55th Inaugural Lecture

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By

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DECISION PROBLEMS: OF THE ANALYST AND THE DECISION MAKER

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Deputy Vice-Chancellor (Academics),

Deputy Vice-Chancellor (Administration),

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Other Principal Officers,

Provost, Deans and Directors,

Distinguished Colleagues,

Staff and Students of Lagos State University,

Gentlemen of the Press,

Distinguished Guests,

Ladies and Gentlemen.

Introduction

I give thanks and glory to God, the Almighty, for the privilege to stand before you to deliver this Inaugural Lecture. The Holy Bible says "It is not of him that willeth, nor of him that runneth, but of God that showeth mercy." – Romans 9:16. I am a living witness of the fulfillment of this Bible passage (Romans 9:16). I thank the Vice-Chancellor for giving me the opportunity to deliver the 55th Inaugural Lecture of this great University. This lecture is the 3rd in the Faculty of Engineering and the 1st in the Department of Mechanical Engineering since its establishment in 1986 and 1988 respectively. The 1st lecture in the Faculty of Engineering (which was the 37th inaugural lecture in LASU) was delivered by Professor Simeon Olumide AJOSE of the Department of Electronic and Computer Engineering on October 28, 2008 while Professor Oladokun Olopade of the same Department delivered the 2nd lecture on 17th February, 2009 (the 39th inaugural lecture in LASU).

Industrial engineering, my field of study, is a branch of engineering that is concerned with the development, improvement, implementation and evaluation of integrated systems of people, money, knowledge, information, equipment, energy, materials, analysis and synthesis, as well as the mathematical, physical and social sciences together with the principles and methods of engineering design to specify, predict, and evaluate the results to be obtained from such systems or processes (Definition by American Institute of Industrial Engineers). Modern Industrial Engineering is concerned with the integration of resources and processes into cohesive strategies, structures and systems for the effective and efficient production of quality goods and services in any undertaking. Industrial Engineering draws upon specialized knowledge and skills in the mathematical, physical, behavioural, economic, and management sciences, and fuses with the principles and methods of engineering analysis and design, to find optimal and practical solutions. A major focus of Industrial Engineering is on productivity improvement, with concern for the human aspects of work as well as with finding the right combination of resources to ensure that the organization performs at its best. Using the latest computer-based analytical and modeling technologies, Industrial Engineering bridges the gap between management and operations, applying organizational development, continuous improvement, total quality management, ergonomics and production systems expertise.

What Industrial Engineers Do

Using mathematics and science, industrial engineers develop economical solutions to technical problems. They use scientific advancements to create commercial applications in order to meet consumer needs. Also, industrial engineers, while developing new products, consider several factors in the process. They determine precise functional requirements, design and test components, create a final design, and evaluate the design's overall effectiveness, cost, safety and reliability. Beyond development and design, many industrial engineers work in production, testing or maintenance. They often supervise factory production, test product quality or determine the cause of product malfunctions. Industrial engineers use computers extensively in their work to simulate system operations, generate specifications for parts, produce and analyze designs, monitor quality and control efficiency.

Industrial engineers make a product or provide a service by determining the most effective ways to use the five basic factors of production: Machines, materials, energy, information and people. Industrial engineers focus on increasing productivity through the management of technology, people and methods of business organization. They often study product requirements and then use mathematical methods and models to design the most effective manufacturing and information systems to meet such requirements. Industrial engineers develop management control systems to aid cost analysis and financial planning. They also design production control and planning systems to ensure quality. Some industrial engineers improve or design new systems for distributing goods and services as well as determining the most efficient locations for plants. They also carry out job evaluation programs and wage & salary administration systems. From the foregoing, it is clear that industrial engineers may be employed in almost any type of industry, business or institution, from retail establishments to manufacturing plants to government agencies to hospitals. Some would say, 'anywhere work is done; you need an industrial engineer!'

Mr. Vice-Chancellor Sir, within the field of Industrial Engineering, my area of specialization is Operations Management (OM). Operations Management deals with the design and management of products, processes, services and supply chains. It considers the acquisition, development, and utilization of resources that firms need to deliver the goods and services desired by their clients. The scope of OM ranges from **strategic** to **tactical** and **operational** levels. **Strategic** issues include determining the size and location of manufacturing plants, deciding the structure of service or telecommunications networks, and designing technology supply chains. **Tactical** issues include plant layout and structure, project management methods, and equipment selection and replacement. **Operational** issues include production scheduling and control, inventory management, quality control and inspection, traffic and materials handling, and equipment maintenance policies.

Within the Operations management sub-field, my research interest is in the area of Production Scheduling. Production scheduling is the management and allocation of resources, events and processes to create goods and services. A business organisation adjusts its production schedule based on the availability of resources, client orders and efficiencies. Production scheduling covers all aspects of operations, from workforce activities to product delivery. It is primarily concerned with the efficient use of resources. A scheduling problem is essentially a decision making problem. Decision Making arises at all levels of human endeavour. Decision Making is very useful for the successful operation of organizational activities. It is a critical tool for the successful operation of any business. Indeed, decision making helps to utilize the available resources (the 6Ms: Men, Money, Materials, Machines, Methods and Markets) for achieving the objectives of the organization.

Over the years, I have been working on tools to aid decision making. Thus, this was responsible for the choice of the topic of this lecture "Decision Problems: Of the Analyst and the Decision Maker". This lecture is in three parts. I intend to discuss decision problems in the first part of the lecture while the role of the stakeholders (the Analysts and the Decision Makers) will be discussed in the second part of the lecture. The third part of the lecture will highlight some of my contributions to knowledge in these areas over the years. I will conclude by making appropriate recommendations.

Part I: Decision Making/Problems

DECISION MAKING

Mr. Vice-Chancellor Sir, decision making is as old as man. The Holy Bible says, "So when the woman saw that the tree was good for food, that it was pleasant to the eyes, and a tree desirable to make one wise, <u>**she took of its fruit and ate**</u>. <u>**She also gave to her husband**</u> with her, ***and he ate***". – Gen 3: 6. Eve took three decisions: 1) to take the fruit 2) to eat the fruit 3) to give the fruit to her husband. Adam also took two decisions based on Eve's actions:

1) to collect the fruit from his wife 2) to eat the fruit. Decision making may be defined as choosing one course of action from among several alternatives. Each of these alternative courses of action has various outcomes. The task of decision making is to select the alternative that results in the preferred set of all the possible consequences and/or rewards. Inherently, the decision making process involves: **gathering of information about the problem and the alternatives**, **developing and analyzing possible courses of action**, and **making a choice from the alternatives**.

The decision making process is often broken down into three steps (Simon, 1955; Baker et al., 2002):

Intelligence activity: As it is being used in the military, this means, gathering information about the environment and the alternatives. This also involves identification and diagnosis of the problem.

Design activity: This is the process of developing and analyzing possible courses of action. Under this activity, the problem is compared with existing standards and procedures to see if it could be solved using any of these existing procedures. Otherwise, a new procedure is developed for solving the problem.

Choice activity: This is the final stage of decision making and it involves making the choice of the preferred alternative.

Decision Making arises at all levels of human endeavours.

COMPLEXITIES OF DECISION PROBLEMS/MAKING

Mr. Vice-Chancellor Sir, it is not easy to make a decision. This is because; decision problems are very complex by nature. An algorithm is said to be "efficient" if it's running time is a polynomial function of the size of the input, and "inefficient" otherwise (Edmonds, 1960). Thus, a problem is considered easy to solve (tractable) if it has a polynomial time solution and difficult (intractable) if it does not. Thus, this differentiates between two classes of decision problems (Class *P* and Class *NP*). The relation between the complexity classes ***P*** and ***NP*** is closely linked with the resources required during computation to solve a given problem (French, 1982). The most common resources are: **time** (how many steps it takes to solve a problem) and **space** (how much memory it takes to solve a problem). Both classes (*P* and *NP*) are briefly described below.

CLASS *P* OF DECISION PROBLEMS

The Class *P* consists of the set of decision problems that can be solved easily within a short time. They are often referred to as the class of polynomially solvable decision problems. Class *P* contains all the sets of decision problems in which solutions may be found by an algorithm whose running time is very short.

For example, if there is an algorithm that can produce the correct answer for any input string of length n in at most cn^k steps, where k and c are constants and independent of the input string, then we say that the problem can be solved in polynomial time and we place it in the class ***P***. Thus, the class *P* of decision problems is considered as the set of efficiently solvable problems. Generally speaking, the practical computation of decision problems in class *P* resides within polynomial time bounds.

CLASS *NP* OF DECISION PROBLEMS

This is the class of problems that one will love to solve but unable to do so exactly due to prohibitive time and computational resources they required. **For example, consider an examination scheduling problem for which a school has *n* courses and five days in which to schedule examinations**. An optimal schedule (solution) would ensure that no student takes two examinations on the same day and at the same time. This seems like an easy problem, but there are $O(5^n)$ possible different schedules. If one uses a computer, that could check a million schedules every second, to evaluate all the schedules, then the time spent checking for a value of $n = 50$ would be about **200,000,000,000,000,000,000 years! (200** Quintillion years). Obviously, no one lives for up to the number of years it will take to solve this problem that looks simple. Thus, this class of decision problems (though, we believe, they have solutions) is very complex in nature. They are called *Nondeterministic Polynomial (NP) Hard* problems. Unfortunately, many decision problems belong to this class (*NP*) of problems.

