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Published in:
Computers and Operations Research

Published: 01/12/2022

Document Version:
Final Published version, also known as Publisher’s PDF, Publisher’s Final version or Version of Record

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Publication record in CityU Scholars:
Go to record

Published version (DOI):
10.1016/j.cor.2022.105983

Publication details:

Citing this paper
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Three-echelon slot allocation for yield and utilisation management in ship liner operations

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ARTICLE INFO

Keywords:
Maritime container transport
Slot allocation
Optimisation
Multi-echelon
Genetic algorithm
Deep neural network

ABSTRACT

In the highly competitive maritime liner business, liner companies face the ongoing risk of mismatches between supply and demand and intense price-cutting by their rivals. Most of them continuously work to improve the use of mega-vessels and form alliances to lower their operation costs and enhance their service network. International liners run long-haul services and fill their vessel slots with shipments from multiple trade lanes, chosen on the basis of shipment yields and empty repositioning from the perspective of local, regional and global slot planning operations. Here, a novel model for multi-echelon slot allocation was developed that accounts for the dynamics among local, regional-hub and global scales in terms of container loading and discharge at various vessels in multiple ports. A two-stage optimisation was proposed to improve usage and yield via slot exchange amongst liner companies in an alliance and cargo shifting amongst multiple trade lanes and service loops. Four optimisation methods for the three-echelon slot allocation were developed based on branch-and-bound search, genetic algorithm and deep neural network theories. The simulation results and model sensitivity of the developed algorithms were evaluated. Single-, two- and multiple-service routes with cargo shifting cases were simulated and analysed. The developed slot allocation model will assist trade and traffic planners in various echelons to coordinate and maximise slot usage and yield and ensure that cargo dimensions and weight fall within the cargo payload capacity and verified gross mass requirements, which further prevent vessel damage, excessive fuel usage and the unnecessary emission of greenhouse gases.

1. Introduction

In ship liner operations, shipping companies use containerships to deliver cargos from port to port on fixed routes and regular schedules in various trade lanes. Under the dynamic trading environment, ship liners often encounter with uncertain demand and highly fluctuating markets. Excess capacities in mega-vessel deployment create the possible mismatch of supply and demand. These lead to frequent changes in supply chain pattern due to the changes of trading, demand and supply. To become more competitive, there is an increasing trend for ship liners to form alliances to improve their service networks and lower their operating costs. This trend has accelerated since the formation of the 2 M alliance and the Hanjin bankruptcy (Fig. 1). The formation of alliances can also facilitate slot exchange among liners in the alliance, thus allowing the maximisation of slot utilisation and overall vessel revenue (Zhen et al., 2019). This creates a crucial need for research into slot allocation planning, from optimisation modelling and revenue analysis (Rashed et al., 2021; Guo et al., 2018; Kayıkçı and Çatay, 2017; Ting and Tzeng, 2016) to slot exchange and vessel alliances (Croitti et al., 2019; Yang et al., 2011; Song and Panayides, 2002). The complexity of vessel slot allocation has increased as more factors have come into consideration, such as the increasing numbers of service routes offered, alliance vessels involved, and loading regions.

Recent research into slot allocation mechanisms in liner shipping has
covered various aspects including vessel safety (Cristian, 2011; Wang et al., 2022), network design and operational productivity (Agarwal and Ergun, 2010; Chen et al., 2008), revenue management (Hu et al., 2019; Fu et al., 2016; Wang et al., 2015), alliance strategies (Crottì et al., 2019; Chen and Yahalom, 2013; Lu et al., 2010b) and environmental sustainability (Qiu et al., 2018; Parthibaraj et al., 2015; Haraldson, 2015).

Research into slot allocation planning usually focuses on optimising allocation with reference to vessel or slot revenue, shipment freight contribution and vessel utilisation (Lu and Mu, 2016). In defining slot allocation, it refers to allocating vessels slot spaces for containers delivering shipments from loading port to discharging port on a given service route. The slot allocation planning considers various factors including types of containers, vessel capacity, region loading demands, shipment yield, project accuracy, historical performance of loading regions, and customer profile. Most common slot allocation problem in research is determining an optimisation model in solving and optimising the allocation of spaces for containers loading on a vessel on several call ports of a sailing in a single service route. Ting and Tzeng (2004) developed an optimal allocation model with the consideration of freight contribution and applied it to the Asia-Europe services of a liner company. Conflicting objectives regarding the carrier’s freight contribution and the agents’ degree of satisfaction were evaluated. Chen and Zhen (2009) applied a nonlinear goal programming model to slot chartering and allocation. The authors extended previous studies by including cooperation between vessels in consecutive voyages of a service route. Fu et al. (2016) addressed the slot allocation problem with minimum quantity commitment, which especially affects Trans-Pacific Trade. They modelled the problem as a mixed-integer linear programming problem with uncertainty in demand and with containers being transported along the calling ports of a vessel on a single specified service route. Kayıkçı and Catay (2017) proposed two slot allocation models. The first model was formulated using stochastic integer programming for slot allocation with consideration of long-term contract market sales. The other model is focused on dynamic pricing in a short-term spot market sale formulated by stochastic nonlinear programming. The objective was to maximise the total freight contribution on a shipment with reference to the origin-destination pair of a vessel sailing on a designated service route. Guo et al. (2018) established a stochastic allocation model and formulated it as an integer linear programming model, with consideration of the long-term contractual customer booking requirements. However, the synergy of cargo shifting, multiple service loops and multi-echelon parties, i.e. involving local, regional and global trade planners, collaborating in slot allocation has seldom been discussed and analysed.

Most of the above studies have focused on slot planning for a single routing service instead of multiple routes (Guo et al., 2018; Ting and Tzeng, 2016; Lu et al., 2010a). The slot allocation involved has not considered cargo shifting amongst multiple services with similar ports of call and schedules (Kayıkçı and Catay, 2017; Lu and Mu, 2016; Feng and Chang, 2008; Lu et al., 2010a). Some of the models only evaluate allocation to the regions of the vessel’s port of call, instead of all traffic loading regions including transshipment cargos (Guo et al., 2018). Slot planning models have been formulated for long-haul services without consideration of the actual process of utilising short-haul shipments on the same vessel (Ting and Tzeng, 2004). The slot management process in the existing vessel allocation models does not usually integrate slot exchange amongst alliance partners (Zurheide and Fischer, 2012; Zurheide and Fischer, 2015 Chen and Zhen, 2009). As for work considering slot exchange in multiple trade routes, slot-swapping and fleet planning, investigations could be extended from specific services to incorporating alliance operations (Lu et al., 2010a; Lu et al., 2010b; Chen et al., 2021; Chen et al., 2022). The papers pointed out the need to expand the scope by considering more market variations such as the uncertain estimation of slot demands and the application of more effective algorithms to handle larger cases. Indeed, to improve the shipment yield and vessel utilisation in these complex liner operations, with thousands of containers loading and discharging from multiple ports of various service routes, comprehensive and accurate slot allocation planning is required.

