Stochastic multi agent-based warehouse model

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***Abstract*— Simulation constitutes a crucial part of designing and operating logistics warehouses. An agent-based modeling (ABM) allows to capture various elements of such a system, which may include human workers, material-handling equipment and different kinds of autonomous subsystems. Warehouse operate in a complex supply chain system and must meet its requirements. Customers expect higher responsiveness, which translates into completion times shortening. Robotic systems are deterministic, while human-based picker-to-parts warehouses are not. This paper presents novel agent-based stochastic distribution center (DC) model, which uses distributional gradient boosting machine learning (ML) to introduce pickers' uncertainties associated with human behavior. Obtained modeling approach is validated using full-scale DC environment and real-time warehouse data.**

***Index Terms*— agent-based model; warehouse; stochastic models; picking time, distributional gradient boosting**

I. Introduction

Agent-based models constitute strong modeling concept, which is now firmly underestimated especially in relation to the fashionable and overused neural-based machine learning models. Both approaches, ABMs and MLs, are characterized by their inherent advantages and disadvantages. Each type of modeling has its own range of applications in which it is the most effective. ML models are ideal for modeling unknown processes using blind empirical data sets. ABM models, on the other hand, are ideal for reflecting complex processes consisting of many simple cooperating elements, such as road traffic, evacuation systems, smart cities, and human crowds behavior. Thus, they are ideal for modeling human-operated warehouses [1], [2].

Although current research focuses on robotic and autonomous warehouses or mixed layouts [3], manually operated CDs are more common than automated warehouses: 80% warehouses in Western Europe are manual ones [4]. ABM application to the human operated DC centers is quite common [5], though they have to face various stochastic issues [6]. Uncertainties are associated with of human behavior, which erratic and unrepeatable, stochastic demand properties, varying external supply chain fluctuations, resources seasonality, accidents, natural disasters ot terrorism [7].

This paper addresses the subject of human picking process, which inherently depends on varying human performance. The analysis of real data shows that pickers may differ significantly, with as much as a fourfold difference. Such a large spread of lead times inside the warehouse clearly shows the need to use proper stochastic models, as a deterministic approach can lead to serious inaccuracies. Each worker must be modeled in a different way. We propose to use the eXtreme Gradient Boosting for Location Scale and Shape (XGBoostLSS) [8], which extends Generalized Additive Models for Location Scale and Shape (GAMLSS) [9] by using gradient boosting.

Above formulation of the probabilistic forecasting allows to model the entire conditional distribution of a univariate picking time. It allows to use the same model type for each picker, differing in its parameters, which can be identified using historical picking time data gathered as time logs from the Warehouse Management System (WMS). The XGBoostLSS approach is incorporated into the warehouse ABM proving not only the picking time model effectiveness, but also high performance of entire warehouse model.

The proposed modeling approach is validated using full-size DC and real picking data. Following Section II describe methods and algorithms used during the modeling. Next the application of the XGBoostLSS to the picking time is investigated in Section III, while Section IV presents the final warehouse model. Section V concludes the paper and shows possible research opportunities.

II. Agent based modeling

The developed agent model is implemented using the Python and its libraries. Initially the works stared from the evaluation of existing platforms, like Mesa [10] or NetLogo [11], but due to their constraints it was decided to develop custom own solution.

The ABM consists of three main elements: agents, their interactions and the environment of their operation. The agents are generally human workers in the warehouse. They may perform a set of atomic activities, while each of them may be characterized by different set. It is analogous to the real warehouse, where each worker has certain responsibilities and certified authorizations. Generally, these atomic activities may include the following actions: moving (on foot or using a forklift), picking up and putting away a forklift, picking the good from the rack and placing it on the carrier, lifting and putting down the pallet. perform wrapping, printing and applying labels, performing up-and-down operations, and many others. The list is open and can be extended if needed.

These basic activities are characterized by a specific execution time, which depend on workers experience. This time may be fixed (deterministic), randomly drawn from selected distribution or generated by XGBoostLSS stochastic predictor. Observation of real data proves that each execution

*This work was not supported by any organization

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time varies with time disclosing outlying observations [12] that appear due to system errors or external reasons. Time models are calibrated according to historical data., so the limitation to the deterministic values is an oversimplification. Authors use distributions, like for instance exponential or Poisson [13].

The use of stochastic prediction allows to use the family of distributions and obtain random times according to the specific human operation profile [14].

Moreover, these times does not have to be constant and may vary with time. In such a case we may model workers tiredness or self-learning [15]. It is also possible to allow agents' self-learning using dedicated machine learning approaches.