The knowledge that a decision problem is *NP-Hard* provides us valuable information about the lines of approach that have the potential of being most productive. Certainly, for such problems, the search for an efficient, exact algorithm should be accorded low priority. It may be more appropriate and more beneficial to concentrate our efforts on other less ambitious approaches. For example, one might look for efficient algorithms that solve various special cases of the general problem. We might also look for algorithms that, though not guaranteed optimal (best) results, but produces results that are as close as possible to the optimal within a reasonable amount of time (polynomial time).

Solving the decision problems (be it Class *P* or *NP*) requires a number of stakeholders (the decision maker and analyst), with each having distinct roles to play in the solution process. The stakeholders in the decision making are the subject of discussion in the next section of this lecture (Part Two).

Part II: STAKEHOLDERS IN DECISION MAKING

Mr. Vice-Chancellor Sir, two major stakeholders can be identified in the decision making process. These are: the decision maker and the analyst.

THE DECISION MAKER

The first major stakeholder in the decision making process is the Decision Maker (DM). Generally, the decision maker is a person who is assumed to know the problem under consideration and also he is able to provide preference information related to the objectives and/or different solutions in some form. In some situations, the DM may be a unique and distinct individual, whereas in some other situations, the DM may consist of a group of people that takes decision. In any of these cases, it is assumed that the decision maker is rational. If appropriate means are chosen to reach the desired results, the decision maker is said to be rational, otherwise, irrational. It is the desire of the decision maker to choose the optimal decision. Thus, the solution process needs the involvement of the DM in the form of specifying preference information and the final solution is determined by his/her preferences in one way or the other.

THE ANALYST

The second major stakeholder in the decision making process is the analyst. The analyst is a person who is responsible for the mathematical modeling and computing sides of the solution process. The analyst is expected to help the decision maker (DM) at various stages of the solution process, most especially, in eliciting preference information and in interpreting the information coming from the computations. Among other things, the analyst is expected to:

1) generate the set of the best and most acceptable (Pareto optimal) solutions reliably,

2) help the DM to get an overview/understanding of the set of Pareto optimal solutions (this should not require too much time from the DM, the information exchanged between the analyst and the DM should be understandable and not too demanding or complicated), and
3) support the DM in finding the most preferred solution as the final one so that the DM could be convinced of its relative goodness. He is not expected to force his opinion on the DM neither is he expected to choose/select the final solution for the DM.

To be able to do the foregoing appropriately, the analyst is expected to know the specifics of the solution methods to be employed. He is also expected to help the DM at various stages of the solution implementation process. The analyst, by virtue of training and experience, has adequate knowledge of the properties of different solution methods available; hence, his recommendation is expected to fit the needs of the DM in question. The roles of the analyst cut across the first two activities (Intelligence activity and Design activity) of the decision making process which was mentioned earlier on.

INTERACTIONS BETWEEN ANALYST AND DECISION MAKER

The involvement of the DM in the solution process can be classified into the following three classes: a priori, interactive, and posteriori (Van Veldhuizen and Lamont, 2000).

A Priori

In the a priori case, the DM first articulates preference information in the form of aspirations or opinions; he then discusses these with the analyst who then designs solutions for the decision problem (taking into consideration the preference information of the DM). The drawback of this approach is that the DM does not necessarily know the possibilities and limitations of the problem beforehand and may have too optimistic or pessimistic expectations.

Interactive

The power of interactive methods in facilitating learning during the solution process can, perhaps, be best described by the popular Chinese proverb "Tell me and I will forget, show me and I may remember, **involve me and I will understand**". The last part of this proverb can be traced to the Holy Bible (Gen. 1: 26 -And God said, “<u>let us</u> make man in <u>our</u> image, after our likeness; and let them have dominion over the fish of the sea…"), where God demonstrated the need for involvement in the creation of humanity. In the interactive approach, an iterative solution process is formed, its steps are repeated and the DM specifies preference information progressively during the solution process. Usually, the phases of preference elicitation and solution generation alternate until the DM has found the most preferred solution (or some stopping criterion is satisfied, or there is no satisfactory solution for the current problem setting). Essentially, after every iteration, the analyst gives some information to the DM and he/she is asked to answer some questions concerning a critical evaluation of the proposed solutions or to provide some other type of information to express her/his preferences. The new information from the DM is used to construct a more or less explicit model of the DM's local preferences and new solutions (which are supposed to better fit the DM's preferences) are generated based on this model. In this way, the DM directs the solution process. Normally, during the solution process, the DM is at liberty to specify and correct his/her preferences and selections.

Some of the advantages of the interactive method include:

i. The DM does not need to have any global preference structure and he/she can learn during the solution process. This is a very important benefit of interactive methods because getting to know the problem, its possibilities and limitations is often very valuable for the DM.

ii. The interactive methods overcome the weaknesses of both a priori and posteriori methods because the DM does not need a global preference structure.

iii. Only the set of acceptable (Pareto optimal) solutions that are interesting to the DM are generated. This results to tremendous savings in computational cost.

An important assumption underlying the successful application of interactive approach is that the DM must be available and willing to actively participate in the solution process and direct it (backward or forward) according to his/her preferences. In the solution process, two phases of interactive method can be identified: learning phase and decision phase. During the learning phase, the DM learns about the problem and feasible solutions therein. The DM progressively builds a conviction of what is possible (i.e. what kind of solutions is available) and confronting this knowledge with his/her preferences that also evolves. At the decision phase, the most preferred solution is found in the region identified during the learning phase.

Posteriori

In the posteriori method, the analyst designs solution process to seek/generate the Pareto optimal set and then presents it to the DM who selects the one that best satisfies his/her preferences as the final solution. Also, the analyst presents the implications of each solution to the DM. This is to make it easier for the DM to select the most preferred solution. The drawbacks of this method include:

1) The generation process is usually computationally expensive and sometimes difficult.

2) Often times, it is hard for the DM to make a choice from a large set of alternatives. This has attracted researcher's attention.

NIGERIA AS A DECISION PROBLEM

The Nigerian project can be viewed as a decision problem. The decision makers are the President and Commander-in-Chief of the Armed Forces at the Federal level, the Governors at the State level and Local Government Chairmen at the Council level. The Analysts are the knowledgeable individuals on certain critical sectors of Nigerian project/economy - technocrats. It is imperative for the President, Governors, and LG Chairmen to ensure that these technocrats (Analysts) are appointed as Ministers, Commissioners and Councilors to oversee the critical sectors of Nigeria. Now it is not enough to appoint these technocrats (Analysts) as Ministers, Commissioners, and Councilors; the President, Governors and LG Chairmen need to listen to (interact with) them before taking decisions in these critical sectors of Nigeria. In fact what is recommended is the kind of interaction reminiscent of what was discussed above. **(Please, refer to the article posted on Nigeriana (online news) on 29th March 2016 captioned "How Well Does President Buhari Use The Experts He Appointed?")**

LASU AS A DECISION PROBLEM

The Lagos State University can also be viewed as a decision problem. Here, the decision maker is the Vice Chancellor while the Deputy Vice Chancellors, Provosts, Deans, HODs, Professors, Chair Persons of Advisory Committees are the Analysts. Shortly after his appointment as the 8th Vice Chancellor of LASU, Professor Fagbohun set up not less than 32 advisory committees which cover critical sectors of the Lagos State University. Since assumption of office, Professor Fagbohun has been having regular interactive meetings with Provosts/Deans, HODs, Professors and Chair Persons of all the advisory committees and indeed all the stakeholders in the LASU project. This initiative of our Vice Chancellor is highly commendable.

Part III: My Humble Contributions

Mr. Vice Chancellor Sir, over the years, my research efforts have concentrated on two major areas with notable impact. They are:

i. **Scheduling Problems**

ii **Service Quality Assessment**

SCHEDULING PROBLEMS

Scheduling deals with the problem of allocating resources (machines) over time to perform a number of tasks (jobs) with the aim of minimizing cost or maximizing profit. The problem is essentially a decision-making problem which occurs frequently in almost all facets of life. Examples include (Oyetunji, 2006):

a. Jobs waiting for processing in a manufacturing plant

b. Programs to be run on a computer system

c. Bank customers waiting for services in front of tellers' windows

d. Airplanes awaiting clearances to land or take off at an airport

e. Patients waiting for treatment in a hospital

f. Cars waiting to be repaired in a garage

The real problem of scheduling is how to determine the schedule that best meets the set objectives (Oyetunji and Oluleye, 2008c). Scheduling consists of sequencing and timing. Sequencing is the order in which a set of jobs is to be processed on a number of machines/processors (Oyetunji and Oluleye, 2007). Figure 1 gives a sequence showing order.

