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INVESTIGATING PRODUCTION YIELD EFFECT ON INVENTORY CONTROL THROUGH A HYBRID SIMULATION APPROACH

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ABSTRACT

Production Planning and Control (PPC) plays a key role in stabilizing and improving manufacturing processes under external and internal uncertainties by providing transparency in the whole system. This study focuses on PPC with internal uncertainties such as losses of work-in-process products during a contact lens manufacturing process. Although such losses are expected, the yield rates are uncertain and vary at different production stages. A hybrid agent-based simulation (ABS) and discrete-event simulation (DES) approach was utilized to resemble the underlying dynamics of the manufacturing system with uncertain yield rates. The results of the simulation experiments demonstrated that a simple average yield approach for production planning would cause potential backlogs and extra holding costs for the excess inventory. The proposed hybrid simulation could be used to support the decision-making process on a weekly basis to help a production planning team make a schedule that would improve efficiency and customer satisfaction.

1 INTRODUCTION

The development of manufacturing technologies for a variety of different products increases the need to use advanced analytics to solve complex manufacturing problems and help companies to stay competitive under dynamic market changes (Jeon and Kim 2016). Optimization and simulation techniques are widely used in addressing manufacturing challenges allowing to analyze the processes and make informed decisions through production planning and control (PPC) (Jeon and Kim 2016). Companies can analyze the performance of their production systems, identify potential bottlenecks, and find solutions for them, by simulating the behavior of multiple machines in a production line (Farsi et al. 2019; Barrera Diaz et al. 2021; Bouaziz et al. 2022; Rocha and Lopes 2022). Nevertheless, PPC is a challenging task that has to deal with internal and external uncertainties such as production losses (yield rates) and dynamic demand. A substantial amount of research has been done in the PPC area focusing on different manufacturing processes and uncertainties (Hilmola and Gupta 2015; Costas et al. 2023). However, most of the work has been focused more on external uncertainties such as customer demand from different perspectives, while only a few studies were conducted on yield fluctuations (Lowe et al. 2016). Including internal uncertainties in PPC would bring a significant improvement to the entire planning process, allowing improved control of the inventory levels and potential system losses.

Consequently, one of the most significant obstacles due to internal uncertainties that must be overcome during the planning of production schedules for a manufacturing process is considering the expected yields or output from the production process. According to Lean Six Sigma, yield is defined as the percentage of the produced items that meet customer quality or specification requirements. Therefore, one of the goals of a production planning team is to create a schedule that maximizes production efficiency and minimizes waste while considering the expected yield of the process. The expected yield depends on the kind of machines used for the different processes a product will be assigned to, the state of the chosen machine, and other process factors that can impact production losses (Adipraja et al. 2022). Also, due to the requirement of in-depth analysis of the machines and the production processes in practice, estimating the actual per-machine yield rates is a challenging step (Chincholkar and Herrmann 2008; Cawley 2018; Mehmeti et al. 2018; Patel et al. 2001). If the estimate of the process yield is not accurate, there may be issues with overproduction or high inventory, underproduction or low inventory, and wasted resources, which significantly impact the profitability of the manufacturing operation. Additionally, the chosen yield rate might affect the level of customer service by creating backlogs due to re-scheduling orders after unexpected losses.

The typical procedure for yield-based planning is to use the average yield rate across all processes and schedule the order sizes accordingly. This method is not necessary accurate and may estimate yield with a large variation from the true yield that depends on the assigned machine and how well that machine will perform. Therefore, considering the complexity of calculating the actual yield rate, this study attempts to answer the questions of how the actual yield rate differs from the average yield rate and how yield rates impact production outcomes. We proposed the hybrid agent-based simulation (ABS) and discrete-event simulation (DES) framework that would help to extend PPC by simulating the underlying dynamics of the manufacturing system and modeling the behavior of different system components. The framework offers an opportunity to study how the average yield rate and inventory levels are related to each other, the impact of the chosen rate on different order sizes, and which order size is more sensitive to yield rate variability and inaccurate estimates. The proposed simulation model could support the decision-making process on a weekly basis to help a production planning team create a schedule that would improve production efficiency and customer satisfaction and decrease losses, and extra holding costs.

