Biomedical Machine Maintenance Scheduling

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Abstract: Tissue banks procure approximately 45,000 tissue donations per year, providing nearly 9,000,000 individuals (about half the population of New York) with life-enhancing and life-saving medical procedures. Proper biobank machine maintenance is imperative to this process. Mandatory forms of maintenance are critical to avoid unexpected malfunctions, which can halt operations and render samples unusable. Each machine has a unique reliability rate within the system; although some can quickly be repaired or replaced, many processes rely on limited machinery where even planned downtime can significantly influence the tissue processing. AlloSource, one of the largest tissue manufacturers in the United States, too often schedules these preventive events unnecessarily or inconveniently, resulting in machines breaking down at inopportune times. In response to these inefficiencies we ask, *"What is the best consolidated and standardized equipment maintenance schedule that maximizes monthly maintenance events to ensure increased equipment availability while meeting the demand of the biomedical manufacturing network?"* We use an optimization model to consider equipment reliability, downtime, availability, and demand to develop a preventive maintenance schedule. Our model focuses on scheduling the maximum number of events the maintenance crew can conduct each month to ensure vital equipment to the allograft process is available, which provides more opportunities for tissue therapies. In doing so, the maintenance crew is also able to complete more events, driving up annual throughput while driving down equipment downtime.

Keywords: Tissue Bank, Biobank, Machinery, Optimization, Preventive Scheduling, Reliability

1. Introduction

Beginning in the early twentieth century, the concept of tissue banking has evolved to its current state that includes harvesting, processing, storing, and transporting human tissues for clinical use. Tissue banks have modernized to process thousands of donations yearly, currently enabling them to aid nearly 9,000,000 patients annually, in part through the production of allografts, a cleaned tissue used for medical treatment such as knee replacements, bone grafts, spinal fusions, and skin grafts (Armada Medical Marketing). Notably, a single donor can impact over 200 people in need of treatment. Tissue bank organizations are complex systems that require technical expertise to manage a time-sensitive and machine-dense work facility (Narayan, 2012). Specifically, biobank machinery is critical to the production of these life-saving tissue donations. According to McDonald (2010), "human tissue biorepositories have an increasingly visible and important role within industrial enterprises in supporting biomedical research, including the rapidly advancing fields of proteomics, pharmacogenomics, and molecular epidemiology." Specifically, recent studies have highlighted the importance of tissue banking in the study of the biology of cancer and its development (Christiansen, 2007). While extremely important, these complex systems require hundreds of forms of machinery for the processing system to function successfully. These machines help to store, clean, and prepare allografts before they are shipped to medical professionals for transplants.

AlloSource, a nonprofit organization, is one of just 120 of these biobanks in the U.S. that manufactures cartilage tissue (used to repair joints) and skin allografts (used for the healing of severe burn injuries). It is one of the largest tissue manufacturers in the country with over 450 employees and manufactures upwards of 200 types of custom-made allografts to donate to medical facilities (Armada Medical Marketing). Donations of ligaments, tendons, bones, joints, musculoskeletal structures, and skin are used in lifesaving and enhancing medical procedures.

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1.1 Problem Statement

To create a maintenance schedule most beneficial to AlloSource, we focus on delivering a consolidated and standardized schedule encompassing all maintenance, calibration, and validation events. All three event types are different and necessary in their own ways. Maintenance includes all services or routine check-ups; calibration checks cover measurement accuracies such as making precise cuts of tissue; and validation confirms that products meet the correct equipment specifications and requirements of intended purposes. These events are strategically planned in a preventive manner with predicted downtimes to ensure smooth production operations. When these preemptive events are not conducted properly, unplanned breakages or repair issues arise, causing vital equipment to go down for longer periods of time. With these considerations, we formulated our research question: *"What is the best consolidated and standardized equipment maintenance schedule that maximizes monthly maintenance events to ensure increased equipment availability while meeting the demand of the biomedical manufacturing network?"*

Our goal is to improve AlloSource's maintenance scheduling to ensure that the organization is processing as many tissue samples as possible. While doing so, we also reduce the number of unexpected maintenance calls through an increased predictability for the maintenance crew. Therefore, our model allows AlloSource to conduct their life-saving processes in a more uninterrupted and fluid manner. Additionally, our model produces consistent monthly maintenance scheduling to provide the maintenance crew with predictability and reliability to carry out their work. Finally, the model sets aside unplanned maintenance hours in case equipment goes down unexpectedly so crew members are not overwhelmed with both planned and unplanned events. In short, the model provides numerous improvements in the production system while improving day-to-day operations for the maintenance crew.

