Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

ROUTE SELECTION IN MIXED-FLEET WAREHOUSES

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ABSTRACT

Warehouse systems are progressively shifting towards mixed fleet models where automated and manually operated vehicles work together sharing the same floorspace. This is posing communication and co-ordination challenges from both a design and an operational perspective. Mixed fleet co-ordination is particularly challenging from a traffic control viewpoint due to the erratic behavior that human drivers may exhibit. In this work, an optimisation framework that aims at selecting the optimal route among candidate ones in a mixed fleet warehouse environment is developed. More specifically, the foundational deterministic components of the framework are described and an interactive dashboard used for verification purposes is presented. The development work of the stochastic component and the simulator is still ongoing. Initial feedback based on virtual testing conducted by an industrial partner suggests that a static optimisation approach based on historical traffic information may not lead to optimal choices when the human behavior is neglected.

1 INTRODUCTION

Like any industrial sector, intralogistics is experiencing times of transition towards more automated and smarter models. The thrust to adopt newer approaches in warehouse management solutions stems from the current shift in manufacturing market models that indicates that "Lot size one" and very small runs of products are becoming the norm, a trend expected to be accelerated in the following years.

The need for smarter and more dynamic solutions to support warehouse operations becomes even more pressing considering the emergence of "hybrid" warehouse models where manual pickers and automated guided vehicles (AGVs) or autonomous mobile robots (AMRs) co-work in a shared floorspace. Today, the co-ordination of these hybrid fleets within the warehouse relies exclusively on the experience of the shift Supervisor or Warehouse Manager, often utilising commercial Warehouse Management Systems (WMS). The main challenges in these mixed fleet systems concern communication and co-ordination aspects. Communication challenges between vehicles of mixed fleet in a facility-agnostic environment stem from the presence of multi-vendor AGVs and forklifts Fleet Management Systems (FMS) that must interface with the WMS. Although readily available communication channels between the vehicle elements and the WMS exist, bespoke middleware solutions are usually required to make warehouse systems work. Co-ordination issues involve different aspects of order picking operations which range from order batching and sorting, vehicle dispatching and traffic management.

In Fleet.Int, a collaborative research project funded under the European SMART Eureka programme, we are trying to develop a unified pick order management system which can readily connect to various vendor-specific FMS's and WMS's. In this sense, a standardisation effort is being pursued through the extension of data communication protocols, such as the VDA 5050, and the identification of relevant data sources (i.e., FMS or WMS) for data communication requirements. On the co-ordination side, the optimisation objective is focused on traffic management and, specifically, on the selection of optimal routes among candidates ones considering the presence of various types of vehicles and human drivers in the floorspace.

In this work, a route selection optimisation framework for mixed fleet warehouses is proposed and its deterministic components, which have been developed during the first phase of the project, are introduced. The combination of various approaches for the estimation of travel times, which are used as route selection metrics, represents a novel aspect of this research and is justified by the presence of the human factor. Indeed, human drivers may exhibit an erratic behavior (i.e., not follow the recommended route) and/or not strictly adhere to safety rules (i.e., slow down at cross points, no overtaking in blind spots, etc.); they also generally avail of higher speed privileges than AGVs, which combined with the previous elements, may cause more frequent vehicles blocking, hence, delay the overall order picking process. In this first phase of the project manual vehicles have been treated as pseudo-AGVs, hence, deterministic framework components are presented here. In the second phase of the project, which is ongoing, the route selection approaches described in this paper, will be embedded into a stochastic assessment framework to consider the impact of drivers' behavior on AGVs route planning. Moreover, virtual and real testing environments for the framework will be fully developed and extensive experimentation will be conducted to validate the approaches.

The remainder of the paper is organised as follows. Section 2 summarises the relevant literature on route optimisation in warehouse systems; modelling details and assumptions are described in Section 3. Section 4 introduces the solution framework and details two of the modules that are part of it. Section 5 provides an overview of the validation tools that are being used/developed to test the framework and initial insights from preliminary experimentation. Conclusions are drawn in Section 6.

2 LITERATURE REVIEW

The literature in the field of intralogistics is extremely vast and this reflects the high variety of optimisation opportunities and the high degree of complexity in intralogistics management, in general, and order picking systems, in particular. The high dimensionality of the order picking problem and its various levels of complexity are well captured in De Koster et al. (2007) where a distinction between strategic decisions (i.e., warehouse dimensionality, layout design, mechanisation level, information availability, etc.) and the operational level (i.e., order release, storage assignment, zoning, order batching, routing, etc.) is highlighted. Identifying valid optimisation approaches for each dimension poses significant challenges *per se*; nevertheless, it is evident that co-ordination between the different decision levels must be considered to ensure smooth running of picking operations. However, joint optimal solutions are extremely complex to find and beside the evident need to explore research opportunities in this area (Cano et al. 2018; De Koster et al. 2007) there has been only very few studies addressing joint problems (Van Gils et al. 2018; Yang et al. 2020; Cals et al. 2021). A sequential approach to optimisation has been generally used so far.

