Manpower Planning using Heuristics

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ABSTRACT
In this paper, we focus on manpower planning in one of the service companies which offers premium services to customers. The company has started embarking on its analytics journey and wanted to make the operational decisions based on data. Thus, the model proposed is based on past historical data over 36 months' periods and analyse the service time for each appointment to have a realistic number which will affect the number of staff required for daily operations. A mathematical model for manpower planning is then developed and solved using heuristics. The model developed in this paper help the management to do macro and micro level manpower planning so that the service level agreement is met and the customers' satisfaction is high to maintain good customers' relationship for the company in this competitive business world.

Keywords
Manpower planning, optimization, predictive model, heuristics

1. INTRODUCTION
People are one of the company's biggest assets, and give the company its competitive advantage especially for an organization which provides service. Thus, hiring and recruiting high-quality employees with the right skillsets to do the job well is also a very important task for most organizations. The mindset of employees in recent year has also changed drastically and that affects the relationship between employers and employees. In the past, people may just need a job to earn a living. Thus, job security was more important and they were willing to do routine jobs with limited information and knowledge. Nowadays, many people, particularly younger employees, view employment as a place to grow, learn new skills and enhance knowledge. Everyone is expected to be self-motivated. In the new social setting, however, employability is more important than lifetime employment.

The company has 30 years of experience and has been providing premium service to its customers. Their services are always oversubscribed and only shortlisted applicants will be notified via mail for the appointment date and time to select the service that they desire. When the customers arrive, they will register themselves and wait for the queue number to be called. The management associates (MA) are also scheduled weekly to meet the customers and offer their professional service.

Based on the current practice, each customer is given 45 minutes to be served regardless of the services that they select. For each MA, they are also given 10 to 12 customers to serve daily based on the manager's experience.

However, in the recent months, there has been an increasing number of complaints from customers that the lead time to meet the MA is more than a month, even though the service level agreement is to service all the customers within a month.

Lead time is defined as the time duration when the appointment letter is received to the time when the customers meet with MA. Staff are also unhappy with the appointment schedules given as there is an uneven workload distribution and they always need to work overtime to service the customers.

Due to the competitive business environment, higher management is keen to embark on making a scientific decision based on data. "Let's data do the talking" is the motto from the management and town hall event for all the employees that have been conducted to convey the messages on the importance of data analytics for future decision making. "Don't come to management meeting without data" is also another norm within the business. The Business Analytics Unit (BAU) has been set up in 2015 and the authors have collaborated with BAU for consultancy project and knowledge transfer.

The business objective is to look at past historical appointment data and identify the bottleneck or pain points in the current business processes. Using the insight that we have gained from the data, we need to predict the customer's appointment status and then develop a macro and micro level manpower planning tool so that the manager can use it in their daily work. An effective schedule can lead to better staff satisfaction through balanced workload and efficient utilization of resources while meeting the customers' demand; thereby fulfilling the company objective of providing excellent service to customers and maintain good customer relationships as a long-term goal.

The authors have masked sensitive information such as customers' ID, demographics information due to data privacy and confidentially. Without loss of vital information, the demand and appointment data still remain unchanged and reported the finding as a generalized information. However, all the steps and methods are described in detail in this paper and will be beneficial to others who are keen to start on an analytics journey in the organization for process improvements and gain a competitive advantage over its competitors. In section 2, a literature review of the related industry and topics related to the predictive model and resource planning has been conducted. Section 3 will focus on data analysis and predictive model to predictive customers' demand. In subsequent sections, and the authors build a decision support tool based on mathematical model and heuristics model for manpower scheduling and computation results are shown. Finally, the authors indicate the limitation of the model, challenges that they face and future direction for the research is discussed.

2. LITERATURE REVIEW
Manpower planning is central to most businesses because human resources are scarce and expensive. Two types of scheduling methodology can be found in literature, namely cyclical and non-cyclical scheduling. A cyclical schedule would have the same schedule repeated for the next period

without changing of requirements. It is easy to construct but can be rigid and difficult to adapt to changes such as variability of demand. For non-cyclical scheduling, a new schedule is generated for every scheduling period based on updates to parameters. The approach is more time consuming but adaptable to changes as stated in [17].

