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Assigning Tissue Bank Technicians to Clean Rooms while Considering Dynamic Demand

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Abstract: Tissue banks' innovative products change people's lives. One such tissue bank produces over 200 different products for hospitals that in turn use the products for their patients. This research analyzes the scheduling processes and poses the question: What is the optimal way to both schedule technicians to shifts and map them to clean rooms while considering the dynamic demand of tissue products? The study uses two integer programming models: one which assigns technicians to a weekly shift and the other which assigns technicians to both a room and specific processes, daily. This study finds that by changing variables the tissue bank has control over, the tissue bank could improve the daily output by as much as 11.8%. These results show that the tissue bank has an excess of under qualified employees and should focus on increasing their technician qualifications in order to increase utilization further.

Keywords: Donor, Technician, Product, Room

1. Introduction

AlloSource is one of the largest tissue banks in the United States. It processes human tissue donations 365 days a year and employs over 400 people. AlloSource utilizes its processed tissues, called allografts, to enhance and save people's lives. As a non-profit, AlloSource exists to honor the gift of donation in the best way possible. To do so, AlloSource desires to operate at its best possible efficiency in order to maximize each body received to its fullest potential and remove as many sources of waste. By helping them operate more efficiently, AlloSource is able to enhance the lives of thousands of individuals across America.

Each night, AlloSource manually schedules its technicians for the next day. The employees take several factors into consideration such as clean room capabilities, shift times, and employee qualifications in order to produce the daily schedule. Since the schedule is made by hand, there is no best practice method for determining the daily schedule. The process data that AlloSource collects contains self-proclaimed biases so any attempt at using a distribution to model its processes would have been futile. Instead, we used maximum times to model the processes.

We believe that AlloSource can function more efficiently in two aspects. First, they spend an estimated two hours per day with multiple people creating the daily schedule. Secondly, AlloSource recognizes that it creates its current schedules based on aggregated average times for processes. This method results in the scheduling committee having to overestimate the time it takes to do a process, while not filling up all the clean rooms due to how much time per day it takes to make the schedule. AlloSource admits that its inefficiencies lead to unproductivity when an employee has time to start another process but does not because the schedule did not account for that employee finishing when he or she did. Furthermore, the technicians may only be scheduled to work one 6 hour process when they are scheduled to work for 10 hours. These two issues create inefficiencies in the way AlloSource utilizes its workforce. AlloSource purports that a 1% increase in efficiency is equal to $74,000 saved, money which can be used to increase production quantity.

This study poses the question, what is the optimal way to both schedule technicians to shifts and map them to clean rooms while considering the dynamic demand of tissue products. Answering this question will save AlloSource time and money because we will find the best practice of structuring its daily operations. This study presents an optimal model that considers product demand, available technicians, time constraints and other miscellaneous factors. This model also provides them a way to check their current daily performance and make adjustments where necessary.

2. Related Work

Dong, Chen, & Lu (2015) model a “multi-model multiple assembly line with mixed-line assembly” using different algorithms which optimize total performance of the system in a complex operating environment with poor assembly line usage. The processes for which a product goes through to be completed is very similar to an assembly line, with different stations designed to achieve different goals for the finished product. The different constraints show how to improve utilization, an area AlloSource is looking to improve.

Gurvesky, Hazir, Battaia, & Dolgui (2013) further expound on how to optimize an assembly line by working with a process where the only known times are the upper and lower bounds of how long a product can take. Their process for overcoming this obstacle is to use a robust optimization method taking into account the worst possible manufacturing times. Their work contributes to our work because if a process at AlloSource has experienced extremely varied completion times, then we have to schedule it at the max time, despite the process normally not taking as long as the maximum time.

Furthermore, we evaluate how to maximize clean room usage while knowing how many technicians are working at any given time. Warner & Prawda (1972) schedule nurse personnel in a hospital by taking into account preset time period shifts, their qualifications, and the area in which they are working. They assume a preset demand function that is already known to them and schedule the nurses by minimizing unmet demand. Their method of scheduling closely mimics the scheduling problem that we encounter with AlloSource, so understanding their model benefits us.

Dillon & Kontogioris (1999) allow for flexibility in scheduling based on demand while including employee preference. Prior to their research, US Airways was scheduling their employees a month in advance based on a forecasted demand with the demand constantly changing and subject to change days in advance. Through the work of Dillon and Kontogioris (1999), they developed a model that schedules employees while meeting the massive demand asked from them during one of the largest airline expansions in recorded history. The model fits our narrative because we also are creating a schedule that forecasts a changing demand based on historical data, only on a much smaller scale.