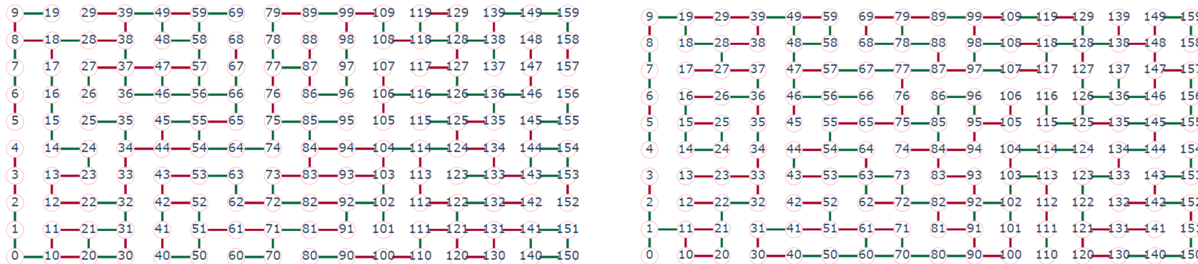
The difficulty in pursuing joint optimisation for strategic and operational decisions is even more evident in Hybrid Order Picking Systems (HOPS) that are defined as systems where autonomous vehicles and human pickers (or human operated forklifts) work together in a shared workspace for a joint target (Winkelhaus et al. 2021). These systems although already used in practice, especially within the e-commerce domain, have not attracted much research attention yet. Design issues in HOPS are investigated using simulation, generally discrete event models supporting the agent-based paradigm (Büth et al. 2017). The fleet composition (i.e. number of humans and robots), the width of aisles, the presence of cross-aisles, assignment rules (i.e. which item class is assigned to human/robot), the turnover rate for each item class (i.e. percentage of items from a class assigned to an order), routing policies (i.e. S-shape, return, largest gap, etc.) and the golden zone impact (i.e. items assigned to middle shelves) are factors that have been investigated in terms of their impact on the warehouse system performance (Coelho et al. 2018; Kauke et al. 2022; Winkelhaus et al. 2022). A critical element that is generally analysed through the use of detailed simulation models is the interaction between vehicles from a traffic perspective which may lead to the frequent occurrence of conflicts or collisions. For instance, human drivers typically have the freedom to choose a route without having visibility into warehouse traffic conditions. The chosen route may interfere with AGVs planned routes or other drivers' routes and cause unpredictable blocking and delays. This is the highest hindering factor to throughput in HOPS and is the focus of this research work. Traffic management is a critical element when it comes to HOPS and although it has been somehow addressed in the literature at a design level, to our best knowledge, it has not received attention at an operational level yet.

The scarcity of relevant literature in HOPS traffic management does not surprise since route planning and traffic control in AGV systems is *per se* very complex. The literature in this field is broad and generally encompasses vehicle dispatching, scheduling and routing (Vivaldini et al. 2015) aspects as they are seen as interlinked elements all contributing towards effective AGV traffic management (Qiu et al. 2002). Scheduling defines the allocation of tasks to vehicles overtime to guarantee conflict-free routes and satisfy time windows constraints. Routing for AGVs in an industrial environment is mainly concerned with finding a route from an AGV current position to the desired destination ensuring a conflict-free travel along the selected path. Distinctions are made between static routing approaches and dynamic ones. In static routing, a route is defined using prior knowledge of the system; generally, collision avoidance is ignored and an additional system is required to manage the path execution and resolve possible deadlocks and traffic jams. In dynamic routing, routing algorithms and path execution evolve simultaneously and collisions are avoided based on dynamic data. Conflict-free route planning generally combines the routing and scheduling aspect while including collision detection mechanisms to foresee the risk of traffic congestions. Strategies used to minimise the risk of conflicts are the selection of the best candidate route among a few alternatives or a delayed start for the AGV task (Zhang et al. 2018; Li et al. 2019); time-window constrained scheduling is often used to solve this problem (Smolic-Rocak et al. 2009; Chen et al. 2013).

Research in the field of traffic condition estimation in urban networks is also very relevant to the work reported in this paper. Intelligent transportation systems generally rely on the quality of different data sources to develop a complete vision of traffic conditions in (near) real time. The sources are either stationary as they are located at roadside fixed locations or Floating Car Data (FCD) from moving vehicles which transmit their locations and speeds (Gitahi et al. 2020). Multi-sensor data fusion has the potential to enhance the estimation of traffic state in real-time by reducing the uncertainty of individual sources, extending the temporal and spatial coverage and increasing the confidence of data inputs (Minh et al. 2019). While a branch of research focuses on how to fuse multi-sensor data (Gitahi et al. 2020), an emerging field of research focuses on how to deal with missing data and the necessity of developing solid methods that can predict traffic conditions even in cases when real-time data are not available. For instance, this situation is common in a crowd-sourcing based system when everyone disables the location services on their phones or when there is no user at the considered road arcs. In these cases, researchers are looking at the use of historical data combined with machine learning techniques to fill the missing data gaps and generate accurate predictions using lightweight approaches (Tan et al. 2021). Recourse to historical traffic conditions to select the best possible route has inspired the static approach developed in this work.