The current approach to slot planning in liner companies operate only with feasible solutions instead of optimising the yield of each service trade lane or vessel utilisation sailing in a service route. Most previous studies in slot management focused only on vessel allocation and slot planning of a single service loop in a single trade lane and neglected the complexity of the real slot planning problem situation. Cargo shifting amongst multiple service loops due to cargo overloading and port omission is often encountered but is seldom reflected in studies. There has been no consideration of cargo loading performance, projection accuracy and shipment yield of traffic regions in slot management planning. On long-haul services, efforts are continuously made to utilise unused space via slot exchange and the use of short-haul shipments.
Some studies have considered the constraints on twenty-foot equivalent units (TEUs) but not individual size types and weights, which must be considered due to the variations in vessel configuration and actual business requirements. Slot exchange models have been developed in some studies but have not been fully integrated with the slot planning models. Improved methods for optimising slot allocation and vessel use and for ensuring effective slot exchange with partners in the alliance consortium are of high importance.

Considering these research gaps, this paper proposes a novel conceptual framework of slot allocation with three-echelon planning in multiple stages. Loading regions from inland, feeder and port locations were considered in the model, reflecting the optimisation of allocation among global, regional and local operations, which has not been studied in previous research. Slot allocation operations were formulated and simulated on multiple services and multiple trade lanes utilising long-haul vessels to optimise vessel yield, cargo shifting and slot exchange through the three echelons. Demand prospect in the slot allocation planning was incorporated into the model by applying three-point estimation on an international liner’s previous weeks’ order data. As a result, an integrated novel three-echelon slot allocation planning model was developed. Upon designing the model, further work was carried out by using branch-and-bound (B&B) algorithm to solve several cases and situations, including single-, two- and multiple-service routes of the mixed-integer programming problem. To evaluate the algorithm’s effectiveness, two other methods, genetic algorithm (GA) and deep neural network (DNN), were developed. Sensitivity analyses of the algorithms developed were carried out to analyse the performance of the three methods. Section 2 introduces the three-echelon framework for multiple-stage slot allocation planning. A mathematically novel slot allocation model for multi-echelon slot allocation planning is developed, and the assumptions, notations, objective functions and constraints are presented in Section 3. A corresponding two-stage multi-echelon optimisation algorithm is developed using the B&B search approach. Further methods, such as GA- and DNN-based slot allocation algorithms, are developed to compare the performance of the solutions. The three algorithm designs are described in Section 4. The results of various scenarios obtained from the three algorithms and their performances in terms of model fitness are discussed in Section 5.

2. Slot allocation planning framework

Under a consortium alliance with a shared service route network and vessels calling on designated ports of call, the alliance members determine the number of slots allocated to the vessels on specific trade lanes and plan the spatial allocation to the respective traffic control regions. The slot allocation planning is collaboratively planned via a three-echelon network comprising a headquartered global traffic planner (GTP), a regional traffic planner (RTP) and a local cargo-loading planner (LCP). The GTP plans the service network, vessel deployment, alliance and regional allocation. The planning of slot allocation mainly focuses on laden containers and sometimes include empty containers in certain trade lanes. The RTP analyses regional traffic allocation and prospect projection. The LCP reviews customer demand and projects future cargo loading volume. This allocation is analysed with reference to the global cargo demand, historical cargo loading trends, local projection accuracy and cargo yield. The regions that receive the allocations further distribute vessel spaces to their respective local loading ports. The collaborative planning process is triggered a period of n weeks in advance (e.g., 4-week rolling forecast and allocation), based on a vessel-sharing agreement and basic slot allocation (BSA).

Under three-echelon multiple-stage slot allocation planning, the GTP issues regional laden-container allocations with respect to TEUs, weight and size types on multiple service loops in a trade route, with consideration of empty repositioning allocation. These are commonly occurred in various trade lanes, such as Trans-Pacific trade (TPT). Regional allocations and local prospects are issued and revised during the n-week period up to one week before loading. Cargos under rollover or misconnection are shifted amongst service loops to utilise vessels’ open spaces. Slot exchange is carried out by the GTP in the event of booking upsurge or lack of allocated spaces in vessels. The empty available slots can therefore be utilised by buying and selling amongst alliance members based on the BSA ratio. This three-echelon integrated slot allocation plan is depicted in Fig. 2. The GTP collaborates continuously with multiple regions on regional allocation and rolling prospects, with reference to historical projection accuracy and cargo yield. The regions collaborate further with local cargo loading offices on their respective allocations and prospects.

Following carrier consolidation and global changes to the alliance landscape, the alliances that existed in 2016 (2 M, Ocean Three, G6 and CKYHE) have now become 2 M plus HMM, THE Alliance and Ocean...
Alliance (OA). Take, for example, the Asia Suez Express (AZX) service and China East Coast (CEC) routes, representing TPT services of one of the member companies of OA. The AZX service routes are eastbound: Hong Kong [HKG]–Colombo [CLB]–Singapore [SIN]–Laem Chabang [LCB]–New York [NYK]–Savannah [SAV]–Norfolk [NFK]. There are two CEC eastbound routes: South CEC (HKG–Shekou [SKZ]–Yantian [YAT]–SIN–LCB–NYK–SAV–NFK) and North CEC (Pusan [PUS]–Qingdao [QIN]–Ningbo [NIN]–Shanghai [SHA]–NYK–NFK–SAV). Each service has multiple ports of call in Asia, with 23 cargo-loading regions loading containers of various sizes and types. The loading regions, with allocation provided, indicate their prospects at one or more ports of a service for further revised allocation, if needed. Fig. 3 shows the typical multiple service loops in the service network of TPT. Cargo shifting can be carried out in ports of calls with connected trunk or barge services for rollover or misconnected cargos.

### 3. Multi-echelon slot allocation planning model

A model for the three-echelon collaborative slot allocation planning, which features the planning efforts of the GTP, RTP and LCP of a liner in an alliance setting, is illustrated below for a two-stage simulation. The assumptions, decision variables, objective functions and constraints are described as follows.