In [4], the authors discussed a cyclic weekly schedule was developed and re-used with minor modification for the next week in scheduling weekly tours. Their objective is to determine a set of tours so that the demand for the tour agents' services is well-utilized while minimizing the total labor cost of the staff. They started with the classical covering formulation of [5] and then derived the shift scheduling formulation for the daily model that satisfied a set of requirements. A new integer programming model for the weekly tour was then defined by merging seven daily shift scheduling models in a network flow framework and produced feasible weekly tours that satisfied the daily shift in tours, the days off and the difference between the starting times of any two consecutive shifts. The model is flexible and can accommodate seven different daily models depending on the chosen level of detail. It can also handle different requirements for the days-off.

Generally, most of the scheduling problems are NP-hard and these operational levels of decision problems are solved using a heuristics approach within a reasonable time. [2] began with an integer programming formulation to find the minimum cost pool of employees needed to meet the forecasted labor requirements during each period of the day for each day of the week. To handle large scale integer programs, they modified the model by introducing a solution algorithm that consisted of a truncated branch-and-bound routine and a heuristic which was invoked whenever an all-integer solution failed to materialize within a fixed CPU time. If an optimal solution was found, it would assign breaks to shifts and the shifts to tours. Otherwise, it would terminate the all-integer solution before invoking the heuristic method to find upper and lower bounds which would converge speedily to near- optimal solutions.

[1] addressed lecturer timetabling at a Nigerian University, and uses an iterative process to generate schedules based on the degree of violation of hard constraints. [6] developed a two-stage procedure for a department providing structured curricula for well-defined groups of students. The procedure includes a relaxation approach for computationally heavy constraints and subproblems to obtain timetables for each day of the week. [8] described a Genetic Algorithm – based system for professional course scheduling using strategies such as pre-assigning subsets of courses. [9] used a network-based model considering the dimensions of faculty, subject, time, and room for the College of Business Administration at Texas A&M University. Other articles describing heuristic approaches to course scheduling in university environments include [3], [6], [7] and [10].

[11] proposed a new hybrid method which is a combination of a great deluge and artificial bee colony algorithm (INMGD-ABC) to solve the university timetabling problem. Artificial bee colony algorithm (ABC) is a population-based method that has been introduced in recent years and has proven successful in solving various optimization problems effectively. However, as with many search-based approaches, there exist weaknesses in the exploration and exploitation abilities which tend to induce slow convergence of the overall search process. Therefore, hybridization is proposed to compensate for the identified weaknesses of the ABC.

[12] developed a mathematical model to solve teacher assignments and course schedule for a master course. An initial solution is obtained by a mathematical programming approach is based on Lagrangian relaxation. This solution is further improved by a simulated annealing algorithm. The proposed method has been tested on instances from a university in Indonesia, as well as on several randomly generated datasets, and the corresponding computational results are reported.

[13] considered integrated teacher assignment and course scheduling at a university in Indonesia, and used a heuristic based on Lagrangian relaxation. The models were solved in phases using CPLEX. The authors developed a computer program to automate the scheduling process, considering conflicts among core required courses, and among electives within areas. The program was used by an administrator in the student services office.

[14] developed a prototype system for the examination proctor assignment at Konan University. They focused on the proctor assignment and the target model considered some different types of constraints to workload in a day. A mixed- integer programming model was proposed and an optimal solution was derived through CPLEX, commercial optimization software. The resulting assignment sounded acceptable for the registrar staffs nevertheless some additional practical conditions were neglected for simplification of the mathematical model. This study extends the previous model and discusses the usefulness of the system for system users in the practical assignment task.