Similar scheduling problems appear in many different fields. The National Hockey league use integer programming, a technique that we plan to use, to schedule their regular season games. Fleurent and Ferland (1993) presented their integer programming technique that was presented to league managers as a potential way to handle the NHL’s scheduling problem. They create an assignment problem that assigns a home team to play an away team on a certain day in the season. Their model was used by the league in 1992 to allocate games for the regular season. In the same way Fleurant and Ferland (1993) scheduled NHL teams we will use integer programming to assign technicians to processes throughout their day. Fleurant and Ferland (1993) use an objective function to minimize what they call exception games. In this way, they penalize the model for deviating from the regular allocation.

Finally we want to take into consideration employee satisfaction because keeping employees happy is a crucial part of any organization. Srimathy Mohan (2008) writes an integer programming model to schedule part-time personnel to maximize employee satisfaction. Her objective function maximizes employee satisfaction while meeting demand requirements for shifts. She tests her method with randomly generated preferences. We develop off of her objective function and constraints in order to create an integer programming model that takes satisfaction into account.

3. Methodology

We decided to make two integer programming models. The first model assigns technicians to shifts for the week. The second model assigns technicians to rooms to a process for a time period. The first model feeds into the second model, providing the shifts scheduled as constraints. The output is a comprehensive list of technicians’ assignments that assign a technician working a shift to a room and a process.

3. 1 Weekly Assignment Problem

The first model assigns technicians to specific shifts throughout the week. AlloSource currently divides their technicians into five shifts. The first three are ten hour shifts Monday – Thursday and the last two are twelve hour shifts worked Friday – Sunday. The weekly assignment problem assigns the technicians to their shifts worked throughout the week. The objective function takes into account the technicians’ preferences for their shift and also the utility of the technicians working a shift based on a weight parameter that AlloSource will assign to each process. The utility of a technician is based upon how many processes a technician is qualified to perform, with more qualifications increasing a technicians overall utility. The weight variable prioritizes higher demand processes and is how we deal with the dynamic demand in both the weekly problem and the daily problem. For the sake of our simulation we assigned random values to these processes but

AlloSource will be able to assign weights based on their demand and this will be used here to maximize the utility of a shift based on how high in demand a process is.

In order to write out the mathematical model for the weekly assignment problem, we need notation to define variables parameters and sets. We denote the model using the notation in Appendix A.

The model is summarized in Appendix A. This objective function simply handles assigning technicians to shifts. The first part considers the technician's preferences for which shift they want to work. The second part of the objective function is a utility function. We multiply the weight of the process by the binary variable if a technician is qualified to work that process. This method is done in order to give technicians who are qualified for high value processes more weight than technicians qualified for lower value processes.

3.2 Daily Assignment Problem

The second model takes into account which technicians are working which shifts and then assigns their work schedule for that shift. It will again use a similar objective function as the weekly model to maximize the utility of the output the technicians produce in a single day. This is done by using the same weight variable that was used in the weekly problem. For this formulation, we only consider one normal day during the week which consists of three 10 hour shifts in a sixteen hour work day. Another key assumption made was that process times are rounded to the nearest hour and have little deviation. To account for this rounding, we overestimated the amount of time it takes to do a process. In order to handle processes being completed in a specific order, we assigned process codes for groups of processes that must be done sequentially. This ensures that the second step in a process does not take place before the first step. Finally to account for lunch breaks in a technician's shifts, we shortened their shift by an hour. In this model, a technician has nine working hours where he is expected to be working and we assume the technician will take a break sometime in the middle of his shift up to his discretion.

In order to write out the mathematical model for the daily assignment problem, additional notation is required. This notation is separate from the notation used in the weekly model. We denote the model using the notation in Appendix A.

The model is summarized in Appendix A. This objective function maximizes the same utility function used in the weekly problem. This is to prioritize high demand processes in our daily schedule to mirror how AlloSource prioritizes certain processes to meet its dynamic demand.

Because of these assumptions, the model produces a good starting point for AlloSource to schedule but is mainly used to analyze their process. This model measures the daily performance of a day based on the desired processes set by the company for that specific day. AlloSource can compare daily output when the weight parameters are the same. A shortcoming of this model is it only accounts for processes and not the products themselves. AlloSource has over 300 products which are completed using these thirty processes so the company must know which processes are associated with which products and find a way to prioritize those processes in order to meet the dynamic demand for the different products every day.

The first additional assumption we made was to not take into consideration the order of the processes. This assumption means that while a product may need to go through a specific order of processes to be produced, we do not require a product to accomplish these processes in order. As long as a product goes through all the required processes, the product is completed. The second assumption made is that the time required to do a process includes the set up and clean up time. Due to the nature of tissue manufacturing, rooms must be set up following a strict cleaning regiment, and afterwards cleaned carefully as to eliminate contamination. The third assumption with regards to our models is that the preferences for processes are the same for all the tests we will run. This assumption is made in order to ensure continuity and consistency in our numbers and to identify areas of improvement. When the preferences are changed, the model properly adjusts the output. The preferences we use are merely for analysis and are able to be changed. Also, we assumed that it only takes one technician per process, whereas in reality it could take multiple technicians to complete a process. This is done because we were not provided the information regarding the number of technicians required for each process.