**Assumptions.** The fundamental assumption of this model is that all containers are measured in TEUs and forty-foot equivalent units (FEUs), with one 20-foot general-purpose (GP) container as one TEU and one 40-foot GP container as one FEU. An additional 0.3 TEU is counted in high-cube (HQ) containers; for example, a 40HQ is counted as 2.3 TEU, which is not an integer value. Further assumptions include the following:

1. The average maximum loading weight of each container is 10.5 tons per TEU in the space allocation planning stage if the shipper is unable to provide the loading weight at the booking stage.
2. The slot planning process caters to various container sizes and types, including 20, 40 and 45 feet as the possible container sizes and GP, HQ and reefer (RF) containers as the container types. Both laden and empty containers are considered in slot allocation planning. Awkward and bulky cargos are initially not included in the model because these irregular cargos account for less than 5% of the total quantity.
3. Slot exchange amongst multiple ship liners is based on their share in the service loop and the BSA ratio in the agreement.
4. The slot charging price and slot unit cost and so on vary with the route options and call ports of an individual service, as considered by a liner in practice.
5. The price of a slot exchange is based on the slot cost defined in the agreement rather than an ad-hoc spot price.

### Decision Variables.

- $\chi_{klr}$ the number of slots by TEU allocated to category $k$ containers through service route $r$ on leg $l$
- $\psi_{klr}$ the number of slots purchased by a liner without enough category $k$ container slots from an alliance member on the same vessel in TPT on leg $l$ of service route $r$
- $\phi_{klr}$ the number of slots sold by a liner with surplus category $k$ container slots to another liner on the same vessel in TPT on leg $l$ of service route $r$
- $\delta_{l}$ a binary variable representing the decision of selling or purchasing slots, which takes 1 if the decision is taken to sell, and 0 if the decision is taken to purchase
- $\nu$ the number of vessels from a liner deployed to service route $r$ ($r \in R$)
- $\varphi_{kl}$ a binary variable representing the decision of accepting or rejecting order $m$, which can comprise the deliveries of containers via distinct legs handled by different service routes; $\varphi_{kl}$ takes 1 if order $m$ is accepted and shipped by route $r$ and taken 0 otherwise ($m \in M, r \in R$)

### Input Parameters.

- $s_m$ source of shipment order $m$
- $t_m$ destination of shipment order $m$ ($m \in M$)
- $d_k^m$ demand for category $k$ containers by unit from order $m$ ($m \in M, k \in K$)
- $\pi^r_m$ the number of vessels from other alliance members deployed to service route $r$ ($r \in R$)
- $i^r_l$ the number of legs that start at port $i$ ($l \in L, r \in R$)
- $j^r_l$ the number of legs that end at port $j$ ($j \in R, l \in L$)
- $\lambda$ the number of available slots in TEU from the alliance for category $k$ containers of leg $l$ through service route $r$
- $\lambda^r_k$ the number of slots in TEU allocated in previous stages for category $k$ containers of leg $l$ through service route $r$ ($k \in K, l \in L, r \in R$)
- $\rho$ HQ/RQ conversion factor of category $k$ containers
- $\omega_k$ the average weight of category $k$ containers ($k \in K$)
- $W$ the average maximum weight limit in tons per vessel
- $C$ the average capacity in TEU per vessel
- $N$ the number of available vessels
- $B$ a big number

---

Fig. 3. Multiple Service Loops of a TPT Service Network.
Cost Parameters.

\( R_m \) the revenue of satisfying the demand of order \( m \)
\( P_m \) the penalty cost of not satisfying the demand of order \( m \) (\( m \in R \))
\( c_{ij}^p \) the unit cost of handling the demand for category \( k \) containers from port \( i \) to port \( j \) via service route \( r \)
\( c_{ij}^p \) the unit cost of purchasing a slot for category \( k \) containers from port \( i \) to port \( j \) via service route \( r \)
\( \rho_{ij}^p \) the expected profit of selling a slot for category \( k \) containers from port \( i \) to port \( j \) via service route \( r \) (\( i \in R, k \in K, r \in R \))
\( \omega \) the operating cost per vessel, which is assumed to be independent of vessel type

Derived Quantities.

\( I(r, l) \) the loading port of leg \( l \) of service route \( r \)
\( I(r, l) \) the unloading port of leg \( l \) of service route \( r \)

Objective Function.

The initial objective function is to maximise profit by optimising slot utilisation. This is done by optimising the slot allocation plan of all cargo-loading regions along the loading and transhipment ports by GTP, RTP, and LCP, as well as slot exchange among the alliance members. The optimisation applies to both short-haul and long-haul routes.

\[
TP(H) = \sum_{k \in K} \sum_{r \in R} \left( R_m \times \sum_{c \in C} c_{ij}^p \right) - \sum_{k \in K} \sum_{r \in R} \left( P_m \times \left( \sum_{c \in C} c_{ij}^p \right) \right) - \sum_{k \in K} \sum_{r \in R} \left( \rho_{ij}^p \times \sum_{c \in C} c_{ij}^p \right) - \sum_{k \in K} \sum_{r \in R} \left( \phi_{ij}^p \times \sum_{c \in C} c_{ij}^p \right) - \sum_{k \in K} \sum_{r \in R} \left( \omega \times \sum_{c \in C} c_{ij}^p \right)
\]

The mixed-integer programming optimisation of slot allocation using Eq. (1) is conducted in two stages, with the first stage handling the allocation process of the long-haul TPT shipments. It is then followed by slot exchange, which aims to seek more slots from alliance members for excessive orders or sell extra slots to alliance members to use up the unused ones, as the second stage. The allocation plan is completed after this stage. The iterative procedure in each stage includes inputting sets of orders, demand prospects and allocations from the three echelons, evaluating projection accuracy and yield, estimating values of demand distribution and solving the program to obtain the optimal solution set \( \alpha_{krl} \), where \( (i) \) represents the stage of optimisation, as described at the beginning of Section 2. Mathematically, the two stages of optimisation can be presented as follows.

- **Stage 1: TPT**
  
  Maximise: \( TP(H) \)
  
  Subject to: \( \alpha_{krl} = 0, \alpha_{krl} = 0, (k \in K, l \in LR, r \in R) \) (2).

- **Stage 2: Slot exchange**
  
  Maximise: \( TP(H) \)
  
  Subject to: \( \alpha_{krl} = \alpha_{krl}, (k \in K, l \in LR, r \in R) \) (3).

Constraints.

The initial constraints are set up considering the vessel fleet, vessel capacity, weight, demand, order loading, slot exchange, slot availability and routing. They are listed as follows.

1. Vessel fleet constraint: the total number of vessels deployed to service routes is not greater than the number of available vessels and is governed by.

\[
\sum_{r \in R} V_r \leq N.
\]

Table 1: Numerical Experiment Simulating the Slot Allocation on a Service Route.