A prescriptive analytics study of similar nature of optimization and simulation was conducted by [15], where it seeks to determine an optimal number of in-counters at the airport to service a predicted passenger load, in accordance with stipulated service level agreements. In the study, it used a six-step methodology to solve passenger load and check-in counter requirement problems. The first part of the methodology includes using past historical data such as past load, flight information, and region, to develop a decision model for passenger load to forecast passenger load and transfer load. Other information such as passenger arrival patterns, average service times and queue times were then derived from the historical data. Together with the derived information and forecasted passenger loads and transfer load, these data were inputs for the simulation model to determine the optimal number of check-in counters required and resource utilization. The author also conducted simulation models using Excel to visualize how various input parameters would impact the number of counters required and service level. Through the simulation, it allows the airport operator to decide on the number of counters required, whilst achieving performance standards. This methodology can be adapted for this problem statement, and past historical data can be used to derive inputs for the mathematical model.

[16] developed a resource planning model for the airport using the predicted passenger load at the airport for arriving passengers and estimating the number of immigration counters required at different time horizons during the day. It serves as the decision support tool for the airport operator to use it on a daily basis.

Macro-level human resource planning is beneficial in helping the organization to forecast the number of skilled manpower required to identify manpower gaps and allow lead time for training of this skilled manpower to ensure business-as-usual, efficient and smooth operations daily.

We are pursuing a study in this area as the business problem is domain-specific and organization focused, thus needing to build a customized model to address the business problem. Though there are many other studies in the area of macro planning resource optimization, the business problem is unique to the organization and therefore requires a different approach to solve. Currently, resource planning is performed manually, based on the rule of thumb and gut feeling, without a mathematical approach to manage manpower resources.

3. UNDERSTANDING THE DATA

Due to the advancement of technology and cheaper computation and storage power, organization today are flooded with vast amount of data. Most of the historical data are exported from the databased servers to Excel format for analysis. There are more than 42 data fields comprising of application information such as appointment detail, customers' demographic information as well as the daily manual staff schedule and the manpower strength during the period. We have also requested for a real-time appointment data which includes appointment ID, customer ID, planned scheduled start time, actual registration time, actual appointment start time, actual appointment end time, status of appointment (i.e. new, waiting, in-progress, no show, completed, canceled) and the rating given by the customers after the service as well as the staff, management associates (MA) ID who is servicing the customers. Some of the data fields were not used for manpower scheduling problems and were excluded from analysis (e.g. customers' feedback).

When the appointment is scheduled, the status is "new". On the day of the appointment, when the customer registers, the status of the appointment is changed to "waiting". When the customer is called to meet the MA, the status of the appointment is changed to "in-progress". There may be cases when the customer is no longer interested in the service after being shortlisted, they may cancel the appointment via phone call or email. Then the time slot will be released to other customers. However, some customers didn't show up for the appointment, in those cases, the status of the appointment is changed to "No show". It is a concern for the management if the no show numbers are high as it means a loss of revenue, as well as the manpower has been scheduled and wasting of resources. Thus, the first problem in this case is to develop a predictive model to predict the status of an appointment as "Show" or "No Show" and the appointments are demand and the staff are needed to fulfil the demand. The predictive model is vital for better manpower planning. When the customer has completed the service, MA will close the appointment record and the status will be updated as completed as well as the appointment end time is captured.

After predicting the demand, the customers service time at the counters is studied in detail. As stated earlier currently the average service time of 45 minutes is allocated to all the shortlisted customers. However, by analyzing past three years of appointment data revealed that the service time for "Show" and "No show" differ greatly for the various age groups. The customers are also grouped into the various age groups based on the customers' age, (A1 - represents Young (Age between 21-35), A2 - represents Middle-Aged (Age between 35-50) and A3 - represents Elderly (Age between 50 to 65). There is also a significant difference in the customer's service time between various age groups. Without the support of data analysis, the manager does not realize that it will cause a big issue in the customer waiting time, service quality and staff productivity. The service time distribution and the service time for "Show" and "No Show" for various age groups are