The rest of the paper is structured as follows. Section 2 represents the literature review of manufacturing problems where DES, ABS, and hybrid simulation methods were used to solve them. The hybrid model design with all agents' behaviors is represented in section 3. Next, the manufacturing of contact lenses as a case study is described, followed by experiments and results. Finally, we discuss the findings from the experiments of how the average yield scheduling approach affects inventory levels and the future directions of this study.

2 LITERATURE REVIEW

Simulation methods have often been used to address different manufacturing problems. In this paper, we review publications that used discrete-event simulation (DES) and agent-based simulation (ABS) to plan production and manufacturing. There is also a review of production planning problems that use scrap rate as a main parameter. Ruane et al. (2023) used a DES approach for manufacturing performance improvement and evaluated the system's performance using the throughput rate, cycle time, and work-in-progress inventory. Previously, Huynh et al. (2020) used a DES method to optimize the production process and track the status of each station over time.

While the DES approach allows to describe a manufacturing process, ABS helps to describe the behavior of different systems and how they interact. Thus, Najid et al. (2002) applied a multi-agent system to the job shop scheduling problem. Denkena et al. (2005) developed concurrent planning and scheduling methods using ABS modeling. Caridi and Cavalieri (2004) also focused on multi-agent-based production scheduling problems. Li and Chan (2013) applied ABS to the design of multi-level control and feedback architecture, especially planning and scheduling in port container terminal operations. As mentioned earlier, Costas et al. (2023) used an ABS method to analyze the cost of uncertainty in production systems. The authors simulated a production system to describe system behavior using the agent-based simulation method and calculated the average throughput to estimate the efficiency for each scenario under different levels of uncertainty.

Both DES and ABS models have benefits when describing production systems and solving manufacturing issues. However, the combination of both these approaches would build stronger models to support the decision-making process in PPC (Jeon and Kim 2016). For example, Khedri Liraviasl et al. (2015) used a hybrid approach that combines ABS and DES techniques for modeling reconfigurable manufacturing systems. The two simulation approaches were utilized for describing the model at two different levels. DES was used at a macro level to define sequences of operations, order arrivals, queueing, events times, and system utilization, while ABS was used at a micro level to model the behavior of different elements by using state charts. The agent-based method helped with autonomous decision-making, decentralized system control functions, and improvements in collaboration and functional objects, and the discrete-event simulation technique was implemented for process modeling, sequencing of operations, and comparing different configurations. Other integrated simulation models that combined DES and ABS were introduced for the semiconductor manufacturing process (Sadeghi et al. 2016; Khemiri et al. 2021). Sadeghi et al. (2016) created a model that allowed to investigate the potential problems in the production stages such as cycle time and drive the potential changes to the dispatching rules. However, the model did not include some aspects such as equipment downtimes, maintenance, and material transfers that were addressed in the hybrid simulation model (Khemiri et al. 2021).

Some research focused on measuring and improving manufacturing performance by reducing scrap or, in other words, increasing the yield in a manufacturing system. Shokri (2019) developed research to reduce scrap in manufacturing SMEs through Lean Six Sigma. The paper suggested changes to the manufacturing process, such as improving equipment maintenance, changing operating procedures, and employee training to improve skills and knowledge (Shokri 2019). Hilmola and Gupta (2015) Hilmola et al. studied the impact of scrap rates on the performance of a manufacturing company using the Theory of Constraints (TOC) and throughput accounting (TA) frameworks (Hilmola and Gupta 2015). They suggested that reducing the scrap rate could lead to significant improvements in throughput and profitability. In the semiconductor area, the yield improvement of wafers production was demonstrated through the yield deep learning prediction models based on the wafer maps (Jang et al. 2018). The yield performance of semiconductor machines was addressed in the scheduling process through mixed integer programming that helped to improve the quality of the product (Doleschal et al. 2015)

Despite the wide applications of simulation methods including agent-based methods, no study has used them for assessing the yield effect on inventory management. The proposed model would enhance existing research by providing insights into the diverse perspectives of yield uncertainties and their influence not only on the manufacturing critical problems but also on the inventory, holding/material cost, and backlogs.