<table>
<thead>
<tr>
<th>Region</th>
<th>Std Alloc (TEU)</th>
<th>PSP (TEU)</th>
<th>Rev Alloc (TEU)</th>
<th>Solved (TEU)</th>
<th>20GP (Unit)</th>
<th>20RF (Unit)</th>
<th>40GP (Unit)</th>
<th>40RF (Unit)</th>
<th>40HQ (Unit)</th>
<th>WDT (Ton)</th>
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<td>60</td>
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Fig. 6. Deep Neural Network Algorithm Workflow for Slot Allocation Problems.

Fig. 7. Deep Neural Network Structure for Slot Allocation Problems.

Fig. 8. Optimised Results from Five Approaches with Respect to Utilisation and Yield of ECCI Services during Week 14 to 18.

Table 2
Simulation Results of Various Methods in Optimising Slot Allocation in ECCI Service.

<table>
<thead>
<tr>
<th>Port</th>
<th>Standard Allocation</th>
<th>Prospect</th>
<th>Revised Allocation</th>
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<td>(Ton)</td>
<td>(TEU)</td>
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<td>Total</td>
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<td>5,525</td>
<td>711</td>
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</tbody>
</table>
Fig. 9. Optimised Results from Five Approaches with Respect to Utilisation and Yield of ECC1 Services during Week 14 to 18.

Fig. 10. Optimised Results from Five Approaches with Respect to Utilisation and Yield of ECC1 Services during Week 14 to 18.

Fig. 11. Optimised Results from Five Approaches with Respect to Utilisation and Yield of ECC1 Services during Week 14 to 18.

Fig. 12. Optimised Results from Five Approaches with Respect to Utilisation and Yield of ECC1 Services during Week 14 to 18.

Fig. 13. Optimised Results from Five Approaches with Respect to Utilisation and Yield of ECC1 Services during Week 14 to 18.

Fig. 14. (left) Fitness of Slot Allocation Model against HKG Demand and Optimised HKG Slot Usage in Week 18.
2. Capacity constraint: for any service route $r \in \mathcal{R}$, on each vessel in service route $r$,
\[
\frac{v_r + n_r \times C}{v_r} \leq C
\]

The capacity on service route $r$ is given by.
\[
\frac{v_r + n_r \times C}{v_r} \leq C \times (v_r + n_r) = v_r C
\]

(5)

The capacity constraint on service route $r$, for any leg $l \in \mathcal{L}_r$, is designed by GTP and RTP, and given by.
\[
\sum_{k \in \mathcal{K}} \left( x_{krl} + q_{krl} + z_{krl} \right) \leq v_r C.
\]

(6)

3. Weight constraint: the weight constraint on service route $r$, for any leg $l \in \mathcal{L}_r$, is designed by GTP and RTP, and given by.
\[
\sum_{k \in \mathcal{K}} \omega_k \left( x_{krl} + q_{krl} + z_{krl} \right) \leq v_r W.
\]

(7)

4. Demand constraint: for each leg in the transshipment, as indicated by LCP and RTP, the demand of accepted orders is satisfied by the allocated slots. The demand can be estimated by various methods, such as three-point estimation, bottom-up estimation, parametric estimation and analogous estimation. Readers are referred to Goodpasture, 2003 for illustration of different methods in details. In this study, the demand uncertainty is introduced into $d_{km}$ by applying three-point estimation on historical slot order data to produce a distribution with best-case, most likely and worst-case estimates (Haralick et al., 1991; Rosenblueth, 1975), from which integral values are adopted. The three-point estimate is adopted here because of its capability in modelling different demand distributions. The other three are only limited to point estimation. Three-point estimation can not only estimate expected value but also variance and standard deviation, and further apply to various distributions, including normal distribution. For any $k \in \mathcal{K}$, $l \in \mathcal{L}_r$, $r \in \mathcal{R}$,
\[
x_{kl} + b_{kl} \geq \sum_{m \in \mathcal{M}} \left( I_{l_s \leq l} \leq l_t \right) \times d_{km} \times \delta_m
\]

(8)

where $I$ ( ) is the indicator function checking if there exists a leg to transport containers of order $m$ from port $s$ to port $t$. Its value is 1 if so and zero otherwise.
5. Order loading constraints: the following constraints ensure that the demands of an accepted order are loaded and unloaded at the respective ports through the service route operated by LCP.

For any \( m \in \mathcal{M}, r \in \mathcal{R} \),

\[
\delta_{r}^{m} \left( l_{r}^{s} - l_{r}^{t} \right) \leq |\mathcal{L}_{r}| \tag{9}
\]

and

\[
\delta_{r}^{m} \left( l_{r}^{s} - l_{r}^{t} \right) \leq |\mathcal{L}_{r}| \tag{10}
\]

where \( |\mathcal{L}_{r}| \) represents the total possible number of legs of a service route \( r \).

The following constraint ensures that accepted demands are loaded before they are unloaded.

\[
\delta_{r}^{m} \left( l_{r}^{s} - l_{r}^{t} \right) \leq 0
\]

6. Slot availability constraint: the constraints designed by GTP assure that the number of slots purchased cannot exceed the available slots of the alliance partners. For any \( k \in \mathcal{K}, l \in \mathcal{L}_{r}, r \in \mathcal{R} \),

\[
b_{kl}^{i} \leq a_{kl}^{i} \tag{12}
\]

7. Restriction on selling or purchasing slots by GTP: for any \( k \in \mathcal{K}, l \in \mathcal{L}_{r}, r \in \mathcal{R} \),
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standardised procedure. However, the initial set manipulating the constraints and the objective function simplex method usually finds a set of continuous decision variables by nonlinear programming optimisation is modelled. The conventional integral or binary decision variables. Given this, a mixed integer function were the slot allocation quantities of a vessel, which must be listed constraints, and these variables for maximising the objective solutions. The decision variables identified were subject to the above- were developed to compare the performance of their respective optimal methods, namely, the GA- and DNN-based slot allocation algorithms, problem was optimised with the use of the B algorithm. Further three-echelon slot allocation optimisation algorithms 4. Three-echelon slot allocation optimisation algorithms

