Proceedings of the 2014 Industrial and Systems Engineering Research Conference
Y. Guan and H. Liao, eds.

An Entropy-based Approach to Improve Clinic Performance and Patient Satisfaction

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Abstract

The patient scheduling problem in outpatient clinics has been studied extensively in literature with several mathematical, simulation and heuristic based solutions. Factors that influence a clinic's decision to follow a specific scheduling method depend on the patient arrival factors and the expected encounter time. A significant number of small clinics use Bailey's rule or an adaptation of the Bailey's rule for patient scheduling due to its simplicity and lack of resources to invest in a complex scheduling software system. Often there are competing factors that a scheduler or decision maker has to evaluate. These include maximizing clinical resource utilization levels from an economic standpoint versus attempting to minimize waiting time for patients from a patient satisfaction/ quality of care standpoint. Additional parameters that make the scheduling problem challenging are the variability in patient arrival time, no-shows, variability in patient-physician encounter times, emergency patients, and several related factors. This research studies the patient scheduling problem in an outpatient clinic using entropy as a common measure to classify the dominating factors that contribute towards intended clinic performance criteria and patient satisfaction criteria. The goal is to provide an effective and insightful method to study the clinic outpatient scheduling problem which can benefit the clinic and the patients.

Keywords
Patient scheduling, outpatient clinic appointment, simulation, entropy

1. Introduction
Frequently, the performance metrics of an outpatient clinic are characterized by utilization or idle time of the clinic system and waiting time of patients. Patient arrival time, no-show, service time and appointment rule have been identified as key factors impacting the performance of outpatient clinics according to a number of research studies in literature. There are three primary questions related to these factors: How does one factor or several factors affect the clinic system utilization and average patient waiting time? Are their impacts on the performance significant? Can these factors be classified by relative importance? Majority of the research studies in this area focus on answering the first question by either studying one factor while keeping the remaining factors fixed or evaluating choices among several levels of factors. This paper intends to explore all of the three questions by identifying dominating factors and investigating the potential impact ranking of all the input factors towards intended clinic performance criteria. To achieve this objective, simulation experiments are designed to control and compare the effects of these factors. Shannon Entropy is introduced as a measure to quantify the relative importance of these factors. The rest of the paper is arranged as follows: Section 2 discusses the relevant literature review, followed by the methodology in Section 3. Section 4 shows the simulation results and data analysis, followed by concluding remarks in Section 5.

2. Literature Review
According to Cayirli and Veral's [1] literature review, "environment factors" of outpatient clinics include: number of services, number of doctors, number of appointments per clinic session, unpunctuality of patients, no-show probability, walk-ins, presence of companions, service time, lateness and interruption of doctors, and queue discipline. These factors and their effects on clinic performance have been studied extensively over the past few decades. A number of these studies are based on investigation and experiments due to the complexities involved in analytically

modeling and solving such problems. Welch and Bailey [2] provided constructive suggestions on setting the punctuality of patient and doctor, service time and scheduling rules to reduce the cost of idle time of both doctors and patients. Huarng and Lee [3] proposed a few alternatives to improve the queuing problem in the clinic. There are several studies that explore one specific factor. Examples include Bailey [4] that studied the effect of appointment scheduling rules. In the following half century, “Bailey’s rule” has performed very well under the tests with different scenarios. Ho and Lau [5, 6] also studied scheduling rule and discover the inner relationship of this factor and three other factors: the probability of no-show, the coefficient of variation of service times, and the number of patients per session. Gupta and Denton [7] provide a comprehensive review of research on scheduling rules. Zhu et al. [8] study the optimal appointment number for clinics. Klassen and Yoogalingam [9] discuss the effect of physician interruption and lateness. Hofmann and Rockart [10] as well as Bigby et al. [11] address the no-show rate problem. Although none of these papers have explored the three questions that are mentioned at the beginning of this paper, they provide valuable insight on parameter settings and experiment design in our work.

Experimental design is an effective way to detect the impact of effects. It has been widely used in the health care domain for research and practical implementations. For example, Provost [12] describes an experimental design to analyze the influence of source of reminders, timing of reminder and clinic appointment number on no-show probability. Swisher and Jacobson [13] introduce fractional factorial design into a simulation experiment on a family practice healthcare clinic. Schruben and Margolin [14] simulate the patient paths in a hospital and attempt to reduce the variability in response surface parameter estimates where the response is the expected number of patients per month unable to enter the hospital facility due to space limitations. So far we did not find any research studies in the literature related to mixed linear model of experimental design and ANOVA analysis that is presented in this paper. These approaches are reliable and helpful from the perspective of both practical feasibility and theoretical validity.