3 MODEL DESIGN AND APPLICATION

To demonstrate the effect of choosing a production yield rate for manufacturing scheduling of orders on inventory, potential backorders, re-scheduled orders, and production schedule disruptions the Hybrid Agent-Based Simulation (ABS) and Discrete-Event Simulation (DES) model was developed.

Hybrid simulation offers the advantage of providing a more precise and realistic representation of complex systems compared to basic simulation. Straightforward simulation techniques, such as discrete-event simulation or agent-based simulation, have limitations in their ability to depict complex systems. While the behavior of manufacturing processes can be accurately modeled using DES, a more effective representation of individual actors such as machines, production orders, and planners can be achieved with ABS. By merging these two simulation techniques, hybrid simulation can capture both the behavior of the manufacturing process and the behavior of individual agents, resulting in greater accuracy and realistic description of the system (Khemiri et al. 2021). This enables a more comprehensive analysis of the system, leading to improved decision-making and process optimization, which is the motivation behind our use of this method. Our research aims to incorporate more complex actions in future steps, which can only be accomplished through the hybrid simulation approach.

The case study was demonstrated on the manufacturing of surgical contact lens hypothetical process. The high-level process is shown in Figure 1.

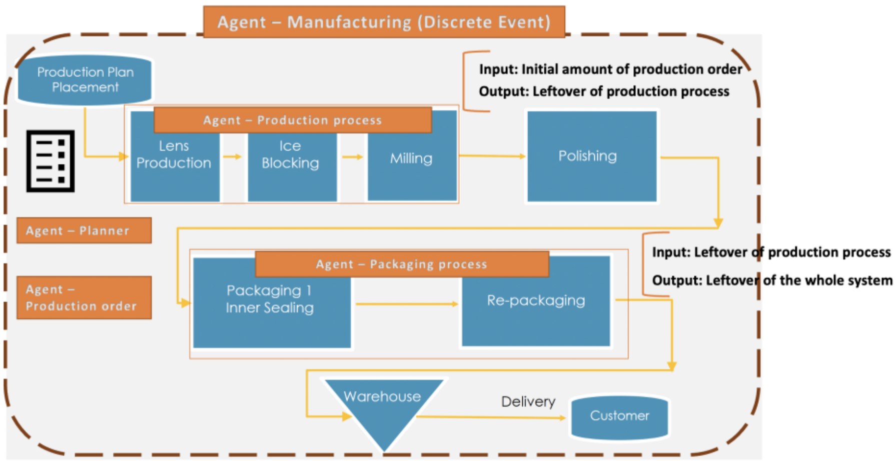

Figure 1: Manufacturing process steps for surgical contact lens.

Surgical contact lenses are produced in product-specific batches, with each batch undergoing all the manufacturing stages outlined in Figure 1. At the production step, a quality inspection is conducted for each batch. If any lens from the batch fails to meet the standards, it is discarded, and the batch proceeds to subsequent steps with a reduced quantity, known as the production order leftover. The packaging step follows a similar inspection process, where lenses with issues from the batch are removed. The quantity of the batch is defined by the Planner as Initial Production Order.

3.1 High-level Design

The production schedule planning process for the given example has to go through specific steps. In order to manufacture a batch of contact lenses, the production planner receives the customer orders first, then creates the production order (PO) quantity and sends the production schedule to the manufacturing process. The PO must go through several manufacturing steps (Figure 1):

1. Production Process includes the lens production process, ice blocking period, and milling.
2. After the lens is produced, it goes through the polishing step.
3. After polishing is done, each lens from the order will be individually packaged (packaging process).
4. The final packaged order will be sent to the warehouse.
5. From the warehouse, it will be delivered to the customer (distribution center (DC) in our example).

The model was designed as a hybrid agent-based and discrete-event simulation using AnyLogic software. The main process was represented as a discrete-event, where some manufacturing stages were represented as agents with their own behavior. The potential yield losses can happen whether in the production or the packaging process where defective unfinished lenses will be removed from the manufacturing process. Then a batch with smaller quantity will follow to the next operation with "good" lenses, which have passed the inspection. Steps 4 and 5 are out of the scope of this work as the main focus was on the losses in the manufacturing process and their effect on the inventory.