Having developed the mathematical model, the slot allocation problem was optimised with the use of the B&B algorithm. Further methods, namely, the GA- and DNN-based slot allocation algorithms, were developed to compare the performance of their respective optimal solutions. The decision variables identified were subject to the above- listed constraints, and these variables for maximising the objective function were the slot allocation quantities of a vessel, which must be integral or binary decision variables. Given this, a mixed integer nonlinear programming optimisation is modelled. The conventional simplex method usually finds a set of continuous decision variables by manipulating the constraints and the objective function $f(x)$ with a standardised procedure. However, the initial set $\hat{x}^3$ of solutions $\{X\}$ obtained is not optimal as they ignore integer constraints, thus the B&B method is required to refine it iteratively to a final discrete set of decision variables $L$ for searching the optimal solution $\hat{x}^k$ (Stanzani et al., 2018). The B&B method recursively partitions the space of solutions into smaller bounded regions $S_1, S_2, \ldots, S_r$ and evaluates the solutions. Each revised set of allocation quantities $\hat{x}^{k-1}$ is rounded for the new objective function values until all constraints have been met and the objective function is maximised. The main coding features of the B&B algorithm to maximise an objective function are shown below.

$$q^\text{set} \leq B q^\text{set}, \text{ and (13).}$$

$$b^\text{set} \leq B(1 - \alpha^\text{set}) \quad (14)$$

8. Order-route constraint: each order operated by GTP is carried by at most one route. For any $m \in M$,

$$\sum_{r \in R} \delta_{mr} \leq 1. \quad (15)$$

4. Three-echelon slot allocation optimisation algorithms

Fig. 18. (right). Fitness of Two-service Slot Allocation Model against Vessel Demand and Optimised Vessel Slot Usage of ECC1 in Week 18.

The B&B method potentially consumes long computation times, especially for the large number of variables and constraints in the slot allocation problem. The solution search may become intractably long as the size of the B&B tree grows exponentially, without improving or obtaining the best solution. Given this, a GA-based slot allocation algorithm was developed to facilitate an improved solution search with higher diversity by mimicking genetic crossover and mutation. Potential solutions, comprising the decision variables of slot allocation quantities, were encoded into a real-valued chromosome. The algorithm design and flow of the model are shown in Fig. 4. Fig. 5 shows an example of a chromosome containing the decision variables of a two-service slot allocation solution.

In each run of the optimisation process, the number of generations $GEN$, the number of chromosomes in each population $POP$, the crossover rate $R_c$, and the mutation rate $R_m$ are modifiable parameters prior to the start of each optimisation run. After evaluating a fitness value $\Phi(x^i)$ for every $i$th chromosome in the $k$th generation, the chromosomes are subjected to the operations of selection, crossover, mutation, and elitism until certain pre-set stopping criteria are met, such as a predefined number of generations $GEN$ or an acceptable level of convergence $\varepsilon$ of the solution fitness. While selection ensures chromosomes with higher fitness to be paired up for the exchange of their genetic information,
### Table 4

<table>
<thead>
<tr>
<th>Region</th>
<th>Traffic (TEU)</th>
<th>ECC1</th>
<th>ECC2</th>
<th>ECX1</th>
<th>ECX2</th>
<th>SEAP-EC</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAN</td>
<td>–</td>
<td>126</td>
<td>126</td>
<td>126</td>
<td>126</td>
<td>126</td>
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<tr>
<td>CCN</td>
<td>–</td>
<td>175</td>
<td>176</td>
<td>175</td>
<td>176</td>
<td>179</td>
</tr>
<tr>
<td>FUJ</td>
<td>–</td>
<td>65</td>
<td>64</td>
<td>65</td>
<td>64</td>
<td>63</td>
</tr>
<tr>
<td>HSH</td>
<td>–</td>
<td>370</td>
<td>365</td>
<td>370</td>
<td>365</td>
<td>352</td>
</tr>
<tr>
<td>HKB</td>
<td>–</td>
<td>184</td>
<td>187</td>
<td>187</td>
<td>183</td>
<td>186</td>
</tr>
<tr>
<td>KOR</td>
<td>–</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>MAL</td>
<td>275</td>
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<td>220</td>
<td>220</td>
<td>220</td>
<td>220</td>
</tr>
<tr>
<td>PAK</td>
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<td>20</td>
<td>15</td>
<td>18</td>
<td>14</td>
<td>20</td>
</tr>
<tr>
<td>PHP</td>
<td>14</td>
<td>20</td>
<td>15</td>
<td>18</td>
<td>14</td>
<td>20</td>
</tr>
<tr>
<td>MMK</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>KHR</td>
<td>20</td>
<td>55</td>
<td>36</td>
<td>55</td>
<td>20</td>
<td>55</td>
</tr>
<tr>
<td>THI</td>
<td>322</td>
<td>341</td>
<td>374</td>
<td>341</td>
<td>374</td>
<td>341</td>
</tr>
<tr>
<td>TWN</td>
<td>184</td>
<td>215</td>
<td>213</td>
<td>213</td>
<td>213</td>
<td>213</td>
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<tr>
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<td>3</td>
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<td>4</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

The evaluation results showed that the GA-based slot allocation algorithm outperformed the B&B approach, generating high-quality solutions in a short computation time, but the algorithm was not able to guarantee an optimal solution. Deep neural networks (DNNs), which are machine learning methods that are trained on one data set and tested on another, have been explored as a third algorithmic approach to slot allocation optimisation. The strengths of a DNN lie not only on its abilities to predict and classify data, but also to approximate the objective function in optimisation problems (Villarrubia et al., 2018). A resource optimisation algorithm can be treated as a “black box” and the input/output relation is then learned by using DNN (Beşikçi et al., 2016; Sun et al., 2017). To resolve optimisation problems, a multilayer perceptron is applied to approximate the objective functions. With sufficient training data and well-trained hidden layers to avoid underfitting and overfitting during its learning process, the time required to optimise a specific input data set in real life during the testing phase can also be shortened while ensuring high prediction accuracy, especially in the time-sensitive decision-making processes of slot allocation operations. Here, the input training data \( x \), as represented by standard allocation quantities and container demand prospects in the past weeks (see the 4th and 5th columns in Table 1), were used as the training set for the development of the objective function for the slot allocation process of a DNN. Standard allocation and prospect data of the slot allocation for various container size types in the week to be modelled were then used to test the DNN to predict the revised allocation plan. The notation of parameters used in the DNN model is as follows:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x )</td>
<td>Input training data in DNN</td>
</tr>
<tr>
<td>( y )</td>
<td>Output training data in DNN</td>
</tr>
<tr>
<td>( x^* )</td>
<td>Input test data in DNN</td>
</tr>
<tr>
<td>( y^* )</td>
<td>Output test data in DNN</td>
</tr>
<tr>
<td>( \phi_k )</td>
<td>Weight from ( k )th neuron in ((l-1)^{th}) layer to ( l^{th}) neuron in ( l^{th}) layer</td>
</tr>
<tr>
<td>( \beta_j )</td>
<td>Bias from ( j^{th}) neuron in ( l^{th}) layer</td>
</tr>
<tr>
<td>( M_k )</td>
<td>Maximum number of iterations</td>
</tr>
<tr>
<td>( M_L )</td>
<td>Maximum number of layers</td>
</tr>
<tr>
<td>( e )</td>
<td>Threshold error</td>
</tr>
<tr>
<td>( \eta )</td>
<td>Output of layer ( l ) using forward propagation</td>
</tr>
</tbody>
</table>

The algorithmic flow of the DNN-based slot allocation model is shown in Fig. 6, and the structure of the DNN is shown in Fig. 7. The input layer of the testing phase uses raw data in the current week. The data then propagate through three hidden layers, in which the rectified linear unit (ReLU) function is adopted to process the data between the layers. Finally, the output layer transforms the data into the proposed slot allocation quantities.