Additionally, their movement velocity and speeds of forklifts are set according to the historical data and carriers specification.

Their interactions are relatively simple as there are no operations requiring simultaneous cooperation of two workers in the warehouse. Generally, all actions are performed by one person (single agent) and the interactions are on the causal basis, i.e. once one activity is accomplished the new performed by the same or other agent may be started. For instance as one pallet is filled and put in the waiting place it may be picked by another agent, labeled and taken for wrapping. The scheduling of these activities, tasks and process is done according to the general schedule, which in real distribution center is managed by the warehouse management system (WMS).

The warehouse processes are implemented in a three-level hierarchical agent-based model structure, which is presented graphically in Fig. 1.

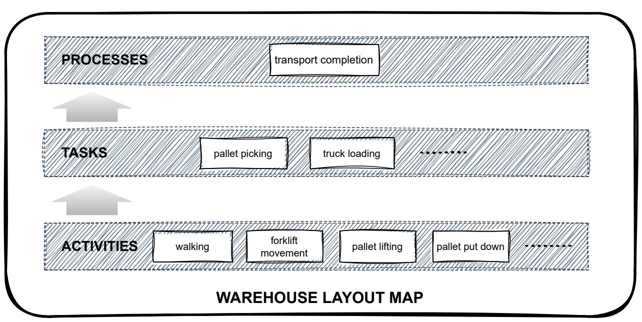


Fig. 1: ABM warehouse model structure

The functionality of each process layer is organized as follows:

– **Atomic activities** are the basic components of the model. They are conducted by a single agent (by a single person in the real warehouse). They are characterized by a specific execution time, which can be deterministic or stochastic. Parameters of these atomic activities can be set separately for each agent. Human operator walking, pallet lifting or pull down are examples of such activities.
– **Tasks** consist of conditional causal relationships between atomic activities. Similarly to them, tasks are performed by a single agent as well. Their realization time depends on times of component activities, so it may be deterministic or stochastic. Pallet picking, truck loading or unloading are perfect examples of tasks.
– **Processes** constitute top level model entity. They represent conditional causal relations between tasks (one or many) or atomic activities. A given process is conducted by one or many agents. Similarly to tasks, process may be deterministic or stochastic depending on the definition of utilized activities. Truck transport completion is an example of the process.

Agents operate (move) in defined geo-spatial environment, which is constructed according to real warehouse layout. Fig. 2 depicts sample layout of a distribution center. In practice, the layout is build using warehouse construction drawings with real dimensions.

III. XGBoostLSS picking model

Stochastic definition of the picking execution times, or any operation times or movement speeds can be deterministic, drawn from a predefined probabilistic density function (PDF) or may be customized using ML model – XGBoostLSS.

The research on modeling of fundamental processes that are responsible for generation of a given observations is a guiding principle in statistics and ML. These processes should be identified in as much detail as possible. Thus, the ultimate regression goal should be to find out the whole conditional distribution $F_Y(y|\mathrm{x})$ of the process behind the data. The estimation should not be limited only to the conditional mean $E(Y|\mathbf{X}=\mathrm{x})$, assuming that they are constant. It should incorporate in modeling as well higher moments of this conditional distribution [16]. Classical regression models that use ℓ_2 norm as a cost function are not enough, not even talking about its zero breakdown point and lack of robustness to even a single outlier [17]. Moreover, the ℓ_2 norm is simply equivalent to Gaussian normal distribution with constant variance.

We need to model the entire conditional distribution. Recently the research on probabilistic time series forecasting started to investigate this area, especially taking into account the context of deep learning. Now, model parameters are estimated (learned) across a set of related time series, instead of modeling each time series individually [18].

XGBoostLSS uses ideas extends concepts of both XGBoost [19] and LightGBM [20]. They are treated as computational backbones and remain largely unchanged. XGBoostLSS enables to model all conditional moments of some PDF or to approximate the conditional cumulative distribution function (CDF) using Normalizing Flow (NF) [21]. The method is entirely likelihood based, i.e. evaluation and sampling are exact and efficient using likelihood functions, which are easily dealt with.

