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DECISION-MAKING IMPACTS OF ORIGINATING PICKING WAVES PROCESS FOR A DISTRIBUTION CENTER USING DISCRETE-EVENT SIMULATION

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ABSTRACT

Discrete-Event Simulation is a powerful tool in modeling logistic systems, especially picking operations, usually the most costly activity in warehouses. However, is not a common practice to include human decisions in Discrete-Event Simulation projects. This paper reports a Discrete-Event Simulation model designed to evaluate picking waves strategies in a distribution center of the optical industry's leader in Brazil. It was necessary to model 4 scenarios of picking waves generation process to evaluate the best picking wave strategy. In the best scenario, we achieved an average reduction of 10% in total operation time, along with an average reduction of 4% in the total picker's walking distance.

1 INTRODUCTION

The optical industry continues growing over the years despite worldwide and regional economic crises, since it is related to health care, and in the last 50 years the number of nearsighted Brazilian people has doubled to a third of the population. The projections point to reaching half of the Brazilian population by 2050 (Folha de São Paulo 2017). This project was developed in a worldwide group of the optical industry focused on design, manufacturing, and distribution of glasses across more than 150 countries (due to a non-disclosure agreement, transaction volumes cannot be stated). The company's main South American logistics center is located in São Paulo (Brazil), dealing with eyewear (EYE), apparel, footwear, and accessories (AFA) sold through physical stores and e-commerce. Customer orders are collected daily, with particularities specific to each customer or carrier. To assure that all criteria are taken care of, at the very beginning of each operating day, a merging methodology is applied to the orders by the operations room management. Each group of orders with the same criteria, called picking waves, are inputs for the Warehouse Management System (WMS), which creates picking lists. Every picking list is run by a picker that collects a cart and starts picking products using a scanner. After finishing the picking list, the picker heads to one of the delivery points, Audit Process Spot (AUD), or Valued Added Service (VAS) location. Then, a new picking list is taken and the process restarts, as shown in Figure 1.

Currently, the picking wave generation is carried out without any kind of standard, based entirely on the logistics operator employee's experience. In this sense, human behavior takes a crucial place in the picking process, which leads to the company's main concern: how to increase the picking process performance, as a function of the picking wave technique, carried out by individuals.

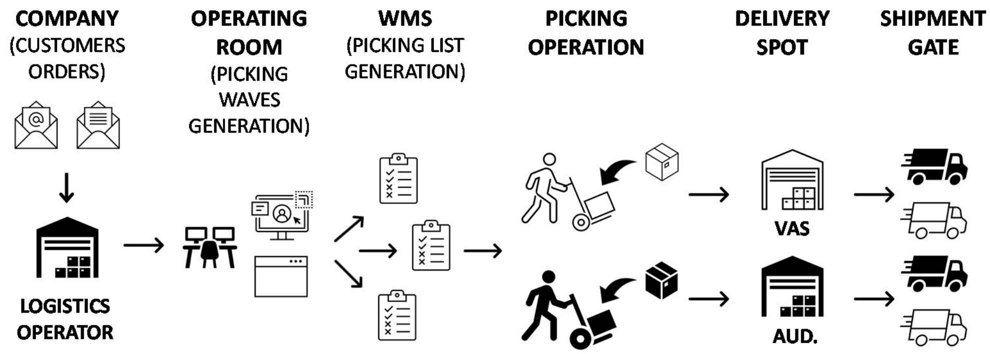

Figure 1: Operating deliveries flow.

A simulation model was built to represent the current operation and different wave creation approaches. As depicted in Figure 2, wave origination scenarios were designed to deliver picking waves as inputs to Warehouse Management System (WMS), to generate picking lists that fed the model, in which suited Key Performance Indicators (KPIs) were used to evaluate every scenario's benefits.

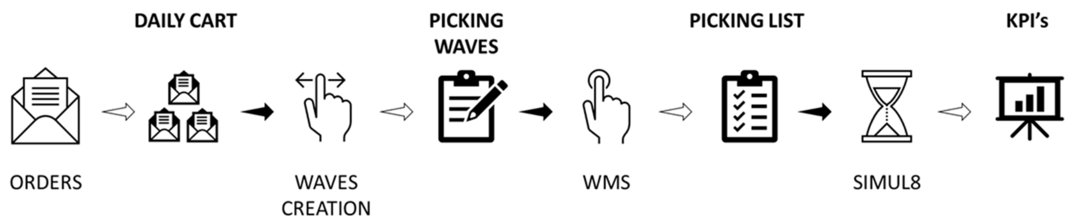

Figure 2: Process inputs and outputs.

