematically expressed as an optimization problem with a goal function of the STSM output. With this approach, the STSM acts as the black-box representation of the simulated system. The optimization problem can be expressed as Eq. (2):

$$Minimize : f\left(D^1_{od}...D^N_{od}\right) = T_O + C_o \tag{2}$$

$$Subjectto : 0 < D^N_{od} < T_L, fori = 1toN,$$

where $f\left(D^1_{od}...D^N_{od}\right)$ is a function representing the STSM output, $D^1_{od}...D^N_{od}$ is the dispatching delay vector for the successive SFT trips, T_O is the total delay of all operated SRTs, T_L is the upper limit value for the SFT dispatching

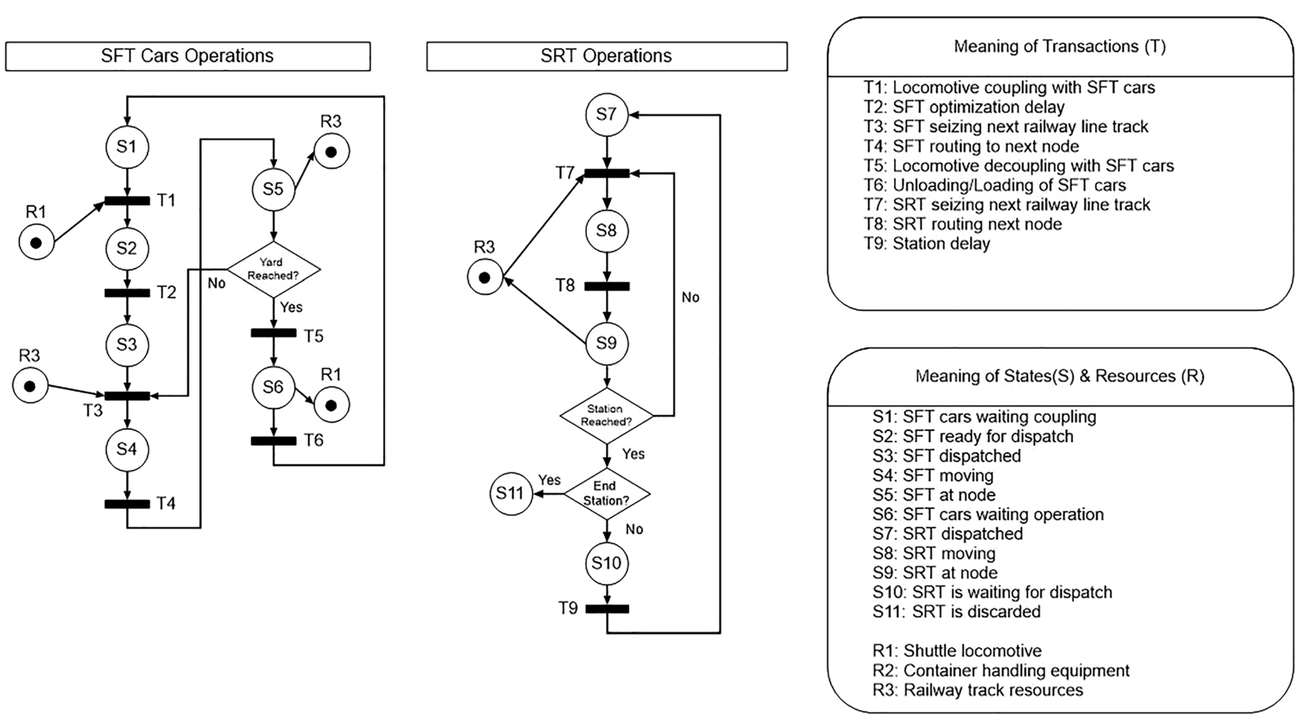

Fig. 2 The hierarchical structure of the agent states, transactions, and resources of the model

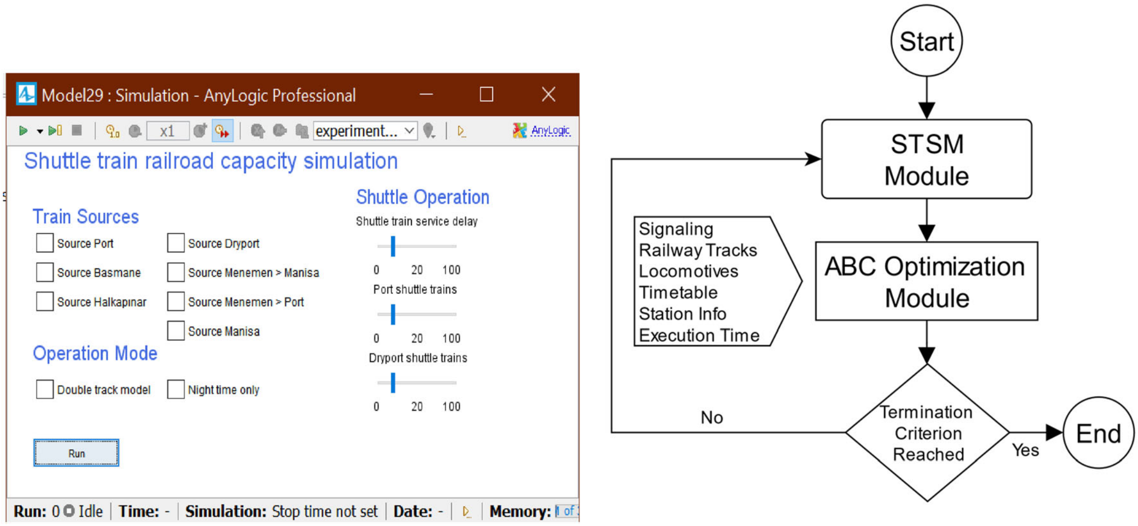

Fig. 3 **a** The view of the simulation GUI of the operational model, and **b** STSM and ABC optimization integration

delay, C_o is a dummy variable for penalizing unfeasible solutions, and N is the number of total completed SFT trips in the analysis period. The optimization module tries to evolve a suitable dispatching delay vector for the SFTs by systematically shifting SFT trips across time. The mechanism for solving SRT delays with the simulation–optimization approach is shown in Fig. 4.

