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Article

Ocular Prosthesis Fabrication Scheduling Using Genetic Algorithm

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Abstract. This research examines an ocular prosthesis centre's operation and incorporates scheduling decision techniques to optimise its fabrication. A customised eye prosthesis is a make-to-order product which involves several labour-intensive processes and inherently poses scheduling challenges. As a result, patients' fitment dates are appointed with extra time to account for potential delays. The objective of scheduling is to minimise both total completion time and tardiness. The methodology begins with a process review of the customised eye prosthesis fabrication and criteria. Subsequently, a Mixed Integer Linear Programming (MILP) model is formulated to solve the assignment and sequencing problems. It is found during this stage that computational time increases significantly as the number of orders increases. To solve this problem, a Genetic Algorithm (GA) is proposed to find a near-optimal solution in a reasonable computational time. Instances selected for experiment are based on characteristics of a tertiary hospital's ocular prosthesis centre. Small instances are experimented to validate the proposed algorithm against the MILP model. The GA demonstrates near-optimal solutions with a variance of one percent, with reasonable computational time. Practical-size problems are subsequently solved using the proposed algorithm. In conclusion, the proposed GA yields satisfactory solutions with acceptable runtime for this application.

Keywords: Mix integer linear programming, scheduling, assignment, sequencing, genetic algorithm.

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1. Introduction

Vision is the most important of all five human sensing abilities according to a literature by Enoch et al. [1]. The unfortunate loss of an eye caused by trauma, end-stage ocular diseases or congenital malformation [2-5], creates tremendous physical and emotional distress on a person's livelihood. An ocular prosthesis (prosthetic eye) is an artificial spherical shaped object designed to physically fill the patient's eye socket. Even though the prosthetic cannot restore the patient's vision, it provides physical and psychological healing which lead to improved social and professional life. In general, an acceptable fitting period for an ocular prosthesis is four to twelve weeks after the surgery [5-8]. However, a study by Chin et al. [6] found that earlier fitting post eye-removal affords better fitment and lesser overall irritation for patients. Hence, replacing a patient's loss eye with a prosthetic with relative urgency is crucial and must be considered [4].

There are two types of ocular prostheses available; ready-made and custom-made prostheses. Custom-made ocular prostheses are preferred in comparison with ready-made ones as they offer superior fit, comfort, and aesthetic [3,8-13] and will be the focus of this research. Customised ocular prostheses are made with acrylic resin due to its superior durability and ease of fabrication [4,8,9,14,15]. Although different techniques exist in creating a customised prosthetic, key steps in the fabricating process all involve [3,8,9,11-17] (i) formation of an impression mould and sclera fabrication (ii) fabrication of an iris (iii) sclera finalization (iv) placement of iris on sclera, painting the eye prosthesis and processing a conjunctiva and (vi) finishing and polishing eye prosthesis. Since a custom-made ocular prosthesis must be fitted to each patient's eye socket and matched the remaining eye colour, such production requires delicately skilled ocularists [7,9] who must be trained and have been practising for three to five years at a minimum, depending on a country's regulation [7].

An ocular prosthesis centre provides patients who have lost an eye with a custom-made ocular prosthesis. It designs and produces personalized prosthetic eyes for patients to help ease the psychological effects of losing an eye and restore the aesthetics needed to improve patients' quality of life. The average fabrication time of a custom-made ocular prosthesis is between six to ten hours [7,8,10]. A personalized eye prosthetic is carefully fitted to each patient's prescription by trained ocularists at the centre. Due to limited staff and delicate tasks involved, scheduling such an operation is rather difficult, and additional slack time is normally built into the schedule to ensure no final patient's fitting appointment is missed. Too long waiting time post-eye removal can result in a patient's eye socket deformation, which will negatively affect the wearing of the prosthetic. Therefore, scheduling is an integral tool that incorporates planning and decision making to reduce patients' waiting time to final fitting. Scheduling at the ocular prosthesis centre revolves mostly around the ocularists as they are the main driving force behind this operation.

Effective scheduling mostly relies on the accuracy of input data. Appropriate data analysis and forecasting technique provides an informed decision about the future conditions. Cheevachaipimol et al. [18] implemented a hybrid deep learning method to predict flight delays. Chaowai and Chutima [19] applied an exponential smoothing technique in demand forecasting and found improved forecasting accuracy of fast-moving consumer products. Other than quantitative techniques, qualitative tools such as Delphi technique was implemented in the study of Chuaykoblap et al. [20] to improve data accuracy.

Heuristic algorithms are introduced to determine the near-optimal solutions to the optimization problems, Thongsanit et al. [21] applied heuristic to determine the lower bound and upper bound of the completion time for the task-worker assignment problem. Lehuang and Kongkeaw [22] studied the precast production scheduling using the variable neighbourhood search algorithm. Chew et al. [23] applied Genetic Algorithm (GA)-based optimization in the control system as GA technique has been widely used to solve complex optimization problems. Kamsopa et al. [24] developed a metaheuristic approach that combines hybrid genetic algorithm and variable neighbourhood search algorithm to solve the multi-period vehicle routing problem.