The paper's importance originated from an unconventional approach, that human decision and behavior modeling can be engineered in a Discrete-Event Simulation model, increasing productivity in a real-world problem of the optical industry leader in logistics management of the picking process.

This paper is organized as follows. Section 2 describes Discrete-Event Simulation applied to logistics and picking processes and also how human behavior can be addressed in simulation models. Section 3 describes this project's context in a leading optical industry and the steps taken to build the computational model. Section 4 describes the pros, cons, and difficulties of human decision-making modeling. Section 5 summarizes our conclusions and presents areas for future work.

2 LITERATURE REVIEW

2.1 Discrete-Event Simulation Applied to Logistics and Picking

A model is a virtual representation of a real environment and its processes. To achieve better results for productive systems, simulation can be applied to evaluate operational and financial impacts for alternative scenarios, aiming for better costs and performance balance (The Operational Research Society 2021).

Chwif and Medina (2014) state that simulation leads to a better understanding of systems, transforming it even into a communication tool in the business environment. It is best suited in "what-if" situations, as in "what happens if we increase our headcount by one worker in the picking process?", notably in Discrete-Event Simulation (DES).

Discrete-Event Simulation modeling is very suitable to Logistics, defined by the Council of Supply Chain Management Professionals (CSCMP) as “the process of management, implementation and flow control of information, goods and services in a highly effective and efficient level from raw material to finally industrialized towards the customer expectations” (CSCMP 2021). One of those logistics processes is order picking, identified as the most intense and costly logistic activity by De Koster, Le-Duc, and Roodbergen (2006), accounting for 55% of operational costs. So, it is considered as the main priority to obtain performance growth in a logistics operation. It consists of collecting the right product in a warehouse, in the required quantity, reaching the agreed service level and quality (Gontijo 2012).

Santini et al. (2012) evaluated the implementation of a new picking system, estimating possible problems that the new system could face, even before its physical building. The same authors applied discrete-event simulation in an optical products warehouse, with the purpose of resource management, aiming for better picking headcount. As result, increased service level and more comfortable decision-making were obtained, leading to better operational performance.

Urzúa et al. (2018) presented a simulation study to improve the order fulfillment time in a distribution center. The authors considered the current operation scenario and projected scenarios that included three different picking strategies. The proposed strategies allowed great improvements such as a 54% reduction in the order fulfillment time.

Pedrielli et al. (2016) developed a simulation model for a fashion e-commerce industry warehouse with high demand variability and short shelf life. The authors proposed both a new picking list algorithm and new picking strategies, combining zone-based and order-based picking with batching, outperforming the current FIFO order picking strategy.

Unlike most approaches, Garg and Maywald (2021) applied Discrete-Event Simulation to optimize warehouse picking using Autonomous Mobile Robots (AMR) combined with manual pickers. They considered both traditional and cross-aisled warehouse layouts. The results showed that optimum performance was obtained with a 2:1 AMR to picker ratio.

Beyond this use, the mix of Discrete-Event Simulation and Agent-Based Modelling allows developing a computational model even more realistic once it is possible to understand each consequence of a decision making, based on historic operational necessities. Despite all advantages, the study of the impacts of decision-making using discrete event simulation is still an underexplored path (Kandemir et al. 2020). Care must be taken that heavy simulation models could bring detailed results, perhaps operationally useless, so simplicity bias is the key to a viable, functional, and profitable tool.

2.2 Human Behavior Modeling in Simulation

Working processes done by humans are, somehow, affected by their behavior. In complex environments, individual decisions may lead to overall inefficient process performance and rising costs. Structured and planned decisions result in better and organic evolution, avoiding prejudice and damaging consequences.

Agent-based modeling is a computer simulation method focused on socio-economic systems and human interactions with the environment. To Aerts et al. (2018), it usually simulates individual behavior, where personal interests are represented by agents that can switch their behavior due to past experience. To enrich the study of complex systems, agent-based modeling is a technique that is a perfect fit when different people or agents interact with each other. To Zhang et al. (2020), agent-based modeling is used for ongoing interactions of multiple agents, providing a useful tool for researchers to study decision impacts. Agent-Based modeling provides an atmosphere, called by Perello-Maragues and Noriega (2020) as an "artificial society", that allows distinguishing mind frames and a variety of decision-makers.