The ABM operation time perspective requires to have a PDF function for a given human operation. Moreover, it's good to have it for each worker separately. The use of quantiles might be enough for modeling and risk analysis. However, the shape of the respective PDF or CDF gives

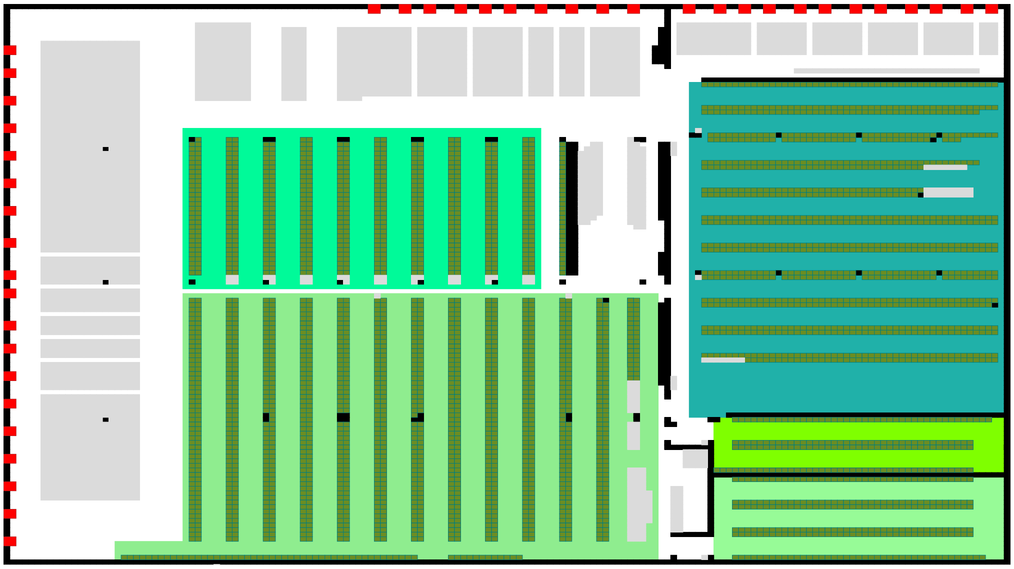


Fig. 2: Simulated warehouse layout: dark green blocks – shelf racks, light green backgrounds – sub-warehouses, gray floor – waiting areas, red rectangles – gates

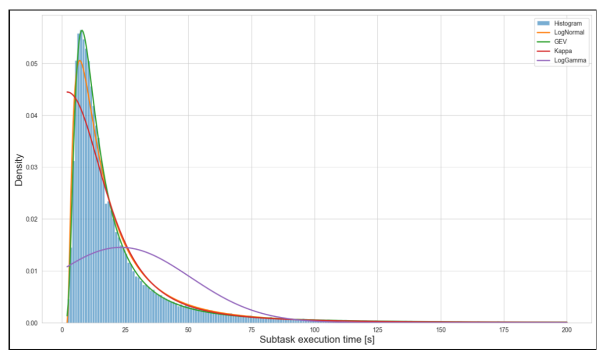
additional insight and understanding of the atomic activities and allows better design. The use of the XGBoostLSS extends classical PDF fitting approach shown in Fig. 3a. We see that it is not clear, which distribution should be selected.

The normal distribution certainly does not give any reasonable results and extreme distributions should be used. In this case, generalized extreme value (GEV) or potentially log-normal seem the best, although other authors suggest an exponential distribution. The family of kappa (four-parameter kappa) PDFs does not guarantee a certain solution either. The use of XGBoostLSS as in Fig. 3b closes the discussion of which distribution to choose by facilitating the modeling process and making it independent of uncertain decisions. In the presented example XGBoostLSS selects between Weibull, log-normal and Gumbel selecting log-normal as the best candidate.

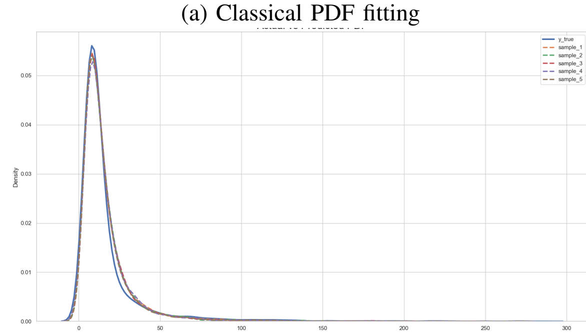
IV. Warehouse model

The study is performed using real retail distribution center located in Europe. Fig. 2 presents the warehouse layout. The storing area, equipped with single-level racks consists of five zone, in which different groups of products are stored. These zones (sub-warehouses) are distinguished with different light green shades. The shelf racks are marked as dark green rectangles. Gray sections represent various waiting zones, like for instance empty or already filled pallets, labeling or wrapping zones, or storage loading zones close to truck gates, which are denoted as red squares.