Figure 4a shows the paths of the SRTs heading to the seaport (T_1 and T_2) and to the dry port (T_3 and T_4). Figure 4b shows the path of the SFT (S_1) and its blockage effect on T_1 and T_2. In Fig. 4c, the path of S_1 is shifted by a specific dispatching delay at the seaport marshaling yard, so that the delay D_1 is avoided for T_2. S_1 also starts its return trip after waiting for a delay time of D_2, including the coupling/decoupling and dispatching delay. To avoid unfeasible solutions with conflicts in train paths, a penalizing approach can be used for measuring violations of constraints. For penalizing conflicting train paths, a linear weighting method [47] is implemented for the objective function using a dummy variable C_o. The dummy variable for each STSM execution is calculated with Eq. (3):

$$C_o = (N_{to} - N_{ts}) \times \varnothing, \tag{3}$$

where N_{to} is the number of SRTs, N_{ts} is the number of SRTs that successfully reach their destination in the STSM execution period, and $\varnothing$ is a large positive number for penalizing train path conflicts.

3.3 Artificial Bee Colony Optimization Algorithm

In this study, a swarm-based Artificial Bee Colony (ABC) algorithm is used for optimization. The ABC algorithm mimics the intelligence of honeybees for locating profitable food sources scattered within a search space [48]. The ABC systematically uses a group of employer, onlooker, and scout bees to search for food sources

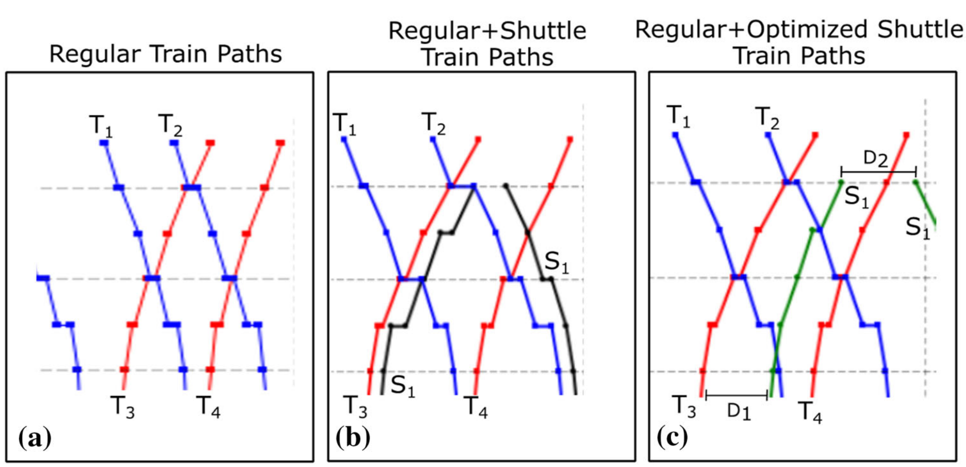

Fig. 4 Mechanism for minimizing regular train delays by applying an optimization delay to SFTs

corresponding to singular optimal SFT dispatching delay vectors. For each food source, an employer bee is assigned. Employer bees search the neighborhood of food sources to find more feasible solutions; this represents a local search of the candidate solution [49]. The algorithm includes stages for initialization, employer bees, onlooker bees, and scout bees. In the initialization stage of the algorithm, food sources (initial solutions) are randomly generated using Eq. (4):

$$A_{ij} = x_j^{min} + \varnothing_{ij}\left(x_j^{max} - x_j^{min}\right), \tag{4}$$

where $i = \{1, 2, \ldots, NF\}$, $j = \{1, 2, \ldots, D\}$, NF is the number of food sources, D is the number of parameters to be optimized, x_j^{max} and x_j^{min} are upper and lower bounds of the jth parameter and $\varnothing_{ij}$ is a random real number in a range of -1 to 1. At the employer bee stage, bees search the neighborhood of the existing food sources and a new solution $\overrightarrow{s}_i$ is generated by modifying $\overrightarrow{A}_i$ using Eq. (5).

$$s_{ij} = x_{ij} + \varnothing_{ij}\left(x_{kj} - x_{ij}\right), \tag{5}$$

where $i = \{1, 2, \ldots, NF\}$ and j is a parameter randomly selected in the range of 1 to D, k is a randomly chosen solution other than i. The fitness of the generated solution is evaluated using the cost function. The algorithm replaces the old solution with the new one if the fitness of the new solution is better. Otherwise, the old solution is kept, and a counter is increased for tracing the exhausted food sources. After the employer bee stage, the algorithm begins the onlooker bee stage to select profitable food sources based on a probabilistic roulette wheel rule. The selection probability of food source p_i is calculated based on the fitness value of each solution (fit_i using Eq. (6):

$$p_i = \frac{fit_i}{\sum_{j=1}^{n} fit_j}. \tag{6}$$

The selection of food sources by onlooker bees is performed by comparing a uniformly random real number in the range of 0 to 1 with p_i for food source $\overrightarrow{s}_i$. If the random number is less than p_i, the onlooker bee locates another food source in the vicinity of $\overrightarrow{x}_i$ using Eq. (1). If a better neighborhood solution is reached, it is kept in the food source population. After the employer bee stage, the counters for each $\overrightarrow{s}_i$ are examined, and if a limit value is exceeded, the exhausted food sources are removed. Instead of an exhausted solution, a new solution is generated using Eq. (1). The cycle of the ABC algorithm continues until specific halting criteria are met. For integrating the STSM with an optimization framework, the STSM is linked with the Matlab framework as an external Java application. The encapsulated simulation–optimization framework iteratively generates candidate dispatching delay vectors for each algorithm cycle followed by the realization of the candidate vectors by the STSM. The evaluated objective function is fed back to the optimization framework for generating new candidate vectors. The best global parameter is kept inside the optimization framework and the algorithm is terminated if halting criteria are reached. The schematic diagram of the STSM and the ABC optimization framework integration is shown in Fig. 3b.