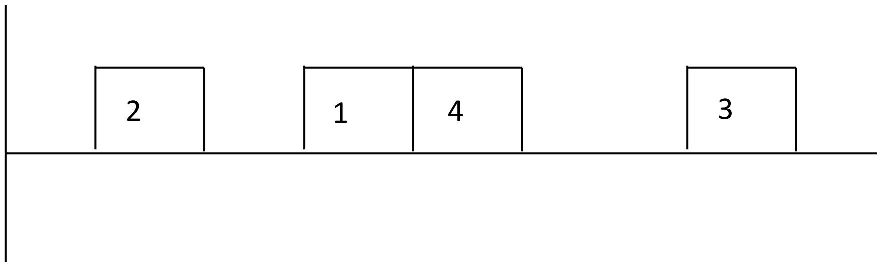

Fig. 1. Gantt chart showing a hypothetical sequence

Timing, on the other hand, involves determination of the start and finish times of the jobs (Oyetunji and Oluleye, 2007). Figure 2 shows the start and finish times for scheduled jobs.

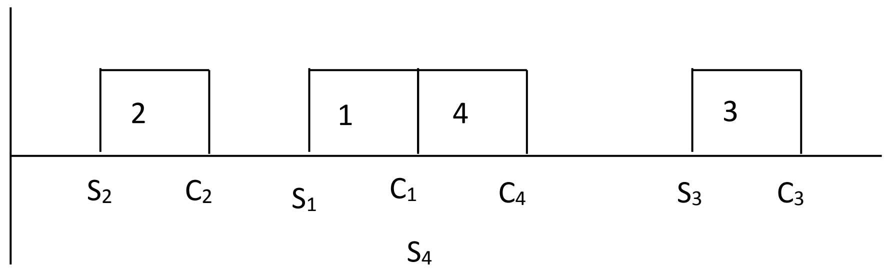

Fig. 2. Gantt chart showing a hypothetical sequence with timing information

The vital elements in scheduling problems are **resources**, **tasks**, and **objectives**. Resources (also called processors or machines) are typically characterized in terms of their qualitative and quantitative capacities, so that in a scheduling problem, each resource is described by its type and number. Tasks (the fundamental units of jobs) are typically described in terms of such information as their resource requirement, duration, the time at which they may be started, and the time at which they are due. Sometimes a collection of tasks is described in terms of precedence constraints that exist among the tasks. Scheduling objectives (also called criteria) represent the measure of performance (Oyetunji, 2006). Scheduling objectives are usually measures of goodness of solution (Oyetunji and Oluleye, 2008c). Scheduling problems may be classified into Single Objective Scheduling Problems (SOSP) and Multi Objectives Scheduling Problems (MOSP). My research efforts covered the two classes (SOSP and MOSP).

Single Objective Scheduling Problems (SOSP)

Mr. Vice Chancellor Sir, as the name suggests, the Single Objective Scheduling Problems are Scheduling Problems involving only one objective (or performance measure or criterion). These Problems may sound tractable, but they are not. This is because; there are additional two dimensions of complexities for Scheduling Problems. These are complexities arising from the number of jobs/tasks and number of machines/processors. Thus, the higher the number of jobs involved in a scheduling problem, the more complex the scheduling problem becomes. This assertion also holds with the increasing number of machines (Oluleye and Oyetunji, 1999).

Given the fact that; multi machines scheduling problems can be disaggregated into their respective single machine sub problems and the fact that once we are able to solve efficiently single machine scheduling problems, then we have succeeded in solving the multi machines scheduling problems since the solution methods can easily be scaled up under different problem loadings. Although there are numerous scheduling objectives or criteria (Oyetunji, 2009), the following scheduling criteria have attracted my attention in my study of single objective scheduling problems: Makespan, Total Completion time, Number of Tardy jobs, Maximum Earliness, and Total Flow time. In real life, single machine problems represent bottle neck processes or composite processes that impact each other given their relatedness.

-Makespan

In pursuit of solutions to the single objective scheduling problems, the first problem that attracted my attention is the scheduling problem of minimizing the makespan (maximum completion time or the completion time of the last scheduled job) under the flowshop environment. The desire to maximize the production and minimize the mean idle time of machines makes the makespan an acceptable measure of performance to most researchers and indeed manufacturers (Oluleye and Oyetunji, 1999). In order to solve this problem within a reasonable and acceptable time limit, three new heuristics (A1, O1, and O2) were proposed and evaluated with two other heuristics (CDS and DAN) selected from the literature. The results obtained from the performance evaluation carried out for small and medium size problems are shown in Tables 1 and 2, respectively.

Table 1: Mean of Makespan of some problem sets for each heuristic (Small-Sized Problem)

Problem Size	CDS	A1	01	02	DAN
5 × 3	371.37	385.82	392.94	370.02	
5 × 6	551.47	552.82	565.49	558.96	567.33
9 × 4	715.67	724.84	746.76	720.51	732.49
9 × 5	692.00	704.27	736.37	702.69	710.61
15 × 3	888.51	908.27	927.65	893.94	898.49
15 × 6	1096.45	1101.41	1137.06	1114.55	1125.27

Table 2: Mean of Makespan of some problem sets for each heuristic (Medium-Sized Problem)

Problem Size	CDS	A1	01	02	DAN
5 × 8	610.96	611.77	631.18	633.08	638.75
5 × 15	985.48	989.97	1004.59	996.46	1009.59
9 × 8	844.49	831.48	865.14	873.51	882.04
9 × 14	1149.12	1151.30	1180.40	1176.67	1191.04
15 × 9	1215.22	1179.85	1220.30	1261.26	1286.34
15 × 14	1518.24	1515.87	1569.12	1564.99	1583.83

It was observed that the CDS heuristic obtained better solutions with respect to small-sized problems (problems for which the number of machines is less than 8) while the A1 heuristic obtained superior schedules for the medium-sized problems (problems in which the number of machines range from 8 to 15 inclusive). Tables 3 and 4, which show the mean range of the proportion of superior schedules for the small-sized and medium-sized problems respectively, corroborated the above observation. Statistical tests showed that the observed differences were significant at 5% ($p < 0.05$).

Table 3: Mean range of proportion of superior schedules (Small-Sized Problem)

	Number of Machines				
Heuristic	3	4	5	6	7
CDS	69.1	45.7	49.4	46.0	54.0
DAN	42.6	27.14	19.9	13.7	15.7
A1	30.6	27.4	26.6	35.4	27.4
01	17.4	16.8	13.4	12.6	11.7
O2	62.0	47.1	43.7	34.3	34.6

Table 4: Mean range of proportion of superior schedules (Medium-Sized Problem)

	Number of Machines							
Heuristic	8	9	10	11	12	13	14	15
CDS	34.8	24.0	37.1	44.3	50.6	46.8	53.7	53.4
Dan	4.3	3.1	6.6	5.4	6.0	6.6	6.6	6.9
A1	62.6	64.0	60.6	58.6	48.3	47.4	42.6	41.7
O1	13.1	21.7	14.6	16.6	14.0	13.1	13.4	11.7
O2	10.0	8.8	12.6	11.14	15.4	16.9	17.4	19.1

The consequence of the above results for decision maker or production manager is that for the general flowshop scheduling problem of minimizing makespan, the CDS heuristic should be used for the small-sized problems while for the medium-sized problems, the A1 heuristic which we proposed is recommended in obtaining the production schedules. This recommendation reinforces the belief that in problem solving ‘one size does not fit all’.

- Total Completion time

The second scheduling objective that attracted my attention in my pursuit of solution methods to single objective scheduling problems is the total completion time (C_{tot}) (Oyetunji and Oluleye, 2007). It is the sum of the completion time of all the jobs. The total completion time has been noted as an important scheduling criterion or objective (Hall et al., 1996; Oyetunji and Oluleye, 2008b). This is because minimizing the total completion time also implicitly minimizes at least five other related scheduling objectives (these includes: total flow time (F_{tot}), total lateness (L_{tot}), average completion time (C_{avg}), average flow time (F_{avg}), and average lateness (L_{avg})). A key feature of the total completion time is that it gives an indication of inventory characteristics. Focusing on inventory, helps manage space and the appropriate investment in product pools.

To this end, in 2007, I explored the single machine scheduling problem of minimizing the total completion time of jobs with release dates. This problem has long been tagged “NP-Hard” (Chakrabarti et al., 1996; Karger et al., 1997; Philips et al., 1998; Chekuri et al., 2001). In order to solve this important scheduling problem, two heuristics (AEO & HR1) were proposed and tested against the best known polynomial time approximation algorithm (called Best Alpha or BESTA algorithm) developed to date (by Chekuri et al., 2001) for the same problem (single machine scheduling problems of minimizing the total completion time of jobs with release dates) (Oyetunji and Oluleye, 2007). Mr. Vice Chancellor sir, the computational experiment carried out showed that one of the proposed heuristic (AEO) performed better than the BESTA algorithm (which was earlier on noted as the best approximation algorithm to date for minimizing the total completion time of jobs with release dates) when the number of jobs exceeds 5 (pls see Table 5). Also, the AEO heuristic is faster (more efficient) than the BESTA algorithm (Table 6). Statistical tests carried out on Tables 5 and 6 showed that the differences were significant at 5% ($P<0.05$). Thus, decision makers who pay premium on both effectiveness and efficiency are encouraged to adopt the AEO heuristic when confronted with the single machine scheduling problems of minimizing the total completion time of jobs with release dates. This has the practical implication of obtaining low inventory within a short time.