presented below in Fig. 1 and Table 1 based on past 3 years data. Based on the historical data, 69% of the customer showed up and the no show rate is 31%. It is much higher than the industry benchmark of 25%. Hence, management has to identify the reason to reduce the no show rate and one of them is to reduce the lead time of appointment. With better predictive model and manpower planning, it can be achieved.
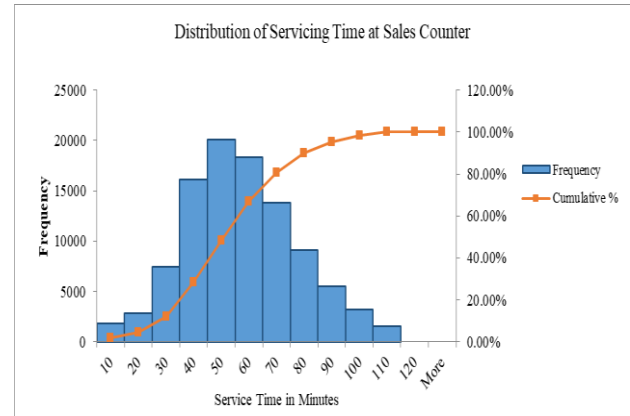

Fig 1: Histogram showing the service time

Table 1. Service time based on Age Groups

Age Group	Status	Avg Service Time (mins)	Total Count
Elderly	No Show	4.50	5523
	Show	42.17	8533
Elderly Total			**14056**
Middle-Aged	No Show	5.48	17576
	Show	50.21	34792
Middle-Aged Total			**52368**
Young	No Show	4.23	27948
	Show	48.37	72991
Young Total			**100939**
Grand Total			**167363**

The service time for Elder for "Show" appointment is 42.17 minutes, for Young is 48.37 and the Middle-Aged takes the longest and the service time is 50.21 minutes. The "No Show" time for 3 different age groups is quite similar between 4.23 to 5.48 minutes.

There are also outliers that the service time is more than 120 minutes (2 hours) are removed. Any service time less than zero is also discarded as wrong system input. After cleaning the data, 95% of the data are used for further analysis. The working hour per employee is 8 hours daily and they are multi-tasking. There is 15 staff available, our model assumes that there are 22 working days in a month as they need to work 5.5 days including a Saturday half day. But they should not be 100% utilized to be realistic thus the model needs to capture this operational constraint. They only spend a proportion of their time to service the customer; at other times they also need to support other business operations like preparing the quote and liaising with various vendors. Staff utilization rate denotes the percentage of time an employee

will spend on serving the customers. The utilization rate of the staff varies between 0 to 100% and the default is 60%. All these parameters are user-specified input and they can change it based on the situation. If there are a lot of appointments, they can increase the utilization rate and if the staff is unavailable due to training then utilization rate can be adjusted to zero.

This system is designed with flexibility in mind to allow users to change the input based on the business requirement and allow them to run different scenarios using the models.

4. MODEL DEVELOPMENT

The authors have used 3 years of appointment data with 160,000 shortlisted customers' records and 42 columns of variables including demographics such as age, gender, income, and target variable as the appointment status. The first model developed is the predictive model to predict the appointment status of the customer based on the target variable, "Show" (status - 1) and "No show" (status – 0). The data has been partitioned based on 70% training and 30% testing or validation. The authors explored various data mining models such as logistic regression, decision tree, neural network, and gradient boosting method and evaluate the performance of each model and select the best model for implementation. Table 2 shows the models' comparison result, decision tree performance is the best among all others based on misclassification rate and average square error. Some of the important variables which will affect the show rate are staff attending the customer, Age Group and Quarter of the year when appointment is scheduled. The decision tree has the lowest misclassification of 3.5% and the highest accuracy rate of 96.5% as compared to other models where the misclassification rate is about 20%. Thus, decision tree has been chosen as the best model for implementation and the rules are also easily understood and accepted by the business unit. The output from the decision tree model has been used for the manpower planning in the next stage.