In general, scheduling in healthcare focuses on reducing costs, improving patient flow and optimising personnel production [25]. Special considerations are given to work assignments in past studies. For instance, Idigo et al. [26] deduced a patient scheduling method with priorities given to improving patient flows in a tertiary hospital's radiology department. In a study by Malekian et al. [27], Luo et al. [28], Amindoust et al. [29], Nobil et al. [30], and You and Hsieh [31], each developed a mathematical model that allowed shifting and allocating of medical personnel to accommodate varying skills and work conditions. The work of the ocularists, however, requires considerations of both assignment and sequencing due to varying work experience, hence the time it takes to produce a prosthetic is different for each ocularist. There are existing health system research that offer solutions to both problems, such as the study of Pham et al. [32] presenting a treatment schedule for patients treated with radiation therapy by sub-dividing the solution into two parts: assigning patients to radiation machines and sequencing treatments. However, the work of the ocularists is also a fabricating process, which differs in characteristics and working conditions from the work of a typical healthcare system. A compartmentalized problem solving technique used in the above example cannot yield the best solution for problems requiring simultaneous solving such as the ones contained herein. Therefore, this research has adopted a task-based scheduling methodology to account for the production variance found in personalized ocular prosthesis fabrication.

At present, research on healthcare systems that utilize production system scheduling remains limited and does not cover all functional units of the healthcare. Such examples include Pham et al. [33] applying a multi-mode blocking job shop model for scheduling surgical cases to reduce the makespan, Fan et al. [34] studying a patient flow scheduling problem at an ophthalmology clinic to minimise the completion time of all the patients going through several processes, and Vali et al. [35] finding that patient scheduling was similar to the problem of flexible job-shop scheduling, so the concept was used to optimise patient flow in the patient flow management problem. The summary of the literature is shown in Table 1.

Table 1. Summary of the literature review.

Author(s)	Problem		Fabricating process	Methodology
	Assignment/ Allocation	Sequencing		
Malekian et al. [27]	✓			Mathematical model and GA
Luo et al. [28]	✓			Queuing theory and mathematical model
Amindoust et al. [29]	✓			Mathematical model and hybrid GA
Nobil et al. [30]	✓			Mathematical model
You and Hsieh [31]	✓			Mathematical model and hybrid GA
Pham et al. [32]	✓	✓		Mathematical model and simulation
Pham et al. [33]	✓	✓		Mathematical model
Fan et al. [34]	✓	✓		Hybrid heuristic
Vali et al. [35]	✓	✓		Hybrid heuristic
This study	✓	✓	✓	Mathematical model and GA

None of the research mentioned require fabricating process consideration as does the work at an ocular prosthesis centre, where different conditions affect the problem formation. This study aims to address the research gap by implementing an efficient scheduling method to assign and sequence ophthalmologists' ocular prosthesis orders to ocularists in a tertiary hospital's ocular prosthesis centre in Bangkok, Thailand. The scheduling objective is to minimise the total completion time and tardiness of ocular prosthesis orders. A Mixed Integer Linear Programming (MILP) model is formulated to simultaneously solve two sub-problems; the order assignment and operation sequencing required to schedule the fabrication of the personalised ocular prostheses. Subsequently, the authors enlisted a Genetic Algorithm (GA) to solve the practical-size problems.

2. Problem Description and Formulation

This section starts with the studying of the ocular prosthesis fabrication process at a case study ocular prosthesis centre and conditions in which the ocularists operate, then presenting a mathematical formulation for assigning and sequencing of the procedures.

2.1. Problem Description

This research examines real-life problems of the case study ocular prosthesis centre with primary focus on scheduling improvement. The centre provides custom ocular prosthesis fitting, fabrication and maintenance services. The fabrication work is performed throughout the week, but patient visitations are limited only to office hours on Wednesdays for ocular impression, fitting, and maintenance services. The ocular impression is typically performed by an ophthalmologist to map the contour of an eye socket, and the impending ocular prosthesis order is initiated, complete with annotated levels of fabrication difficulty (type), ranging from standard to advance. Standard orders can be tackled by any ocularists, while advanced orders must be fulfilled by senior ocularists. Once the orders are submitted for fabrication, the scheduling for ocularists is kept current on a weekly basis. The orders are manually assigned by matching order types with the ocularists' required experience and availability. Due to highly customization levels involved, each eye prosthetic, once assigned, is fabricated entirely by the same ocularist from start to end to ensure continuity and prevent rework. Presently, the fabrication sequencing and duration of an eye prosthetic is at an individual ocularist's discretion as one controls the entire fabrication process per order.

Based on the current fabrication process at the case study centre, the fabrication can be organised into five procedures as per Fig. 1.

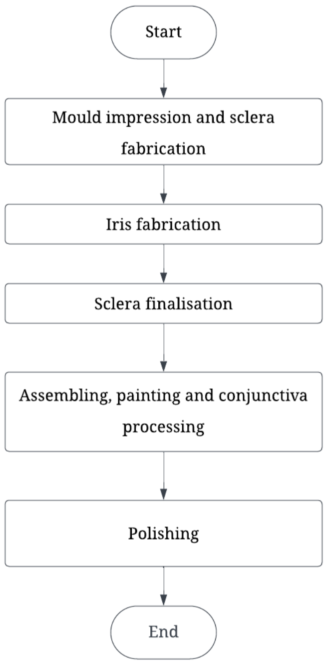

Fig. 1. Fabrication process.