3 SYSTEM DESCRIPTION

Warehouse layouts are typically assumed to be rectangular grids in the intralogistics literature. This assumption is realistic especially in automated or semi-automated warehouse environments where parallel aisles are used to maximise floorspace usage and increase the efficiency of picking operations. A fully connected rectangular grid layout will be used to represent warehouses where mixed fleet of vehicles work together. The dimension of the graph is determined in 2D by the number of nodes in the horizontal and vertical directions; graphs are also characterized by a level of sparseness which defines the portion of missing arcs. For instance, in Figure 1a, the arcs connecting nodes 4 and 5 are removed and the graph presents a level of 40 % sparseness, meaning that 40 % of arcs are missing. Nevertheless, the graphs are assumed to be fully connected which ensures that any node in the graph can be reached by any other node through a series of arcs, called paths (or routes). In an orthogonal connected graph, each node can be connected to a single arc (i.e., mimicking an end of lane, such as node 4 in Figure 1a) or up to 4 orthogonal



(a) AGVs map. (b) Forklifts map.

Figure 1: Example of warehouse layout with alternate traffic (red) and dual traffic (green) arcs for different vehicle classes.

arcs (i.e., a cross point such as node 37 in Figure 1a). We assume that all existing arcs are bi-directional and can either be crossed by one vehicle at a time in either directions (i.e., alternate way) or have capacity for two vehicles to travel in opposite directions (i.e., dual way with capacity of one vehicle along a direction). In Figure 1, a colored scale is used to represent traffic constraints in terms of alternate way arcs (red) and dual arcs (green) for two vehicle classes. It is worth noting that the bi-directional assumption can easily be removed for dual traffic arcs since these are modelled as parallel uni-directional arcs. Overtaking is not allowed while a vehicle is engaged in a task but can happen if the vehicle to overtake is in parked position at a pick location (node). These assumptions have been suggested by the industry partners sponsoring this research as they reflect what implemented at their customers sites. Each arc is also characterized by additional properties: length (which may not be reflected in the graphical representation) and max speed allowed (which is also considered the standard travel speed for travel time calculations).

In order to model zoning restrictions for different vehicle classes, different maps are used for each class. To exemplify this, we can assume that the map in Figure 1a models arcs that are accessible to all AGVs that operate in the system. Using the same grid frame, alternative maps can be built in terms of alternative arcs and different speed limits/privileges. For instance, Figure 1b can refer to routes applicable to forklifts that operate in the system. It is worth noting that the two maps can share some arcs as they also share all nodes; we assume that shared arcs are characterized by same directional properties (i.e. alternate vs dual way). For each vehicle class, a different number of vehicles can operate in the system.

Using the layout assumptions detailed above, the objective of this work is to identify the optimal route for a pick task considering the vehicle class to which the task is assigned. The optimality of a route generally refers to it being associated with a minimal likelihood of traffic accidents which may happen during the journey. These events ultimately cause delays and significantly impact the travel time. Typical KPI's considered to reflect traffic related delays are the following:

- Order execution time – pick time: considering that retrieval and picking tasks generally require the same amount of time, the minimisation of order pick times generally reduces to the minimisation of travel times (De Koster et al. 2007). Estimation of travel times, including potential delays caused by traffic, will be used to drive routing optimisation.
- Delay time: this measures the delay observed when traffic events that slow down a vehicle happen. These events include, collisions, deadlocks, vehicles slowing down due potential conflicts ahead, etc. Delay times can be derived from accurate travel time estimates by comparing these with standard travel times (calculated using the maximum speed allowed).
- Energy consumption: main contributors to energy consumption in order picking operations are the type of vehicle used and the travel time (Djenadi and Mendil 2022). Considering that vehicle dispatching is not addressed here, energy consumption minimisation can principally be achieved through the minimisation of travel times.

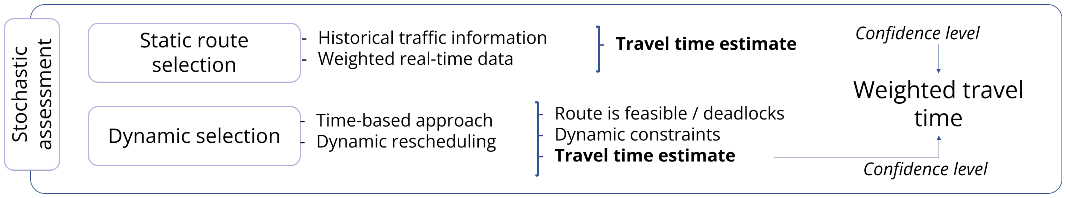


Figure 2: Solution framework for route selection.