Table 2. Predictive models performance

Selected model	Model	Misclassification rate	Average square error
YES	Decision Tree	3.5%	0.06648
	Logistic Regression	20.3%	0.30502
	Gradient Boosting	14.1%	0.30502
	Neural Network	20.3%	0.30502

Currently, manpower planning is done manually, and they are using the average service time of 45 minutes for all appointments. From Table 1, we observed that there is a big variation in the service time between "Show" and "No show" and by age group and the "No show" rate is 31%. Therefore, in this study, the authors seek to address the business problem by translating the real-world business problem into a computational system for effective manpower planning. Furthermore, based on the historical data, if MA is assigned all "No Show" customers which need only 10% of the time needed to service the "Show" appointment. Thus, when assigning appointment to the staff, the service time for each appointment should be taken into consideration rather than

using fixed number of appointment like 10 to 12 appointment per day. To create a happy working environment for the staff, staff utilization rate and workload distribution should be taken into consideration during daily operation. The desired goal of is to use data analytics to predictive the appointment status by "Show" or "No show" and make use of the service time distribution to schedule the appointment to the staff and determine total man-day required to clear a certain pool of shortlisted applicants. This macro planning model can also determine the number of staff required to meet the desired appointment lead time.

The manpower scheduling model is to determine the appointment schedule as well as the timetable for each staff daily. The model first select the number of appointments based on the total staff time and total service time available for a day. The total time required for all the appointments should be less than the total staff time which is equivalent to all the staff time add up together (i.e. supply >= demand) as the first check before running the manpower scheduling model (M1).

The authors have developed an Integer Programming (IP) model to assign the appointment i to the staff j daily. The model will also generate the appointment schedule, that includes the start time and end time of appointment as well as to generate the daily timetable for each staff.

The following assumptions were made for the model,

i. Inputs are based on historical data assumed that the future trend will follow the historical trends.

ii. All MAs are equally competent and efficient in servicing the applicants.

iii. The applicants in the same age group need the following service time depicted in TABLE I.

The following subscripts are used:

Let i be the index for appointment, i = 1, 2, 3, …, N

Let j be the index for staff, j = 1, 2, 3.., J

t_i be service time requirement for appointment

C_j be the daily working hour of staff j

u_j be the utilization rate of staff j

s_i be the appointment i, start time

e_i be the appointment j, end time

v_j be the start time of staff j

w_j be the earliest end time of staff j

x_{ij} be binary decision variable

c_{ij} be the cost of assigning appointment i to j

$$x_{ij} = \begin{cases} 1, if\ i\ has\ been\ assigned\ to\ staff\ j \\ 0, otherwise \end{cases}$$

Manpower Scheduling Model (M1):

Objective: min $\sum_{j=1}^{J} \sum_{i=1}^{N} c_{ij}\ x_{ij}$

$$\sum_{j=1}^{T} x_{ij} \geq 1, \forall\ i = 1,2, … N \qquad (1)$$

$$\sum_{i=1}^{N} t_i * x_{ij} \leq C_j * u_j, \forall\, j = 1,2,\dots,J \qquad (2)$$

$$\sum_{j=1}^{J}\sum_{i=1}^{N} t_i * x_{ij} \leq \sum_{j=1}^{J} C_j u_j \qquad (3)$$

$$s_i = \sum_{j=1}^{T} v_j x_{ij}, \forall i = 1,2,..N \qquad (4)$$

$$e_i = s_i + \sum_{j=1}^{J} t_{i} x_{ij}, \forall i = 1,2,..N \qquad (5)$$

$$w_j = v_j + \sum_{i=1}^{i'} t_i x_{ij}, where\ i' \in \{x_{i'j} = 1\} \qquad (6)$$

$$s_i \geq s_{i'}, \forall i \geq i' \qquad (7)$$

$$x_{ij} \in \{0,1\} \qquad (8)$$

The objective of the IP model is to reduce the overall operational cost of assigning appointment i to staff j.

Equation (1) ensures that we need to assign all the appointments to staff and we can only assign 1 appointment to 1 staff. Equation (2) denotes that the total time assigned to each staff should be less than or equal to total staff time available which is the product of daily man-hour available with the utilization rate. Equation (3) is quite similar to (2) such that the total sum of appointment service time required is less than or equal to all staff available time. The remaining of the equations (4) (5) and (6) will set the service start time and service end time for the appointment based on the staff start time and the earliest end time of the staff. Staff j, earliest end time is updated. Equation (7) is to denote the assignment start time for earlier appointments should be less than those appointments with a higher index number or queue number (i.e. first come first served principal). The decision variable should be binary 0 or 1.