Shannon Entropy and information gain is widely used in machine learning, but it is seldom used in health care. Entropy has been introduced to facilitate experimental design. For example, Box and Hill [15] use the expected increase of Shannon Entropy as a criterion on model selection. Bernardo [16] sets the Shannon Entropy as the expected utility of the experimental design. Ng and Chick [17] propose an entropy-based design criterion to identify important parameters and reduce the variance of parameter estimates. Malakar and Knuth [18] present an entropy-based search method to select most informative experiments. These studies have led us to explore entropy-based method to determine the importance rank among contributing factors.

3. Methodology

3.1 Simulation Model Design

A simulation-based approach is used here to study the performance of an outpatient clinic. In the simulation model, the service processes of the clinic are treated as a single server process. We set one hour as a session period, so the pattern of appointments repeats each hour. For patients in the clinic, the service will have accumulated delay from previous session period to successive session period. An eight-hour work day is set as the simulation run-length in order to observe the daily performance of the clinic. As found in typical small practice settings, a one-hour lunch break is considered in addition to the eight-hour work day. Given these considerations, there are some assumptions being made while developing the model.

- Patient arrival time follows the appointment schedule with certain deviation and no-show probability.
- Walk-in patients (patient served without and appointment) are not considered.
- The clinic keeps seeing patient until all patients have been seen. Absence or lateness of clinic staff is not considered.
- No patient arrives during the lunch break (arrival deviations are not included), but the clinic will still see patients during the lunch break.
- Warm-up period at the start of each day is not considered for the simulation experiments.

There are several processes in an outpatient clinic setting, such as check in, interaction with nurse, physician encounter, and check out. For the purpose of simplification, the service processes of the clinic is treated as a single server process focusing primarily on the physician encounter. Simio is used as the simulation tool to build the model. The simulation model is shown in Figure 1. The source object, referred to as Enter, creates patient arrivals in the form of discrete entities. The server object, referred to as SeePhysician, simulates the wait and delay associated with the physician encounter process. If needed, the process can be easily expanded to represent all the processes associated with an outpatient clinic. The sink object, referred to as Exit, represents the departure of each patient after completion of service. The arrival pattern of patients is controlled by the source object, which determines the arrival time of each entity through three types of input data: schedules patient arrival time, arrival deviation and no-show probability. The service time for each patient is controlled by the server object. Once an entity is created, it is sent to the server immediately; similarly, once the service is completed on an entity, it will be sent out of the system immediately. As the output of the experiments, resource (physician) utilization and average waiting time of patients are collected during each run.

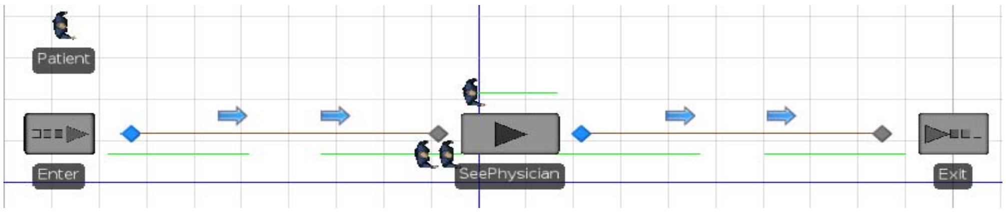

Figure 1: Simio Model for Outpatient Clinic System.

3.2 Experimental Design

Input factors for this simulation model are labeled as: SR: Scheduling Rule, ST: Service Time, AD: Arrival Deviation, and NP: No-show Probability. Each of these factors has several levels, and a full factorial design involves all possible combinations of these levels across all factors. The notations $l_{SR}, l_{ST}, l_{AD}, l_{NP}$ represent the number of levels of each factor, and 365 replications (one-year) are used for each combination. The total number of runs of the experiments is:

$$N = 365 \times l_{SR} \times l_{ST} \times l_{AD} \times l_{NP} \tag{1}$$

T is the interarrival time of patient, μ and σ are the mean and standard deviation of service time t, δ is the arrival deviation and η is the no-show probability. Based on practical considerations and literature review, the levels of each factor are determined as follows:

- Service Time: In the literature, the service time is always considered using certain distributions, such as gamma [2, 8], lognormal [8], uniform, exponential [5, 6] and a few other choices. Here we set:

$$\mu = 10 \text{ minutes}; \;\; \sigma^2 = 1\,, 2; \;\; t \sim normal(\mu, \sigma^2) \tag{2}$$