1.2 Related Work

The unique complexity of this multi-machine system is evident through the work of Alkhamis and Yellen (1995). The authors utilize an integer programming (IP) model to formulate an optimal maintenance schedule that minimizes unit idle time while satisfying the operational and maintenance constraints of the respective machinery. Boland et al. (2012) provide a mixed IP optimization model based on a network flow approach to formulate their problem and maximize the total annual throughput, which is highly correlated with equipment downtime, for a coal chain. This system includes multiple equipment types and processes that each need to run properly for the entire system to be successful. The authors also suggest breaking down the problem through a sequence of shorter problems. Cassady (2005) also uses this technique with small scheduling problems, making it easier to coordinate preventive maintenance planning decisions. This integrated model allows for total enumeration of sub-problems.

Ruiz-Hernandez et al. (2020) also try to maximize throughput, but by preventing equipment failures. They focus on scheduling maintenance interventions at decision points, suggesting the effectiveness of a standardized schedule that considers more imminent maintenance events (weekly), but also incorporates annual activities for less frequent requirements. Conversely, Schlunz (2012) reports that the most useful economic objective is the minimization of operating cost, a function of production and maintenance costs. To effectively address this goal, he emphasizes the importance of minimizing disruptions to an existing schedule and uses an adapted method of simulated annealing combined with IP to optimize a preventive maintenance schedule for power generating units. Preventive scheduling allows for a longer life expectancy of the machinery and reduces the probability of unplanned outages.

The reliability of medical machinery is imperative to maintenance scheduling. Khalaf et al. (2010) utilize a different approach to mixed IP with a focus on reliability through binary variables. They optimized reliability and strategically chose variables that directly affect the medical equipment's effectiveness, emphasizing the importance of focusing on higher impact (based on patient risk and mission criticality) machines. The authors began the modeling process first by determining a machine's probability of being operational, then adding a time component. The logic follows a depreciating trend over time; after reaching a certain threshold, the equipment is flagged for maintenance. This approach also places more importance on higher impact machines along with those that pose the most risk if down for maintenance.

Despite numerous studies and methodologies, preventive maintenance scheduling has proven to be a complex issue unique to each situation. Unlike previous studies, our problem deals with various types and frequencies of maintenance. Since there is no single superior method, we have focused on creating a model that provides consistency and standardization to secure long-term benefits.

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2. Methodology

The primary metric used to evaluate the effectiveness of our model is total events scheduled; other metrics such as equipment downtime, number of maintenance crew, and unplanned maintenance hours are additional considerations during the optimization process. Our model produces a preventive maintenance schedule that incorporates planned maintenance events and a period for unplanned maintenance such as breakage and repairs.

2.1 Data

We cleaned and consolidated maintenance data for all equipment from 2018 to 2020, retrieved from AlloSource's RAM database, for use in our model. This data highlighted that only 20% of the equipment types contributed to the majority of the maintenance events (approximately 80%). In accordance with the Pareto principle, we therefore limited our analysis to approximately 60 equipment types to narrow our model's focus only towards equipment that notably impact maintenance scheduling. We further limited our data to only maintenance events that were completed in their entirety between 2018 and 2020; events logged as cancelled or on hold (fewer than 1% of records) were removed. We then categorized each observation by the general event type: maintenance, calibration, or validation. Lastly, we assigned each observation an event time interval (e.g. daily, weekly, etc.), indicating the period in which the respective maintenance type consistently occurs. Thus, a single observation in the data would provide a unique asset identifier (ID), an equipment type, a unique work number, the date and duration of the event in hours, the type of event (maintenance, calibration, or validation), and the time interval of event (e.g. annually, monthly, etc.).