3.4 Key Performance Indicators

Optimization performance and SFT service transport capacity are evaluated using a set of KPIs. To quantify SFT service capacity, the total number of completed trips per day (N_{SFT}^{T}) is used. The uncompleted SFT trips during the analysis period are not counted. The punctuality and reliability of the trains are addressed using the number of station stops, average trip delay, and station delay. The KPIs used in this study are depicted in Table 1. Railway operators often utilize different LoS criteria and goals for different services, such as freight versus passenger transport services. These criteria are not well defined for shuttle train services for dry ports. For this reason, this study evaluates the capacity and LoS using KPIs without a standard specification.

4 Experimental Study for Alsancak Seaport

The proposed simulation–optimization framework was implemented for the railway corridor between the Alsancak seaport and a dry port in Manisa city. The dry port is located at a logistics center operated by the Manisa Industrialized Zone at the town of Muradiye. The railway corridor is 51 km long, and consists of both single- and double-track line sections, with intermediate stations and autoblock nodes. A satellite view of the railway corridor is shown in Fig. 5a, and the seaport marshaling yard is shown in Fig. 5b.

The railway corridor includes nine stations and eight autoblock nodes separating the railway tracks. At intermediate stations, SRTs can wait for passenger boarding or train meetings at sidetracks. SFT trips take place between the Halkapınar and Muradiye stations. Service tracks connect the stations to the marshaling yards (see Fig. 5b). It is assumed that there are enough sidetracks available at marshaling yards for all coupling/decoupling operations. The sum of coupling/decoupling delays (D_{cdp}) for the SFT locomotives is assumed to be 15 min. The station kilometers, sidetrack lengths, and the characteristics of track sections of the railway corridor are shown in Fig. 6. The

Table 1 KPIs for evaluating model performance

KPI	Description	Unit	Type	Calculation
N_{SFT}^{T}	Number of completed SFT trips	–	C	–
N_{SFT}^{S}	Number of SFT station stops	–	P	–
N_{R}^{S}	Number of SRT station stops	–	P	–
D_{SFT}^{T}	Average SFT trip delay	Min/trip	P	Total trip delay $/N_{SFT}^{T}$
D_{SFT}^{S}	Average SFT station delay	Min/stop	P	Total station delay $/N_{SFT}^{T}$
D_{R}	Average SRT trip delay	Min/trip	P	T_0/N_{R}^{T}

C capacity type (throughput), *P* punctuality type

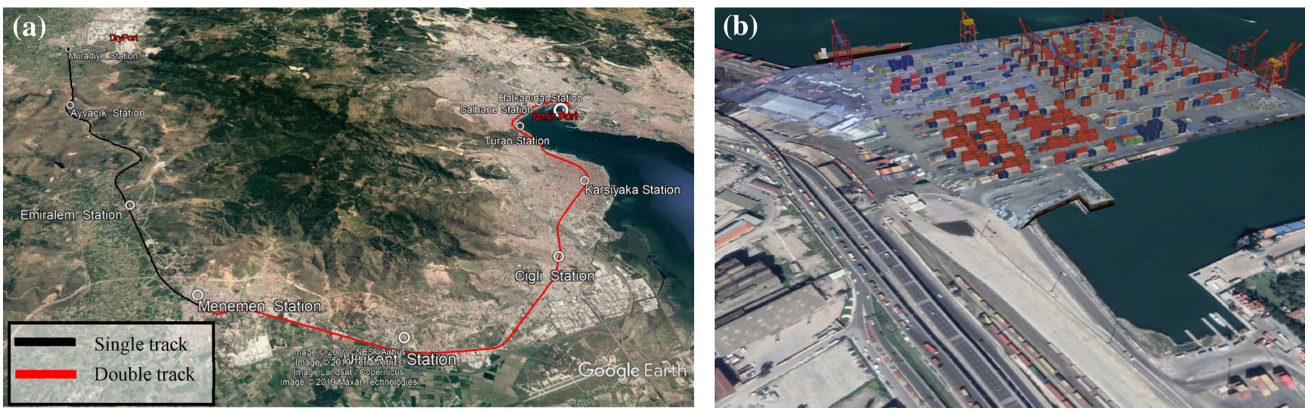

Fig. 5 **a** Railway corridor route and **b** marshaling yard at seaport

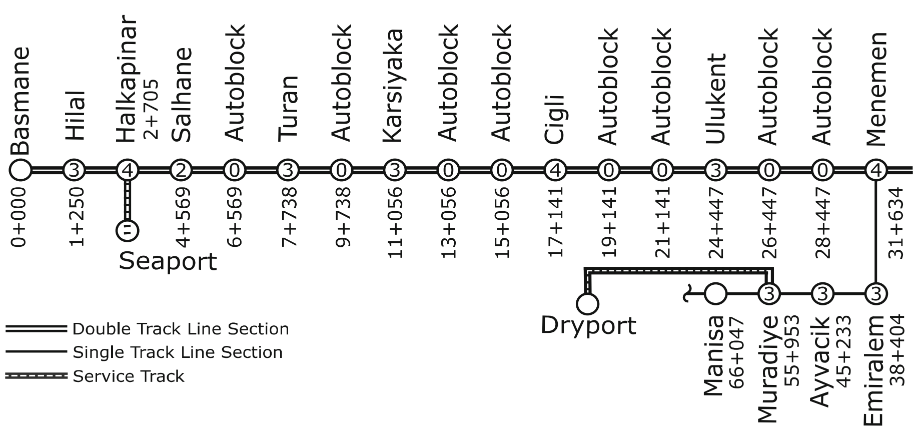

Fig. 6 Schematic layout of the railway corridor

number of sidetracks for each station is indicated inside the station node.

4.1 SFT Operation Scenarios

Two experimental scenarios were considered: operating single (S1) and couple (S2) SFT locomotives. For the S1 scenario, the SFT locomotive was dispatched from the seaport and for the S2 scenario, two SFT locomotives are simultaneously dispatched from the seaport and dry port. At the start of the STSM execution, the SFT locomotives were already coupled with the SFT cars. It is assumed that SFT cars are handled before the arrival of an SFT locomotive. The SFT trips were realized using the existing SRT schedule (TOI: 33,012). The STSM execution period was 24 h, starting at midnight. SRT schedules were obtained from the General Directorate of Turkish State Railways including dispatching and station arrival times, initial and final stations, and planned waiting times at stations for passenger boarding and train meetings. The daily SRT schedules are shown in Table 2.