  Since the service time is a random factor, we adopt random effect model to study the experiment results.
- Scheduling Rule: Scheduling rule defines the arrival pattern of patients specifying the number of patients scheduled for a session period. Bailey [4] proposed the cornerstone of the scheduling rules, which suggests assigning multiple patients at the beginning of a session, and one patient thereafter with an interval equaling the average service time. Ho and Lau [5, 6] designed more than 40 scheduling rules and tested them under various scenarios. For our experiments, since $\mu = 10$ minutes, then for a session period of one hour, the average number of patients served is

$$\frac{60}{\mu} = 6 \tag{3}$$

  Based on (2) as well as practical experience and literature review, we have designed three scheduling rules. Let T_i^j be the interarrival time of the i^{th} patient of the j^{th} level, then we have:
  - Rule 1: assign two patients every quarter of the first half hour and one patient every quarter of the remaining half hour, i.e.

$$T_i^1 = \begin{cases} 0, & i = 1, 2, 4 \\ 15, & otherwise \end{cases} \tag{4}$$

  - Rule 2: (Based on Bailey's rule) assign one patient every ten minutes, i.e.

$$T_i^2 = \begin{cases} 0, & i = 1 \\ 10, & otherwise \end{cases} \tag{5}$$

- Rule 3: (Based on Bailey's rule) assign two patients at the beginning of the period, and one patient every twelve minutes, i.e.

$$T_i^3 = \begin{cases} 0, & i = 1, 2 \\ 12, & otherwise \end{cases} \tag{6}$$

- Arrival Deviation: Based on data from Welch and Bailey [2], we set seven levels of arrival deviation ranging from -3 min to +3 min, where a negative value means that the patient arrives earlier than scheduled time. Let δ_j be the j^{th} level of arrival deviation, then we have:

$$\delta_j = -4 + j, \quad j = 1 \sim 7 \tag{7}$$

- No-show Probability: Bigby et al. [11] stated that no-show probability of patients for medical centers are in the range of 10% to 30%, however, using telephone and mail reminder, the no-show probability and be reduced significantly. In their experiments, Ho and Lau [5, 6] set no-show probability as high as 20%. Considering text and email reminders are common in modern clinical appointment systems, we set the no-show probability from 0 to 10%. Let η_j be the j^{th} level of no-show probability, then we have:

$$\eta_1 = 0,\ \eta_2 = 0.02,\ \eta_3 = 0.05,\ \ \eta_4 = 0.1 \tag{8}$$

Let Y_k be the average response of the k^{th} model, then the linear relationship between output and input factors are:

$$Y_k = a + \beta_{SR}\ T^{j_1} + \beta_{AD}\ \delta_{j_2} + \ \beta_{NP}\ \eta_{j_3} + \alpha t_{j_4} + \ \epsilon_k \tag{9}$$

In (9), a is the grant mean, β is the coefficient of fixed factors SR, AD, NP, and α is the coefficient of random variables ST, ϵ_k is the error of the k^{th} model, where $\alpha \sim normal\ (0,\ \sigma_\alpha^2)$, $\epsilon_k \sim normal\ (0,\ \sigma_\epsilon^2)$. In this paper, we have two responses, resource utilization and average waiting time of patient. We analyze these two response variables according to (9). Table 1 is the factor-and-level table of the experiments.

Table 1: Factor-and-level Table of the Experiments.

		Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**	**Level 6**	**Level 7**
Factors	SR	Rule 1	Rule 2	Rule 3				
	ST (min)	norm(10,2)	norm(10,1)					
	AD (min)	-3	-2	-1	0	1	2	3
	NP	0	0.02	0.05	0.1			

3.3 Data Analysis Methods

We apply ANOVA on the output data from the simulation experiments to obtain brief information about the significance of each factor. The P-values from the F-test in ANOVA table offers an intuitive explanation whether a factor is significant (P-value < 0.05) or not (P-value > 0.05). Using ANOVA we can easily answer the question whether a factor's contribution to the response is significant, while we are still unable to answer the question about the extent of a factor's effect on the response. The use of clustering analysis and entropy measurement can provide further insight.

Before we evaluate the impact rank of the factors on response Y, we need to measure different levels (or classes) of the response. A clustering analysis approach makes it convenient to classify the response. Here we adopt two different methods to divide the response data into clusters. The first one uses customized boundary to split the data. For resource utilization, we use 80% as the boundary to split the data into two subsets. For waiting time, we use 0.08 hours (or 4.8

minutes) as the boundary to split the data into two subsets. The second method is to use fuzzy C-means clustering analysis to divide the data into two or three clusters.