Although there are few reviews about agent-based decision-making and human behavior, topics like health care, consumption, and manufacturing are some of the most applied subjects according to recent bibliographic review analyzes (Negahban and Smith 2014). That was the case of Kandemir et al. (2020), that applied Agent-Based Modelling for a better understanding of the relationship between food cycle life and human decisions that may result in food loss, waste, and packaging in the home, to estimate the impact of human behavior by the best before date, in different scenarios.

According to Taylor et al. (2015), human behavior modeling, as its predictions and effect on operations performance is recognized as currently the most significant and unanswered modeling challenge. As Greasley and Owen (2018) express, every process can be heavily impacted by human decisions that may be induced by individual preferences and working practices, reflecting a poor application of organizational policies. Modeling people's decisions can be understood as a decision point, which is defined by logic data in a process flow undertaken by an agent. It can be modeled using probability distributions or using conditional ("if-then-else") sentences. In addition, to get a broad sense of the impact of human decisions, the simulation model may have these individual preferences making it possible to evaluate performance impacts of personal decisions.

Regarding warehouse picking operations, Elbert et al. (2015) developed an agent-based simulation model to study blocking in a manual order picking system. Each agent was represented as an individual performing order picking with its own rules (e.g. routing policies), walking in narrow aisles. When blocking occurs, there are priority negotiations between agents. The simulation allowed to achieve the lowest mean throughput times by combinations of all scenarios.

Thus, Agent-Based Modeling is proven to be a suitable tool for human behavior modeling, though there are few applications for picking processes.

2.3 Human Behavior/Decision-Making in Discrete-Event Simulation

In traditional discrete-event simulation models, it is unusual to include people's behavior or human decision (Kandemir et al. 2020). Besides agent-based modeling, discrete event simulation techniques are also utilized to represent more realistic and flexible entity interactions, even though it is much more computationally efficient than agent-based modeling, conquering its space in the simulation scope. An agent-based model would require large computational resources in a simulation of a large-scale system, being preferred in systems with rule-driven response operations, as it can help entities behave in response to environmental changes (Wu et al. 2008).

One of the few attempts to model human behavior was due to Schmid (2005) that proposed the PECS reference model, which considers Physical, Emotional, and Cognitive aspects of human behavior. Brailsford and Schmidt (2003) developed a Discrete-Event Simulation model combining PECS with the Health Belief model to simulate attendance for diabetic retinopathy screening.

In summary, our literature review showed that Discrete-Event Simulation models with human-decision modeling are very few with respect to the majority of discrete event model literature.

3 SIMULATION MODEL

3.1 System Description

The scope of our simulation model will only comprise the business unit called EYE, whose products (eyewear) provide higher revenues. Several hypotheses were taken in agreement with the company's management contribution to decrease the computational modeling efforts, e.g.: the picker would take the shortest path with no speed difference between workers and the picker would pick each product at a central point of the pick face.

The picking operation process flow was designed for understanding support of how to use simulation activities to represent the real operation. Figure 3 depicts this process flow: the picker's shift, from the start, when the trolley collection is made, then each picking interaction, walking and collecting products until the last listed item, and relative displacement up to the deposit spot, which can be VAS or Audit Spot, starting all over again during the working period.

Since a full working day is simulated, for each day, it corresponds to a terminal simulation model, with no need for a warm-up period definition. There are two possibilities of deposit locations due to the possibility of additional treatment for some orders (the default path is straight to the audit process). This additional treatment is named Value Added Service (VAS) and consists, for some customers' orders, of a tagging process with the final selling price.

3.2 Conceptual Model

The proposed conceptual model includes simulation objectives, scope, level of detail, alternative scenarios, model description, modeling hypotheses, input data, logical processes, and output data. Weekly meetings were set with the company's transportation coordinator, who shared suggestions and corrections until the final conceptual model validation.