Table 5 Mean of total completion time obtained from the heuristics Problem Mean of total completion time

Problem	Mean of total completion time		
Size	BESTA	HR1	AEO
3x1	276.54	276.80	276.74
4x1	438.20	440.36	438.20
5x1	675.56	675.86	675.71
6x1	888.98	896.10	886.10
7x1	1129.96	1151.70	1128.78
8x1	1501.42	1526.56	1501.16
9x1	1866.66	1906.20	1862.48
10x1	2231.88	2290.62	2219.48
12x1	3049.12	3147.12	2991.58
15x1	4721.42	4885.90	4601.14
20x1	8272.64	9127.78	8221.60
25x1	12178.68	13808.12	12020.16
30x1	16393.18	19124.84	16129.30
40x1	29668.08	35168.04	28865.44
50x1	46142.70	58126.32	45846.62
100x1	180653.96	242729.36	176951.82
120x1	265219.70	359756.20	260872.84
140x1	337468.84	470049.64	334757.04
200x1	703515.28	986663.44	694816.12
300x1	1586458.44	2246853.16	1566830.10
400x1	2795523.38	4004104.44	2777808.10
500x1	4385929.38	6239629.10	4311286.66

Sample size = 50

Table 6 Mean of time taken to solve an instance of a problem

Problem Size	Mean of time taken [sec] BESTA	HR1	AEO
3x1	0.2724	0.0002	0.00218
4x1	0.2284	0.0001	0.0018
5x1	0.4596	0.0005	0.0018
6x1	0.4887	0.0004	0.0024
7x1	0.5347	0.0004	0.0028
8x1	0.5553	0.0008	0.0046
9x1	0.5571	0.0003	0.0056
10x1	0.6118	0.0009	0.0065
12x1	0.6543	0.0005	0.0099
15x1	0.7831	0.0012	0.0148
20x1	1.2336	0.0023	0.0280
25x1	1.7877	0.0028	0.0457
30x1	3.2545	0.0013	0.0742
40x1	5.1702	0.0054	0.1184
50x1	6.6969	0.0062	0.2046
100x1	16.1500	0.0152	0.9703
120x1	20.5060	0.0212	1.4887
140x1	25.2036	0.0283	2.0465
200x1	40.9729	0.055	5.8150
300x1	88.9435	0.1153	16.2571
400x1	150.7314	0.2046	34.2864
500x1	259.2708	0.3168	59.8488

Sample size = 50

In order to demonstrate the utility of the AEO heuristic, it was applied to a real-life problem in a Printing Company (Oyetunji and Oluleye, 2008e). The company has many customers bringing work orders (jobs) which are processed on first-come first-serve basis. Real life data were collected from the company and its production practice (first-come first-serve policy, also called FC) was compared with AEO and BESTA algorithms. The intention is to recommend to the company a better sequence of processing the work orders. The basic data required are the release date, processing time and due dates of each job. The date the work order was brought was used as the release date of the job. It was assumed that scheduling starts from the 1st day of the month, so if a work order was brought on 12th of January, the release date is 12. This represents the earliest date the job can start. The date the work order is required was used to compute the due date. The estimated processing time of each work order was used as the processing time of the work order. This estimate is normally carried out by the production manager. The results of the analysis carried out show that the Company's total production cost per day can be reduced by up to 41.12% by adopting the AEO heuristic instead of its first-come first-serve production practice (see Tables 7 and 8). In view of this substantial gain, the AEO algorithm was recommended to the Printing Company for operational scheduling of printing jobs. The effective use of the algorithm is in the company balance sheets of profitability.

Table 7: Means of Total Completion Time (days).

Problem Size	Solution methods BESTA	AEO	FC
10x1	95.59	97.05	136.61
15x1	206.71	204.88	305.18
20x1	348.89	345.22	540.19
25x1	518.23	518.80	835.83
30x1	717.87	715.90	1174.98
35x1	975.35	973.10	1615.15
40x1	1273.03	1270.90	2134.51
45x1	1613.89	1610.65	2720.72
50x1	1992.40	1989.56	3379.19

Sample size = 10

Table 8: Percentage Reduction (%) in Cost by Solution Methods.

Work Order	BESTA	AEO
10	30.03	28.96
15	32.27	32.87
20	35.41	36.09
25	38.00	37.93
30	38.90	39.07
35	39.61	39.75
40	40.36	40.46
45	40.68	40.80
50	41.04	41.12

Sample size = 10

My quest for better solution methods to scheduling problems continues, and encouraged by the impressive performance of the AEO algorithm over the BESTA algorithm whose approximation ratio was considered tight by Uthaisombut (2000), I embarked on the search for further solution methods for this important scheduling problem. These efforts eventually paid off with the development of a new algorithm (called MM algorithm) for the scheduling problem of minimizing the total completion time on single machine with release dates (Oyetunji and Masahudu, 2009). In order to assess its performance, the MM algorithm was compared against the AEO and HR1 heuristics. It is observed that the MM heuristic gave the least values of the total completion time for all the problem sizes considered. This was followed by the AEO while the HR1 heuristic lagged behind across various problem sizes (Table 9). Also, in terms of efficiency, the MM heuristic took less time (faster) than the AEO heuristic for all the considered problem sizes (Fig. 3). Therefore, the MM heuristic is recommended to decision makers, who pay strong premium on both effectiveness and efficiency, for solving the scheduling problem of minimizing the total completion time on a single machine with release dates.

Table 9: Mean of the total completion time by solution methods and problem sizes

	Mean of the total completion time		
Problem Size	MM	AEO	HR1
3x1	259.40	279.10	283.37
4x1	552.20	593.03	598.90
5x1	614.60	726.53	760.40
6x1	772.77	937.97	980.30
7x1	967.17	1221.93	1355.10
8x1	998.30	1465.67	1616.10
10x1	1777.70	2363.17	2704.87
20x1	6761.03	8947.80	9603.30
25x1	8657.03	12125.00	14152.30
50x1	28597.47	31365.17	34924.97
100x1	29968.30	37859.63	40068.47
200x1	40631.20	47845.60	50268.30
300x1	76801.63	88055.60	90834.73
400x1	86501.65	98155.60	109814.37
500x1	1020835.00	1241789.00	1447865.00

Sample size = 30

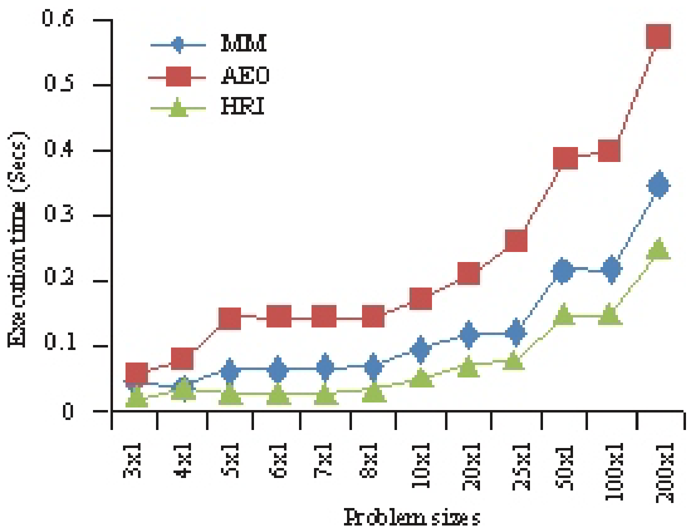

Fig. 3: Comparison of execution time of MM, AEO and HR1 for 3 to 200 problem sizes

Number of Tardy Jobs

The number of tardy jobs (NT) is the third scheduling objective (criterion or performance measure) that attracted my attention as I continued the search for solution methods to scheduling problems. The number of tardy jobs is also an important performance measure in scheduling as it has great practical implications in an organization. A job is said to be tardy if it is completed after its due date. Customer's goodwill would surely be lost and there might be financial penalties as well when promised delivery dates are not kept (Pinedo, 2002). In a number of shop floor environments and even in some service organizations, the lateness penalty may be great thereby resulting in grave consequences for the organization. Such consequences may include: seeking alternatives, instituting legal action to claim for damages, etc. It is, therefore, the desire of a decision maker to satisfy as many customers as are possible by ensuring that their jobs are completed on or before their due dates. However, because of problem complexities (release and due dates constraints), it may be practically impossible to complete all jobs by their respective due dates at all times. Hence, any schedule that yields lower values of the number of tardy jobs for any given problem is preferable. The number of tardy jobs criterion is particularly useful in organizations where the lateness penalty depends on whether a job is late or not as against by how much a job is late. For example, if an aircraft is scheduled to land at a time after which it will have exhausted its fuel, then the results are just as catastrophic whatever the scheduled landing time. So considering the number of tardy jobs as a performance measure is much more relevant in practical scheduling settings.

The general one-machine scheduling problem of minimizing the number of tardy jobs with release dates is classified as NP-Hard (Baptiste et al., 2003). Therefore, in the effort to solve this important scheduling problem in polynomial time, three heuristics (tagged EOO, HR2 and HR3) were proposed by Oyetunji and Oluleye ((2008c). The effectiveness and efficiency of the heuristics were evaluated along with the DAU heuristic proposed by Dauzere-Perez (1995) for the same general problem. The results obtained, with respect to effectiveness (quality of solution); show that the EOO heuristic gave the lowest number of tardy jobs for all the problem sizes considered (Table 10).