The effect of the hidden layer in a DNN is to reduce the computational time needed to process large input data sets while enhancing predictive accuracy and avoiding overfitting. The binary allocation quantities are calculated as follows:

1. Initialise the 1st generation of chromosomes \( x^1 \);
2. For each generation \( k = 1 \) to \( GEN \);
3. Crossover between \( x^k \) and \( x_{parent}^k \) based on \( R_c \);
4. Mutation on all \( x^k \) based on \( R_m \);
5. For each chromosome \( x^k \);
   6. Calculate \( \Phi(x^k) \);
   7. If \( k \geq 2 \) then
      8. Elitism and Selection on \( x^k \) to form \( x^{k+1} \);
      9. If \( \Phi(x^k) - \Phi(x^{k+1}) \leq \epsilon \) persists for a pre-set no. of generations then
         10. Break;
   11. Return \( x^k \) and \( x^*_{min} \).
included to augment the training input data set. The three hidden layers in the proposed DNN represent the yield factor, accuracy factor and historical loading performance factor of slot allocation planning. ReLU functions are used in data processing. In the training phase, the standard allocation quantities and container demand prospects in past weeks serve as a sample input \( x \). The shipment revenues in past weeks serve as a sample output \( y \). The loss function, \( f \), used in this study, which measures the predictive accuracy of DNN, is the Euclidean norm given by the equation:

\[
f(\varphi, \beta, x, y) = \frac{1}{2}||y - f(x)||^2
\]  \hspace{1cm} (16)

To force the procedure to stop, a maximum number of iterations, \( MI \), is predefined. The procedure can also stop if the error \( \varepsilon \) falls below a certain threshold. The outcomes of the training phase are the matrix of linearly related coefficients, \( \varphi \), and the bias vector, \( \beta \). The main coding features of the DNN algorithm are shown below.

1. Initialise \( \varphi \) and \( \beta \) as a random value;
2. for iter = 1 to \( MI \)
3. for each input sample tuple \((x, y)\)
4. Use forward propagation to calculate \( f(x) \), output of each layer;
5. Use backwards loss function \( f \) to calculate output of each layer;
6. for \( l = 1 \) to \( ML \)
7. Update \( \varphi_l \), \( \beta_l \);
8. if \( \Delta \varphi_l \leq \varepsilon \) and \( \Delta \beta_l \leq \varepsilon \), \( \forall l \in MI \) then
9. break;
10. return \( \varphi \) and \( \beta \).

The forward propagation using linear processing and the ReLU incentive function is shown below:

Table 5
Calculated Slot Utilisations (%) in Manual and B&B Solver-optimised Five-service Slot Allocation Models (ECC1, ECC2, ECX1, ECX2 and SEAP-EC) with Cargo Shifting in Week 18.

<table>
<thead>
<tr>
<th>Traffic Control Region</th>
<th>ECC1</th>
<th>ECC2</th>
<th>ECX1</th>
<th>ECX2</th>
<th>SEAP-EC</th>
<th>ECC1, ECC2, ECX1, ECX2, SEAP-EC</th>
</tr>
</thead>
<tbody>
<tr>
<td>-----</td>
<td>------</td>
<td>-------</td>
<td>-------</td>
<td>------</td>
<td>-------</td>
<td>-------</td>
</tr>
<tr>
<td>BAN</td>
<td>–</td>
<td>–</td>
<td>108.0</td>
<td>87.8</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>NCN</td>
<td>–</td>
<td>–</td>
<td>97.7</td>
<td>88.0</td>
<td>104.9</td>
<td>113.7</td>
</tr>
<tr>
<td>CCN</td>
<td>98.5</td>
<td>96.9</td>
<td>95.6</td>
<td>117.6</td>
<td>109.6</td>
<td>87.2</td>
</tr>
<tr>
<td>FUJ</td>
<td>87.6</td>
<td>98.9</td>
<td>–</td>
<td>–</td>
<td>89.7</td>
<td>90.2</td>
</tr>
<tr>
<td>HKG</td>
<td>114.3</td>
<td>92.9</td>
<td>50.0</td>
<td>100.0</td>
<td>10.0</td>
<td>25.0</td>
</tr>
<tr>
<td>JPN</td>
<td>107.1</td>
<td>128.6</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>MAL</td>
<td>–</td>
<td>–</td>
<td>108.8</td>
<td>100.0</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>PAK</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>PHL</td>
<td>107.1</td>
<td>128.6</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>SIN</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>MMK</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>KHR</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>37.5</td>
<td>37.5</td>
</tr>
<tr>
<td>SRI</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>THI</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>116.1</td>
<td>105.6</td>
</tr>
<tr>
<td>TBN</td>
<td>115.8</td>
<td>103.3</td>
<td>–</td>
<td>–</td>
<td>114.0</td>
<td>100.0</td>
</tr>
<tr>
<td>AUS</td>
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<td>–</td>
<td>100.0</td>
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<td>Total</td>
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<td>100.0</td>
<td>100.0</td>
<td>99.7</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Fig. 19. Manual and Revised Yields of Individual and Five Combined Services in Week 18.
After training the corresponding DNN structure, the slot allocation data of the current week, which are needed to evaluate and obtain the proposed slot allocation plan, are input. The DNN output data represent the solution to the allocation problem.