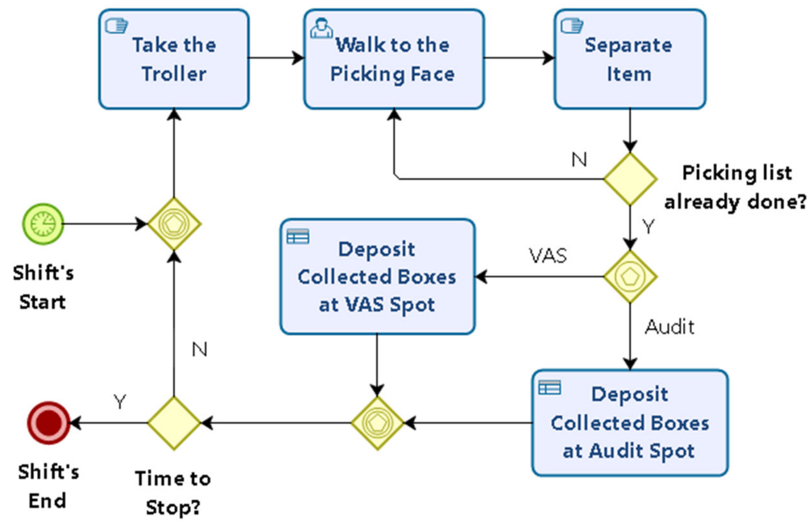

Figure 3: Picking process flow.

Initially, an Excel® codification was developed to transform a list of orders into picking waves, which will be detailed in Section 3.3 to address the human rationale of this process. At first, the database of customer orders to be sent is run by this code, which originates waves with a singular criterion, as unique as possible, just like the current operation used to work. This data is the input for the Warehouse Management System (WMS), which uses its intelligence to output picking lists, aiming for better routes. This picking list is input for another Excel® coded sheet that calculates the minimum distance run by each picker in each displacement. The result of this last process is the input for the simulation model, which converts distances into duration times. In this case, despite the simulation model's capacity to calculate the distances, to increase its performance, the distances were already calculated in an input data spreadsheet. The picking sequence was considered to address the shortest distance between pick faces, in an approximation to the WMS algorithm that generates real operation routing.

For the next stage, simulation model coding in SIMUL8 software, we attempted to use data analytics research to identify the most significant variables on the picking duration, passing through multiple and linear regression studies on variables such as walking distance, the number of collected products, and the quantity of picking faces visited. On the other hand, the usage of speed probability distribution was found as an alternative, as a result of data analytics on the Stat::Fit® software, which delivered a Gamma probability equation as an adequate data model for picker speed. This is further used in the simulation model to convey distances into times.

In our SIMUL8® simulation model, three stages were set to represent operational phases, as shown in Figure 4. The first one, called Picking List, is from the moment the picker takes the trolley to finish the picking list, as it was understood as having a very long time representation between picking faces, face to the time spent collecting boxes, once eyewear boxes are tiny, small and light, which allows the picker to pick many boxes in a single picking move. At this point, the speed probability distribution was set to calculate the time spent on each picking list.

The second stage was split into "VAS Delivery" and "Audit Delivery", pointed on Figure 5 representative warehouse map. This phase represents the walking path between the last picking face and the delivery spot, a distance traveled without stops.

As soon as the picker leaves the products in the delivery spot, it is necessary to go back to the initial point to collect the next trolley and picking list. If the delivery spot was "VAS Return", there is a fixed distance of 12.4 meters, and if the delivery spot was "Audit Return", there is a fixed distance of 34.4 meters, since the audit spot is placed at a fixed location, close to shipping point, as the VAS spot.

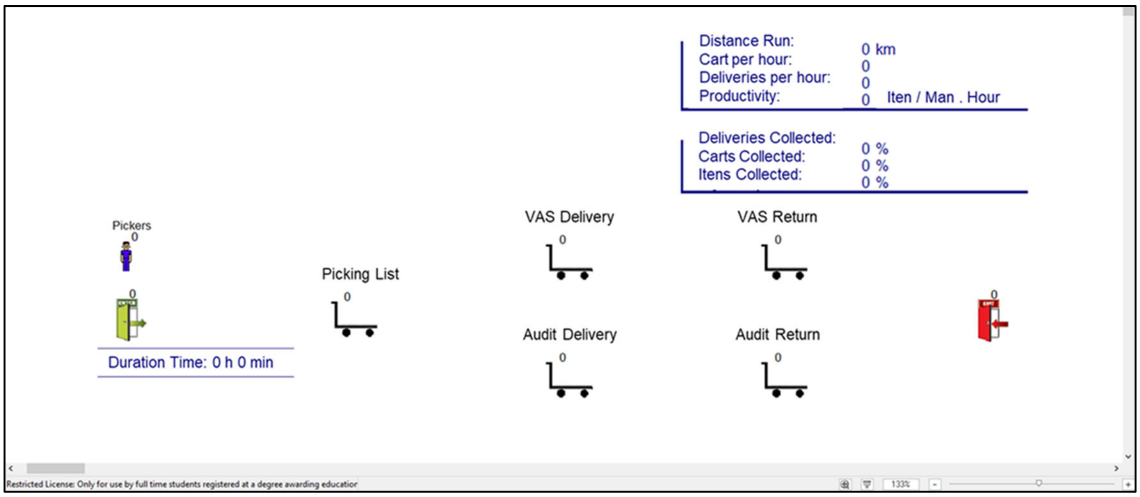

Figure 4: SIMUL8® simulation model.