The distribution center is quite large as it handles several dozen of truck delivering goods to final customers on daily basis. A few hundreds people are employed at the warehouse ensuring its continuous operation on a 24-hour basis. More than half of them participates in the picking process, which is the focus of this study. Pickers operate forklifts that may pick one or two pallets depending on the sub-warehouse. We



(a) Classical PDF fitting



(b) XGBoostLSS based PDF

Fig. 3: Stochastic modeling of the picking time

assume that each truck carries on maximum number of 33 pallets. However, we have to keep in mind that the standard picking process incorporates less number of carriers as some space must be left for other goods that are booked in a different way. The study focuses on main picking process and other auxiliary operations, like the replenishment, wrapping, labeling or quality control are excluded.

There are four types of carriers: wooden pallets and half-pallets, freezer containers and storage boxes. Each of two-pallets forklifts generally carries two pallets, four half-pallets, up to 4 containers and boxes, or any available combination of them.

The goods are grouped into carriers by the WMS system. Furthermore, the carriers are grouped into the batches, i.e. for one forklift with human operator. Picker rides across the warehouse, collects the goods and fills carriers. The plan how to ride through the warehouse, what goods should be picked and in which order is decided by the WMS and passed to the human worker using voice system or mobile panel.

Allocation strategy of goods to individual carriers and carriers to the batches is not in focus of this paper. This work focuses on the representation of real picking process using the agent modeling framework. This ABM simulation study considers preparation of pallets for 30 truck transports. Parameters of each considered transport picking process is described in Table I. Each transports is grouped into certain number of batches and carriers. The number of visited shelves during the picking is also shown in the table. We assume that all shelves have enough products to be picked up and no replenishment is required. Summarizing, 448 picking paths are modeled.

TABLE I: Parameters of simulated truck transports

Id	shelves	batches	pallets	half-pallets	containers	boxes
1	740	14	16	1	4	1
2	923	17	17	4	3	1
3	725	14	13	4	4	1
4	851	21	18	2	7	2
5	682	12	13	2	4	1
6	718	16	21	2	4	1
7	748	15	16	3	5	1
8	775	16	19	2	5	1
9	734	16	18	5	5	1
10	738	15	18	3	5	1
11	721	14	15	3	4	1
12	864	16	21	2	6	1
13	786	14	17	4	6	1
14	769	14	15	3	5	1
15	718	14	16	1	6	1
16	772	18	11	8	5	2
17	894	20	15	4	5	3
18	751	18	13	4	8	3
19	805	16	17	5	4	1
20	735	14	15	3	4	1
21	715	19	13	4	4	2
22	742	17	13	5	6	2
23	822	13	12	4	4	1
24	826	19	14	7	7	2
25	802	22	17	6	6	2
26	904	19	18	6	8	2
27	740	19	14	6	6	2
28	796	18	14	7	6	2
29	715	15	18	3	4	1
30	754	14	18	1	5	1

We also have to be aware that each human picker assigned to the process is characterized by different parameters. New ones perform picking relatively slowly. Despite the fact that all use the same equipment, they drive their forklifts slower, it takes more time for them to find certain shelf and they stack the goods on the carrier with more attention. They make errors more frequently, which may require repetition of some actions. Experienced pickers may perform the same atomic activities even four times faster. The above shows that the modeling of picker-to-parts human-operated warehouse is challenging. Assumption about fixed speeds and operations' times oversimplifies the task providing unrealistic results.

A. *Agent warehouse modeling results*

Presentation of the ABM results is split into two stages: stochastic modeling of the picking time and other human atomic activities, and an overall model of the picking process.

1) Picking time model: The time of human operations is modeled using stochastic XGBoostLSS framework. There are several types of human activities modeled separately in the system, while the separation is not only in an action abut also distinguishes workers. The analysis starts from drawing histograms. Single operation of product picking is presented in more details as an example of the modeling process.

Fig. 4 shows a histogram of picking activity consolidating data for all workers and all picking activities within the scope of the modeling case study. As one can see, the histogram is clearly one-sided with a very long right tail. As this histogram consolidates performance of all workers, it loses the distinction between the effectiveness of individual people. Therefore, two histograms for individual workers, the fast and the slow, are shown in Fig. 5.