5. Slot allocation simulations and analysis

The developed multi-echelon slot allocation model was applied in one, two, and five of the TPT service routes of an international ship liner under the OA. Sets of container-loading parameters with standard allocation (Std Alloc), revised allocation (Rev Alloc), prospects (PSP) and weight (WDT) in terms of TEU and units in a designated week were the input of the optimisation model. All these parameters refer to the container spaces on vessels. In particular, Std Alloc is the number of slots on a vessel assigned to individual ports by GTP. Upon collecting and consolidating the demands from all local and regional customers, LCP and RTP pass the PSP, which are slot demands, back to GTP for review. Finally, GTP manually revises the submission before issuing the Rev Alloc. The results of an initial numerical experiment of slot allocation on a single service in a particular week are shown in Table 1. The optimised solution will assist traffic planners in deciding the allocation of slots to all cargo loading regions in the Asia-Pacific region with reference to yield, project accuracy and historical performance.

In the slot allocation simulations, the Std Alloc, PSP and Rev Alloc are based on the actual operations data of the ship liner. The PSP is
The two- and five-service simulations in this paper were investigated in a way similar to the single-service experiment. For example, the two vessel service routes with sets of allocation and prospect figures were then optimised using the developed objective function and major constraints, including vessel, capacity, weight, demand, order loading, slot availability and order-route constraints. The allocated vessel spaces in terms of size types, loading ports, trade lanes and service loops were obtained as a slot allocation plan for the two services, namely East Coast China 1 (ECC1) and East Coast Express 1 (ECX1) in the OA. The port rotations of the two services are as follows:


The developed GA-based and DNN-based algorithms were again used to generate the solutions, followed by comparing the results, in the below case scenarios.

### 5.1. Single-service simulation and optimisation

The allocation in week 18 of a service route, ECC1, was first found through the B&B, GA and DNN algorithms with the use of Excel Solver for B&B and MATLAB for all three algorithms, i.e. ‘B&B – Excel Solver’, ‘B&B – MATLAB’, ‘GA – MATLAB’ and ‘DNN – MATLAB’. With the regional prospects provided, the revised allocations were optimised, and the results are compared against manual allocation in Table 2. The manual allocations of Fujian (FUJ), HKG, Japan (JPN), Philippines (PHI) and Taiwan (TWN) were originally 64 TEU, 324 TEU, 16 TEU, 15 TEU and 213 TEU respectively, with the vessel’s overall slot utilisation at 97% as shown in Fig. 8. After optimisation, all revised cases achieved 100% slot utilisation and weight capacities on the vessel.

The slot utilisations of ECC1 from week 14 to week 18 with the use of the five slot allocation methods (manual allocation, B&B – Excel Solver, B&B – MATLAB, GA – MATLAB, and DNN – MATLAB) are shown in Figs. 8–12. Slot utilisation is defined as the quantity of actual cargo loading slots for a cargo loading region as a percentage of its standard allocation. Here, the slot utilisations at the service level of the manual allocation fluctuated between 97% and 106% over week 14–18, showing either cargo loading within or exceeding the standard allocation. A slot utilisation of over 100% means the number of slots for total cargo loading regions with containers of bookings to be loaded on a port exceeds its overall standard allocation. This could be further considered to rearrange cargo to load at other ports in which the same vessel is going to berth at these ports, or shift to other service routes with the same loading and discharging ports. In the case of slot exchange, spare slot spaces owned by partners in a ship alliance on the same vessel are used to carry the extra containers. Slot resources on vessels are reshuffled for maximising the utilisation of a vessel when transporting containers to different ports. After optimising the 5-week simulation, the utilisation stabilised at 100%, maximising loading but also preventing overload to ensure voyage safety. This was achieved by re-allocating slots among ports. For example, improvements stemming from the re-allocation of more slots to FUJ and HKG instead of TWN and PHL in week 18 are shown in the revised cases of Table 2. Fig. 11 shows that the utilisations of FUJ and HKG in the manual slot planning were increased by 10% and 7% through the use of GA. Regardless of the optimisation algorithm, all four of the proposed approaches obtained better allocation plans than manual slot planning. By revealing the potential diversity of optimised allocation plans to achieve more efficient slot utilisation of the service, the results demonstrate that optimisation is a crucial and arguably overlooked step in daily operation.
In addition to achieving high slot utilisation, high-yield cargos to be loaded onboard liners departing the Far East is expected in slot allocation planning to maximise the profit in each voyage. An international liner’s slot charges and unit costs specific for call ports of a service were used as a measure of a service’s revenue performance in this study. The yield here refers to the profit on the average price per unit sold (e.g., TEU or FEU) in each vessel slot for loading units of containers on the vessel. Yield here refers to the profit. Due to confidentiality, only the yields were used as a measure of a service’s revenue performance in this study. The yield here refers to the profit on the average price per unit sold (e.g., TEU or FEU) in each vessel slot for loading units of containers on the vessel.

### Optimisation of two-service model with cargo-shifting

To utilise the available slots in vessels sailing to the United States on the service routes of TPT, cargo shifting of laden containers is carried out among service routes with common ports of call during the slot planning operations. For example, suppose the total prospects of ECC1 and ECX1 in week 18 are 711 TEU and 1844 TEU, respectively, as shown in Table 3. Both vessels, with voyages operating in the same week, might have regions that are not making full use of their own allocated spaces. Therefore, cargo shifting between the two services was explored to utilise the possible unused spaces. The manual cargo shifting process increased the accepted amount of cargo to 2356 TEU, made possible by allowing six ports (CCN, FUJ, YCN, PHL, TWN and VND) to accept more than their individual standard allocation by taking spare slots from other ports and another vessel. Efficiency was improved by optimising the same cargo shifting model using GA, with 24 more containers accepted (i.e., a total of 2380 TEU). Five ports (CCN, FUJ, HKG, PHL and TWN) were observed to have accepted more than their individual standard slot allocations, with FUJ exceeding its standard allocation the most, by 28 units, to reach 249 TEU. These extra slots were obtained from other ports. As shown in Table 3, the optimised total number of containers handled was 1214 TEU, exceeding the total standard allocation.
of HKG on both ECC1 and ECX1 by 20 TEU. These additional 20 TEU were catered to with the spare slots from other ports. Therefore, cargo shifting between ECC1 and ECX1, together with re-allocation of standard allocation of ports on the same ship, contributed to the ability to handle more containers. A similar observation was made when ECC1 reached its allocation limit. The fitness of the entire two-service model kept rising due to the availability of slots from ECX1.