We then created a second file that tracks each event associated with each equipment type, based on its asset ID. Specifically, we maintain information on when specific maintenance events were last conducted. Our model evaluates the time interval of each event (e.g. daily, etc.) and projects the next due date. For example, if a quarterly event last occurred January 2021, that event would be included on the schedule for events due in April.

2.2 Assumptions

We make several assumptions about the available dataset in developing our solution, each validated by our clients. First, we assume that the RAM database is accurate—it includes all required maintenance events with accurate asset descriptions, event start dates, and maintenance durations. This is necessary in understanding true maintenance demand. We also assume equipment age is irrelevant; each equipment type has standard maintenance requirements independent of a specific machine's previous usage. Finally, we also assume that maintenance crew availability is consistent and can therefore perform required maintenance as needed.

2.3 Scheduling Model

Our model produces a standardized maintenance schedule for the upcoming month. Using a computer-based algorithm, it first calculates the total maintenance hours available for the upcoming month based on number and type of days (i.e. weekday vs. weekend) and the maintenance crew's expected schedule. The model tracks each unique equipment item through its asset ID and monitors every maintenance event associated with that item, identified by maintenance type (maintenance, calibration, or validation) and time interval (e.g. weekly, monthly, etc.). It then determines when each event was last conducted, and therefore when it should next be scheduled. Using the average historical duration for each event, we find the expected duration of all events to be scheduled in the upcoming month.

We reserve 10% of the available hours in the upcoming month for unplanned maintenance events in case of equipment breakdown and subsequent repair requirements. If the expected duration of scheduled events is within the remaining 90% of maintenance hours available, all events are scheduled. If, however, the total hours needed exceeds the hours available, the model executes an algorithm to prioritize planned maintenance events.

First, all equipment types are assigned an asset priority ranging from one (most important) to four (least important) based on a ratio of available equipment items to number of work orders recorded annually (Equation 1). This approach ensures that the scarcest resources (in terms of equipment) are prioritized when some events cannot be completed within a month's available maintenance time. Equipment types with the lowest ratio are assigned the highest priority (i.e. priority 1). Based on a quartile system from our 2018 to 2020 dataset, the cutoffs for priority assignment are as followed: Priority 1 encompasses all ratios less than or equal to 1:133; Priority 2 from 1:132 to 1:44; Priority 3 from 1:43 to 1:10; and finally Priority 4 includes ratios 1:9 and smaller. Next, we prioritize events, again from one to four, by looking at the frequency of each event, one again being the highest; the lower the frequency, the higher the priority (Equation 2). Events such as two-year validations occur infrequently, so it is crucial that their scheduling is conducted in a timely manner to avoid possible delays. Once again using a quartile system from our dataset and the cutoffs for the number of occurrences are as followed: Priority 1 events have a frequency fewer than 14 between 2018 to 2020; Priority 2 includes 15 to 65; Priority 3 includes 66 to 300; and Priority 4 is 301 and higher.

$$equipment\ priority_i = \frac{number\ of\ available\ equipment\ type_i}{number\ of\ work\ orders\ for\ equipment\ type_i} \tag{1}$$

$$event\ priority_i = frequency\ of\ event\ type\ _i\ from\ 2018 - 2020 \tag{2}$$

If the total number of maintenance hours required exceeds the available hours, then the prioritization algorithm is applied to drop events from the schedule. First, the model drops all equipment Priority 4 events and re-calculates the expected duration for all remaining events. This process is repeated for equipment Priority 3 and Priority 2 events as necessary until there are enough available hours to complete all scheduled events. If only equipment Priority 1 events remain and the number of available hours is still insufficient to accommodate all remaining events, a similar approach is used to eliminate events based on their event priority.

When dropping events in this last step, the model retains all daily events because these are crucial for the upkeep of equipment and have relatively short durations of only fifteen minutes, on average. This approach ensures that there is always equipment available and ready to process allografts.