The input to the manufacturing process is the PO lens quantity placed by the planner through the production schedule based on customer orders received from the demand planning team and manufacturing constraints. The system output is leftover lens quantity from the Initial PO order after the yield losses from the production and packaging processes.

The hybrid system consists of five agents: Planner; Production Order; Manufacturing Process; Production machines; Packaging machines.

3.2 Agents' Attributes and Behaviors

3.2.1 Agent – Planner

Before the PO can be placed, the planner has to analyze the customer orders and create a schedule based on manufacturing constraints and losses in the system. The goal is to produce the exact number of lenses that are listed in the DCs' (customers') orders, enabling prompt shipment. The customer orders are generated by the demand planning team based on inventory, orders from DCs, and customer demand, and the planner has no control over them. However, the planner needs to place a production schedule in the way to satisfy the required quantities of products shipped on time. Due to losses in the system, it is necessary to schedule slightly more units than required. Therefore, the behavior of the planner is dynamic and depends on various factors. As a result, it needs to be modeled as a separate agent.

There are two main attributes (parameters) used:

- Customer Initial orders – received by Planner from demand planning team
- Average Initial Yield – the known number after the analysis of historical losses of the manufacturing system

The behavior and interaction of the planner with other agents such as the manufacturing process are defined through the event – "Production Order Generation Event" on an hourly basis, which includes:

- Receiving Customer Initial Order i CO (generated inside of the event) based on the uniform distribution (Hilmola and Gupta 2015): $CO(i){\sim}U(a,b)$, where a- minimum possible order quantity and b – maximum possible order quantity -
- PO Calculation for each i:

$$PO(i) = (2 - AY)CO(i) \tag{1}$$

(ex., Average Yield *AY*=85%, then *PO*= 1.15% * Initial CO)

- Adding Orders to "Production Order" Population
- Sending PO to Manufacturing through a message

3.2.2 Agent – Manufacturing Plant

The main structure of the Manufacturing Plant agent is modeled using DES to capture the entire contact lens manufacturing process. Every PO goes through several specific steps in production sequentially and eventually leaves the system. DES is deemed suitable for modeling this process due to its linearity nature.

PO enters through the enter point – "poProcess", which receives the message from the planner about the *PO(i)* quantity. The message delivery is ensured through "connections". The main steps: production, polishing, packaging processes are modeled as service blocks with their own serving time (production rate/cycle time). Since the schedule is usually placed for a week, queue blocks are created before each process to capture the order waiting in line while machines are busy with other orders. Once the PO has successfully passed through all the necessary steps, it is removed from the system entirely at the "sink" stage. The sink is a representation of the case when the final quantity of PO leaves the manufacturing system and is sent to the warehouse for shipment to the customer. The whole discrete process is represented in Figure 2.

Each order goes through the whole manufacturing process based on the First In First Out (FIFO) process.

- Production Process n=1 depends on the Resource Pool – Production Machines j (agent).