4.2 Model Verification and Validation

Verification and validation are two important steps for evaluating a simulation model before conducting simulation experiments. With verification, the model's code is compared to its model specifications to check if it is correct. Validation examines the fit of the model to the real-world system and checks if the model correctly mimics the underlying system behavior. The STSM was verified by analyzing the generated train paths for any unresolved train conflicts or deadlocks. From the initial model executions, it was concluded that the STSM successfully simulated operation scenarios without any train deadlocks. The STSM was validated by comparing the generated train paths with the original SRT schedules. The generated SRT paths for STSM validation are shown in Fig. 7. In the figure, the 14 SRT paths towards the dry port are shown in red and the 15 SRT paths towards the seaport are shown in blue. The vertical axis corresponds to the ranks of the intermediate stations and sidetrack nodes. The location of the dry port (DP) and seaport (SP) yards are also shown on this axis.

5 Results and Discussion

5.1 Unoptimized SFT Trips

Before the optimization step, the STSM was executed with the optimization module deactivated to generate the SFT paths without dispatching delays. At this stage, the KPIs were collected to compare the optimized performance with unoptimized SFT operation. The train paths for S1 and S2 scenarios are shown in Figs. 8 and 9, respectively. In these figures, the SFT paths are shown in black. At the end of the STSM executions, the numbers of completed SFT trips were 18 and 36 for the S1 and S2 scenarios, respectively. Train delays were often observed for single-track line sections as indicated with circles. The observed train delays can be classified as direct delays or secondary delays. Direct delays result from the interaction between trains when a railway track segment was occupied by another train. Most of the SFT delays were direct delays at stations, because an SRT already occupied the next track resource.

In several cases, SFTs were additionally delayed at the dry port, since the railway tracks were already occupied. The SFT operations were also delayed, since priority to seize the railway tracks was given to the scheduled trains. The SRT delays were caused by direct interactions with the SFTs and secondary delays developed from the disturbances of the timetable. The secondary delays also propagated with time, and future delays were triggered for both the SRTs and SFTs. An expected outcome of the S2

Table 2 Daily SRT schedules

#	TOI	T_{DP}	S_I	S_F	V_{MAX}	#	TOI	T_{DP}	S_I	S_F	V_{MAX}
1	72,008	05:48	M	B	110	16	33,322*	19:30	HP	MM	80
2	33,044	15:10	M	HP	80	17	32,605	11:00	B	M	110
3	32,606	07:02	M	B	120	18	32,007	20:15	B	M	120
4	32,603	15:00	B	M	120	19	32,602	11:06	M	B	120
5	32,601	07:40	B	M	120	20	33,042	09:45	MY	MM	120
6	33,041*	15:30	HP	MY	80	21	33,311*	12:14	MM	M	80
7	22,006	08:08	M	B	120	22	32,604	16:53	MM	B	120
8	32,009	17:15	B	M	100	23	13,130*	13:15	M	MM	80
9	32,001	08:30	B	M	120	24	32,004	21:17	M	B	120
10	32,012	17:30	M	B	120	25	32,002	12:46	M	B	120
11	32,010	08:50	M	B	120	26	33,323*	22:05	MM	HP	80
12	32,005	18:05	B	M	110	27	32,003	14:00	B	M	120
13	37,306	10:16	HP	MM	120	28	37,310*	22:49	MM	HP	80
14	32,011	18:40	B	M	120	29	23,234*	14:25	M	MM	80
15	33,012*	11:17	HP	MM	80						

TOI train operation ID, T_{DP} SRT departure time, S_I initial station name, S_F final station name, V_{MAX} maximum train speed (km/h), *B* Basmane, *M* Manisa, *HP* Halkapınar, *MY* Muradiye, *MM*: Menemen