The model ultimately outputs an Excel file that automatically fills all upcoming maintenance events for AlloSource for the subsequent month. It also produces important metrics associated with that output, including the total maintenance hours due that month, total maintenance hours available, and the total unplanned maintenance hours allotted. Our model flow process is pictured below in Figure 1.

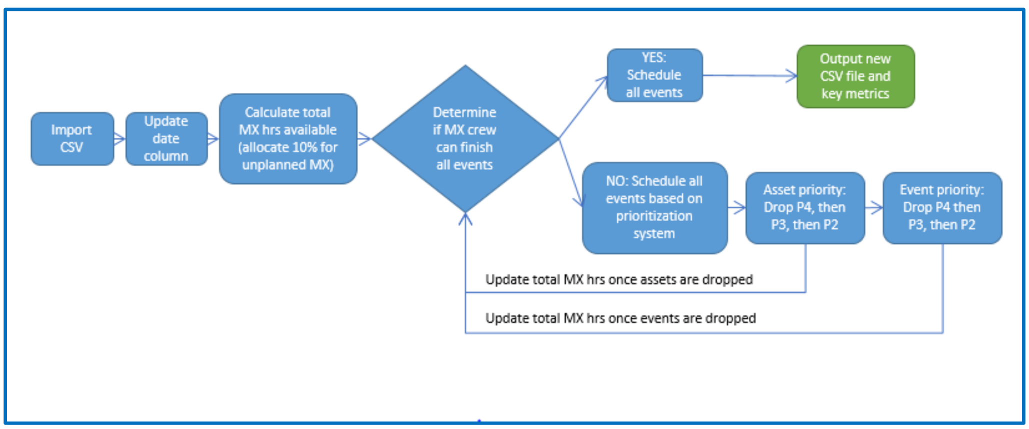

Figure 1. Model Flow and Priority Breakdown

3. Results

In the end, our model produces a preventive maintenance schedule for the next month, a sample of which is depicted in Table 1 below. The key output of the schedule includes all events that need to be accomplished within the month, the date on which they are due, and the expected duration (in hours) of each.

Table 1. Sample Maintenance Schedule Output, April 2021

Work ID	Asset ID	Asset Description	Event Name	Time Frame	Due Date	Average Duration	Asset Priority	Event Priority
MNT-213833	GF1	Mon/Inj Glycol	Weekly Mx	Weekly	4/06/2021	0.77	1	3
MNT-213902	PWS1	Purified Wtr Sys	Weekly Mx	Weekly	4/07/2021	3.94	1	3
MNT-213816	INC1CHA	Incubator	Weekly	Weekly	4/05/2021	0.20	1	3
VAL-000054	VHP1	Autoclave	Ann Valid.	Annual	4/24/2021	0.93	1	2
MNT-211372	DCR10	Chart Recorder	Semi-Ann Mx	Semi-Ann	4/07/2021	0.33	1	2

In testing our model against current data (i.e. creating a schedule for April 2021), we find that there are 1150.4 hours of maintenance events that need to be accomplished. Utilizing sequential experimentation, we ran the model three times, testing maintenance efficiency with two, three, and four maintenance crew members. As shown below in Table 2, each additional crew member significantly increases the total maintenance hours available. Notably, as the schedule shifts from two to three crew members, the number of available maintenance hours approaches the necessary 1150.4 hours needed for the month. Furthermore, when the maintenance crew availability was raised to four members, our model indicated that the number of maintenance hours available exceeded what was necessary. In other words, planning for three crew members throughout the month will allow AlloSource to meet its maintenance requirements while still maintaining more than 10% of the available maintenance hours for potential unscheduled events.

In accordance with an increase in available maintenance hours, additional crew members also increase the amount of unplanned maintenance hours that can be allotted for the month; each additional crew member increases the unplanned maintenance hours by approximately forty-two hours on average. In the event that unplanned requirements are fewer than the allotted number of hours, the excess can be directed in any manner the AlloSource crew sees fit, most notably adding events that may have been dropped from the schedule due to the prioritization process. This allotment of unplanned maintenance hours is expected to increase the morale and satisfaction of the work crew as they have more flexibility when it comes to completing all the events due that month.