4. Results

From the information provided to us, we were able to achieve a baseline model that gives us a measure of how well AlloSource is producing desired output in a given day. We calculated that in a given day AlloSource completes 202 processes. We also validate this number by comparing our model's room utilization with AlloSource's room utilization. In an average day AlloSource has a room utilization of 33%. Our schedule we generate has a room utilization of 33.2%, verifying that we successfully model AlloSource's processes.

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The weighted output or the objective function value of our daily problem we used to compare how much the different scenarios improved AlloSource's processes. The baseline model has an objective function value of 539. This number is only valuable when compared to other values.

The first and most significant improvement in this metric we found was by shifting from a three ten hour shift schedule to two shifts in a day with 12 hour shifts. The 12 hour shifts use 20% fewer workers but produced an 11.8% increase in our objective function value.

The next significant result we found was that we could decrease the number of technicians in our baseline model without any significant decrease in the objective function value. Figure 1 shows the change in the weighted output as we decrease the number of technicians we put through our model.

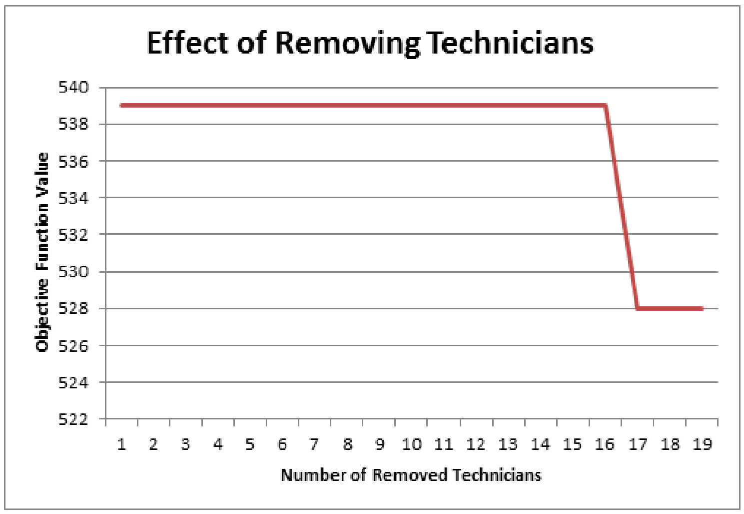

Figure 1. Change In Objective Function Value With Decreased Technicians

The final variable we analyzed was how the objective function was affected by adding clean rooms. We discovered a linear trend that with each clean room added, we could increase our model output by 1%. This meant that one additional process was being completed every day. We checked room utility with each added room and found that the room utilization was not significantly affected by the additional rooms. Figure 2 shows the linear trend we discovered by adding rooms.

Figure 2. Change in objective function by adding additional rooms.

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5. Conclusion

From this analysis, we determined the best practices for AlloSource in its daily scheduling. Our tool successfully modeled AlloSource's current operations. This tool was validated by achieving the same room utilization rate as AlloSource with our baseline model. Also, we validated the assumptions made by changing the inputs and comparing the results. Because changing the inputs did not change the number of processes completed in a day, the results from our self- generated inputs can be assumed to accurately depict the scheduling process.

Our results show that there are ways that AlloSource can improve its output. We show that adding a room allows for one extra process to be completed in a day without significantly changing room utilization. For this reason, AlloSource may want to invest in more of its standard rooms to increase output. However, this comes at a cost and AlloSource must determine if the extra process is worth the cost of adding a room.

We also found that longer shifts allow for more output. The 11.8% increase is most likely due to the technicians being able to complete processes they would not normally have time to complete in a standard day. AlloSource should focus on scheduling employees for longer shift periods to give them the extra time they need to accomplish their processes.

One of the initial complaints AlloSource had was that its technicians have too much down time. We verified this complaint by deleting fourteen technicians without hurting the output. We hypothesize that this observation is because the technicians are qualified for so few processes that there is no work to be done even if there was a room available to work in. Each technician is only qualified for an average of six processes.

For future work, we would like to get better information on the specific processes and how the demand for different processes changes over time. Having this information would allow us to create a more useful tool that better maps technicians to clean rooms. Because of this assumption we made in the model, we were unable to provide any sensitivity analysis relating to how increasing technician or room qualifications would improve the processes. We hypothesize this to be the biggest limiting factor to AlloSource's processes and solving this problem could be the key to optimizing its output.