IP problem is NP-hard (non-deterministic polynomial-time hardness) and the heuristic method can be used as an alternative approach to find the near optimal solution. The authors use one-day appointment data and run the scheduling problem using ILOG CPLEX and it took a few hours to get the optimal result. Thus, they have decided to develop a heuristic model based on the mathematical model. A heuristic is a greedy algorithm that produces 'good' and 'feasible' solutions to some difficult or abstract problems by understanding the problem, analyzing the data structure or applying some basic rules. The main objective is to solve the problem within a reasonable time frame to be used in operations.

The authors developed a heuristic method by applying logic rules capable of finding near 'optimal' solutions for daily appointment scheduling. For the weekday, the daily working hour for each staff is 8 hours. If the day of the week is a Saturday, the working hour is only half day 4.5 hours.

Initialize all the start time and end time of all staff. (v_j, w_j)

Let T_j be total time available for each staff, $T_j = C_j u_j$

For each appointment i, I = 1, 2, …, N

{

      Find the earliest end time among all staff say, $\min(w_j)$

        If $(T_j > 0)$

          {

             Assign staff j to appoint i, $x_{ij} = 1$

             Start time of appointment, $s_i = w_j$

             End time of appointment, $e_i = s_i + t_i$

        Start time of staff j, $v_j = w_j$

             Earliest end time of staff j, $w_j += t_i$

             Update total time available, $T_j -= t_j$

If $(T_j \leq 0)$

{   Update earliest end time, $w_j = 9999$}

Increment i, i++ }

Else   {

Remove staff j from the available list by updating earliest end time, $w_j = 9999$

} }

The heuristic developed is based on the mathematical model described in M1, it can produce good feasible solution in polynomial time and the heuristic method is coded using VBA in Excel as the client is using it for daily use. The heuristic model is a greedy algorithm and its result is comparable to CPLEX optimal result in many scenarios. However, the runtime for the exact solution increases exponentially with the increased in the number of variables. Furthermore, using the heuristic, for any big problem size of 150 appointments and 15 staff, it can find a good "feasible" solution within 5 minutes as compared to hours using CPLEX branch and bound optimization engine. Thus, heuristics is good enough to be used for daily operations.

The authors also compared the IP solution and the heuristic model results for both actual and predicted inputs against the actual appointment data. They used two sets of inputs which were the actual classification and the predicted classification for experimenting with the developed heuristic model. Based on a 60% staff utilization rate, the scheduling model can complete the appointments in 36 days, while the actual result takes 44 days. Using the predicted result, we can shorten the total service time by more than 20% as compared to current manual planning using the same number of staff for a given period. The result has been very encouraging and the management would like to use the models in the near future. The authors can conclude that the heuristic method yielded a good optimal solution.

5. CONCLUSION
In this paper, the authors outline the development of the intelligent decision support systems from predicting the customer demand to manpower assignment and scheduling using heuristics. The system captured the whole customer flow from appointment booking to the scheduling of the appointment to optimize the manpower utilization as well as to shorten the time to clear all the appointments within the service level agreement. The manpower planning is done based on the predicted status and estimated service time of each appointment thus ensuring balance workload among staff. The tool also helps to improve the productivity and shorten the total service time by more than 20% and thus it is worthy to use it for daily operation.

For the future research direction, the authors would like to

recommend a business process change to the company to provide an online booking system so that the customers can choose the appointment after being shortlisted. To obtain the optimal number of staff required to service all the number of shortlisted applicants, the authors have suggested the company to have a steady number of shortlisted applicants by opening a fixed number of booking each month via an online portal. Customers can see the available number of booking next month after they are shortlisted and book online. If all the bookings are filled up, the company won't be opening up any new slots for the month, and the unfulfilled customers need to apply again. This will ensure that all customers are served within a month. If the human resource requirement is steady, and the staff doesn't need to work overtime, which is charged 1.5 times the normal pay. It will be a win-win situation for the customers and the company.

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