Let Y be the set of response elements gained from each experiment model, x be any fixed or random input factor of the model, l_x be the number of levels of factor x. After classification, we can use the information gain of the response set Y to measure the expected reduction in entropy due to one factor. Let $G(Y,x)$ be the information gain of response vector Y on factor x, let $H(Y)$ be the Shannon Entropy of response vector Y after clustering, then we have:

$$H(Y) = -\sum_{Cluster\ i} p_i \log_2 p_i \tag{10}$$

where p_i is the proportion of response elements in Cluster i. It is the ratio of number of response elements in Cluster i to the total number of response elements $|Y|$.

If we classify the response set Y by the levels of x associated with each response elements, then we get l_x subsets of Y. Then we perform clustering analysis on each of the subset. Let $H(Y_x)_j$ be the Shannon Entropy of the response subset classified on level j of factor x, then the information gain on factor x can be calculated by:

$$G(Y,x) = H(Y) - \sum_{j=1}^{l_x} q_j H(Y_x)_j \tag{11}$$

where q_j is the proportion of response elements in the subset on level j of factor x. It is the ratio of number of response elements in the subset on level j of factor x to the total number of response elements $|Y|$. $H(Y_x)_j$ is also called the conditional Entropy, i.e.

$$H(Y_x)_j = H(Y \mid \text{level of } x = j) \tag{12}$$

Information Gain in (11) shows the relevance of factor x to the response. The higher the information gain on x, the more important factor x is.

4. Experimental Results and Analysis

4.1 Plot for Experiment Results

We set inputs for the simulation model according to the factors and levels shown in Table 1. The total number of combinations of levels is $3 \times 2 \times 7 \times 4 = 168$ and we set 365 replications for each combination, so the total number of runs is 61320. We take the average resource utilization and patient average waiting time (in hours) over 365 replications for each combination as our Y, and plot the responses against each factor. Figures 2 to 5 show the scatter plot of responses versus each factor.

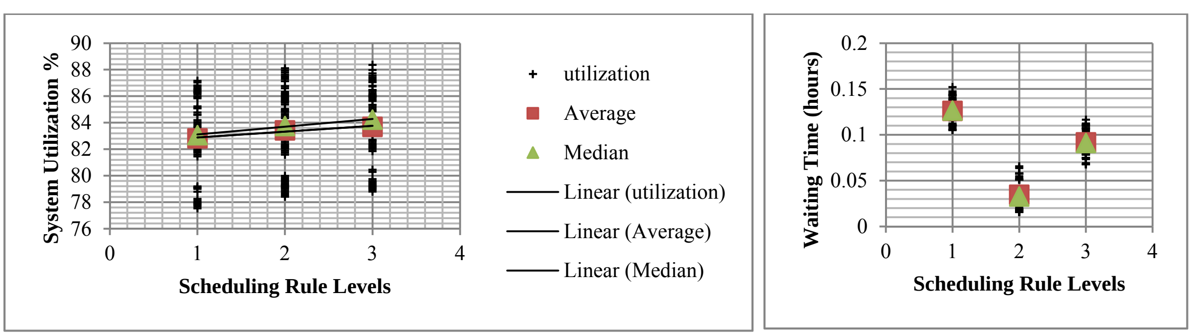

Figure 2: Scatter Plot of Responses vs. Scheduling Rules.

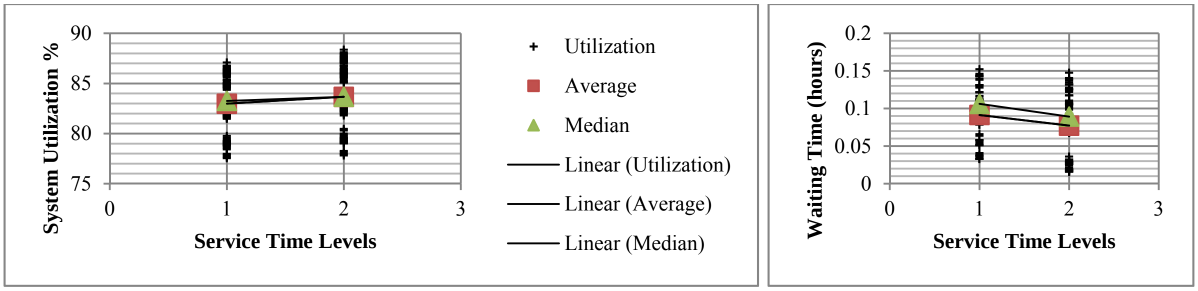

Figure 3: Scatter Plot of Responses vs. Service Time.