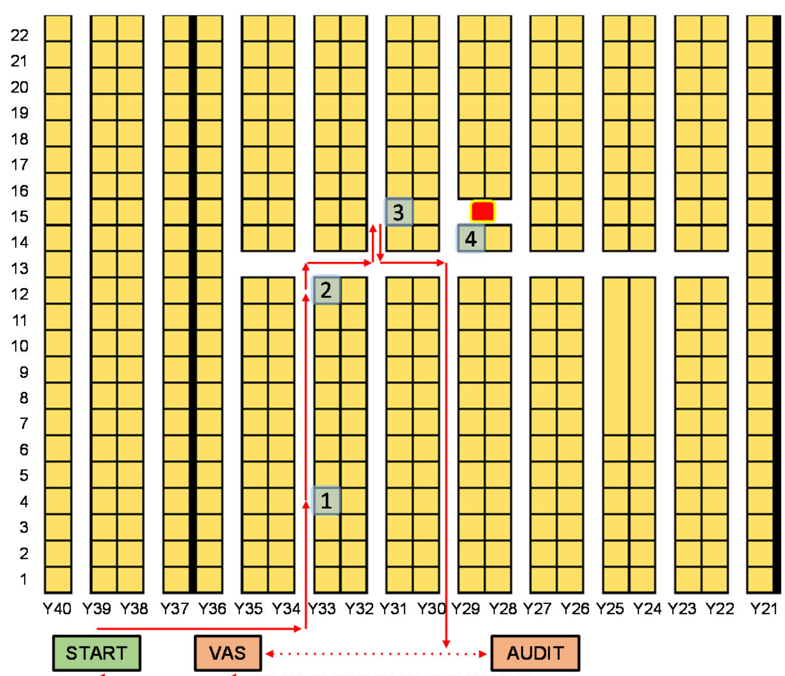

Figure 5: Warehouse map.

A verification process was performed on the simulation model, making sure that every step taken was delivering results as expected. For example, the simulation model was run in slow motion to track each picking list and to ensure it was delivering the products at the correct delivery spot. Once the verification process was completed, the validation process was started, focusing on data output against historical data, in order to validate the model. The key performance indicator used to compare the simulated operation against historical data was the operation completion time, setting hour by hour the headcount used on EYE business unit. The data comparison was made for 16 working days with a picker availability of 70%. As shown in Figure 6, errors (simulation - historical data) fluctuated between -17.7% (-3.30 h, on July, 3) and +35.5% (5.36 h, on July, 18). The average variation was 2 minutes (1.02%).

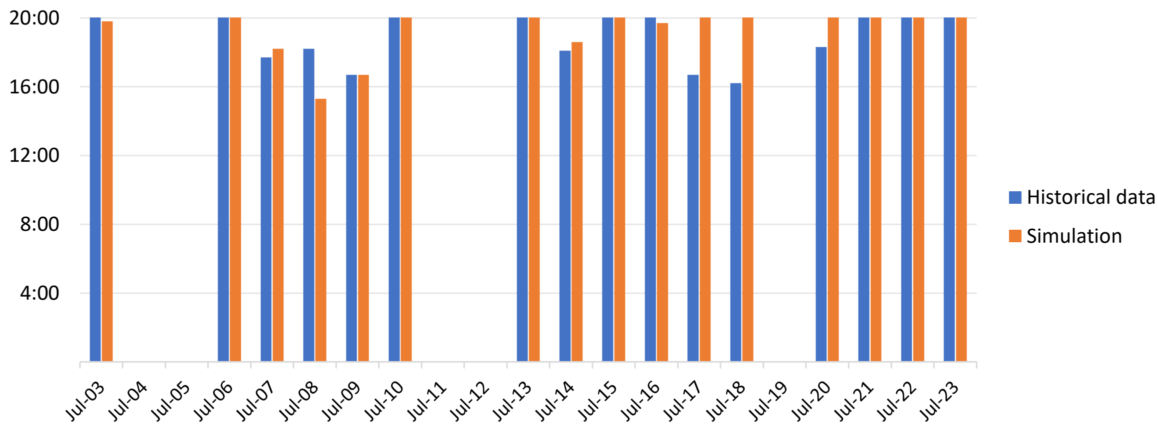

Figure 6: Simulation results.