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Appendix A: Problem Formulation

Weekly Problem

Sets

$i \in I$: *set of all possible technicians.* $i = 1 \ldots 130$
$j \in J$: *set of possible processes.* $j = 1 \ldots 31$
$t \in T$: *set of all shifts.* $t = 1{:}5$

Parameters

$\lambda_{ij} = Utility\ for\ tech\ i\ to\ work\ process\ j$
$p_{it} = preference\ for\ technician\ i\ to\ work\ shift\ t$
$w_j = weight\ of\ importance\ for\ process\ j$

Variables

$X_{it} = \begin{cases} 1\ if\ tech\ i\ is\ assigned\ to\ shift\ t \\ 0\ otherwise \end{cases}$

$Y_{ijt} = \begin{cases} 1\ if\ tech\ i\ is\ assigned\ to\ process\ j\ during\ shift\ t \\ 0\ otherwise \end{cases}$

Objective Function:

$$Maximize \sum_{i,j,t} w_j \lambda_{ij} Y_{ijt} + p_{it} X_{it}$$

subject to

$Y_{ijt} \leq X_{it}\ \forall i,j,t$ (1)

$\sum_t X_{it} \leq 1\ \forall i$ (2)

$\sum_t Y_{ijt} \leq 1\ \forall i,j$ (3)

and

$X_{ijk} \geq 0$ (4)

Constraint 1: This constraint allows us to have two different decision variables. The x is the only decision variable we are interested in because that simply assigns technicians to shifts. The y decision variable assigns technicians to shifts and processes. This constraint forces x to be 1 if y is 1 so that there is continuity between the two decision variables.

Constraint 2: This constraint only allows the technicians in the y decision variable to be assigned to one shift.

Constraint 3: This constraint limits the technicians in the x decision variable to be assigned to one shift.

Constraint 4: This constraint ensures no variable is less than one.

Daily Problem

Sets

$i \in I$: *set of all possible technicians.* $i = 1 \ldots 130$
$j \in J$: *set of possible processes.* $j = 1 \ldots 31$
$c \in C$: *set of possible process codes.* $t = 1 \ldots 31$
$k \in R$: *set of all possible rooms.* $k = 1 \ldots 37$
$s \in S$: *set of all shifts.* $t = 1 \ldots 3$
$t \in T$: *set of all times.* $t = 1 \ldots 16$

Parameters

$a_{is} = \begin{cases} 1\ if\ tech\ i\ can\ work\ shift\ s \\ 0\ otherwise \end{cases}$

$m_{kj} = \begin{cases} 1\ if\ room\ k\ is\ able\ to\ do\ process\ j \\ 0\ otherwise \end{cases}$

$h_{ij} = \begin{cases} 1\ if\ tech\ i\ is\ qualified\ to\ work\ process\ j \\ 0\ otherwise \end{cases}$

$w_j = weight\ of\ importance\ for\ process\ j$
$e_j = time\ it\ takes\ to\ perform\ process\ j$
$d_j = code\ for\ process\ j$

Objective Function:

$$Maximize \sum_{i,j,t,k} w_j X_{ijtk}$$

subject to

$X_{ijtk} \leq h_{ij}\ \forall i,j,t,k$ (5)
$X_{ijtk} \leq m_{rj}\ \forall i,j,t,k$ (6)
$\sum_{j,t,k} X_{ijtk} \leq 9\ \forall i$ (7)
$\sum_{i,j} X_{ijtk} \leq 1\ \forall t,k$ (8)
$\sum_{i,k} X_{ijtk} a_{is} = 0\ \forall i,j,t = (12 \ldots 16), k, s = 1$ (9)
$\sum_{i,k} X_{ijtk} a_{is} = 0\ \forall i,j,t = (1,2,14..16), k, s = 2$ (10)
$\sum_{i,k} X_{ijtk} a_{is} = 0\ \forall i,j,t = (1..5), k, s = 3$ (11)
$while\ a < e(j), X_{ij(t+a)k} = 0\ \forall i,t,j,k, a\ in\ e(j)$ (12)

and

$X_{ijtk} \geq 0$ (13)

Constraint 5: This constraint states that each technician must be qualified to conduct a specific process.

Constraint 6: This constraint states that each room must be able to hold a specific process.

Constraint 7: This constraint says that a technician can only work for nine hours a day. Even though he is scheduled for a 10 hour shift, this alots one hour for a lunch break which each technician is given.

Constraint 8: This constraint handles room overlap so that a room cannot handle more than one process at a time.

Constraint 9: This constraint checks to see if a technician is scheduled to work during shift one and does not allow him to work if he is outside the constrained hours.

Constraint 10: This constraint is similar to constraint 5 but for shift 2.

Constraint 11: This constraint is similar to constraint 5 but for shift 3.

Constraint 12: This constraint only allows a technician to be working on one process at a time. It states that a technician must finish one process before starting a different one.

Constraint 13: This constraint ensures no variable is less than one.