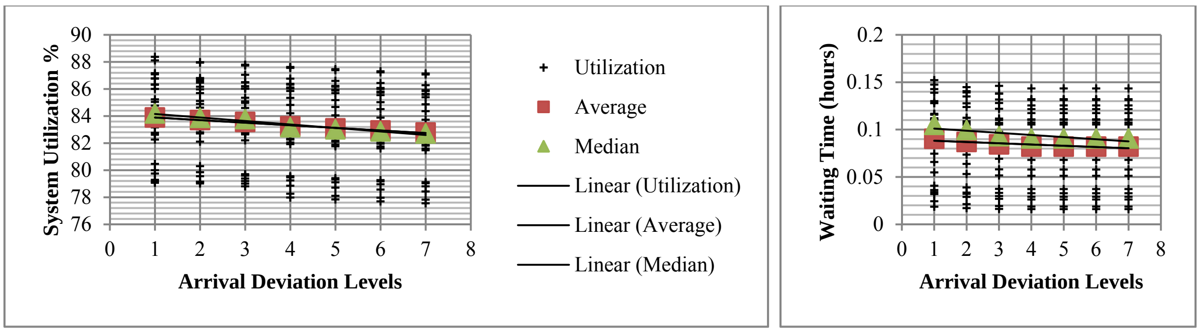

Figure 4: Scatter Plot of Responses vs. Arrival Deviation.

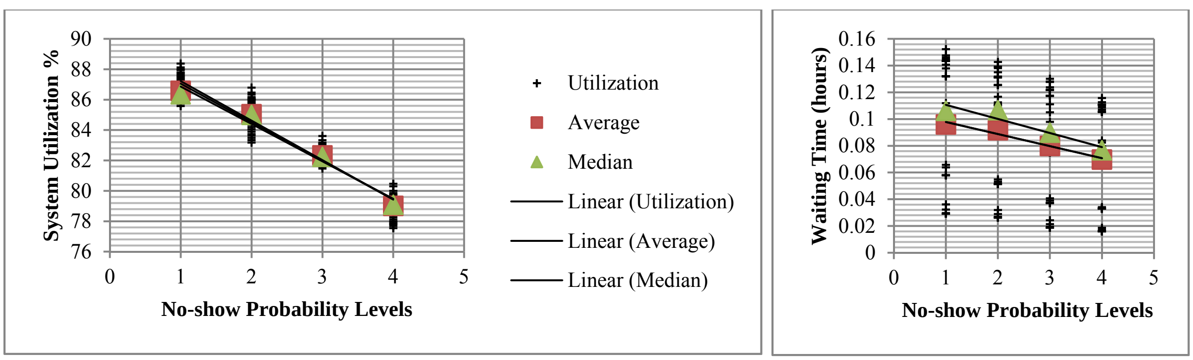

Figure 5: Scatter Plot of Responses vs. No-show Probability.

From Figure 2 we can see that Rule 3 and Rule 2 lead to higher utilization level than Rule 1, and also lead to lower average waiting time than Rule 1. This proves that Bailey's Rule contributes to better system performance. Figure 3 implies that given the same mean, service time with lower variance can lead to higher utilization and lower average waiting time. Figure 4 shows that patients arrive later than the scheduled time will cause lower system utilization although the average waiting time drops. From Figure 5, it is clear that utilization and waiting time decreases with increasing no-show probability is. Among the four factors, we see that patient arrival deviation and no-show probability cannot reach consistent trends on the two responses. Thus to achieve a better system performance, the clinic can choose Rule 2 or Rule 3, reduce the service time variance, and create an intervention to improve the patient punctuality and no-show probability to draw a balance between resource utilization and average waiting time.

4.2 ANOVA Tables of Experiment Results

The plots in section 4.1 offer an intuitive way to observe the impacts of factors on the responses. An ANOVA analysis is required to show whether the impacts of factors are statistically significant. Table 2 summarizes the results of ANOVA analysis using MINITAB. The row names, SR, ST, AD and NP, represent the four factors. In the columns, DF is the degree of freedom for each factor. The degree of freedom equals $l_x - 1$, the total degree of freedom is 168

– 1. SS is sum of squares, MS is the mean of squares, F is the test value of F test of the factor, P is the p-value for the F test. The test results in Table 2 show that all the four factors are have a significant effect on the two responses.