Table 10: Mean of number of tardy jobs obtained from the heuristics by problem size

Problem	Mean of number of tardy jobs			
Size	EOO	DAU	HR2	HR3
3x1	0.6	0.94	0.76	0.74
4x1	1.38	1.68	2.02	1.9
5x1	1.58	2.44	2.54	2.42
6x1	2.3	2.94	3.48	3.28
7x1	2.74	3.62	4.8	4.52
8x1	3.46	4.6	5.74	5.46
9x1	4.18	5.16	6.72	6.16
10x1	4.76	5.74	7.28	6.94
12x1	5.92	6.82	9.58	9
15x1	8.2	9.48	12.42	11.98
20x1	11.5	12.2	17.82	16.9
25x1	14.5	15.58	22.26	21.84
30x1	17.36	18.72	27	26.22
40x1	23.8	25.9	37.02	36.44
50x1	31.02	32.64	47.32	46.78
100x1	62.86	63.7	97	96.72
120x1	75.88	77.76	117.02	116.82
140x1	87.64	89.04	136.92	136.94
200x1	125.26	126.68	196.4	197.08
300x1	188.88	190.16	296.48	296.84
400x1	251.4	252.44	296.16	397.04
500x1	314.36	315.18	496.7	497.16

Sample size = 50

It is interesting to observe that the EOO heuristic is also faster (more efficient) than the well-known DAU heuristic most especially when the number of jobs exceeds 180 (Figure 4). For example, the EOO heuristic required 30% less time to solve a problem involving 500 jobs when compared to the DAU heuristic(see Figure 4).

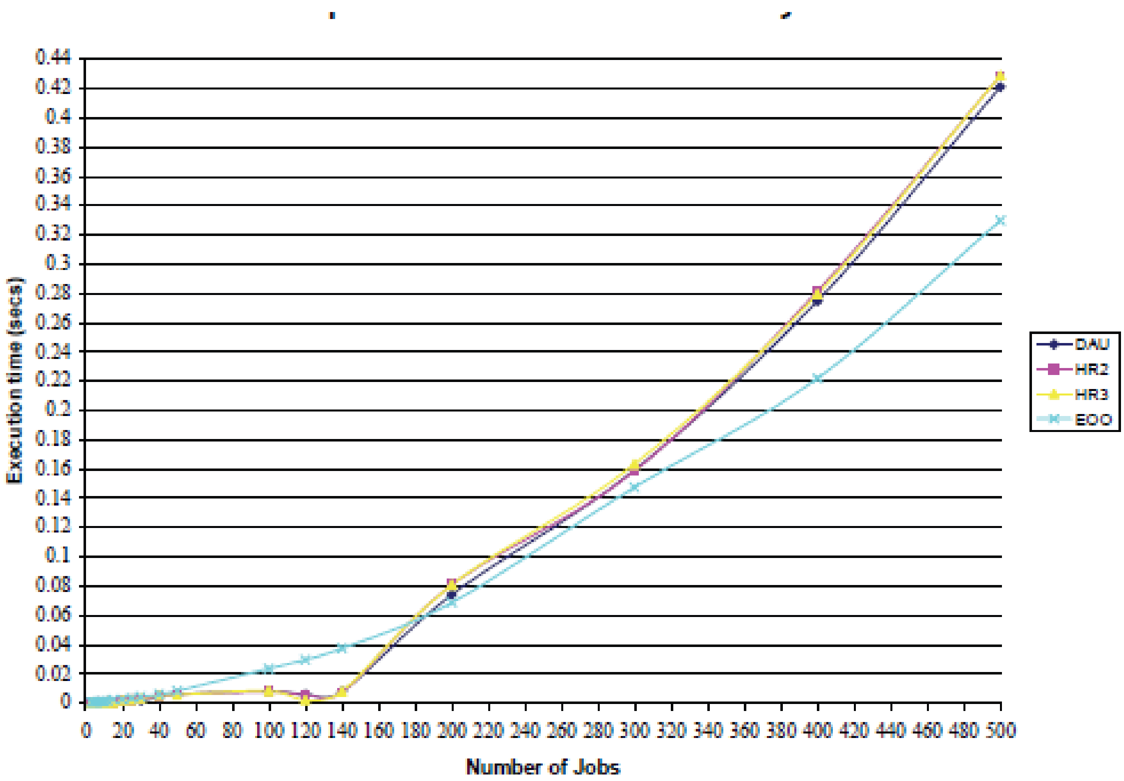

Figure 4: Time taken by EOO, DAU, HR2, and HR3 methods for 3 to 500 jobs

The summary of the results obtained are shown in Table 11, the solution methods in both the effectiveness and efficiency columns have been ordered in ascending order of effectiveness (value of the number of tardy jobs) and efficiency (execution time) for each problem size. For example, the mean value of the number of tardy jobs given by EOO (effectiveness column) is significantly different from (better than) that of DAU, HR2, and HR3 ($P \leq 0.05$) for $3 \leq n \leq 200$ problems, meaning that the quality of solution given by the EOO heuristic is much better than that of the DAU, HR2, and HR3 methods when the number of jobs is less than or equal to 200 (Table 11). Thus, the EOO heuristic provides the decision maker with an effective and efficient way for obtaining production schedules.

Table 11: Performance with respect to effectiveness and efficiency

Problem Size	Effectiveness				Efficiency			
	A	B	C		D	E	E	
3x1	EOO^{*A,B,C},	DAU,	HR3,	HR2	DAU,	HR3,	HR2,	EOO
4x1	EOO^{*A,B,C},	DAU,	HR3,	HR2	DAU,	HR3,	HR2,	EOO
5x1	EOO^{*A,B,C},	DAU,	HR3,	HR2	DAU,	HR3,	HR2,	EOO
6x1	EOO^{*A,B,C},	DAU,	HR3,	HR2	DAU,	HR3,	HR2,	EOO
7x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
8x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
9x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
10x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
12x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
15x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
20x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
25x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
30x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
40x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
50x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
100x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
120x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
140x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
200x1	EOO^{*A,B,C},	DAU^{*B,C},	HR3,	HR2	DAU,	HR3,	HR2,	EOO
300x1	EOO^{*B,C},	DAU^{*B,C},	HR3,	HR2	EOO,	HR2,	DAU,	HR3
400x1	EOO^{*B,C},	DAU^{*B,C},	HR3,	HR2	EOO,	DAU,	HR3,	HR2
500x1	EOO^{*B,C},	DAU^{*B,C},	HR3,	HR2	EOO,	DAU,	HR2,	HR3

Sample size=50

Note:
*A,B, C indicates significant result at 5% level from solution methods in columns A, B and C.
*B, C indicates significant result at 5% level from solution methods in columns B and C.

- Maximum Earliness

The maximum earliness (E_{max}) is the fourth scheduling objective that has attracted my attention. A job is said to be early if it is completed before the due date. In the current competitive environment, effective sequencing and scheduling has become a necessity for survival in the market place. Companies have to meet shipping dates committed to the customers, as failure to do so may result in a significant loss of goodwill and also being conscious of the facts that earliness of jobs before the due date may on the other hand, increase inventory cost which may be high when compared with the total production cost.

Therefore, activities have to be scheduled in such a way to use the available resources efficiently. In a production setup, inventory cost may arise when jobs are completed too early. The increased inventory cost may indeed multiply the production cost. This observation has encouraged the exploration of the scheduling problem of minimizing the maximum earliness of jobs on a single machine with release dates (Oyetunji, Oluleye and Ayantobo, 2011). Again, the problem has been noted as NP-Hard (Karger et al. 1997). Given this fact, two approximation algorithms (tagged DOA1 and DOA2) were proposed to solve the scheduling problem. In view of the non-existence of any approximation algorithm proposed to date for this scheduling problem, the DOA1 and DOA2 were compared with the Branch and Bound (BB) procedure (known to be optimal but usually at great computing costs due to its implicit enumeration feature). Experimental results, with respect to effectiveness, show that DOA2 performs competitively with the BB method (BB not significantly different from DOA2 ($p < 0.05$) when the number of jobs range from 3 to 10 (Table 12). Also, with respect to efficiency, results show that both DOA1 and DOA2 are faster than the BB method ($p < 0.05$) for 3 to 100 problem sizes (Tables 13). Thus, the DOA2 algorithm becomes the natural choice of a decision maker that places a premium on operational effectiveness and efficiency.