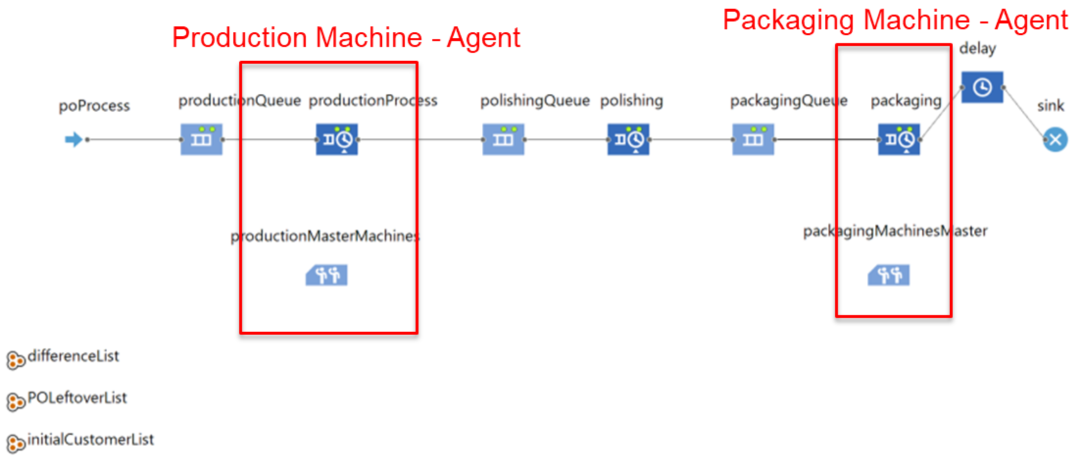

Figure 2: Manufacturing plant agent (discrete event).

- The resource pool includes multiple production machines, and the PO will be randomly assigned to the first available machine. In this process, the message with PO *i* and assigned production machine *j* – *Xp(i,j)* will be sent over to the Production Order Agent, where $Xp(i,j) = 1, if\ order\ i\ is\ assinged\ to\ machine\ j; 0\ otherwise$. This action is done on Seize step.
- Additionally, the variable *POleftover(i,j,n)* of the Production Order Agent will be updated with the rounded-down leftover PO *i* quantity information after yield losses according to (2) – will help to see how many contact lenses were scrapped on this step. This update is done on the exit step. $PY(i,j)$ - production yield for an order *i* depends on the assigned machine *j*

$$POleftover(i,j,n) = PO(i)Xp(i,j)PY(i,j), \text{ where } n=1 \tag{2}$$

- Packaging *n*=2 depends on the Resource Pool – Packaging machines *k*. The same way as the production machines pool, the packaging resource pool includes multiple machines, and PO will be assigned to the first available machine. In this step, another message will be sent to the Production Order agent to update what packaging machine *k* was assigned to each order *j* – *Xpk(i,k)* as well as the leftover PO quantity from both steps - $POleftover(i,k,n)$ calculated based on (3), where the packaging yield - $(PkY(i,k))$ is assigned accordingly for each order *i*. This leftover lens quantity will be the final order quantity that will be sent to the warehouse and inventory status will be defined based on this amount.

$$\mathrm{POleftover(i,k,n)} = \mathrm{POleftover(i,j,1)}Xpk(i,k)PkY(i,k), \text{ where } n=2 \tag{3}$$

3.2.3 Agent – Production Machines

Production machines are modeled as a specific agent type and assigned to the Production Process in Manufacturing Agent through the Production Machines resource pool.

There are three identical production machines defined as a capacity for the resource pool. Each machine has its own behavior:

- New Generation machine - very good yield (fewer losses)

- Good performing machine – “normal” yield (few losses) but in some occasions might not perform that well)
- Old machine - bad yield (high variation) (more losses, due to the variability hard to predict when the loss will be high or low).

$PY(i,j)$ - production yield for an order *i* depends on the assigned machine *j*. The assigned machine *j* is defined in the Production Process block of the Manufacturing agent and the yield is assigned accordingly. The actual yields are not stable and follow a uniform distribution - $PY(i,j) \sim U(c(j), d(j))$, where *c(j)* – the lowest yield % and *d(j)* – highest yield % for a machine *j*.

3.2.4 Agent – Packaging Machines

Packaging Machines are similar to Production Machines modeled as a separate agent and assigned to the Packaging process through the Packaging Machine resource pool.

After the packaging is done, the quality check is performed. The lens orders packages that include any external particles or when the package is damaged will be rejected. This issue is due to the performance of a specific packaging machine. There are two identical packaging machines defined as a capacity for the resource pool that has different performances:

- New Generation machine with very good yield
- An older machine with a “satisfactory” yield but higher variation

The yield for an order depends on the assigned machine. The assigned machine *k* is defined in the Packaging Process block of the Manufacturing agent and the packaging yield - $(PkY(i,k))$ is assigned accordingly for each order *i*. The actual yields are not stable and follow a uniform distribution - $PkY(i,k) \sim U(e(k), f(k))$, where *e(k)* – the lowest yield % and *f(k)* – highest yield % for a packaging machine *k*.