5.3. Optimisation of five-service model with cargo-shifting

Liner companies usually operate several different service routes in a trade lane to increase the network connectivity and exploit economies of scale. Cargo shifting among service routes is more flexible when more service routes are available. Table 4 compares the slot usages of the manual approach with those of a best-optimised five-service slot allocation model (optimised by simplex linear programming), in which the five services are ECC1, ECC2, ECX1, ECX2 and South East Asia Pendulum (SEAP-EC). Without cargo shifting and optimisation, ECC1, ECX1 and SEAP-EC were unable to fully utilise their standard allocations, resulting in an excessive demand of 477 TEU (7066–6589) not addressed by the liner company. After cargo shifting and optimisation, the demand discrepancy reduced to 418 TEU (7066–6468). All vessels achieved 100% utilisation as tabulated in Table 5. The yields of all services before and after optimisation are shown in Fig. 19, showing that ECC1 and ECX2 experienced greater gains than the other services regardless of the optimisation technique adopted. In this round of optimisation, MATLAB integer programming obtained the best optimised overall yield of USD170.7 per ton, which represents approximately 0.8% growth relative to USD169.4 per ton of the original manual operation.

Figs. 20 and 21 show the fitness performance of the five-service slot allocation model. These two figures again show smoother fitness landscapes. The use of spare slots from more vessels is again the major reason for the stability in these fitness graphs.

5.4. Optimisation of five-service model with slot exchange

In addition to shifting cargos onto ships of different services of the same liner, exchanging slots among liners on the same ship can also increase the overall vessel utilisation and reduce the cost of the voyage. Under the alliance, liners can share and exchange slots with reference to the BS agreement. Table 6 compares the optimised slot usages after cargo shifting as discussed in Section 5.3 but before slot exchange, with those after slot exchange.

In the following case scenario, ECC1 and ECX1 were assumed to buy slots from an alliance member to fulfil the extra demand of slots at ports YCN and TWN. Table 6 shows the results when the vessels of services ECC2, ECX2 and SEAP-EC were assumed not to have any slot exchange and therefore their slot usages were the same as shown in Table 4. To implement slot exchange, a maximum of 120 spare slots were assumed to be available individually on ECC1 and ECX1 through purchase from an alliance member. In Table 4, the total prospect at port YCN is 997 TEU. After cargo shifting, only 911 containers were loaded onto ECC2, ECX1 and ECX2, leaving 86 TEU unloaded. After slot exchange optimisation, 62 TEU more containers (=144–82) were loaded onto ECX1. It was observed that not all outstanding containers could be carried by ECC1 because there was still a mismatch between the sizes of the extra slots and that of the remaining containers. At YCN, all 25 remaining containers (=221–196) were finally loaded onto ECC1 as shown in Table 6. The slot utilisations of ECC1 at YCN and ECX1 at YCN were therefore improved significantly, from 87.2% to 153.2% and 103.3% to 116.8% respectively, as shown in Table 7. The overall slot utilisations of all five services at these two ports were therefore raised from 102.4% and 98.0% to 109.3% and 110.5%, respectively.

5.5. Performances of optimisation methods

In this study, four optimisation techniques have been used: B&B – Excel Solver, B&B – MATLAB, GA – MATLAB, and DNN – MATLAB. Their performances in terms of slot utilisation and yield have been shown in single-, two- and five-service optimisations. Table 8 tabulates the average optimisation times in second taken for each method. B&B – Excel Solver, B&B – MATLAB and GA – MATLAB provided satisfactory performances in slot utilisation and yield, although GA – MATLAB required a comparatively long running time. Both linear programming techniques are equipped with the B&B method and were thus able to solve the non-linear slot allocation problem under study. Compared with the time required to manually issue a slot allocation plan, based on trade traffic for the traffic control regions in the daily operations of ship liners, these methods have an edge in their slot utilisation and yield optimisation performances but may lag behind DNN – MATLAB in terms of optimisation efficiency. Similar to B&B – Excel Solver, the last technique serves as the most efficient optimisation option. With its ability to approximate the embedded decision logic with a multilayer perceptron, practitioners in the maritime industry may find its implementation more ready given enough historical data are present for DNN training purpose.

6. Conclusion

Optimising slot allocation planning operations is critical to the revenue of an international ship liner company in this highly competitive and dynamic maritime business. Optimal slot allocation plans increase vessel utilisation, reduce operations costs and increase the overall yield of each vessel sailing. The network coverage is continuously growing, and the operational complexity of traffic planning is increasing. These include the variations on projection prospects, slot space allocation and slot exchange in local, regional and global operations. Thus, the critical problem of slot allocation decisions to each traffic control region on multiple trade lanes and services routes require a comprehensive end-to-end optimisation model. In this paper, a novel multi-echelon model was developed for slot allocation planning, accounting for the dynamics among local, regional-hub and global scales in terms of container loading and discharge at various vessels in multiple ports. A two-stage optimisation model was proposed to improve slot usage and overall yield per vessel sailing through cargo shifting amongst multiple trade lanes and service loops of a ship liner. The slot exchange amongst ship liners in an alliance was incorporated in the model. Most of the slot allocation planning literature were not focusing on the corresponding needs of cargo shifting operations in multiple routes. There were also a lack of studies reflecting multi-echelon processes of prospect estimation, allocation planning and slot exchange. This paper contributes a comprehensive and novel optimisation model addressing the operational need for better vessel utilisation and higher yields. In this regard, four optimisation methods for slot allocation were developed based on the B&B search algorithm, GA and DNN through the Solver and MATLAB programming platforms to test their applicability and abilities to outperform the current manual slot planning operation performance of the liner.

Simulations were carried out in various scenarios, including a single service, two services and five services, on the ECC1, ECC2, ECX1, ECX2 and SEAP-EC service routes. The simulations showed promising results with satisfactory performances in slot utilisation and yield, especially in multiple services with cargo shifting and slot exchange. The four optimisation methods demonstrated better vessel utilisation than the current manual planning operations. The DNN-based slot allocation algorithm illustrated the most efficient optimisation running time among the four methods. The sensitivities of the four slot allocation methods were evaluated via their fitness as a function of vessel slot demands and usages. The stability-of-fitness range in each of the scenarios was investigated. The developed model and optimisation
methods assist trade traffic planners of international ship liners to develop more efficient slot management operations. The methods provide them with advanced decision-support systems for maximising slot usage, vessel utilisation and overall yield on vessel sailings, instead of the current slot planning method, which provides feasible but non-optimal slot allocation solutions. The developed tools will also facilitate better decisions and communication among regions along the slot management chain from front-end local offices to regional and global traffic planning operations. The enhanced cargo selection and allotment could prevent vessels from sailing with excessive weight, which can result in vessel damage, excessive fuel usage and the unnecessary emission of greenhouse gases. Further development of these slot allocation planning models could include cooperation between multiple trade routes on the service loops for achieving the maximum utilisation. For example, short-haul shipment utilising long-haul service routes on the service loops for achieving the maximum utilisation.