3.3 Picking Waves Origination

The beginning of picking waves origination is placed into each customer order received by three files through email to the optic company. With no exception, these orders have some particularities that, by human decision, must be taken care of, for example, the need of Value Added Service (VAS) or their own product, customer, or shipping company needs.

In each file, the particularities are expressed in six spreadsheet columns ("Protocol", "Particularity", "Type of Order", "Unique", "Order Type", and "Shipping Company") whose data are combined to result in a picking wave. The "Protocol" column is the main one, and its data are related to how this product is going to be sent, with possibilities like "Booking", "Take Away", "No Need Information", and other criteria. The second more significant column is "Particularity", which shows the need for Value Added Service ("VAS") and other possibilities such as "AFT Donation", "No Need Information", and other criteria. The "Type of Order" column is due to the need for product swap and the existence of customer priority. "UNIQUE" is tentatively to consolidate orders with a similar destination, "Order Type" for disclosure material (or not), and "Shipment Company" to specify which company will receive those products. Those data combinations can lead to, at least, 2,880 possibilities with extra particularities and exportation orders excluded from counting, as Figure 7 expresses, but as it was not known the impacts of the human decision of using each particularity, four picking waves origination scenarios were designed to measure performance variation between them.

The original scenario ("Reality Replication" - S1) is based on the current picking wave origination, which is used to originate as many as possible waves, creating an additional picking wave for every combination of singular criteria in order to value every singular order, as a human decision is understood to be better, with no research. Figure 7 shows the possibilities of the process executed every day by the employee, and its results of the number of waves created after using each column's data. This one was validated by the company and would allow comparison with the real operation.

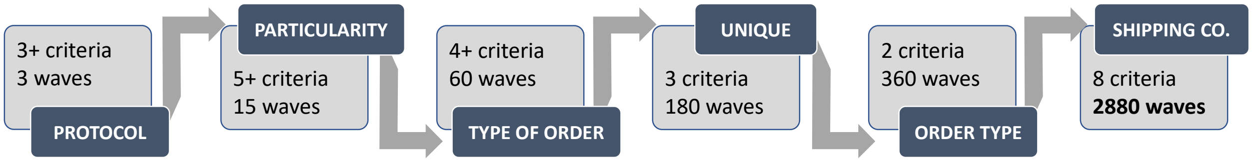

Figure 7: Operational criteria combination (S1).

After mapping the human rationale to generate the picking waves, an algorithm that mimics real human decisions for different picking wave generation was developed in Visual Basic for Excel and its results were fed into the simulation model. Although it was not possible to validate the algorithm outcome against manual picking waves origination directly due to the pandemic period, simulation results compared to historical data (Figure 6) indirectly shows that the algorithm developed was a reasonable representation of reality.

This codification was reused to originate a new codification for the "Minimum SKUs" scenario (S2), including an extra codification that would perform as "S1", but when a wave has had less than 60 items, it would incorporate a single wave with all under 60 items waves.

In the hope of increasing the Warehouse Management System usage of internal intelligence, a third scenario was designed to result in two waves, the "VAS" wave, whose products would receive special service, and the "Consolidated" wave, which would go straight from the picking process to the audit process. The objective of the "Maximum Consolidation" scenario (S3) is to allow the most interference of the WMS as possible, since it has the lowest possible quantity of picking waves and the biggest quantity of products on each wave, which would plan better routes and increase operational performance. For "S3", a new Excel codification was written taking into account only the "Particularity" column: if the data is "VAS" or "VAS/Fotoptica", it would incorporate the "VAS" wave; on the other hand, if the data does not contain "VAS", it would incorporate the "Consolidated" wave.

A fourth scenario, called "Curves" (S4), was the only one that considers the warehouse display for waves origination. It was created from the perspective of creating waves based on the ABC Selling Curve since the warehouse was monthly reorganized with the most selling items close to the VAS spot and audit spot. As the ABC Selling Curve method used by the company was "Best", "A", "B", "C" and "D", it was designed to originate four waves: "VAS" wave, "Best and A" wave, "B, C and D" wave and "Mixed" wave, as some orders could contemplate a mix of products from a different selling curve. In this case, the "S4" codification replicates "S3" codification, but in an interface with a side database that has its selling information, every non-"VAS" order is tagged with "Best and A", "B, C and D" and "Mixed" from a selling curve list to become a wave. Those last two scenario creations are represented in Figure 8.