*Freight train

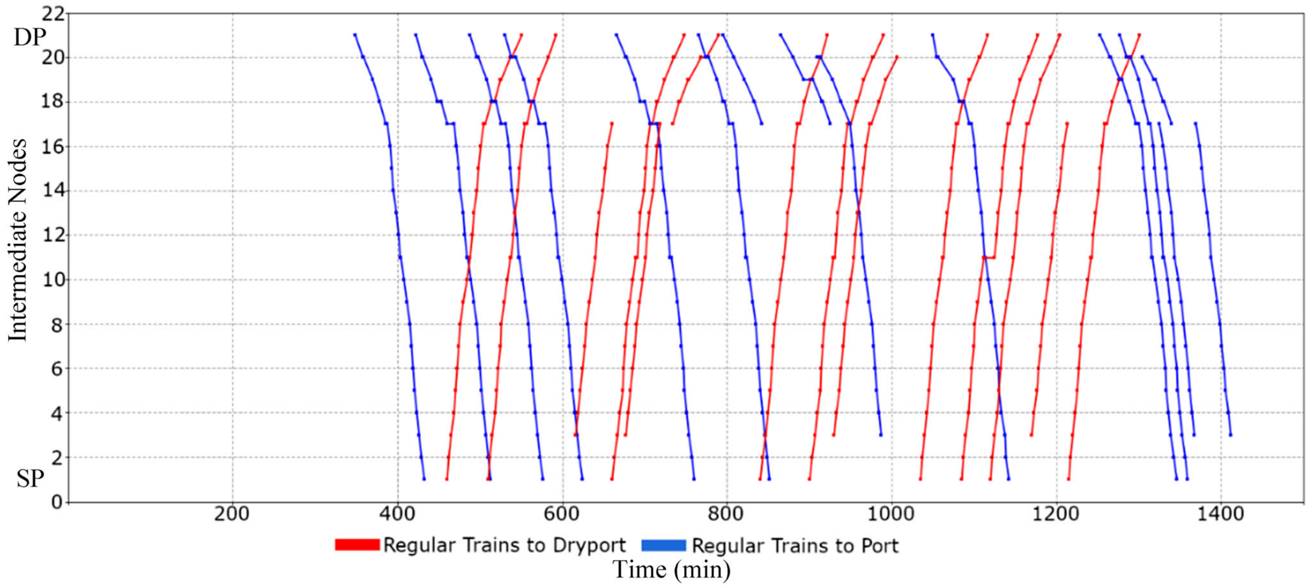

Fig. 7 Generated SRT train paths for STSM validation

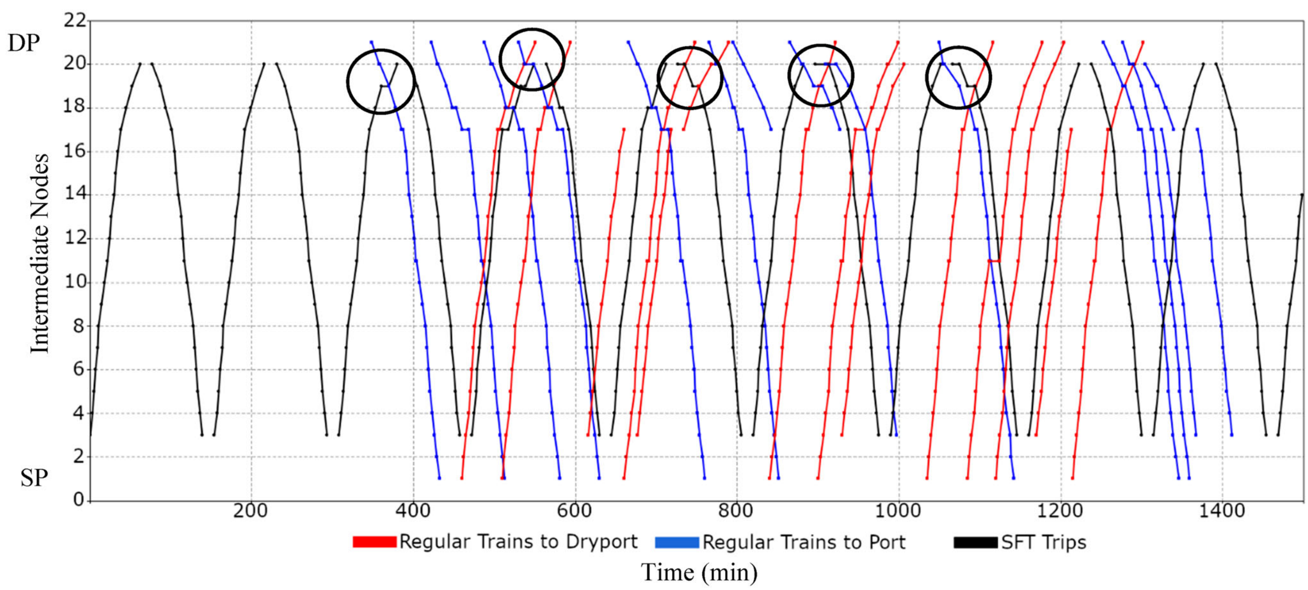

Fig. 8 Unoptimized train paths for S1 scenario. *DP* dry port, *SP* seaport

scenario was that couple SFT locomotives generated more train blockages and delays. The influence of the SFT operations resulted in a total SRT delay of 25.06 min and an average SRT delay of 0.86 min for the S1 scenario. For the S2 scenario, a total SRT delay of 61.15 min and an average SRT delay of 2.10 min were observed. The average SFT trip delay value was 2.83 min for the S1 scenario, and 3.40 min for the S2 scenario.

5.2 Optimized SFT Trips

The optimization study was carried out with the goal of zero SRT delay. The colony size and number of food sources for the algorithm were set at 30 and 15, respectively. The upper and lower bounds for the SFT dispatching delays were 0 and 30 min, respectively. Before the optimization step, the train paths were examined in a preliminary stage to reduce the size of the dispatching delay vector. For the S1 scenario, SFT dispatching delays were not applied for the first SFT trips, since they did not overlap with SRT paths. For the S2 scenario, the size of the