Table 12 Mean value of maximum earliness by problem sizes and solution methods

Problem	Mean of maximum earliness		
Size	BB	DOA1	DOA2
3x1	8.94	17.32	10.80
4x1	4.36	9.22	5.60
5x1	5.98	9.08	7.86
6x1	5.64	9.88	6.58
7x1	3.12	10.56	8.18
8x1	5.06	8.18	6.98
9x1	3.26	6.14	3.36
10x1	1.66	6.86	3.56
11x1	1.38	5.54	3.56
15x1	1.20	4.38	3.38
20x1	0.60	4.24	2.78
25x1	0.54	6.12	2.60
30x1	0.38	5.56	3.06
40x1	0.24	4.92	0.48
50x1	0.10	1.60	1.30
65x1	0.00	2.32	0.62
70x1	0.06	3.30	1.68
80x1	0.00	1.34	0.48
90x1	0.02	4.18	1.76
100x1	0.00	1.50	1.10

Sample size=50

Table 13 Mean value of execution time (secs) by problem sizes and solution methods

Problem Size	Mean of execution time (secs) BB	DOA1	DOA2
3x1	0.0017	0.0001	0.0001
4x1	0.0042	0.0001	0.0001
5x1	0.0040	0.0004	0.0001
6x1	0.0050	0.0001	0.0001
7x1	0.0070	0.0001	0.0002
8x1	0.0081	0.0001	0.0002
9x1	0.0099	0.0001	0.0003
10x1	0.0104	0.0001	0.0002
11x1	0.0131	0.0001	0.0003
15x1	0.0383	0.0002	0.0003
20x1	0.1224	0.0003	0.0003
25x1	0.2618	0.0005	0.0006
30x1	0.7272	0.0008	0.0006
40x1	2.9561	0.0013	0.0011
50x1	7.4596	0.0024	0.0017
65x1	25.0835	0.0042	0.0029
70x1	35.3600	0.0039	0.0033
80x1	80.2251	0.0054	0.0041
90x1	110.0914	0.0081	0.0050
100x1	183.9331	0.0098	0.0069

Sample size=50

Total Flow time

In my quest for efficient and effective solution methods to single objective scheduling problems, another criterion that attracted my attention is the total flow time (also called sum of the flow times). In systems involving queuing and networks, for example, the flow time of a job consists of both the waiting time in the queue and the job processing time on the machine so that minimizing flow time improves service quality. The desire to improve service quality makes the minimization of the total flow time an important scheduling criterion (objective or performance measure). The foregoing motivated us to explore the scheduling problem of minimizing the sum of flow times on a single machine with release dates (Oyetunji, Akande and Oluleye, 2012).

In view of the NP-Hard nature of the problem (Leonardi and Raz, 1997), two approximation algorithms (KSA1 and KSA2) were proposed for the problem and tested against an algorithm (MPSW) selected from the literature (Guo et al., 2004) and a branch and bound (BB) procedure. Experimental results showed that the MPSW algorithm is better with respect to effectiveness (Table 14) while the KSA2 algorithm is preferred with respect to efficiency (Figure 5). Thus, the decision maker who paid more premiums on effectiveness than efficiency will find the MPSW algorithm very useful while the KSA2 algorithm will appeal to the decision maker who pays more premiums on efficiency than effectiveness.

Table 14 Percentage of time solution methods obtain best results by problem sizes

Problem	Percentage (%) of time best result was obtained		
Size	MPSW	KSA1	KSA2
3x1	12	0	0
4x1	56	0	0
5x1	56	0	0
6x1	74	0	0
7x1	100	0	0
8x1	94	0	0
9x1	88	2	0
10x1	90	2	2
11x1	98	0	0
15x1	92	4	0
20x1	80	4	6
25x1	86	0	4
30x1	98	2	0
40x1	96	2	2
50x1	88	4	2
65x1	98	0	2
70x1	98	0	0
80x1	100	0	0
90x1	92	2	2
100x1	100	0	0

Sample size=50

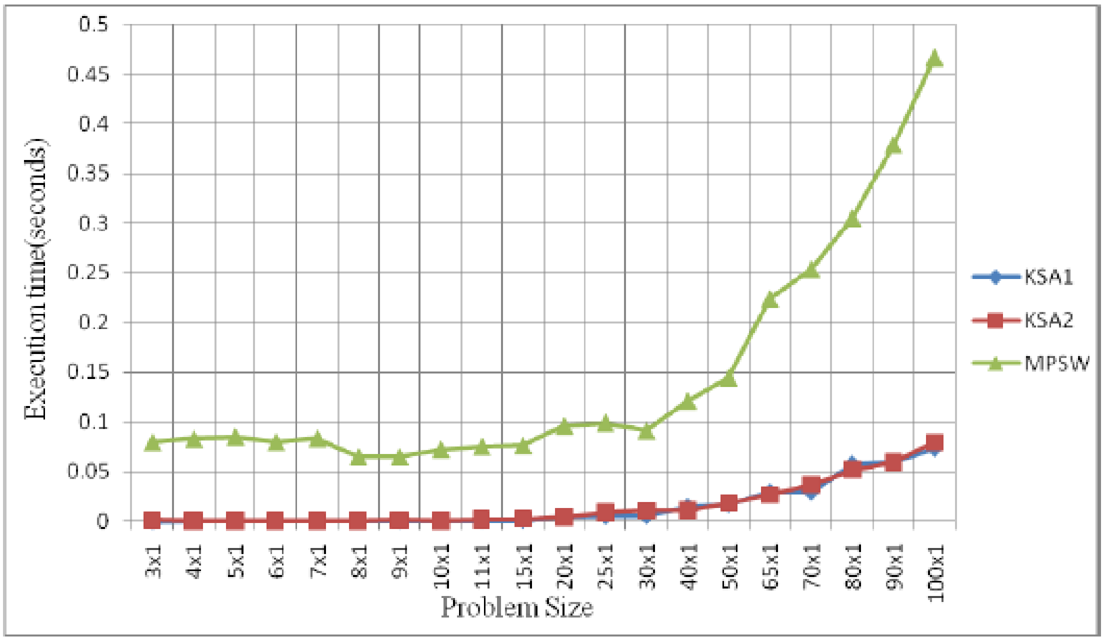

Figure 5 Comparison of the execution time (seconds) taken by three solution methods and problem sizes

Multi Objectives Scheduling Problems (MOSP)

Mr. Vice Chancellor Sir, the multi objective scheduling problems involve optimization of two or more objectives (or criteria) at a time. Having been encouraged by the level of successes recorded with the single objective scheduling problems and because of the practical significance in real-life applications, I ventured into the study of multi objectives scheduling problems despite the acknowledged complexities.

In the past, various criteria have been studied singly (Ehrgott and Grandibleux, 2000). However, in practice, decision makers usually have to consider multiple criteria before arriving at a decision (Hoogeveen and Van de Velde, 1995; Ehrgott and Grandibleux, 2000) . Also, French (1982) reported that the total cost of a schedule is a complex combination of processing costs, inventory costs, machine idle-time costs and lateness penalty costs, amongst others. A performance measure usually represents only a component of the total cost of a schedule. Usually, there are trade-offs in considering several different criteria. These trade-offs provide useful insights to the decision maker. Therefore, considering scheduling problems with more than one criterion is more relevant within the context of real life scheduling problems (Nagar et al., 1995). But a key problem remains on how to evaluate the performance of solution methods for multi criteria scheduling problems. That is, if for an instance of a bicriteria scheduling problem, there are two solution methods, on what basis can solution method 2 be seen as better than solution method 1 or vice versa? This situation becomes complex if the two criteria are conflicting. For example, solution method 1 may perform better than solution method 2 with respect to criterion 1 while solution method 1 performs poorer than solution method 2 with respect to criterion 2. Which of the solution methods is the better or preferred solution method with respect to the two criteria? Two objectives/criteria are said to be conflicting if minimizing the value of one of the objectives leads to a corresponding increase in the value of the other objective.

Mr. Vice Chancellor Sir, major successes recorded under the multi objective scheduling problems includes:

-development of a number of approximation algorithms,

-development of metrics for assessing the Non-Dominated Sets (NDS).

Development of Approximation Algorithms for Multi Objectives Scheduling Problems

There are basically three approaches to the study of multi objectives scheduling problems. These are Pareto-optimal, hierarchical and simultaneous minimization (Fig 6) approaches (Hoogeveen, 1992; Uthaisombut, 2000). I have adopted all these three approaches in my quest for solutions to multi objectives scheduling problems.

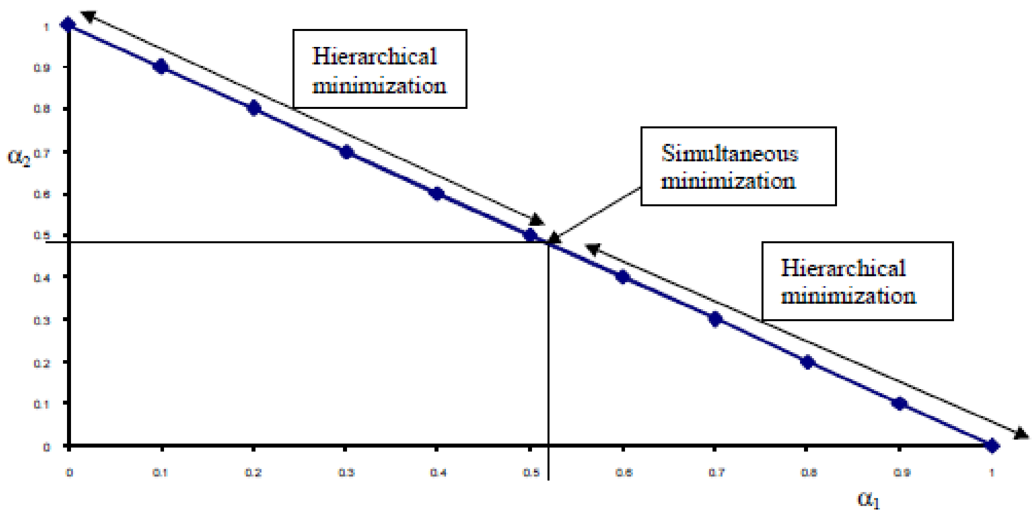

Fig. 6 Graph of weighting factors (a2, a1) showing hierarchical and simultaneous minimization.