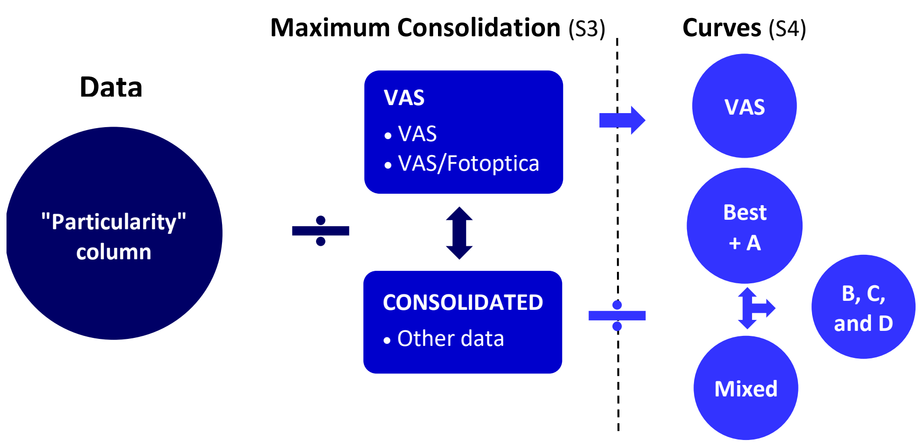

Figure 8: Operational criteria combination.

Table 1 summarizes all four scenarios.

Table 1: Picking wave scenarios.

Scenario	**S1**	**S2**	**S3**	**S4**
Name	Reality Replication	Minimum SKUs	Maximum Consolidation	Curves
Criteria	Reality Replication	Incorporate waves with less than 60 items	Fewer waves	ABC selling curve
Number of waves	Variable	Variable	2	4

4 RESULTS AND DISCUSSIONS

4.1 Operational Results

Initially, a process standard was nonexistent for picking waves origination, so if the person in charge of creating picking waves gets sick, the company could have its performance decreased as it was not possible to measure the impacts of a substitute person originating picking waves. Based on this situation, a standard process with VBA-Excel codification was developed for each scenario created, based on human decision possibilities, which would deliver standard input for the simulation model as a picking operation.

After conceptual model validation, simulation model development, verification and validation, and waves scenarios origination, the testing phase started. At this point, all input data was identical for each scenario, which would allow comparison between scenario simulation outputs. The only difference was the database organization on the designed sheets codification, whose output is the simulation model input.

In terms of scenario comparison, the key performance indicator selected was "Operational Time Needed", since it was irrelevant to measure how much time the operation would spend to finish the workload, but it was important to face all scenarios. So, it was done through 3 historical daily databases, related to August 2020, on days 13, 17, and 18. To extract historical data to feed the model from WMS a very time-consuming manual process was necessary. Due to a lack of resources during the pandemic period, it was possible to extract and process data in only 3 days.

For the final simulation, it was defined that 73 simulation runs should be used, which would reflect under and over 95% of output data confidence that is shown by blue bars in Figure 9. The *y*-axis is related to how long the operation would take to be finished (the selected KPI), so the better result is as low as possible, and in the *x*-axis, each scenario performed. An important issue in this graphic is that overlapping bars should be understood as a tie.

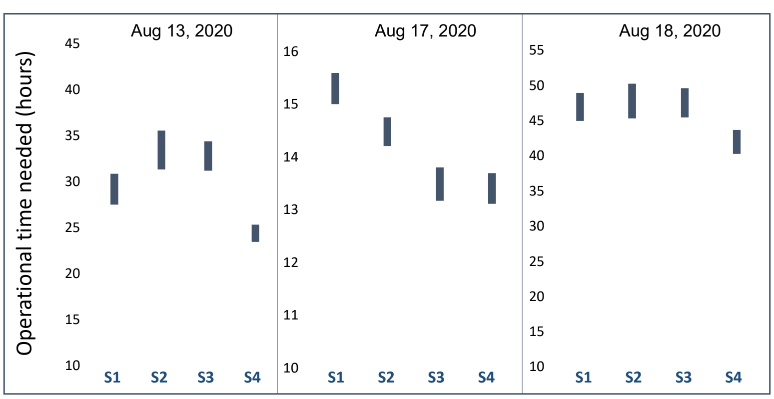

Figure 9: Scenarios results consolidation.