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Once the impression of an eye socket is created, the mould is cast, and a sclera is fabricated. At the end of the sclera fabrication process, thermal curing is required to harden the resin. During the sclera curing, the designated ocularist is available to perform other procedures such as iris fabrication. Once the curing is complete, grinding and polishing are performed to modify the sclera to achieve precision fit. The fabrication of the sclera and iris can be worked separately, as noted. However, the process of assembling the sclera to the iris can only commence after the completion of both parts' fabrication. The eye prosthetic is assembled by placing the iris onto the sclera, then hand-painting is performed to match the appearance of the patient's remaining eye. To process the conjunctiva (a clear membrane that covers the sclera), the transparent acrylic resin is packed onto the eye prosthetic and simultaneously cured. Similar to the sclera curing performed prior, the final assembly curing once again frees up the ocularist to perform other tasks. When the prosthetic is cured, final finishing and polishing are performed, readying it for patient fitting.

The sequencing of the ocular prosthetic fabrication procedures is unique in healthcare industry because each order must be initiated and completed exclusively by a single ocularist. Moreover, during the two curing procedures during the sclera and conjunctiva fabrication, the ocularist is temporary freed up and can perform other procedures or initiate new orders. This increased flexibility affords us additional decision points to further optimize the sequencing within the schedule. The process starts with the ophthalmologist's initial annotation of task difficulty level during order initiation to match ocularists' qualified expertise. Subsequently, ocularist operations are performed sequentially to complete an order. With all the working conditions taken into consideration, the fabrication scheduling is further divided into two sub-problems: job assignment and sequencing of operations.

This study focuses on the problem of assigning ophthalmologist orders to ocularists and sequencing of the fabrication procedures to optimize production over a given time horizon (one week). Since each custom-made ocular prosthetic is individually fabricated with varying degrees of difficulties, matching the ocularists skill levels to tasks at hand is vital. This definition is adopted as constraints to formulate a mathematical model of the problem. The objective of this problem is to minimise the total completion time and tardiness of orders by providing an optimal scheduling scheme for the ocularists, hence reducing the overall patient waiting time.

Completion time and tardiness are typically considered in parallel in scheduling when a delay or wait time is undesirable as were the case in the study of Noori-Darvish and Tavakkoli-Moghaddam [36], Lin et al. [37] and Heydari and Aazami [38]. As the case study centre opens once weekly, any late order will cause at least a week of delay and may result in worsening condition for the patients, considering both completion time and tardiness in the schedule is prudent. When the centre can complete ocular prosthetic orders faster through improved fabrication process, a greater number of orders can be served. Consequently, patients do not have to wait in a long queue for their custom-made ocular prosthetics. Restoring the patient's lost eye with an ocular prosthetic with expediency not only restores aesthetics and confidence to the patient in a timely manner, it also help prevent the patient's ocular socket from shrinking or deforming due to long waits. As such, a mixed integer linear programming model of the problem is formulated to tackle this problem.

2.2. Mathematical Formulation

In this section, modelling assumptions for the fabrication scheduling problem are discussed, then a mathematical model is formulated based on the defined assumptions, indices, parameters, and decision variables.

2.2.1. Modelling Assumptions

To formulate the proposed mathematical model, the following assumptions are considered.

(1) The type of ocular prosthesis order is classified through the impression process by the ophthalmologist as either advanced or standard. Advanced orders can only be assigned to senior ocularists, while standard orders can be assigned to any ocularists.

(2) Each order can only be processed by a single compatible ocularist.

(3) All orders are independent and arrive at once.

(4) Each ocularist can only work on one procedure at a time.

(5) Once an ocularist starts working on any fabrication procedure, it must continue uninterrupted until completion (except curing)

(6) Processing times are different among fabrication procedures and ocularists. Durations are known in advance and estimated based on current practices at the case study centre. The setup time between two consecutive procedures is negligible.

(7) There is no need for ocularists' involvement or interruption during the curing procedure; they are allowed to work on other procedures or orders.

(8) Scheduling is performed once a week.

2.2.2. Notation

The following symbols, including sets, indices, parameters, and decision variables used in the scheduling problem formulation are as defined in Table 2 to 4.

Table 2. List of sets and indices.

Sets and indices	Definitions
I	Set of fabrication procedures, $i \in \{1,2,\dots,5\}$ where $i = 1$ denotes the mould and sclera fabrication procedure (except curing), $i = 2$ denotes the iris fabrication procedure, $i = 3$ denotes the sclera finishing procedure, $i = 4$ denotes the assembling, painting, and processing the conjunctiva procedure (except curing), and $i = 5$ denotes the finishing and polishing of the ocular prosthesis.
J	Set of orders, $j \in \{1,2,\dots,n\}$ where n is the total number of orders
K	Set of ocularists, $k \in \{1,2,\dots,m\}$ where m is the total number of ocularists
P	Set of task sequences, $p \in \{1,2,\dots,q\}$ where q is the total number of task sequences

Table 3. List of parameters.

Parameters	Definitions
AS_{jk}	Binary parameter equals 1 if order j can be assigned to ocularist k, and 0 otherwise
PT_{ijk}	Processing time when procedure i of order j is fabricated by ocularist k
PTC	Curing time
DD_j	Due date of order j
M	A sufficiently large number

Table 4. List of decision variables.