The *POLeftover(i,j,1)* from the Production process *n* will go through the polishing step with no losses and then through the Packaging process. Depending on which machine it will be assigned to and the behavior of that machine at that time period, additional lenses will be lost to the leftover quantity from the production - $POleftover(i,k,2)$.

3.2.5 Agent - Production Order

Production Order Agent tracks each PO during the whole manufacturing process. The behavior of each order is described by the following attributes:

- Parameters:
  - Amount – the initial amount of PO *i* created by the Planner agent – updated during the POgeneration event
  - Planner (SKU number)
- Variables:
  - machineAssigned – $\mathrm{Xp}(\mathrm{i},\mathrm{j}) = 1$ production machine *j* (1-3), where each order *i* was assigned
  - packageAssigned – $\mathrm{Xpk}(\mathrm{i},\mathrm{k}) = 1$ packaging machine *k* (4-5), where each order *i* was assigned
  - customerOrderInit – *CO(i)* - initial customer order *i* quantity
  - *POLeftover(i,n)* – PO leftover quantity after the yield losses in each process
  - *Diff(i,n)* – the difference between *CO(i)* -*POLeftover(i,n)* on each process *n* – will help to define the inventory status for *n*=2 (Packaging step – final)

The variables are updated through the state-chart shown in Figure 3. The state chart is connected with the manufacturing process agent. Production order will move to "ProductionM" state when it will receive the message from the ProductionProcess with machineAssigned information and *POLefover(i,1)*. Then it will move to PackaginM state when the message arrives from the PackagingProcess (during the seize step). When the order is produced and about to leave the PackagingProcess block, another message will be sent with *Diff(i,2)* information, and the order will move to the next state based on its value. The logic is:

- If Diff (i,2)< 0 →move to "LowInventory" state – it means the produced quantity wasn't enough to cover the initial customer order – the order has to be rescheduled and sent back to the production
- If Diff(i,2) >= 0 → move to the next decision block
  - If Diff (i,2)= 0, then move to IDEAL state – the produced order is the exact quantity needed for a customer, and it can be shipped right away
  - If Diff (i,2)> 0 → move to "ExcessInventory" state - the produced order quantity is more than the customer order, so the extra inventory must be kept in the warehouse

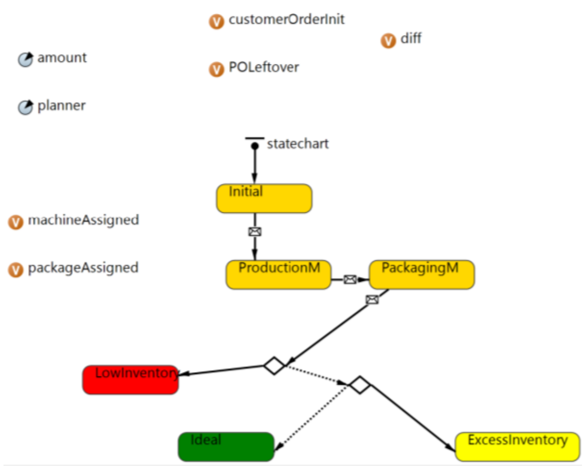

Figure 3: Production order agent state-chart.

4 CASE STUDY

4.1 Model Assumptions

As already discussed earlier, the following hybrid ABS model was demonstrated in the manufacturing of surgical contact lens hypothetical process shown in Figure 1. Three main phases are assumed in the manufacturing process: Production, Polishing, and Packaging. Production plans are the manufacturing system's input, and warehouse inventory is supposed to be its output. It is assumed that production and packaging operations yield rates follow a uniform distribution, but no losses are assumed in the polishing operations.

The Production rate is assumed to be the same, regardless of the losses during the manufacturing of a batch. The throughput of actual manufacturing is 16 hours per order (production 10 hours per order, polishing 1 hour per order, and packaging 5 hours) when there is no waiting time. The manufacturing process runs continuously 24 hours and 7 days a week. No raw materials limitations and manufacturing constraints (like changeovers, downtimes) are considered in defining the model.