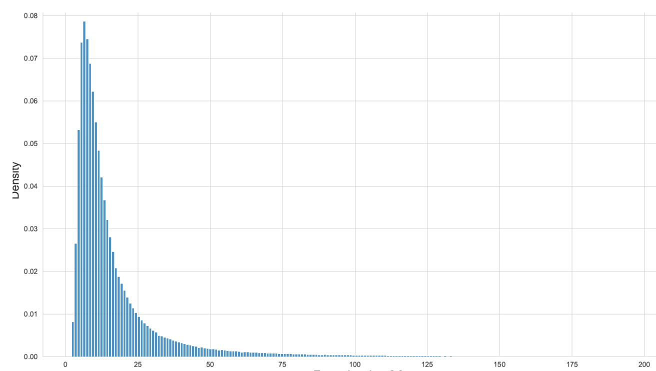


Fig. 4: Integrated histogram for picking time of all available workers

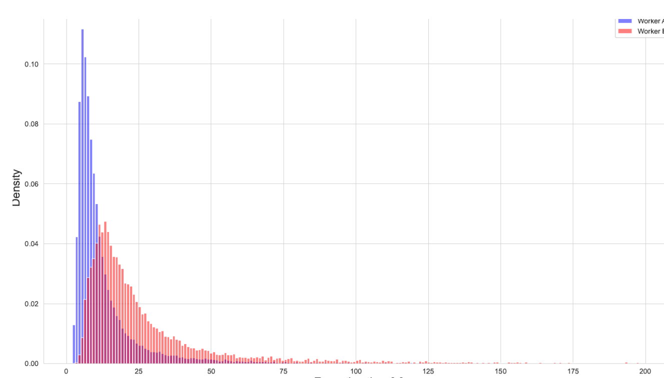


Fig. 5: Detailed histograms for picking time for two workers: (A) the fast and (B) the slow one

We also observe long tails in both histograms, though less significant. There are two reasons explaining these tails. First, the obvious varying effectiveness of human operation due to the fatigue, interaction with other people, problems in picking products from shelves and stacking them on the pallet, distraction and more. The second reason is due to the data collection system which based on "shooting" bar-codes with the reader, which generally can be done in different moments of the picking itself, for instance before or after, and may be forgotten and done after the return.

2) Picking process model: Once the problem of picking operations' times estimation is solved, the entire model is run. Fig. 8 shows traces of selected three picking tasks drawn on the basis of historical WMS data. As the warehouse system does not control exact movement of forklifts/operators their path is only determined by the starting and ending shelves for each atomic picking. The paths and walking distance as such cannot be used to assess model performance.

Therefore, the model is confronted with the reality comparing the picking time between processes. We have remember that the model is stochastic, so single model execution gives random results. The Monte Carlo experiment is used to assess the model. The model is run $N = 99$ times and the median batch picking time $\hat{t}_{\text{op}}$ is used to compare

$$\hat{t}_{\text{op}} = \text{median}\left(\hat{t}_{\text{op},i}\right), \ i = 1, \ldots, N. \tag{1}$$

Next, the time is compared with respective real operation time t_{op} obtained from the warehouse WMS system. The comparison cannot be done on the level of each task, it's conducted on the level of batches. It's due top the fact that the assignment of free pickers is done using simulations, not using real data. We have to be aware that this comparison in not perfect, as our ABM model addresses only base picking operations, discarding auxiliary activities. This auxiliary tasks may affect the picking process as for instance causing heavier traffic in side of the distribution center. Moreover, the assumption about full stack with no need of the replenishment may cause additional differences. The simulation time obtained as a median from $N = 99$ runs of the ABM model $\hat{t}_{\text{sim}}$ is compared with the real time of these picking operations. We calculate median error of all the considered batches.

Table II summarizes obtained results, while Fig. 6 visualizes them. The error are plotted ion the ordered form related to the batch picking time. We clearly observe that short batches are not represented properly, while in case of the longer ones the error starts to stabilize on small values. It is due to the fact that in real case the log data from the WMS system are highly disturbed with the way the picker operates the system. They often take shortcuts in the way they use the system and log operations.