Decision variables	Definitions
X_{ijk}	Binary variable equals 1 if procedure i of order j is assigned to ocularist k, and 0 otherwise
Y_{ijkp}	Binary variable equals 1 if procedure i of order j is assigned to ocularist k as task sequence p, and 0 otherwise
ST_{ij}	Starting time of procedure i of order j
STW_{kp}	Starting time of ocularist k to perform task sequence p
CT_j	Completion time of order j
T_j	Tardiness of order j

2.2.3. Mathematical model

The proposed mathematical model can be written as a MILP model. The objective function of the problem, as presented in Eq. (1), is to minimise the total completion time and tardiness of all orders.

$$Min\ Z = \sum_{j\in J} CT_j + \sum_{j\in J} T_j \quad (1)$$

Constraints (2), (3) and (4) ensure that fabrication procedures of each order must be processed by only one compatible ocularist.

$$\sum_{k\in K} X_{ijk} = 1,\ \forall i \in I, \forall j \in J \quad (2)$$
$$X_{ijk} \le AS_{jk},\ \forall i \in I, \forall j \in J, \forall k \in K \quad (3)$$
$$X_{ijk} \le X_{(i-1)jk},\ \forall i \in \{2,3,4,5\}, \forall j \in J, \forall k \in K \quad (4)$$

Constraints (5) and (6) ensure that each procedure i of any order j that is assigned to an ocularist k can only be sequenced once, and each ocularist can only work on one procedure at a time, respectively.

$$\sum_{p\in P} Y_{ijkp} = X_{ijk},\ \forall i \in I, \forall j \in J, \forall k \in K \quad (5)$$
$$\sum_{i\in I}\sum_{j\in J} Y_{ijkp} \le 1,\ \forall k \in K, \forall p \in \{1,2,\dots,q-1\} \quad (6)$$

Constraints (7) to (11) determine the starting time of each procedure. The second, third and fourth procedures ($i = 2, 3$ and 4) can start promptly after the finishing of the first, second and third procedures ($i = 1, 2$ and 3) respectively, while the third and fifth procedures ($i = 3$ and 3) must be held until the finishing of the curing process.

$$ST_{2j} \ge ST_{1j} + \sum_{p\in P}\sum_{k\in K}(PT_{1jk} \times Y_{1jkp}),\ \forall j \in J \quad (7)$$
$$ST_{3j} \ge ST_{2j} + \sum_{p\in P}\sum_{k\in K}(PT_{2jk} \times Y_{2jkp}),\ \forall j \in J \quad (8)$$
$$ST_{4j} \ge ST_{3j} + \sum_{p\in P}\sum_{k\in K}(PT_{3jk} \times Y_{3jkp}),\ \forall j \in J \quad (9)$$
$$ST_{3j} \ge ST_{1j} + \sum_{p\in P}\sum_{k\in K}(PT_{1jk} \times Y_{1jkp}) + PTC,\ \forall j \in J \quad (10)$$
$$ST_{5j} \ge ST_{4j} + \sum_{p\in P}\sum_{k\in K}(PT_{4jk} \times Y_{4jkp}) + PTC,\ \forall j \in J \quad (11)$$

Constraint (12) prohibits overlapping of tasks.

$$STW_{k(p+1)} \ge STW_{kp} + \sum_{i\in I}\sum_{j\in J}(PT_{ijk} \times Y_{ijkp}),\ \forall k \in K, \forall p \in \{1,2,\dots,q-1\} \quad (12)$$

Constraints (13) and (14) identify relationships between STW_{kp} and ST_{ij}.

$$STW_{kp} \ge ST_{ij} - M(1 - Y_{ijkp}), \forall i \in I, \forall j \in J, \forall k \in K, \forall p \in P \quad (13)$$
$$STW_{kp} \le ST_{ij} + M(1 - Y_{ijkp}), \forall i \in I, \forall j \in J, \forall k \in K, \forall p \in P \quad (14)$$

Constraints (15) and (16) determine the completion time and tardiness of each order.

$$CT_j \ge ST_{5j} + \sum_{p\in P}\sum_{k\in K}(PT_{5jk} \times Y_{5jkp}),\ \forall j \in J \quad (15)$$
$$T_j \ge CT_j - DD_j,\ \forall j \in J \quad (16)$$

Nonnegativity and binary variables are stated in constraints (17) to (20) and (21) to (22), respectively.

$$ST_{ij} \ge 0,\ \forall i \in I, \forall j \in J \quad (17)$$
$$STW_{kp} \ge 0,\ \forall k \in K, \forall p \in P \quad (18)$$

$$CT_j \geq 0 , \forall j \in J \tag{19}$$

$$T_j \geq 0 , \forall j \in J \tag{20}$$

$$X_{ijk} \in \{0, 1\} , \forall i \in I, \forall j \in J, \forall k \in K \tag{21}$$

$$Y_{ijkp} \in \{0, 1\} , \forall i \in I, \forall j \in J, \forall k \in K, \forall p \in P \tag{22}$$

3. Solution Approach

As scheduling must be performed periodically (weekly), a practical solution method for a realistic-size problem should be able to generate a good schedule in a reasonable time. In this research, we propose implementing a GA, a population-based algorithm that can solve practical-size instances to solve this problem. The GA is a reliable algorithm that yields solutions to a problem with three operations: selection, crossover, and mutation [39]. The tactical steps of the GA are demonstrated in Fig. 2.