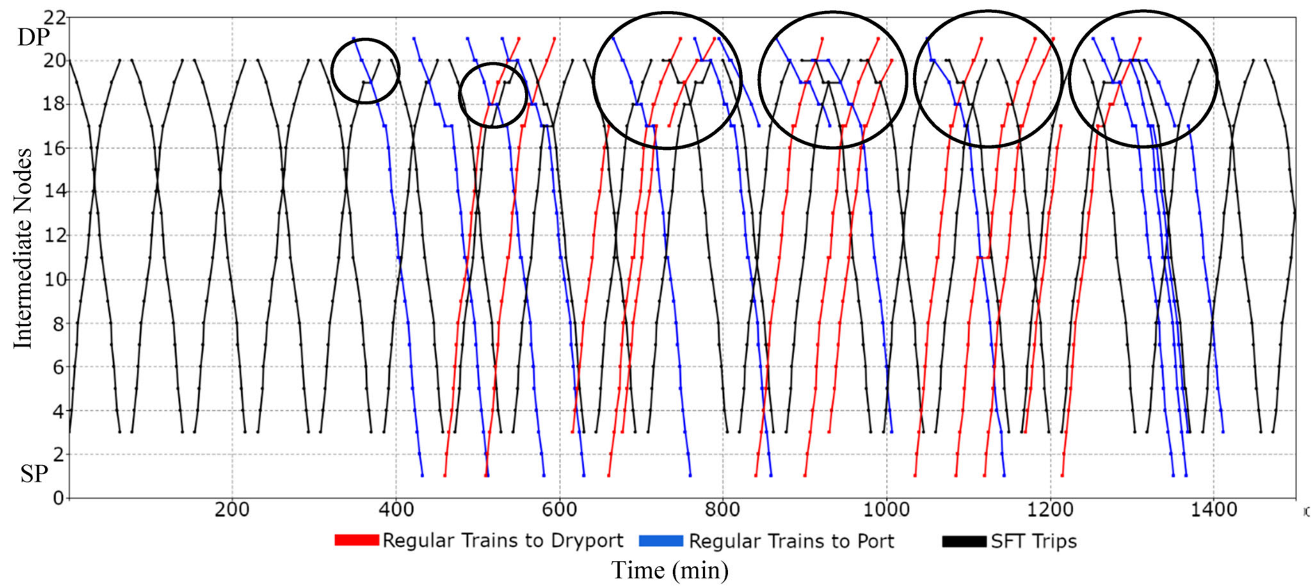

Fig. 9 Unoptimized train paths for S2 scenario, *DP* dry port, *SP* seaport

dispatching delay vector was 21, taking into account the overlapping SFT paths. For the S1 scenario, the optimization algorithm approached the zero SRT delay goal at the eighth optimization iteration with a total optimization time of 2.18 min. For the S2 scenario, the four successive SFT trips for two directions were excluded, like in the S1 scenario. Since more SFT paths were available, a higher iteration number was required for converging on zero delays. The total SRT delay value converged on zero in 104 cycles with a total execution time of 26.67 min. For each optimization iteration, the penalized total delay values were also encountered for food sources, and because of the large penalty coefficient of $\varnothing$, these solutions were not considered for the global minimum. The deviation of D_R with the iteration number are depicted in Fig. 12a and b for S1 and S2 scenarios. For S1 and S2 scenarios, the optimized SFT and SRT train paths are depicted as Figs. 10 and 11, respectively.

In the figures, unmodified SFT trips are shown in black. For these trips, the optimization study returned zero dispatching delays, or they were previously discarded from the dispatching delay vector by preliminary examination. Green paths are the modified SFT trips with dispatching delays greater than zero. The influence of introducing the dispatching delays can be emphasized by examining the circled regions in Figs. 10 and 11 for the solution of the train blockages. With the use of the SFT dispatching delays, SFT dispatching times were systematically delayed, and most of the SFT and SRT conflicts were prevented. The optimized dispatching delay parameters for SFT trips in scenario S1 are shown in Fig. 13a and b, for the dry port and seaport, respectively. Optimization delays in scenario S2 are shown in Figs. 14 and 15 for the seaport and dry port, respectively (Fig. 12).

In Figs. 13, 14, and 15, the D_{od} value indicates the implemented dispatching delays for each SFT trip shown on the horizontal axis and which were taken from the optimized SFT dispatching delay vector. The T_{d} values indicate the SFT trip delays for the unoptimized (no dispatching delays implemented) and optimized SFT paths. In Figs. 10 and 11, x-axes correspond to train paths. The locomotives used for SFT trips (L1 and L2) in scenario S2 are shown in Figs. 14 and 15. The KPIs used to compare optimization performance and assess capacity for unoptimized and optimized STSM executions and their deviations are shown in Table 3.

For single and double SFT operations, 18 and 36 daily trips, respectively, were realized. Table 3 shows that after optimization, the freight transport capacity of the SFT service decreased in both S1 and S2 scenarios. In the scenario S1, the number of completed SFT trips decreased by 11.1% (from 18 to 16), and in the scenario S2, it decreased by 13.8% (from 36 to 31) and this decreases also indicate the drop of freight transport capacity. The average SRT trip delays in an unoptimized state were 0.86 min and 2.10 min for scenarios S1 and S2, respectively. After the optimization phase, the average SRT trip delay and the number of SRT station stops both approached zero for both scenarios. The average SFT trip delays in unoptimized state were 2.83 min and 3.40 min for S1 and S2 scenarios, respectively. After optimization, the average SFT trip delays decreased by 30.7% and 0.58% for the S1 and S2 scenarios. The number of SFT station stops increased by 12.5% (from 8 to 9) in scenario S1, while the average SFT