4.2 Data Collection

Data was created artificially in the system according to different probability distributions and simulated based on the model assumptions.

The average yield of the system is equal to 83%. The production yield follows a uniform distribution. In the production line, there may be machines with different performances. We use three uniform distributions (0.62,0.92), (0.87,0.99), and (0.95,0.99) to simulate the behavior of old, average, and new machines accordingly.

The machines in the packaging operation follow the same behavior as the machines in the production portion. For this phase, two uniform distributions of (0.81,0.99) and (0.93,0.99) are used. The first distribution simulates data for an old machine, and the latter simulates a new machine's performance.

Customer Orders creation follows the uniform distribution (10,200) units (contact lens) per order. The production order is considered a separate SKU number, which means a unique product that cannot be combined with other orders. The number of produced orders per week is approximately 20 orders.

Based on the aggregated machine performance, the average yield across the whole manufacturing process is AY=0.83. The production orders have to be planned 17% more than the original customer order quantity according to equation (1).

4.3 Experiments and Results

For clarity of the experiment, the model was simulated with random seeds 10 times to capture the influence of the chosen average yield on the inventory status. To analyze how the average yield differs across 100 orders that were randomly assigned to different machines of various performances, the true combined yield was calculated and shown in Figure 4. This plot was generated for all ten runs, and one example run is represented in Figure 4. As can be seen, the true yield varies significantly frequently and is not even close to the average estimated. In most cases, the true yield is lower so a planner could end up with more orders that would need to be rescheduled.

Additionally, we studied how the inventory status, described in section 3.2.5, was spread over weekly as planners usually adjust and create a new schedule every week. The average number of orders was calculated for each inventory category: low, excess, and ideal on a weekly basis – 5 weeks of study with an average of 20 orders per week (Figure 5). As demonstrated, over time we have approximately the same split for low and excess inventory and only a few ideal cases. It means the SKU is always at risk of having too much inventory or not enough on the weekly basis as well.

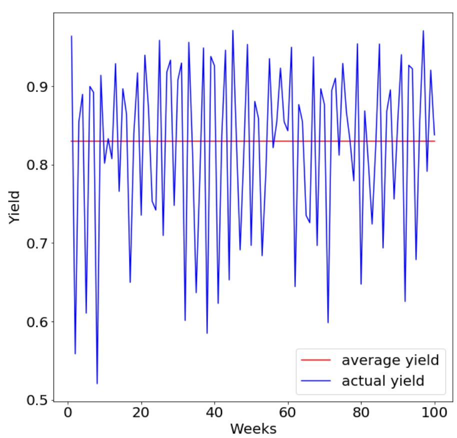

Figure 4: Average yield vs true combined yield for one model run.

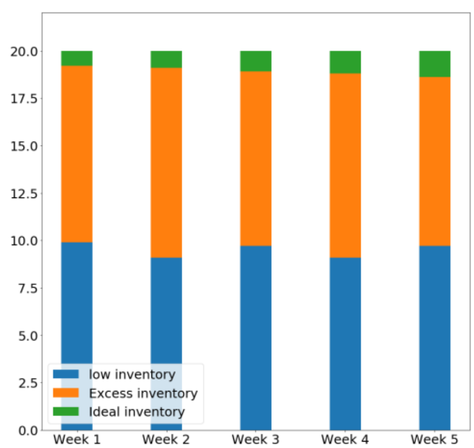

Figure 5: 10 random runs average inventory status over time.

Furthermore, understanding how many lenses of each category were lacking or considered extra would highlight the issue of choosing the average yield approach. Based on 10 experiments, the average number of lenses, which had to be re-scheduled, was 359 units, and 667 units extra were produced. In general, 65%

of the total incorrectly produced amount was related to orders that did not have enough units and had to be sent back for production with missing quantity.