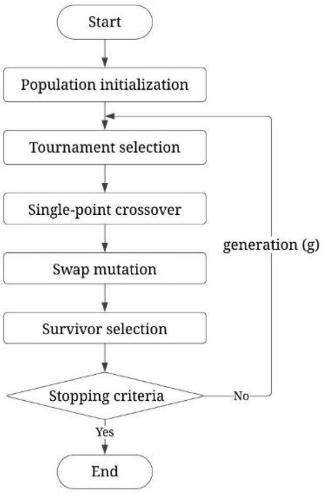

Fig. 2. Steps of genetic algorithm.

```
Genetic Algorithm
Input: Genetic Algorithm parameters (population size, number of generations, crossover
probability, mutation probability), iteration;
Begin
   Encode and initialize population (population)
      population = empty list;
      While population < population size do
         Generate a random sequence of operation (OS)
            For i: iteration do
               Generate a random assignment (AS)
               If AS follow assignment constraint, then
                  Return AS
            End for
         Generate initialize population by OS and AS
      End while
   Determine objective function
   For i: number of generations do
      While parents < population size / 2 do
         Randomly k solutions from population (k is tournament size)
         Select solution that provides the best objective value
      End while
      For i: parents do
         If random probability < crossover probability, then
            Parent1 = parents(i)
            Parent2 = parents(i+1)
            Generate offsprings by single-point crossover (Parent1, Parent2)
            If Offspring1, Offspring2 do not follow constraint then
               Randomly Offspring1, Offspring2 from parents
         Else
            Offspring1 = parents(i)
            Offspring2 = parents(i+1)
      End for
      For i: offsprings do
         If random probability < mutation probability, then
            Offspring = offsprings(i)
            Generate offsprings after mutation by swap method (Offspring)
         Else
            Offspring = offsprings(i)
      End for
      population = offsprings
   End for
   Return the best solution from population
End
```

Fig. 3. The pseudo-code of the proposed GA.

The pseudo-code of the proposed GA is presented in Fig. 3. The GA algorithm starts with population initialization to identify the seeding of initial solutions. The population includes solution alternatives called chromosomes. Each chromosome comprises a set of variables called genes. The chromosome presentation comprises two parts which are assignment of order (to an ocularist) and sequencing of order. Figure 4. demonstrates the assignment of order to the ocularist. The number of chromosomes that will be used in a genetic algorithm is generated as an integer number in accordance with number of orders. Each gene represents the order number (*j*) and the numbers assigned to each gene represent the assignment of order to ocularist. In Fig. 4. order numbers *1* and *3* (*j = 1, 3*) are assigned to the first ocularist (*k=1)*. Order number *2* (*j = 2*) is assigned to the second ocularist (*k=2)* and order number *4* (*j = 4*) is assigned to the third ocularist (*k=3)*. Fig. 5. represents the sequencing of tasks (*p*). In Fig. 5. there are 4 orders (*j = 1, 2, 3* and *4*) where each order contains 5 procedures (*i = 1, 2, 3, 4* and *5*).

J_1	J_2	J_3	J_4
1	2	1	3

Fig. 4. Example of order assignment.

J_2 I_1	J_4 I_1	J_3 I_1	J_4 I_2	J_1 I_1	J_2 I_2	J_1 I_2	J_4 I_3	J_3 I_2	J_4 I_4	J_2 I_3	J_1 I_3	J_1 I_4	J_4 I_5	J_1 I_5	J_3 I_3	J_3 I_4	J_2 I_4	J_3 I_5	J_2 I_5
1	3	2	3	0	1	0	3	2	3	1	0	0	3	0	2	2	1	2	1

Fig. 5. Example of task sequence.

The initial chromosome population is randomly generated with an assignment of orders and sequencing of tasks, then the assignment constraints are checked for violation. If a violation is found, the order must be assigned to other suitable ocularist. an initial solution is generated as demonstrated in Fig. 6.

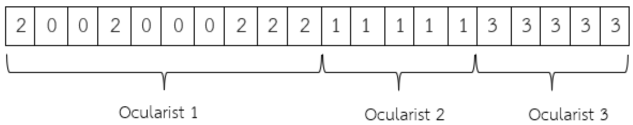

Fig. 6. Example of an initial solution.

The next step is a selection operation. We proceed with a tournament selection algorithm to select an individual chromosome to populate the next generation. Then, a single-point crossover is used to identify the offspring. These chromosomes subsequently produce offsprings using a swap mutation. The initial and additional population will be ranked based on the fitness value during the survivor selection process to carry into the next generation. This process continues for number of generations g.

The proposed GA gains popularity in recent times due to its ability to solve a wide range of problems. A significantly number of studies have applied GA to solve scheduling problem in healthcare. For example, Malekian et al. [27] and Amindoust et al. [29] used GA to solve a nurse scheduling problem with considerations of the nurses' seniority and fatigue factors, respectively. You and

Hsieh [31] also implemented GA to solve a medical staff's scheduling problem with considerations of skill levels and vacation controls. Agnetis et al. [40] and Rivera et al. [41] applied GA to solve surgery scheduling problems. In medical staffing and resource scheduling realm, GA is also used prevalently to schedule patients and medical treatments in health centres as exemplified in the study of Karpagam et al. [42] and Squires et al.[43], respectively. Given GA's presence in healthcare scheduling problem solving and its technical relevance to our problem, its utilization in this study, henceforth, is justified.