It is evident that the selected metrics, which must all be minimised, are interlinked with each other and can be somehow derived from travel time predictions. For this reason, route selection will be based on the expected travel time between the start and destination point of a pick task.

This research work is mainly concerned with warehouse systems where heavy loads (i.e. pallets, reels, silos, pans loaded with lengths of bar stock or pipe, sheet metal bales, etc.) are handled. For safety and design reasons, all vehicles are constrained to follow predefined tracks and free routing is not allowed, hence available solutions for smart routing with dynamic constraints are not immediately applicable.

As the vehicle dispatching problem is out of scope, we assume that whenever the route optimiser is invoked to identify the optimal route between a start and destination node, a vehicle is available at the start node and is ready to execute the task. This is realistic as the action to reach the start node of an assigned pick task can be considered an additional task to be prioritised for the vehicle in question. Dwelling times are considered, if required, on the start and end node of a route to allow performing picking of items and loading/unloading operations.

4 SOLUTION FRAMEWORK

In order to address the route optimisation problem described above and deal with the complexity of having multiple vehicles and the presence of the human factor in the workspace, a combination of approaches has been considered and a solution framework has been developed. The underlying idea in this framework is to increase the accuracy of travel time predictions along a route while taking into consideration the stochastic behavior that may be associated with human drivers. Here, we are not concerned with the generation of candidate routes, which could be obtained off-line using one of the shortest path algorithms (i.e., Dijkstra, A start, Floyd-Warshal, etc.) and are assumed to be provided by the FMS.

The framework schematised in Figure 2 combines a static approach to route planning where travel time estimates are exclusively based on historical traffic information with a conflict-free route planning approach (which will be referred to as dynamic hereinafter). Both approaches are embedded into a stochastic assessment framework that will use AI-based prediction models for drivers' behavior to assess route optimality under stochastic conditions. The stochastic module hasn't been developed yet. The static and dynamic modules, which are deterministic, are introduced in the remainder of this section.

4.1 Static Optimisation

The static optimisation module aims at evaluating alternative routes for a task based on historical traffic information. The available traffic data is such that travel times along each single arc can be derived. Traffic data is continuously collected by the unified FMS and made available through the FMS logs; each entry in the log reports the vehicle ID, its position (typically a node), the vehicle status (the task ID is reported if a vehicle is engaged in a task) and the timestamp. Travel times along arcs are computed by subtracting timestamps of consecutive entries relative to a vehicle, provided that the vehicle is engaged in a task and is located on a node (in case of consecutive multiple entries with the same node, the last entry is considered - this corresponds with the time at which the vehicle leaves the node). When such entries are identified, the two corresponding nodes define the arc to which the travel time observation is associated; the traffic volume crossing that arc is also incremented. Delay times caused by traffic events are implicitly captured in the travel times as the time when the vehicle exits an arc, including possible dwelling time on its end node, is considered. It is worth noting that while tracking of vehicles is typically possible for AGVs, manual vehicles must be sensorised so their location in the warehouse can be tracked; this is part of the data communication challenge addressed in this project. The historical data set which is used by the static approach for routing decisions can be periodically refreshed (i.e., daily or weekly) to enhance the traffic information quality. In this regard, a weighting approach to data refreshes can be considered so that emphasis is given to more recent traffic data.

Using historical travel time data along the arcs, additional properties are derived for each arc and stored in so called heatmaps. Heatmaps are separately defined for each vehicle class and, within each vehicle class, for different timeframes so that different traffic scenarios during a work day can be considered, depending on what observed in reality. For instance, if different traffic conditions are typically observed in the morning and the evening shift, traffic data should be grouped into two separate timeframes (i.e., morning and evening). In order to create a heatmap, "deep copies" of the warehouse graph defined for a vehicle class are created for each timeframe. The following properties are then added to each arc:

- Delay – the arithmetic average of delay factors. These are defined as the observed travel time along an arc divided by the standard travel time along that arc (calculated using the maximum allowed speed for the vehicle crossing).
- Absolute traffic volume – the number of vehicles that have crossed an arc over time – this is equivalent to the number of paths that include that arc.
- Relative traffic volume – this standardises the absolute traffic volume by dividing it by the maximum absolute volume observed across all arcs.
- Own traffic volume – the percentage of traffic volume pertaining to the considered vehicle class. For instance, if heatmaps are being built for AGVs, this arc property will specify the percentage of AGV traffic over an arc. The idea behind this metric is that arcs where the percentage of own traffic volume is higher should be preferred as traffic control can be less challenging.

In this work, a statistical approach is followed to generate heatmaps as averages and sums are used to define arc properties based on historical data. An alternative approach could be considered when historical traffic data volume is big. In this case, classification algorithms could be trained on historical data to automatically identify the level of "delay" (or any other property) expected along a arc for a certain pick task. The tasks attributes (i.e., vehicle, start time, etc.) could be used as classifying factors (see Tan et al. 2021). For continuous scale prediction of properties, alternative machine learning algorithms, such as graph neural networks or regression models, could be considered.