Simultaneous Minimization Approach

This approach involves constructing schedules that try to optimize both criteria simultaneously (Chakrabarti et al., 1996; Wang, 1997; Stein and Wein, 1997; Aslam et al., 1999; Rasala et al., 1999). Usually, the criteria are aggregated into a composite objective function which may be linear or of a general nature. This approach places equal importance on all the scheduling objectives being considered. Indeed, many real-life scheduling problems can be modeled using this (simultaneous minimization) approach. For example, a manufacturing firm may want to satisfy its customer by fulfilling the promised delivery dates and at the same time want to cut down on the production cost by minimizing the makespan (maximum completion time). In adopting this approach, scheduling problems involving the following combinations of objectives have been explored and a number of versatile approximation algorithms proposed:

- Total Completion time (C_{tot}) and Number of Tardy Jobs (NT)

Under the simultaneous minimization approach, the first combination of criteria that attracted my attention is Total Completion time and Number of Tardy Jobs. In 2008, Oyetunji and Oluleye (2008a) explored the problem of simultaneously minimizing the total completion time and number of tardy jobs with release dates on s single machine. One unique feature of this problem is that it addressed both the manufacturer's and customer's concerns. While the total completion time criterion addressed the manufacturer's concerns, the number of tardy jobs criterion addressed the customer's concerns. The relative weight of each criterion was set at 0.5 (indicating that the two criteria are equally important to the decision maker and hence, they were to be minimized simultaneously). To solve this problem, three heuristics (HR4, HR5, HR6) were proposed and compared with the branch and bound (BB) procedure.

The results of the performance evaluation carried out, with respect to both effectiveness and efficiency, showed that the HR6 heuristic performed the closest to the BB method and better than the other two proposed (HR4 & HR5) heuristics and was thus recommended to the decision maker given that the BB would require prohibitive computing costs with marginal benefits. As the efforts to seek a better solution to this important bicriteria scheduling problem continues, an important improvement was recorded by Oyetunji (2010) when he proposed a heuristic (HR7) which was based on the truncation and composition of schedules rule. The HR7 heuristic was compared with HR6 heuristic (which was earlier on proposed by

Oyetunji and Oluleye (2008a) and adjudged the best as at then for the same bicriteria scheduling problem) and also the BB method. The results of the performance evaluation carried out showed that the HR7 had an impressive performance over the HR6 heuristic in terms of both effectiveness and efficiency. Based on this, the HR7 heuristic was recommended to the decision maker for the bicriteria scheduling problem of simultaneously minimizing the total completion time and number of tardy jobs with release dates on a single machine.

With the intent of improving the solution methods for this important bicriteria scheduling problem, Oyetunji and Oluleye (2010b) proposed two additional heuristics (HR9 & HR10). The HR9 & HR10 heuristics were evaluated against the HR7 and BB methods and the results (with respect to effectiveness) showed that the HR7 heuristic outperformed the HR10 heuristic when the number of jobs was fewer than 30. However, for jobs ranges from 30 to 500 jobs inclusive, the HR10 heuristic outperformed the HR7 heuristic. In terms of efficiency, both the HR7 and HR10 performed competitively

-Makespan (C_{max}) and Maximum Tardiness (T_{max})

The second combination of criteria that attracted my attention, under the simultaneous minimization approach, is the makespan (C_{max}) and maximum tardiness (T_{max}). In alluding to the importance of Makepan and maximum tardiness, Allahverdi (2004) stated that "Makespan is a measure of system utilization while maximum tardiness is a measure of performance in meeting customer due dates". Thus, this bicriteria scheduling problem also addressed both the manufacturer's concerns as well as the customer's concerns.

In order to solve this problem, which is also classed as NP-Hard, Oyetunji (2012) proposed an approximation algorithm (called CTA1) and compared it with BB method (in view of the nonexistence of any known approximation algorithm for the said problem as at then). Experimental results (with respect to effectiveness) showed that the CTA1 algorithm performed competitively (differences not significant) compared with the BB procedure when the number of jobs ranges from 10 to 50. Also, with respect to efficiency, the CTA1 algorithm performed exceptionally better than (this is expected) the BB procedure for all the problem sizes considered.

Total Earliness (E_{tot}) and Total Tardiness (T_{tot})

The third combination of criteria explored is Total Earliness (E_{tot}) and Total Tardiness (T_{tot}). The choice of the total earliness and the total tardiness criteria was motivated by the just-in-time (JIT) manufacturing modeling, which emphasizes that goods be produced only when they are needed. In these scheduling models, jobs are scheduled to complete as close as possible to their due dates. In order to solve this problem (which is usually referred to as the Earliness/Tardiness problem), Oyetunji and Oluleye (2011) proposed two approximation algorithms (ETA1 & ETA2). The ETA1 & ETA2 were compared with the MA heuristic proposed by Mazzini and Armentano (2001). Experimental results showed that both the ETA1 & ETA2 algorithms outperformed the MA heuristic when the number of jobs is greater than 8. Also, the ETA1 algorithm performed exceptionally better than the ETA2 algorithm with respect to effectiveness when the number of jobs ranges from 12 to 500 inclusive. It is interesting also to note that the ETA1 algorithm is faster (more efficient) than the ETA2 algorithm when the number of jobs exceeds 150. Thus, the ETA1 algorithm was recommended to the decision maker for the bicriteria scheduling problem of simultaneously minimizing the total earliness and total tardiness on a single machine with release dates.

- Makespan (C_{max}) and Total Completion time (C_{tot})

Another combination of criteria that has been explored is the Makespan (C_{max}) and Total Completion time (C_{tot}). Five different cases of the relative weight of the two criteria were experimented. These are:

Case 1: the case of the makespan criterion being extremely more important than the total completion time criterion. i.e.

$$K1 = 0.01 * \sum_{i=1}^{n} C_i + 0.99 * \max_{1 \le i \le n}(C_i)$$

Case 2: the case of the makespan criterion being more important than the total completion time criterion. i.e.

$$K2 = 0.05 * \sum_{i=1}^{n} C_i + 0.95 * \max_{1 \le i \le n}(C_i)$$

Case 3: the case of the makespan criterion being as important as the total completion time criterion. i.e.

$$K3 = 0.5 * \sum_{i=1}^{n} C_i + 0.5 * \max_{1 \le i \le n}(C_i)$$

Case 4: the case of the total completion time criterion being more important than the makespan criterion. i.e.

$$K4 = 0.95 * \sum_{i=1}^{n} C_i + 0.05 * \max_{1 \le i \le n}(C_i))$$

Case 5: the case of the total completion time criterion being extremely more important than the makespan criterion. i.e.

$$K5 = 0.99 * \sum_{i=1}^{n} C_i + 0.01 * \max_{1 \le i \le n}(C_i)).$$

In solving this NP-Hard problem, an approximation algorithm (NGAlg) was proposed by Oyetunji and Oluleye (2010a) and compared with BESTB algorithm of Rasala et al. (1999). Experimental results indicated that the NGAlg algorithm outperformed the BESTB algorithm under all the five cases mentioned above with respect to both effectiveness and efficiency.

- Generic Combination of the Objectives

Mr. Vice Chancellor Sir, in solving the multi Objectives Scheduling Problems, the usual practice by researchers is to design solution methods (algorithms or heuristics) that are problem specific (i.e. these could be problems focusing on a particular shop environment or problems addressing specific objectives/criteria) (Oluleye and Oyetunji, 1999; Aslam et al. 1999; Rasala et al. 1999; Oyetunji and Oluleye, 2008a). Only few researchers have proposed algorithms that could be applied to wide classes of multi-criteria scheduling problems (Stein and Wein, 1997; Hoogeveen, 2005). In order to address this shortcoming, Oyetunji and Oluleye (2012a) proposed a generalized algorithm (called GAlg). A unique feature of the GAlg algorithm is that it can be applied to large classes of the multi-criteria scheduling problems. In order to assess the performance of GAlg algorithm, it was compared with the HR7 and HR10 heuristics earlier proposed by Oyetunji (2010) and Oyetunji and Oluleye (2010b) respectively. Experimental results showed that the GAlg algorithm performed better than both HR7 and HR10 when the total completion time criterion is more important than the number of tardy jobs criterion whereas the HR7 heuristic performed better than GAlg algorithm when the number of tardy jobs criterion is more important than the total completion time criterion.