For comparison purposes, for every scenario and day simulated, a quantity of ten pickers was set, a quantity less than the current operation, which could overuse working daily time. The time spent was between 23 hours and 36 hours on August 13. Surprisingly, S1 was not the worst scenario on this day, even with non-tactical human decisions on waves creation; but it was still worse than the S4.

On the second simulation day, the original method (S1) was the worst, followed by S2 which was an S1 improvement, but the best results came from S3 and S4, impacted by WMS techniques. Finally, the third simulated database had a triple-tied result, with curves scenario (S4) in the lead.

Examining scenario performances between databases, S4 ("Curves") had a better performance than all others on August 13 and August 18, as on August 17, but in this case, S3 ("Maximum Consolidation") had a very similar performance so is impossible to say which is better for this database. As S4 ("Curves") had a better consistency of results, it is understood to be a better scenario of waves origination and thus it was indicated for the operation.

At the point of developing scenarios to increase performance, S4 ("Curves") had better expectations than other scenarios since all warehouse picking faces were set to place the best-seller products closer to the delivery spot. This means that, if the operation decides to use this method, most of the picking list would perform with short runs, runs that have bigger relevance on time spent picking process than any other variable since eyewear products are light and small, so it does not impact the difficulty of loading and transporting.

4.2 The Importance of Human Behavior Modeling

The original method of creating picking waves, named Scenario 1, was designed to replicate the unstandardized job (no formal procedure for picking waves origination) done every day by the employee in charge. As there was no procedure for this daily job, the employee was free to change the process of the previous day, which heavily impacted the possibility of measuring the assertiveness of the current job against Scenario 1. Therefore, this validation had to be conceptual, with operation managers who understood it to be an acceptable representation, which could be validated when the results of the simulation of Scenario 1 achieved an average of 1% error.

Table 2 shows simulation results facing each scenario to S1 (current operation) in terms of hours and distance to finish each daily database, with absolute average and relative results. S2 and S3 scenarios have similar performances for each day, but their results have a tiny benefit in one specific simulated day and strongly decreased performance for August 13. All data information certifies that with the use of S4 ("Curves") the operation would spend, at least, an average of 10% less time spent on the same job, as this performance increase can be noted in the picker's walking distance reduction of, at least, an average of 4% kilometers.

Table 2: Scenarios performance comparison.

Date	Variable	S1	S2	S3	S4
August 13	Distance to finish (km)	117.8	142.9	144.8	112.2
	Δ (%)	-	21.3%	23.0%	-4.7%
	Time to finish (h)	29.0	33.4	32.7	24.1
	Δ (%)	-	15.1%	12.8%	-16.8%
August 17	Distance to finish (km)	81.8	77.4	69.9	70.6
	Δ (%)	-	-5.4%	-14.5%	-13.7%
	Time to finish (h)	15.2	14.4	13.4	13.4
	Δ (%)	-	-5.3%	-11.7%	-12.2%
August 18	Distance to finish (km)	204.1	204.4	207.4	195.4
	Δ (%)	-	0.1%	1.6%	-4.3%
	Time to finish (h)	46.6	47.4	47.2	41.7
	Δ (%)	-	1.9%	1.3%	-10.5%

5 CONCLUSIONS AND FUTURE WORK

The main objective of the proposed simulation model was to check the impact of picking waves creation on operational performance, which would need human decision modeling. Once the simulation model was verified, the incremental objective was to testify better solutions for creating picking waves by modeling scenarios based on human decision possibilities. Facing every scenario, it was possible to have a better understanding of operation dynamics and the impact of each employee's decision.

The modeling of Scenario 1 was the hardest stage of the project. The output of this phase was a standardized procedure document for the creation of picking waves which is available for any employee to do the job with no difficulty and with predicted results. Although the picking waves creation in Scenario 1 was not directly validated, the simulation model validation could validate itself as Scenario 1 whereas the same database used in 16 days of operation was used as data comparison to validate simultaneously both models (human decision and simulation model) in a single output result.

Human decision modeling is a good approach for bringing operational benefits, but most projects, when using discrete event simulation, tend to develop models to measure resource performance and perform scenarios by adding employees or machines.

A future project could look for optimization, which could bring a better possible performance scenario. This was not done by this project, which used proposed scenarios to pick the best of them.

Another aspect a future project can bring is better performance beyond previous operations described for the clothing business unit (AFA), where there is a need for an additional picker due to picking face height or inbound process (before picking operation) and outbound process (after picking operation).

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