Based on the heatmap properties, metrics for the route selection can be derived as follows:

- Travel time – this is calculated based on the speed limit imposed on the arcs crossed in a route. No consideration on traffic is made. Length and speed limits are the only influencing factors.
- Expected travel time – the standard travel time along each arc crossed is multiplied by the delay factors stored in the relevant heatmap. These times are summed up to give the expected travel time for the route.
- Delay factor – the arithmetic average of delay factors along all arcs crossed.
- Average relative traffic – the arithmetic average of the relative traffic volumes along the arcs crossed by a route. A weighted version could be used instead, where weights are given by the arcs length.
- Average own traffic – the arithmetic average of the own traffic volume along all arcs crossed.

The selection logic is based on identifying the route that ranks best on average for the chosen metrics. Expected travel time, average relative traffic and average own traffic are used as selection metrics. The ranking position for the different metrics is weighted and the route with the best (lowest) combined ranking score is chosen as the optimal static route. Ties are broken in favour of the route with the lowest expected travel time. The static selection approach is exemplified in Section 5.1. It is obvious that the choice of metrics, weights and ranking logic (i.e., considering the relative values for the metrics rather than just the ranking position) are susceptible to optimisation and may depend on the specific warehouse settings. Simulation-based experiments could be run to investigate the sensitivity of the approach to these factors in a more systematic fashion.

4.2 Dynamic Optimisation

In the dynamic approach, considerations on current traffic conditions are made to select the optimal route among alternative ones. A time-based approach inspired by the algorithms used by Smolic-Rocak et al. (2009) to address the shortest path problem with time windows (SPPTW) is developed. Their scheduling approach is adapted to the layout assumptions considered in this work so that either alternate traffic or dual traffic is allowed along arcs. For arcs with alternate traffic, the time-based reservation is expanded to include routes that cross those arcs in both directions; in other words, arcs with alternate traffic are treated as undirected arcs and are scheduled accordingly.

Reserved time windows on consecutive arcs along a route must be contiguous (i.e., vehicles are not allowed residing on nodes while engaged in a task) and overlaps between time windows are not allowed on the same arc (meaning that no more than one vehicle can reserve an arc). A safety time can be added between two arcs of a route to allow a vehicle crossing a node without risk of collisions (i.e., ensure the vehicle has freed the node before this can be reserved by another vehicle).

Time vectors are initialised for each arc (an alternate traffic arc is treated as one arc) so that the start time and end time for which that arc is occupied by a vehicle performing a task is recorded and then used to represent the arc availability. For each task to be performed (and each candidate route), the availability of the arcs forming a route is checked using a recursive approach. Firstly, travel time estimates are calculated on each arc belonging to the candidate route based on the maximum admissible speed for the vehicle assigned to the task. Starting from the task start time and based on the minimal travel times calculated, the time window required for the first arc is defined and the arc availability is checked. If the arc is available at the required start time, the entry time to the downstream arc is determined and the forward logic continues to check the downstream arc availability. If all arcs belonging to the candidate route are available in a contiguous ways, the travel time estimate is readily derived as the arrival time on the target node of the last arc crossed. Alternatively, when an arc is not available at the required start time, the first available time slot on that arc with length greater than or equal to the required time window is identified and the backward logic is triggered: the algorithm recursively returns to the upstream arc to verify whether a time elongation is possible (i.e., reserving the upstream arc up until the downstream arc becomes available) or else the search logic is reiterated on the upstream arc to find the first available slot that allows the vehicle to move to the downstream arc at a time that is greater than or equal to the time at which the downstream arc becomes available. Following this backward logic, it may happen that the algorithm returns to the very first arc in the route, which means the start time of the task is delayed.

Since alternate traffic arcs are considered, the scheduling approach does not necessarily generate deadlock-free solutions, as it happens in Smolic-Rocak et al. (2009). Hence, once a feasible schedule is determined, a deadlock detection logic is applied to ensure that the route is conflict-free. The first step in the deadlock detection logic consists of selecting all previously scheduled tasks that may generate conflicts or deadlocks with the current task/route. These previous tasks are considered of higher priority (i.e. the task priority is considered static and solely based on the task start time) and their route/schedule cannot be changed. The filtered tasks must be active during the time when the current task will be scheduled (i.e., there is a time overlap between the scheduled start time and end time of the tasks and the current task) and share some arcs with the route currently considered. The second step in the deadlock detection logic focuses on searching for closed loops of arcs involving two or more tasks (i.e., vehicles). For each arc i in the route under investigation, the loop search algorithm is triggered. The search logic is based on a recursive function which uses potential loops (progressively built during the recursive approach), the routes/tasks that form them, and the remaining routes/tasks as input arguments. Initially, the potential loop consists of the ith arc of the current route (i.e., (s_i;t_i), with s_i and t_i being the start and end node of arc i), the list of looping routes contains just the current route, and the remaining routes report all filtered tasks. At each iteration, the list of remaining routes is scrolled: if t_i is included in a remaining route k so that (t_i;t_k) is an arc in that route, a copy of the potential loop is created and t_k is appended to it; route k is removed from the list of remaining routes and appended to the list of routes that are forming the loop. Multiple new potential loops can be generated from the original one for the following iteration; however, if t_i is not contained in any of the remaining routes, the original loop is erased and will not be considered in the following iterations. The search recursively continues using the updated potential loops and the corresponding remaining routes until all loops are closed (i.e., deadlocks are found) or no loop remains (i.e., no deadlock is found). The final step in the deadlock logic is applied when deadlocks are found. In this case, the objective is to delay the current task and find a start time for the current route so that the deadlock can be avoided. This is done by retrieving the scheduled time at which the conflicting tasks exit the nodes involved in the deadlock, the maximum exit time across all conflicting tasks is used as the new start time for the current task. This approach is quite conservative since delaying the current task until all the deadlock nodes are freed may not be necessary but guarantees deadlock avoidance. The scheduling logic is then iteratively applied considering the new start time for the current task until a deadlock-free schedule is generated for the route analysed. As a result, no route will be considered infeasible; however, routes that are likely to be involved in conflicts will be naturally penalised as their expected arrival time will increase since their start time is delayed.