Table 2: ANOVA for Responses V.S. Factors.

	Response: Utilization					Response: Waiting Time			
Source	DF	SS	MS	F	P	SS	MS	F	P
SR	2	22.4	11.2	95.71	0	0.239232	0.119616	4627.45	0
ST	1	19.42	19.42	165.98	0	0.008397	0.008397	324.83	0
AD	6	24.59	4.1	35.02	0	0.001518	0.000253	9.79	0
NP	3	1446.93	482.31	4121.86	0	0.017679	0.005893	227.97	0
Error	155	18.14	0.12			0.004007	0.000026		
Total	167	1531.47				0.270831			

4.3 Information Gain

Using (11) and (12) we calculate information gain of each factor corresponding to the two responses. As stated in Section 3.3, we use simple data split and fuzzy C-means clustering analysis to classify the response elements. Tables 3 and 5 use the simple data split with customized boundaries. Tables 4 and 6 are based on fuzzy C-means clustering analysis. The results under both methods are consistent. From Tables 3 and 4 we infer that the rank of importance of factors on resource utilization is: service time > no-show probability > scheduling rules ≈ arrival deviation. From Tables 5 and 6, the rank of importance of factors on average waiting time is: scheduling rules > service time > no-show probability > arrival deviation.

Table 3: Entropy & Information Gain towards Utilization based on Data Split.

Factor	Levels	# of >80	# of <= 80	Entropy	Proportion
Total		73	95	0.9876	
SR	Level1	21	35	0.9544	0.3333
	Level2	25	31	0.9917	0.3333
	Level3	27	29	0.9991	0.3333
Information Gain		0.0058553			
ST	Level1	63	21	0.8113	0.5000
	Level2	10	74	0.5266	0.5000
Information Gain		0.3186468			
AD	Level1	11	13	0.9950	0.1429
	Level2	11	13	0.9950	0.1429
	Level3	11	13	0.9950	0.1429
	Level4	11	13	0.9950	0.1429
	Level5	10	14	0.9799	0.1429
	Level6	10	14	0.9799	0.1429
	Level7	9	15	0.9544	0.1429
Information Gain		0.0027214			
NP	Level1	31	11	0.8296	0.2500
	Level2	21	21	1.0000	0.2500
	Level3	21	21	1.0000	0.2500
	Level4	0	42	0.0000	0.2500
Information Gain		0.2801926			

Table 4: Entropy & Information Gain towards Utilization on Two and Three Clusters.

Factor	Levels	# of < 75.8668	# of > 85.1312	Entropy	Propor -tion	# of < 78.4077	# of < 71.9680	# of > 85.8809	Entropy	Proport -ion
Total		101	67	0.9702		79	29	60	1.4799	
SR	Level1	35	21	0.9544	0.3333	24	14	18	1.5502	0.3333
	Level2	34	22	0.9666	0.3333	27	8	21	1.4391	0.3333
	Level3	32	24	0.9852	0.3333	28	7	21	1.4056	0.3333
Information Gain		0.001489692				0.0148665				
ST	Level1	21	63	0.8113	0.5000	24	0	60	0.8631	0.5000
	Level2	80	4	0.2762	0.5000	55	29	0	0.9297	0.5000
Information Gain		0.426513173				0.58342384				
AD	Level1	13	11	0.9950	0.1429	11	4	9	1.4773	0.1429
	Level2	14	10	0.9799	0.1429	11	4	9	1.4773	0.1429
	Level3	14	10	0.9799	0.1429	11	4	9	1.4773	0.1429
	Level4	15	9	0.9544	0.1429	11	4	9	1.4773	0.1429
	Level5	15	9	0.9544	0.1429	12	4	8	1.4591	0.1429
	Level6	15	9	0.9544	0.1429	12	4	8	1.4591	0.1429
	Level7	15	9	0.9544	0.1429	11	5	8	1.5157	0.1429
Information Gain		0.002755899				0.002243112				
NP	Level1	17	25	0.9737	0.2500	21	0	21	1.0000	0.2500
	Level2	21	21	1.0000	0.2500	21	0	21	1.0000	0.2500
	Level3	21	21	1.0000	0.2500	16	8	18	1.5100	0.2500
	Level4	42	0	0.0000	0.2500	21	21	0	1.0000	0.2500
Information Gain		0.226832933				0.352363581				

Table 5: Entropy & Information Gain towards Waiting Time based on Data Split.