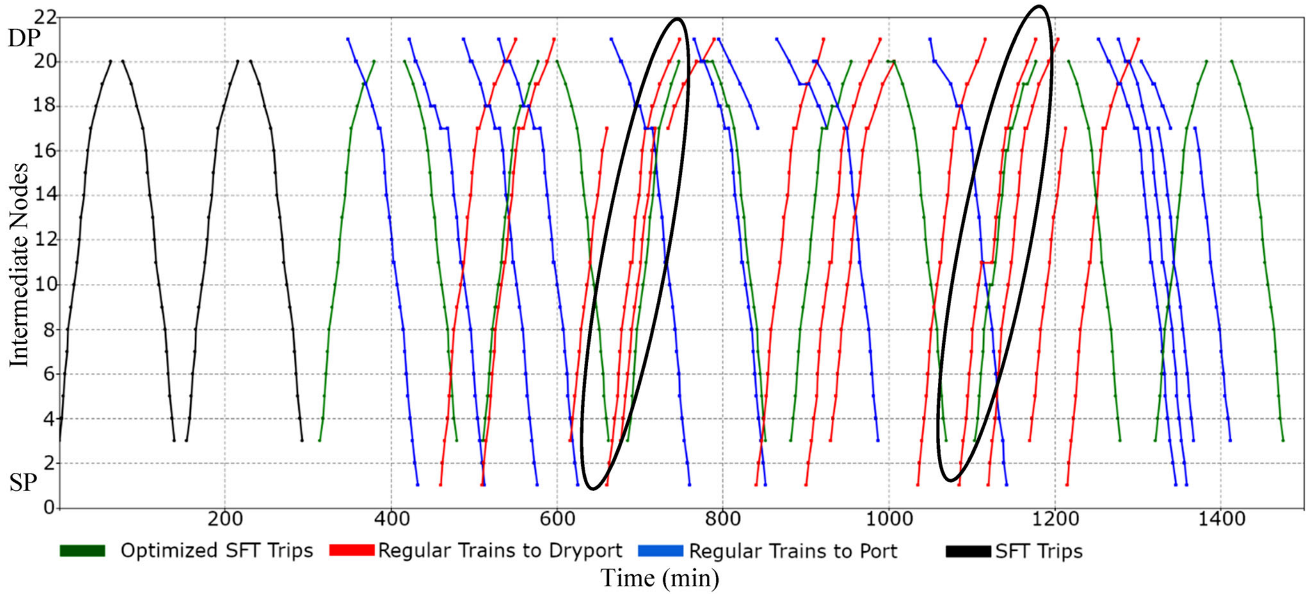

Fig. 10 Train paths for S1 the scenario with optimized SFT dispatching delays

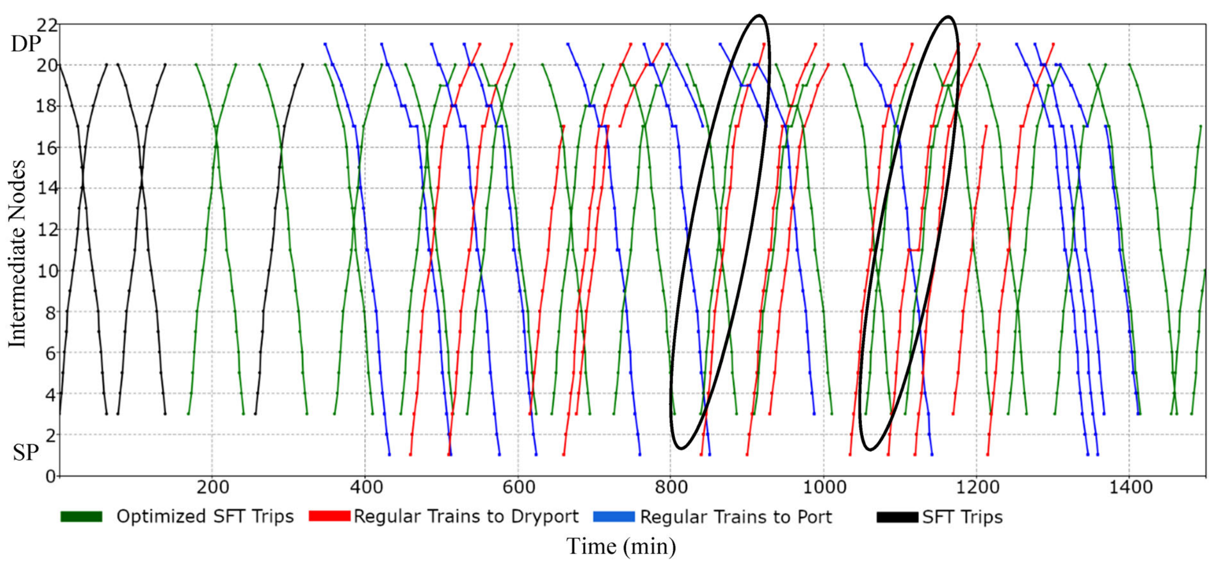

Fig. 11 Train paths for S2 the scenario with optimized SFT dispatching delays

station delay decreased by 45.2% (from 6.37 min to 3.49 min). In scenario S2, although the number of SFT station stops increased by 57.1% (from 21 to 33), the average SFT station delay decreased by 45.6% (from 5.83 min to 3.17 min). The results showed that it was necessary to reduce the SFT freight capacity to keep the existing SRT timetable. Additionally, implementing SFT dispatching delays was beneficial in reducing SFT trip delays.

6 Conclusions

In this paper, we have developed a simulation–optimization framework using a multi-method simulation and meta-heuristic ABC optimization algorithm to schedule SFT trips without disturbing the SRT timetable. The STSM was based on the allocation of successive railway track resources by SRTs, and SRTs having priority over SFTs. The performance of scenarios S1 and S2 before and after optimization were compared using several KPIs. The optimization algorithm was used for searching an SFT dispatching delay vector for shifting SFT paths and