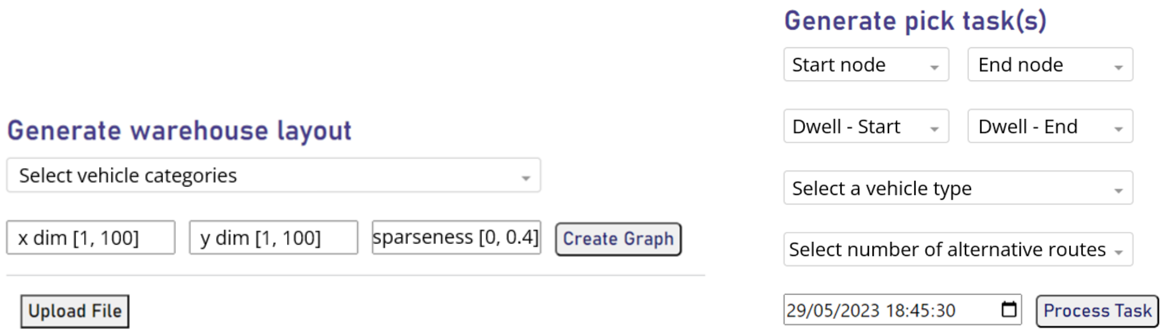
Once the expected travel time is calculated for all candidate routes, routes are ranked based on the arrival time. The ranking position is then weighted with the ranking position of the static approach and, based on the combined score, the final selection is made. After the selection is made, the arcs availability (i.e., time vectors) is updated to reflect the route choice.

5 VALIDATION

5.1 Interactive Dashboard

In order to exemplify the route selection logic and verify the approach under various scenarios, a dashboard has been developed using Dash.Plotly, which is a Python library designed to develop apps rendered in a web browser. The dashboard app is organised in sections allowing both the system definition part (warehouse layout, traffic data generation, heatmaps) and the simulation of pick tasks as it would happen in real settings. Indeed, the dashboard could be used by warehouse managers and supervisors to create a human-in-the-loop approach to the route selection mechanism to verify and edit the selected route and eventually capture the experts' feedback. There are three main tabs in the app: Input (where the system is set up and pick tasks can be created); Output (where the route selection results are displayed); Schedule (where the arc schedule can be explored). In the Input tab, a side bar enables the navigation through the different steps that lead to the creation of pick tasks. The completion of a step is functional to enable the following step – for instance, the traffic maps page is disabled until the warehouse layout is defined, likewise pick tasks cannot be created if no heatmap is available. Maps and heatmaps can be imported or randomly created by inputting design parameters (i.e., graph size and sparseness, vehicle classes, timeframes, etc.) (Figure 3a). The last page of the Input tab allows the creation of pick tasks (Figure 3b) by inputting the start and end node with the corresponding required dwelling time; the vehicle class; the number of alternative routes to consider; and the task start time. Once the "Process task" button is pressed, the requested number of candidate routes is generated using a modified Dijkstra algorithm solely based on route length; the optimisation logic is applied to select the "best" route available.

The output results can be visualized in the Output tab where a side bar allows navigation through tasks (Figure 4). In the main section of the page a message reveals the suggested route to follow for the selected task. A table reports the metrics supporting the selection process: route length; travel time; expected travel



(a) Layout creation page. (b) Pick task creation page.

Figure 3: Interactive dashboard - Input tab.