TABLE II: Picking times for real process and mean ABM

	single order	multiple orders
all task	17.1%	19.0%
tasks > 500 sec	5.3	10.5

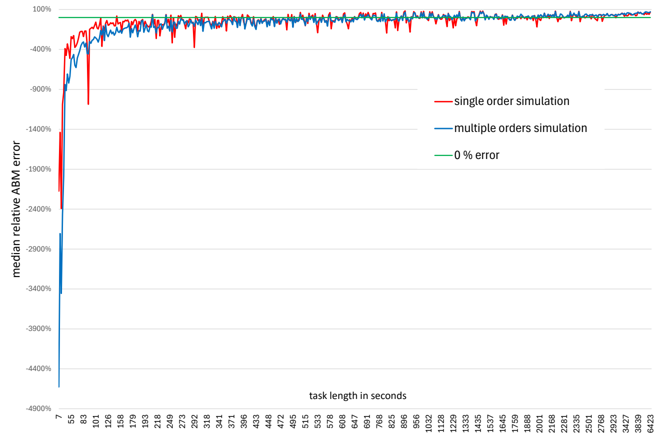


Fig. 6: Ordered median errors of the ABM model

It's well seen in Fig. 7, which shows batches longer than 500 seconds, which actually cover the majority of operations. In such a case we obtain single digit errors, which are acceptable and promising. Adding of all warehousing activities should further improve the modeling accuracy.

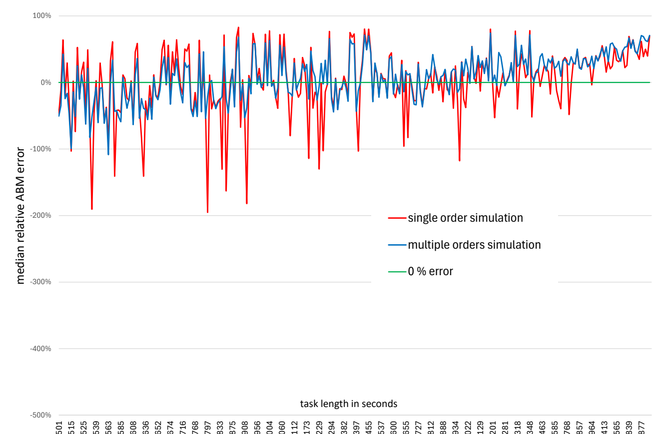


Fig. 7: Ordered median errors of the ABM model for tasks longer then 500 seconds

V. Conclusions and Further Research

This study presents the results of the agent based modeling of the picker-to-parts human operated large distribution center warehouse. The system is modeled on the level of basic picking operations and simulated for the real scale and complex warehouse.

Obtained results are good. They are promising as the simulation considers only basic picking operations. Adding of all auxiliary tasks together with comprehensive model fine calibration should allow to obtain a credible model useful for further optimization studies.

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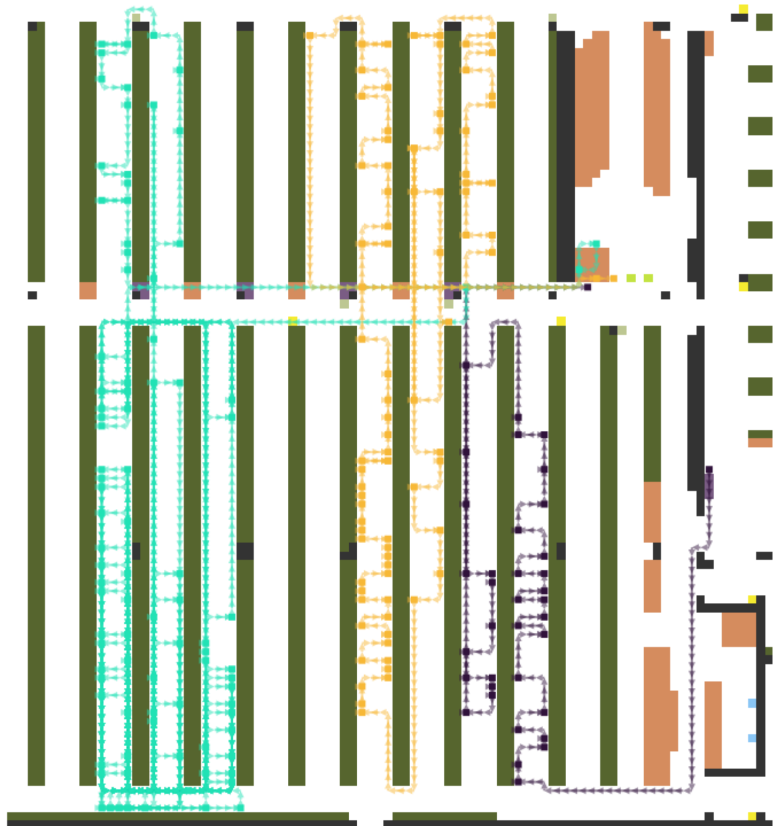

Fig. 8: Routes traces for exemplary three different piking batches across the warehouse

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