4. Results

The developed GA is first validated with small instances against the MILP model using CPLEX solver. Then the GA is empirically studied for the practical-size problem with data collected from the case study centre.

4.1. Validation

In this section, we validate the proposed GA by comparing its performance with the MILP's. We create several instances of small size problems to compare with the MILP model. The data set is randomly generated based on the information collected from the current practice at the case study centre. There is one senior ocularist and two ocularists on staff at this centre. Ophthalmologist orders are classified as advanced or standard orders. For any ocular prosthesis orders, all five fabrication procedures must be completed by the initiating ocularist. The results obtained from the GA are recorded and compared with solutions from the MILP model. The total completion time, tardiness and computational time (runtime) are recorded. Python and IBM ILOG CPLEX Optimization Studio are used to solve the proposed GA and MILP model on an Intel® Core i5-1240P processor with 1.7 GHz notebook computer with 12 GB of RAM. The results of the validation study are demonstrated in Table 5 and 6.

Table 5. Results of the MILP.

(*i,j,k*)	**Total completion time (minutes)**	**Total tardiness (minutes)**	**Runtime (seconds)**
(5,4,3)	1,208.00	0.00	12.66
(5,5,3)	1,635.00	0.00	401.91
(5,6,3)	2,130.00	0.00	710.92

Table 6. Results of the proposed GA.

(*i,j,k*)	**Total completion time (minutes)**	**Total tardiness (minutes)**	**Runtime (seconds)**
(5,4,3)	1,208.00	0.00	21.83
(5,5,3)	1,648.20	0.00	33.70
(5,6,3)	2,149.80	0.00	39.16

Average values of the GA and the MILP solutions are demonstrated. As shown in Table 5 and 6, only small size problems (up to six orders) can be solved using the MILP model. The CPLEX solver does not converge and is forcefully terminated when the number of orders is larger than six. The computational time of the CPLEX solver increases significantly when the number of orders increases. As can be seen in the second and third instances, the computational time increases from 401.91 seconds to 710.92 seconds (a 77% increase) when the order number increases from five to six (an increase of one). The computational time increases dramatically for the CPLEX solver but does not differ much in the GA. When comparing the runtime between algorithms, the GA computational time is significantly smaller than that of the CPLEX solver, with the first instance being the lone exception.

The total completion time and tardiness in each instance is comparable using both methods. The due date is set to complete within one week. The proposed GA generates high-quality solutions with insignificant gaps compared with the CPLEX solutions while requiring far less computational time. As the proposed GA provides near-optimal solutions with a gap of 0.93 % and converges within 39.16 seconds. Therefore, we consider GA a valid solution approach to this problem.

To select the tournament size, probability of crossover and probability of mutation, different levels of these parameters are determined as shown in Table 7. As the largest problem that can be solved using the MILP method is *(i, j, k)* = *(5, 6, 3)*, this problem is used during the experiment.

Table 7. The level of parameters for GA.

Test parameters	**Level**
Tournament size (t)	3, 4
Probability of crossover (P_c)	0.6, 0.8
Probability of mutation (P_m)	0.01, 0.05, 0.1

Table 8. The objective function values of parameters in GA.

Instance	**Parameters**	**Objective values (minutes)**			**Gap**
	(t, P_c, P_m)	**Min**	**Max**	**Average**	
1	(3, 0.6, 0.01)	2,141.00	2,179.00	2,158.00	1.31%
2	(3, 0.6, 0.05)	2,158.00	2,175.00	2,167.80	1.77%
3	(3, 0.6, 0.1)	2,153.00	2,176.00	2,163.60	1.58%
4	(3, 0.8, 0.01)	2,143.00	2,168.00	2,160.20	1.42%
5	(3, 0.8, 0.05)	2,140.00	2,165.00	2,151.80	1.02%
6	(3, 0.8, 0.1)	2,153.00	2,182.00	2,169.80	1.87%
7	(4, 0.6, 0.01)	2,143.00	2,168.00	2,161.80	1.49%
8	(4, 0.6, 0.05)	2,149.00	2,174.00	2,160.60	1.44%
9	(4, 0.6, 0.1)	2,140.00	2,188.00	2,160.40	1.43%
10	(4, 0.8, 0.01)	2,141.00	2,162.00	2,149.80	0.93%
11	(4, 0.8, 0.05)	2,140.00	2,168.00	2,155.40	1.19%
12	(4, 0.8, 0.1)	2,141.00	2,168.00	2,156.80	1.26%

Table 8 demonstrates the results from different level of parameters of GA. The gaps of objective value between the GA and the CPLEX solutions range from 0.93% to 1.87%. The instance which contains tournament size of 4, crossover probability of 0.4 and mutation probability of

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0.01 yields the lowest gap. Therefore, these parameters are used in this study.

Figure 7. Demonstrates the convergence of objective function value obtained by the GA when the number of generations is set to 20 generations.