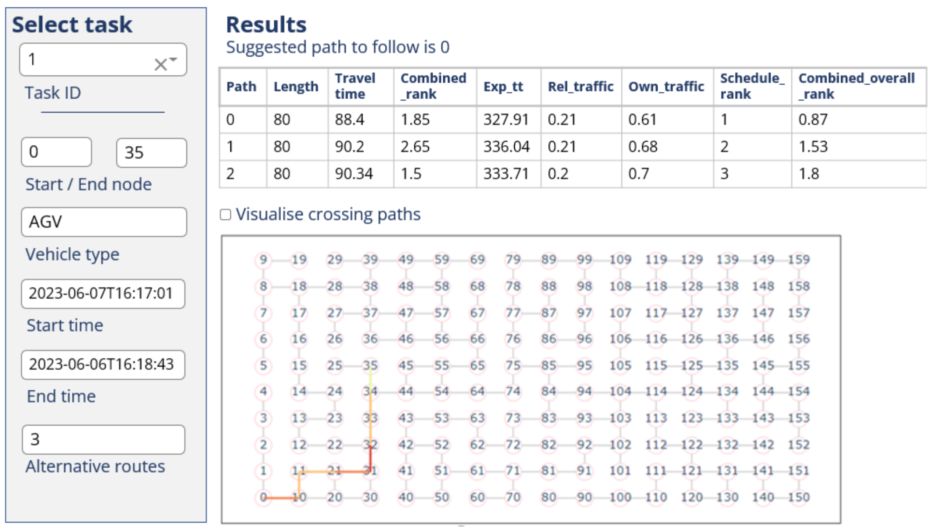


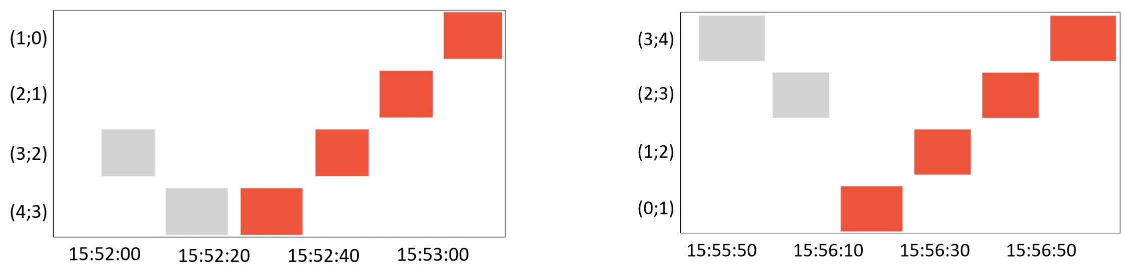
Figure 4: Output tab.

time, average relative traffic volume, average own traffic volume, and the combined ranking position, based on which the selection is made. The table also reports the sequence of nodes in each route which can also be visualized by clicking on the corresponding row in the table; a color scale based on the delay factor of the arcs crossed is used for this. In the example reported in Figure 4, it is evident that the three candidate routes are characterized by the same length; however, the travel time and the expected travel time differ, due to different speed limits applied to the arcs crossed and different delay factors. As previously illustrated, expected travel time based on delay factors, relative traffic and own traffic are considered to generate the combined ranking score for the static approach. Table 1 exemplifies how this score is generated. The weights assigned to the three factors are reported in brackets in the table header. Expected travel time and relative traffic are ranked in ascending order – the minimum metric value gets ranking equal to 1 - whereas the own traffic volume is ranked in descending order. The ranking value for a group of routes with the same metric value is calculated as the mean of the ranks for the group. In Table 1, Route 2 obtains the lowest combined score and is therefore the optimal route from a static viewpoint.

To exemplify the scheduler behavior in terms of how conflicts/deadlocks are prevented, two sets of two pick tasks are simulated in the dashboard using the AGV vehicle class, no dwelling times on start and end nodes, and similar start time (within 2 seconds from each other). The start/end nodes are 0 to 4 and 4

Route	Expected travel time ranking (0.5)	Relative traffic ranking (0.3)	Own traffic ranking (0.2)	Combined static ranking
0	1	2.5	3	1.85
1	3	2.5	2	2.65
2	2	1	1	1.5

Table 1: Example of combined ranking calculation for the static approach.



(a) Second task starting at alternate arcs.

(b) Second task starting at dual arcs.

Figure 5: Example of schedule for alternate traffic arcs.

to 0 (see Figure 1) and vice versa (4 to 0, first, 0 to 4 then). For these tasks only one route is available crossing nodes 1, 2 and 3; moreover, arcs (2;3) and (3;4) are characterized by alternate traffic constraints. For the first set of tasks, the second task (represented in orange in Figure 5a) starts from an alternate arc (i.e., (4;3)) and, for this reason, its start time is delayed until the first task is completed being (3;4) the destination arc of the first task. In the second set of tasks, the second task (from 0 to 4, in orange in Figure 5b) starts from a dual traffic arc; in this case, although an immediate start would be possible (i.e., (0;1) is free), the task is delayed to avoid possible conflicts on the alternate traffic arcs (i.e., (2;3) and (3;4)) and it is scheduled to start after the last alternate traffic arc overlapping with the first task (arc (2;3)) is freed as imposed by the deadlock avoidance logic. In Figure 5, the two tasks are concurrently represented only on arcs with alternate traffic as these arcs are treated as undirected.