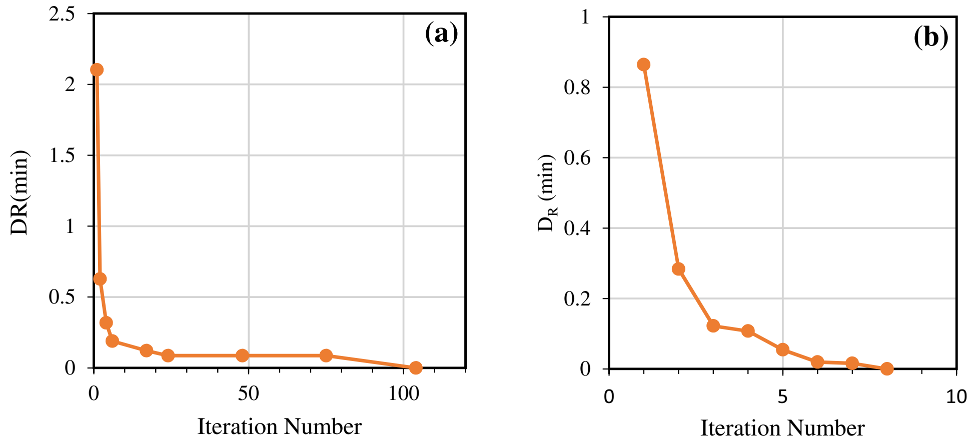

Fig. 12 Deviations of the D_R with the iteration number for S1 and S2

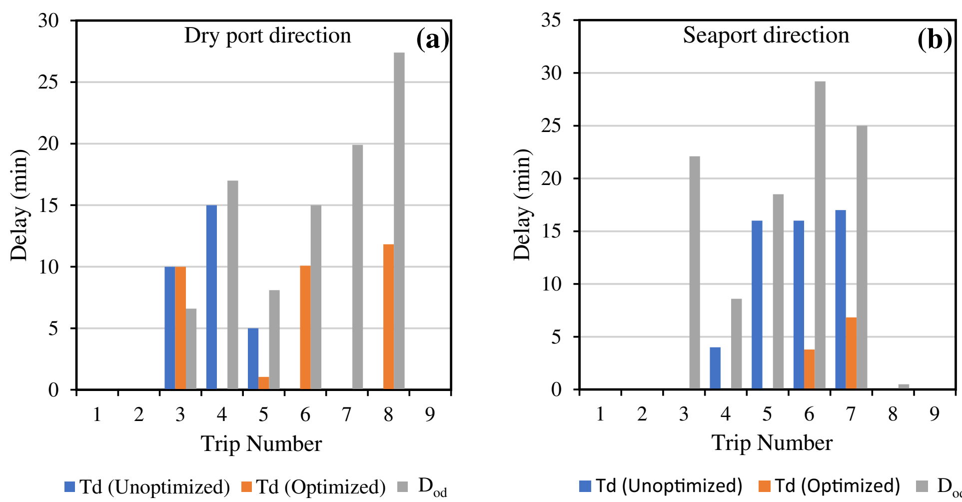

Fig. 13 Trip and dispatching delays of SFTs for scenario S1

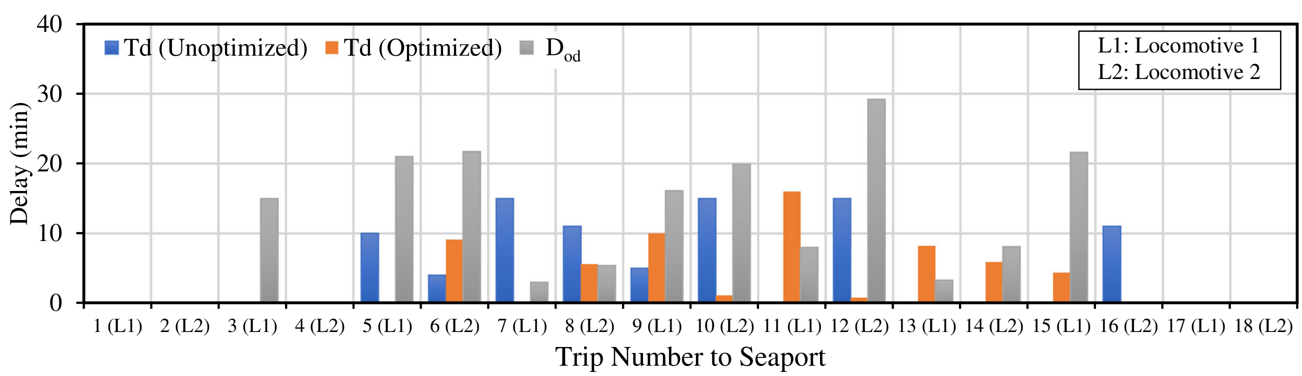

Fig. 14 Trip and optimization delays of SFT paths to seaport direction for S2 scenario

avoiding train conflicts and blockages. To demonstrate the approach, a thorough case study on a railway corridor between Alsancak seaport and a dry port has been carried out, and based on these results, we draw the following conclusions:

- The multi-method simulation technique and simulation–optimization methodology can successfully be used for simulating SFT and SRT trips in a shared railway corridor and determining the freight transport capacity of cyclic shuttle trains.

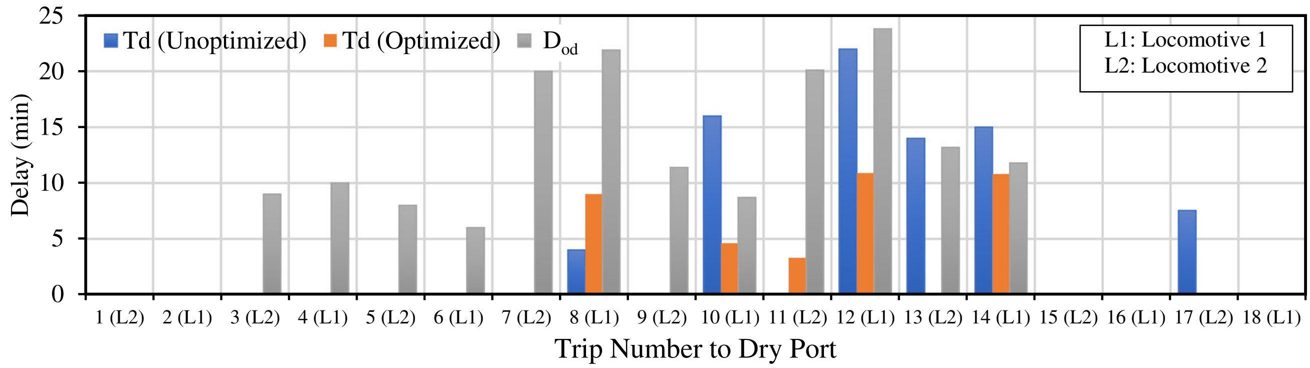

Fig. 15 Trip and optimization delays of SFTs to dry port direction for S2 scenario

Table 3 Comparison of KPIs for unoptimized and optimized operation scenarios

SN	Unoptimized SFT trips						Optimized SFT trips				
	N_{SFT}^{T}	N_{SFT}^{S}	N_{R}^{S}	D_{SFT}^{T}	D_{SFT}^{S}	D_{R}	N_{SFT}^{T}	N_{SFT}^{S}	N_{R}^{S}	D_{SFT}^{T}	D_{SFT}^{S}
S1	18	8	7	2.83	6.37	0.86	16 (– 11.1%)	9 (+ 12.5%)	0.00	1.96 (– 30.7%)	3.49 (– 45.2%)
S2	36	21	14	3.40	5.83	2.10	31 (– 13.8%)	33 (+ 57.1%)	0.00	3.38 (– 0.58%)	3.17 (– 45.6%)

SN scenario name

- The introduction of optimized SFT dispatching delays can be used to maintain an existing SRT timetable and avoid the associated delays.
- According to the case study, this approach inevitably decreases the number of completed SFT trips by up to 13.8%, This decrease can be directly associated with the decrease in freight transport capacity. Additionally, the methodology can also reduce SFT trip delays and station delays by reducing train blockage problems.
- One disadvantage of introducing SFT dispatching delays was the increase in the number of SFT station stops, especially in scenario S2. However, the average SFT trip delays were not increased, since the SFT station delays were reduced after the optimization step.

The assessment of the LoS and capacity in terms of railway operator standards has not been addressed in this study. However, deviations of the capacity and LoS of the SFT service were compared for unoptimized and optimized scenarios to measure the efficiency of the proposed methodology. Future work should include a more detailed study about the behavior of SFTs and investigate additional methods for increasing SFT freight transport capacity without disturbing the existing SRT timetable. For this case, the number of SFTs and double-track line sections can be increased. In particular, assigning additional SFT locomotives at night can also be addressed for utilizing idle train paths. A vast opportunity for further research into the operational configuration of SFTs also exists, such as developing an autonomous SFT decision support system for train dispatching at intermediate nodes or performing train meeting and overtaking operations. The potential growth of seaport throughput and infrastructural modifications, and the growth of passenger train services must also be considered when dealing with future capacity problems of railway corridors and investigating the capacity expansion possibilities.

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