Meanwhile, counting the number of orders that belonged to a specific inventory category helped to conclude how rare ideal cases happened with varying true yields. Most of the orders were not produced in enough quantity (48% of orders) or ended up with excess inventory (47%) according to Table 1. Additionally, the orders were split into the size categories: Large Orders (>150 units per order); Medium Orders([50,150] units per order); Small Orders (<50 units per order). Counting the number of orders for each inventory category per a specific order size would help to analyze the behavior of the system under the different types of orders. Based on Table 1 results, the larger order tended to be more affected by overscheduling while on average it has both issues with low and excess inventory. While in comparison, the small orders had a higher number of orders that could be considered ideal cases and slightly more issues with under-scheduling. That is a logical explanation as a loss in a small order has more effect than a few lenses in a big order.

Table 1: Experimental data study of the effect of the average yield rate on inventory status.

Experiment Data	Low Inventory	Ideal Inventory	Excess Inventory
% number of orders	48%	5%	47%
% number of Large Orders	48%	4%	48%
% number of Medium Orders	48%	4%	48%
% number of Small Orders	43%	15%	42%

To investigate the lacking inventory from the wrong scheduling effect on the order size type, the negative difference was calculated based on absolute values and split proportionally between different sizes – Table 2. Additionally, the same calculation was done for the positive difference – excess inventory (Table 2). Based on intuition, it is expected that large orders (consisting of big quantities from both normal and big lots) would be more susceptible to yield variations. The simulation experiments conducted to validate this observation indeed confirmed that small orders align better with the average yield scheduling approach. While some of these conclusions may appear obvious, it is crucial to substantiate them through experiments that clearly illustrate the critical nature of the problem. Table 2 shows that a lot of big orders will have to be rescheduled and it is clear that would significantly increase the production cost for an order and potentially cost more disruptions in the production. Also, Table 2 indicates that large orders overscheduling will build a lot of unnecessary inventory.

Table 2: Experimental data study of inventory status vs order size.

Experiment Data	Large Order	Normal Order	Small Order
% of the total number of lenses - lack inventory	44%	50%	6%
% of the total number of lenses - excess inventory	42%	52%	6%

5 CONCLUSION AND FUTURE WORK

The hybrid ABS and DES model was developed to investigate how the average yield rate chosen during the scheduling process would influence the final product inventory and increase disruptions in the manufacturing process. The model was inspired by the surgical contact lens manufacturing example. Based on the experiment results, we can conclude that the average yield approach leads to a huge backlog that requires re-scheduling and potential disruptions in production plans for future weeks. Also, the average method leads to an excess inventory for some orders that would increase the warehouse holding cost and potential transportation costs. Orders with low inventory and excess inventory were likely to happen with equal probabilities. However, the total number of lenses that had to be produced additionally was higher than the excess lens units. From the lot size perspective, smaller orders tended to respond better to the average yield scheduling generating fewer losses and less inventory. Large orders are very sensitive to the wrong production quantity planning. In cases when these orders were assigned to the old lines, a lot of units were lost and had to be re-scheduled, while the new generation line would build up extra inventory.

The simulation experiment demonstrated that a simple average yield approach for production planning would cause potential backlogs due to re-scheduling and extra cost holding costs for the excess inventory. A more sophisticated approach is required to capture the fluctuations in yield, taking into account various factors such as the performance of different machines, potential combinations of production and packaging machines, individual specifications for each product type, the dependency of a specific machine's performance on the product type, the influence of order sequencing, and other factors that could impact yield. Implementing a dynamic rate that considers these specific factors for each product type can help improve control over the produced inventory. Employing more advanced methods, like predicting potential losses as demonstrated in (Shin and Park 2010), would be beneficial for simulating different scenarios and their effects on inventory.

The developed simulation model could potentially help the production planners play around with different average yields rate to see how it could potentially impact the final product inventory under different manufacturing scenarios. The information learned from the simulation model, e.g., what could potentially happen under different scenarios, could help reduce losses, improve production efficiency and customer satisfaction, and reduce inventory costs by producing the right product amount.

In future work, the simulation model will be enhanced by considering additional factors to determine a more accurate yield. These factors may include maintenance effects on machine performance, raw material types from different suppliers, downtimes, changeover, and other manufacturing constraints. The simulation model that takes into account all these factors could provide more valuable information to support decision-making during the production planning process.

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