Table 2. April 2021 Schedule Results Varied by Number of Crew Members

Number on Maintenance Crew	**Total Number of Work Orders**	**Total Maintenance Available (hours)**	**Unplanned Maintenance Allotted (hours)**
2	566	766.8	85.2
3 [1]	1,220	1,150.2	127.8
4	1,273 [2]	1,533.6 [2]	170.4

[1] optimal maintenance crew size
[2] all due April 2021

A comparison of the work completed in previous years and what is projected in April 2021 demonstrates a significant increase in the amount of work that can be accomplished by using our projected schedule, as shown in Table 3. This includes a 40% increase in the number of work orders that can be completed and a doubling of the work hours that can be completed. This is important as it allows less frequent maintenance events, which generally take longer, to be completed while still allowing time for unplanned maintenance.

Table 3. Monthly Comparisons

Month and Year	**Total Work Orders**	**Average Duration (hours)**	**Total Duration (hours)**
April 2018	849	0.562	477.0
April 2019	845	0.692	590.6
April 2020	870	0.687	597.3
April 2021 (projected)	1,220	0.943	1150.4

Of note, the majority of April 2021 events are annual maintenance. In contrast, previous years at AlloSource emphasized quarterly events in the month of April, which have much shorter durations; the average quarterly event duration is 0.51 hours and the average annual event is 3.67 hours. Consequently, with more annual events prioritized, a larger total duration is expected. We also discovered that in previous years not all maintenance events were completed as required. Our model corrects this inconsistency without placing undue pressure on the maintenance staff.

4. Conclusions

Medical machine maintenance has proven to be a vital component to the success of tissue banks globally. The complex process of cleaning and preparing tissue donations into allografts for distribution requires a standardized maintenance schedule that enables an uninterrupted production system. We developed a preventive maintenance scheduling model to supply a consistent monthly calendar for all required maintenance events, while retaining flexibility to accommodate unexpected equipment failures. We recommend that AlloSource run this scheduling model at the end of every month to prepare the tissue bank for all maintenance events due in the subsequent month. Although the model initially provides an increase in total maintenance hours, consistent application will avoid unnecessary or poorly timed maintenance, thereby reducing the average maintenance required in the long term.

After examining the data and analyzing our scheduling model results, we conclude that in past years the company has not been utilizing their maintenance crew optimally. In other words, they were not scheduling events in accordance with the maintenance crew availability as our model does. We consistently ensure that all required maintenance events are scheduled in the time frame required, with the hours available for maintenance closely aligning with the expected durations of planned events, yet still reserving time each month for unplanned maintenance activities. With better scheduling alignment and crew utilization, we expect AlloSource's performance to improve overall in the long term as equipment downtime will become more consistent and predictable, meaning that there will be a natural increase in annual throughput and production revenue.

While our algorithm reduces the uncertainty of maintenance operations and increases system functionality, it also naturally reduces the number of unexpected maintenance calls. As a result, our solution will also decrease the amount of tissue donation lost due to unpredicted failures and therefore increase annual allograft throughput. Furthermore, AlloSource utilizes annual revenue totals from medical distributors to assess production performance; implementing this scheduling approach also provides a financial advantage for the company. As production quality and quantity increases, so too does revenue. Moreover, with improved maintenance scheduling the facility should be spending less money replacing equipment. Ultimately, the organization benefits across all spectrums, proving the model successful.

While a monthly maintenance schedule provides beneficial analysis, future work could expand the model to produce a yearly outlook of maintenance events to compare overall performance to previous years. This will allow AlloSource to more accurately assess key metrics such as annual throughput and revenue.

Finally, we found maintenance efficiency is highly dependent on crew size. Thus, future studies should examine how the number of maintenance crew members affects event completion and system functionality, and should consider designating specific crew member to certain events to further enhance schedule efficiency.

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