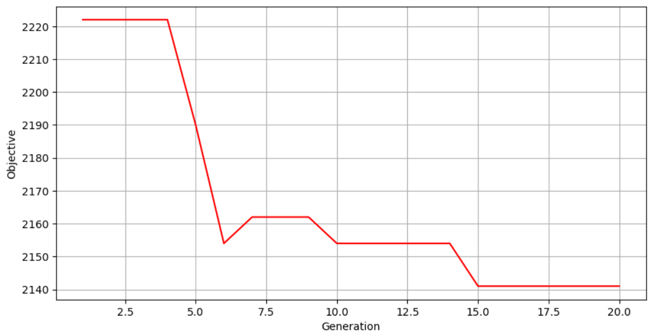

Fig. 7. The convergence of objective function value of GA.

4.2. Case Study

To access the performance of the proposed GA, we conduct experiments on a real set of data obtained from the case study centre. As manual scheduling can be time-consuming, the proposed solution will serve as guideline solution to the scheduling of ocularists at this centre. Unlike in the validation section, the real-size problem is solved herein. The computational results in Table 9 and 10 show that the proposed algorithm can solve instances of up to 26 orders without any tardiness.

Table 9. Total completion time (minutes) of the proposed GA.

(*i,j,k*)	**Min**	**Max**	**Average**
(5,12,3)	6,988.00	7,273.00	7,166.60
(5,18,3)	14,349.00	15,191.00	14,659.00
(5,24,3)	24,072.00	25,746.00	25,123.80
(5,26,3)	28,511.00	29,730.00	29,316.20

Table 10. Total tardiness (minutes) of the proposed GA.

(*i,j,k*)	**Min**	**Max**	**Average**
(5,12,3)	0.00	0.00	0.00
(5,18,3)	0.00	0.00	0.00
(5,24,3)	0.00	0.00	0.00
(5,26,3)	0.00	96.00	34.40

For any instance, several replications are performed with random data. Maximum, minimum, and average value of results are demonstrated. When running the proposed GA on the case study data for a weekly planning horizon, we found that the centre can handle all cases with no late order and with considerably small computational times. An example schedule for ocularists is depicted in Fig. 8.

In this scheduling instance, there are 18 orders ($j = 1, 2, \ldots, 18$) assigned to 3 ocularists ($k = 1, 2$ and 3). The fabrication of each order comprises sequential procedures $i = 1,2,3,4,5$. There are 2 curing procedures required (shaded areas in Fig. 8.) for any fabrication after the completion of procedures $i = 1$ and 4. Each order is unique and its difficulty level varies, hence requiring