Factor	Levels	# of >0.08	# of <= 0.08	Entropy	Proportion
Total		49	119	0.8709	
SR	Level1	38	18	0.9059	0.3333
	Level2	0	56	0.0000	0.3333
	Level3	11	45	0.7147	0.3333
Information Gain		0.330645906			
ST	Level1	39	45	0.9963	0.5000
	Level2	10	74	0.5266	0.5000
Information Gain		0.109397677			
AD	Level1	9	15	0.9544	0.1429
	Level2	8	16	0.9183	0.1429
	Level3	8	16	0.9183	0.1429
	Level4	6	18	0.8113	0.1429
	Level5	6	18	0.8113	0.1429
	Level6	6	18	0.8113	0.1429
	Level7	6	18	0.8113	0.1429
Information Gain		0.008559017			
NP	Level1	21	21	1.0000	0.2500
	Level2	13	29	0.8926	0.2500
	Level3	8	34	0.7025	0.2500
	Level4	7	35	0.6500	0.2500
Information Gain		0.059586473			

Table 6: Entropy & Information Gain towards Waiting Time based on Two and Three Clusters.

Factor	Levels	# of > 0.0873	# of < 0.0092	Entropy	Propor -tion	# of > 0.1133	# of < 0.0664	# of < 0.0032	Entropy	Proporti-on
Total		92	76	0.9934		32	80	56	1.4937	
SR	Level1	56	0	0.0000	0.3333	28	28	0	1.0000	0.3333
	Level2	0	56	0.0000	0.3333	0	0	56	0.0000	0.3333
	Level3	36	20	0.9403	0.3333	4	52	0	0.3712	0.3333
Information Gain		0.680018585				1.036632104				
ST	Level1	56	28	0.9183	0.5000	32	24	28	1.0587	0.5000
	Level2	36	48	0.9852	0.5000	0	56	28	0.3900	0.5000
Information Gain		0.041685253				0.769358311				
AD	Level1	14	10	0.9799	0.1429	6	10	8	1.5546	0.1429
	Level2	13	11	0.9950	0.1429	5	11	8	1.5157	0.1429
	Level3	13	11	0.9950	0.1429	5	11	8	1.5157	0.1429
	Level4	13	11	0.9950	0.1429	4	12	8	1.4591	0.1429
	Level5	13	11	0.9950	0.1429	4	12	8	1.4591	0.1429
	Level6	13	11	0.9950	0.1429	4	12	8	1.4591	0.1429
	Level7	13	11	0.9950	0.1429	4	12	8	1.4591	0.1429
Information Gain		0.000621849				0.004782954				
NP	Level1	28	14	0.9183	0.2500	10	18	14	1.0213	0.2500
	Level2	22	20	0.9984	0.2500	8	20	14	0.9840	0.2500
	Level3	21	21	1.0000	0.2500	7	21	14	1.4591	0.2500
	Level4	21	21	1.0000	0.2500	7	21	14	0.9308	0.2500
Information Gain		0.014282362				0.394898042				

5. Discussions and Conclusions

From the above analysis we find the following properties of relationship between the four input factors, scheduling rules, service time, arrival deviation and no-show probability; and two responses, resource utilization and average patient waiting time:

- As for the scheduling rules, Bailey's rule can reduce the idle time of resources (physicians) and patients. The effect of scheduling rules on reducing average patient waiting time is the most important one. So if the decision-maker has a higher emphasis on patient waiting time for evaluating performance or wants to improve customer satisfaction, they need to focus on determining and implementing the optimal scheduling rule.
- As for the service time, a clinic decision-maker should attempt to standardize the encounter time of physicians to reduce the variance of the service time in order to improve the utilization and shorten patient waiting time. Based on our research, service time is the most important factor related to the performance of a clinic since it strongly impacts system utilization and average patient waiting time. Thus it deserves enough emphasis for improvement with the highest priority.
- As for the arrival deviation, if a clinic can intervene on the punctuality of patients to make them arrive on time, then it is beneficial to do so since zero deviation can reduce the waiting time and improve utilization. Since it has the weakest impact on both responses, so a cost-efficient intervention policy should be adopted.
- The impact of no-show probability on utilization is very strong, so a reminder policy should be adopted to reduce the no-show probability. However, a certain degree of no-show rate can help shorten the average waiting time.
- One should also consider the interaction-effectors of these single factors when making choices.