5.2 Simulation

The dashboard described above has considerably helped the verification process for the route selection logic in terms of making sure the approach suggested could generate practical results and the code captured correctly the logical steps described. In order to validate the results and investigate the efficacy of the route selection logic to generate beneficial impact on the KPIs identified, the route selection logic will be embedded into a real testing environment. Prior to this, virtual testing is deemed essential and, for this reason, valid simulators are being developed. A partner company participating in this work has offered the possibility of using their proprietary simulation software and initial validation experiments have been conducted. The simulator used is very accurate and realistic as all control mechanisms of AGVs are faithfully replicated including the control logic relative to the interaction among vehicles. However, simulation of manual forklifts and their stochastic behavior is not allowed. The experiments run focused on the static selection approach and were mainly concerned with investigating whether a route selection based on historical traffic information would be sufficient to reduce delay times. Three scenarios were considered using the same warehouse layout, the same historical data and the same set of tasks. The difference between the scenarios consists of the number of vehicles available: one; three; and five vehicles, respectively. Historical traffic data for all scenarios were generated by simulating the assignment of a significant number of tasks (> 1,000) to three vehicles. Ten repetitions for each scenario were run using a different set of tasks; the tasks were assigned to given vehicles so that the effect of vehicle dispatching could be ignored. For each repetition, the simulator was run twice using its standard route selection logic, based on the shortest route available, and the static optimisation logic; the difference between the completion time of tasks was used as a performance metric. The results show that the static approach caused an average 10 % increase in pick times for the scenario with one vehicle, a 7 % increase for the three vehicles scenario and a 5 % increase for the scenario with five vehicles. The main finding of these experiments is that the exclusive use of historical data to make routing decision may force the unnecessary choice of longer routes especially when the number of vehicles is small and the historical data used does not reflect the simulated scenario. Indeed, if historical data was generated using just one vehicle, no traffic delay would be experienced on the arcs and delay factors would all be equal to 1 thus leading to the choice of the shortest route (relative traffic and own traffic metrics have a lower decision weight). The reduction of the delay caused by the static approach when more vehicles operate in the warehouse suggests that using historical information may be more beneficial when traffic is more intense and avoiding typically congested routes may lead to lower congestion risk, especially considering the presence of human drivers. Nevertheless, integration of a dynamic approach is necessary at least in an environment where all vehicle classes are treated as pseudo-AGVs, which is expectable.

To enjoy more flexibility in terms of experimenting with different scenarios and testing various impacting factors on route optimisation, a less detailed simulator is being developed based on a Python framework. This simulator is mainly focused on testing whether actual gains are obtained in terms of reducing traffic events, especially in terms of avoiding conflicts and/or deadlocks when different elements of the route selection frameworks are considered. The simulator records the time spent by each vehicle in its different status and, based on this, delay times can be derived. Once this simulator is finalized and validated, experiments will be carried out to compare task completion times and delay times with and without the route selection optimisation logic proposed under various operating scenarios.

6 CONCLUSIONS

As warehouse systems are shifting towards mixed fleet models, new challenges are introduced from both a design and operational perspective. From a traffic management viewpoint, the presence of the human factor introduces stochasticity in traffic control and increases the risk of traffic events, such as congestion, accidents and deadlocks, that may delay order picking operations. For this reason, new route planning approaches are required. In this work, a route selection framework that aims at embedding stochastic aspects and make optimal route decision based on historical and current traffic conditions is proposed. Static optimisation makes use of historical traffic data to identify routes that are typically congested during a certain timeframe and, based on this, derive delay factors for travel time predictions. Complementary metrics, such as traffic volume and percentage of own traffic, are concurrently used in a multi-objective optimisation approach to select the optimal route from a static viewpoint. The static approach is complemented with a dynamic one that is time-based and allows a more accurate estimation of travel times based on current traffic conditions. A recursive scheduling method has been adapted from Smolic-Rocak et al. (2009) and a deadlock detection and avoidance mechanism has been introduced to deal with alternate traffic; routes are ranked based on increasing expected arrival time. The routes ranking from the static and dynamic approach are then weighted to select the optimal route. Ongoing work is focusing on the stochastic assessment of routes optimality based on the consideration that human drivers may not follow the suggested route.

A dashboard app has been developed to demonstrate the route selection approach and also allow experimentation with various warehouse settings. In parallel, a simulator is being developed to conduct experiments on the effectiveness of the route selection framework proposed in a virtual environment and assess its impact of the route selection optimisation on relevant performance metrics, such as delay times and pick tasks completion times. Preliminary experiments on the validity of the static approach have been run using a proprietary simulator owned by a FMS provider company; the initial feedback suggests that in warehouse environments where human operated vehicles are treated as pseudo-AGVs, route selection based on historical traffic information may cause unnecessary delays. Extensive experimentation is needed to test the framework and approaches validity in a range of deterministic and stochastic scenarios.

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