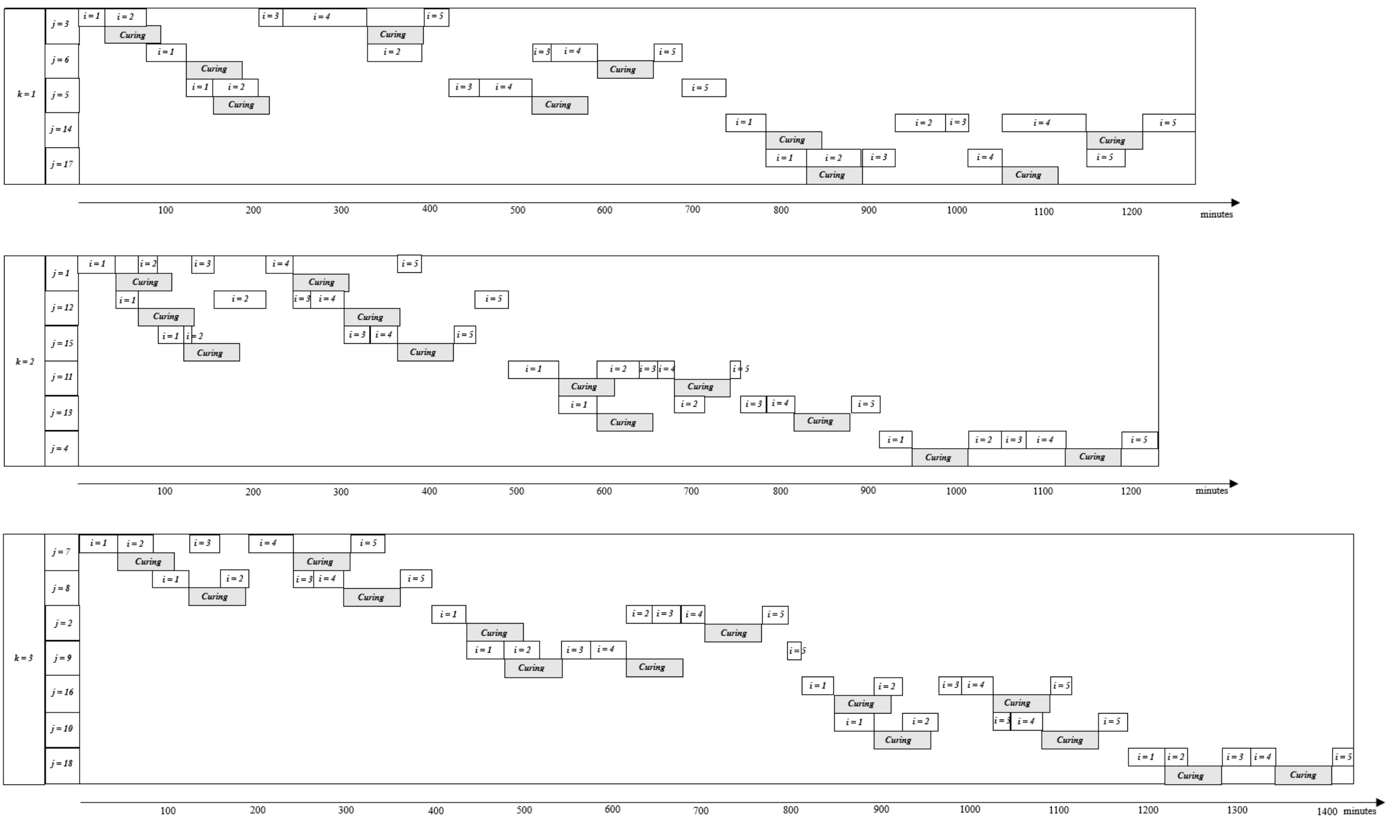

Fig. 8. Example schedule for an ocularist.

different processing time. Moreover, individual ocularists possess varying skill levels which allow them to perform at differing speeds.

The schedule suggests that during curing, an ocularist should initiate a new order or perform a parallel procedure within the same order to eliminate waiting time. These decision points are constantly evaluated to achieve the least total completion time and tardiness on a weekly basis. Current practice at the case study ocular prosthesis centre is that patient orders are received under the first come first serve policy. At the end of the day, when the centre is closed for the patients, the assignment and sequencing of orders are performed all at once considering the difficulties (based on fabrication time), due date, along with the ocularists' preferences. Once the ocularist starts performing on any order, all fabrication processes must be completed sequentially without interruptions. This inadvertently results in large amount of time during the curing process and yields low utilization of ocularists as a result. Under the current circumstance, on average, each ocularist can fabricate 6 ocular protheses per week. In other words, the case study centre can produce up to 18 orders per week. With the proposed solution, multiple orders can now be performed simultaneously. As shown in Fig. 8, an ocularist work on a few orders simultaneously; there is no need to waste time during the curing process as he or she can switch to work on new or adjacent orders. The proposed sequencing method effectively improved ocularist utilization rate substantially and increased the weekly order completion to 26 (from 18) or a 44% improvement.

To determine the effect of completion time and tardiness on the problem, weights (*a* and *b*) are placed on the objective function. When *a* is the weight on total completion time and *b* is the weight on total tardiness. Equation (1) is modified to Eq. (23) while others remain the same.

$$Min\ Z = a\sum_{j\in J} CT_j + b\sum_{j\in J} T_j \tag{23}$$

In this instance, we expand the size of the problem to 30 orders ($j = 1, 2, \ldots, 30$) assigned to 3 ocularists ($k = 1, 2$ and 3). Considering the same fabrication ($i = 1,2,3,4,5$) and curing procedures. The computational results are shown in Tables 11 and 12.

Table 11. Total completion time (minutes) of the proposed GA.

Weight (*a:b*)	Min	Max	Average
(1:0)	37,700	38,501	38,160.6
(0.75:0.25)	37,745	38,465	38,295.0
(0.25:0.75)	38,186	38,756	38,495.2
(1:1)	37,675	38,853	38,382.6

Table 12. Total tardiness (minutes) of the proposed GA.

Weight (*a:b*)	Min	Max	Average
(1:0)	175	777	394.8
(0.75:0.25)	318	665	508.2
(0.25:0.75)	17	169	85.0
(1:1)	125	592	303.8

When considering only completion time in an objective function (Table 11, *a:b* is *1:0*), it yields the lowest completion time, but at the same time also yields the highest maximum tardiness (Table 12, *a:b* is *1:0*). However, when putting more weight to tardiness than completion time (Table 12, *a:b* is *0.25:0.75*), the total tardiness is drastically minimised but does not affect the overall completion time when compared to other weight ratios (Table 11). According to the results above, there is no significant total completion time difference due to varying weight ratios between the completion time and tardiness.

5. Conclusions

The fabrication of custom-made ocular prosthetics relies heavily on the unique skills and experience of ocularists. Since ocularist staffing is fairly limited at any ocular prosthesis centre, optimised job scheduling is of utmost importance at such centres. We study the fabrication process at the case study centre and propose a MILP model to solve the assignment problem (assigning orders to the ocularists) and simultaneously address sequencing problem on a weekly basis. The objective is to minimise the total completion time and tardiness of the schedule. Due to the model's complexity, we propose the use of GA as a solution method to obtain near-optimal solution in a reasonable computational time. We perform computational experiments to validate and compare the performance of the proposed GA model with the MILP model. The staffing and scenarios selected for our instances are based on the actual characteristics of the case study centre. The computational results indicate that the GA algorithm provides solutions with a gap of 1.06% of the CPLEX solutions with considerably less computational time. The practical-size problems are solved using the proposed algorithm that yields acceptable solutions. This methodology and solution can be used as a guideline to formulate and solve scheduling problems for the ocularists at this centre.

Future studies could be conducted to consider order priorities and ocularist preferences. Other heuristic techniques could also be implemented, and results compared with the benchmark model, as well as the GA implementation.

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