This paper studies four factors affecting outpatient clinic resource utilization and average patient waiting time based on a mixed (with fixed and random effects as shown in Formula (9)) linear experimental model. With results generated from simulation experiments, a three-step data analysis method is used to explore the impact of the factors. These three steps are: (i) response-factor plot, (ii) ANOVA table, and (iii) Entropy and information gain analysis. The three-step method starts from intuitive observation and gradually gets more advanced, and presents a progressive analysis. In the meanwhile, each of the steps contains unique information that the other two steps do not offer. The response-factor plot answers the question about the choice of level of each factor to achieve higher system utilization and lower average waiting time. The ANOVA table verifies that all the four factors contribute significantly towards the two responses. The Entropy and information gain analysis introduced from machine learning helps us obtain a clear information on the rank of importance of the factors towards the two responses. All these information form the recommended suggestions for decision-makers. Additionally, the three steps provides a mutual validation for the other two steps. We can observe the consistency among the rank of slopes of the lines in Figures 2 to 5, the rank of F-values in Table 2, and the rank of information gain in Tables 5 and 6. One of the topics of future work is to explain or prove the consistency of the observed experimental results.

References

1. Cayirli, T. and Veral, E., 2003, “Outpatient Scheduling in Health Care: A Review of Literature”, Production and Operations Management, 12(4), 519-549.
2. Welch, J.D. and Bailey N. T. J., 1952, “Appointment Systems in Hospital Outpatient Departments”, The Lancet, 259(6718), 1105-1108.
3. Huarng, F. and Lee. M. H., 1996, “Using simulation in out-patient queues: a case study”, International Journal of Health Care Quality Assurance, 9(6), 21-25.
4. Bailey. N. T. J., 1952, “A Study of Queues and Appointment Systems in Hospital Outpatient Departments, with Special Reference to Waiting-Times”, Journal of the Royal Statistical Society, A14, 185-199.
5. Ho, C. and Lau. H., 1992, “Minimizing Total Cost in Scheduling Outpatient Appointments”, Management Science, 38(12), 1750-1764.
6. Ho, C. and Lau. H., 1999, “Evaluating the Impact of Operating Conditions on the Performance of Appointment Scheduling Rules in Service Systems”, European Journal of Operational Research, 112, 542-553.
7. Gupta, D. and Denton B., 2008, “Appointment Scheduling in Health Care: Challenges and Opportunities”, IIE Transactions, 40, 800-819.
8. Zhu, Z. C., Heng, B. H. and Teow, K. L., 2009, “Simulation Study of the Optimal Appointment Number for Outpatient Clinics”, International Journal of Simulation Model, 8(3), 156-166.
9. Klassen, K. J. and Yoogalingam, R., 2013, “Appointment System Design with Interruptions and Physician Lateness”, International Journal of Operations & Production Management, 33(4), 394-414.
10. Hofmann, P. B. and Rockart, J. F. 1969, “Implications of the No-Show Rate for Scheduling OPD Appointments. Hospital Progress”, 50(8), 35-40.
11. Bigby, J. A. et al., 1983, “Appointment Reminders to Reduce No-show Rates”, JAMA, 250, 1742-1745.
12. Provost, L. P., 2012, “Cal Mason, COO, Metro Children’s Hospital: Planned Experimentation in CQI”, appears in Implementing Continuous Quality Improvement in Health Care, MaLaughlin, C. P., Johnson, J. K., Sollecito, W. A. (eds), Jones & Barlett Learning, LLC., 339-343.
13. Swisher, J. R. and Jacobson, S. H, 2002, “Evaluating the Design of Family Practice Healthcare Clinic Using Discrete-event Simulation”, Health Care Management Science, 5(2), 75-88.
14. Schruben, L. W. and Margolin, B. H., 1978, “Pseudorandom Number Assignment in Statistically Designed Simulation and Distribution Sampling Experiments”, J Amer Statist Assoc, 73(363), 504-525.
15. Box, G. and Hill, W., 1967, “Discrimination among Mechanistic Models”, Technometrics, 9(1), 57-71.
16. Bernardo, J., 1979, “Expected Information as Expected Utility”, Ann Statist, 7, 686-690.
17. Ng, S. H. and Chick, S. E., 2004, “Design of Follow-Up Experiments for Improving Model Discrimination and Parameter Estimation”, Naval Research Logistics. 51, 1130-1147.
18. Malakar, N. K. and Knuth, K. H., 2010, “Entropy-Based Search Algorithm for Experimental Design”, Proceedings of the 30th International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering. AIP Conference Proceedings, Chamonix, France, 1305, 157-164.