Hierarchical Minimization Approach

In trying to minimize two or more objectives at a time (bicriteria scheduling), unless we are extremely lucky, there may be no schedule that achieves the minimum value for both criteria simultaneously. This implies that we have to give in on the quality of at least 1 of the objectives. An approach to this is to rank the criteria in the order of their relative importance to the organization or firm. Then, the less important criterion is minimized subject to the fact that the more important criterion is optimal. This approach is called hierarchical or lexicographical minimization. In many real life situations, criteria often carry unequal weights, thus minimizing two or more criteria simultaneously may be extremely difficult especially when the criteria are conflicting. The hierarchical minimization approach involves setting a constraint on the value of one criterion (primary criterion) and optimizing the other criterion (secondary criterion) subject to the constraint on the primary criterion. In adopting this approach, Oyetunji and Oluleye (2008d) explored the single machine bicriteria scheduling problem of hierarchically minimizing the total completion time of jobs (C_{tot}) and number of tardy jobs (NT) with release time. Two types of hierarchical minimization models were explored. These are: (1) the case of the total completion time criterion being more important than the number of tardy jobs criterion, (2) the case of the number of tardy jobs criterion being more important than the total completion time criterion. Three Heuristics (HR4, HR5 & HR6) were proposed for the bicriteria problems out of which HR4 and HR6 performed comparatively with the branch and bound (BB) method for small (n<12) and large (n>=12) size problems, respectively. This result serves as a benchmark for other researchers.

Pareto-optimal Approach

Mr. Vice Chancellor Sir, the solution to multi objectives scheduling problems is normally not a single value but rather a set of values which are often called *Pareto* set (Fig. 7). A schedule is said to be Pareto-optimal with respect to two criteria X and Y, if there does not exist a schedule that is simultaneously better, in both criteria, than any of the schedules in the set (***Not to bother you with complex mathematical expressions***). In the two approaches described above, the weights are used explicitly to model the preferences of the Decision Maker (DM) with respect to the criteria. However, not all multi objectives scheduling problems lend themselves to formal expressions using scalar functions. In situations like this, a set of Compromise Solutions (CS) on the criteria (called Pareto-Optimal set) is sought (Zitzler and Thiele, 1998).

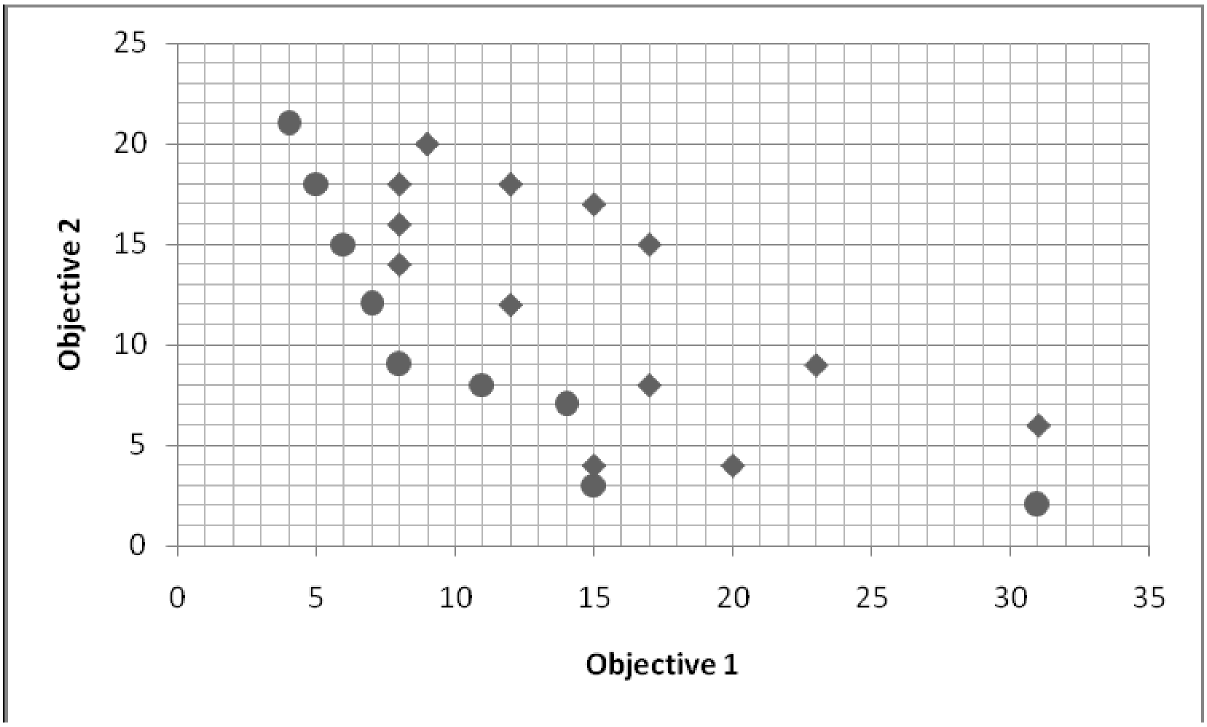

Fig. 7 Pareto-Optimal (Non-Dominated) Points

Development of Metric (MGD) for Assessing NDS

Mr. Vice Chancellor Sir, one major difficulty of using the Pareto-Optimal approach to solve multi objectives scheduling problems is how to compare the non-dominated sets being produced by various approximation methods (Knowles and Corne, 2002), hence the need for metrics for comparing the Non-Dominated Sets (NDS). Essentially, there are two quality aspects desired of non-dominated sets (Deb and Jain, 2002; Zitzler et al., 2000). These are: closeness to the Pareto front and diversity of the sets. They are briefly highlighted below.

i. Closeness to Pareto Front: This is a measure of the distance between the non-dominated sets and the Pareto front. The set of Pareto optimal points is often called the Pareto front or Pareto boundary (Fig 8). The Pareto front of a multi-objective optimization problem is bounded by a nadir objective vector and an ideal objective vector (Hoogeeven, 1992). The components of a nadir and an ideal objective vector define upper and lower bounds for the objective function values of Pareto optimal solutions, respectively. A good non-dominated set should be as close as possible to the true Pareto front. Hence, the shorter/lower this distance (gap) is the better.

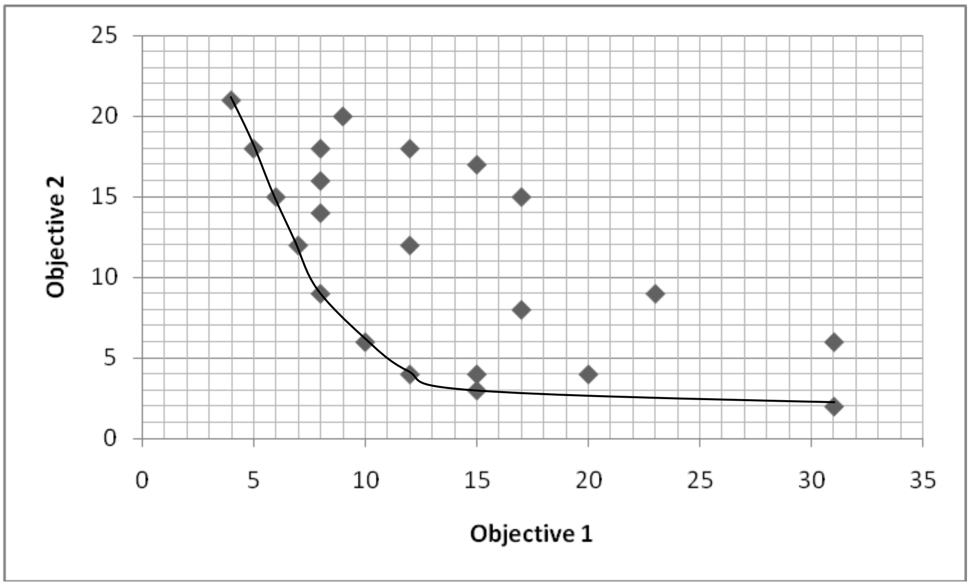

Fig. 8 Pareto Front

ii. Diversity of the Sets: This is a measure of the spacing and spread (distribution) of the sets over the entire Pareto front. A good non-dominated set should cover the whole Pareto front as well as possible. The distribution of solutions along the front should be even. The higher the number of points (solutions) in any particular set, the better the set is.

To evaluate the quality of the non-dominated sets, there is need for some measure of goodness called performance metrics. These metrics help in characterizing the different non-dominated sets. Many of the existing metrics require the knowledge of the Pareto optimal or reference set, the task that is often difficult or impossible in some cases. There is, therefore, the need for performance metrics which covers both closeness and diversity and does not suffer from the burden of the knowledge of the Pareto-Optimal or reference set. In order to address this short coming, Oyetunji and Oluleye (2012) proposed a new metric called Modified Generational Distance (MGD). To compare two non-dominated sets A and B, the MGD assumes that one of the sets is better (say NDS B) and then compute the distance between each point in NDS A (which is now being compared with NDS B) and the corresponding closest point in NDS B. The mean distance over the NDS A is then computed. In order to assess the effectiveness of the metrics for comparing NDS, Oyetunji (2011) carried out extensive experimentation on the MGD and two other metrics (Generational Distance (GD) which was proposed by Van Veldhuizen (1999) and Schott's Spacing (SS) metric which was proposed by Schott (1995). The results show that the MGD is the most efficient out of the three metrics studied. Also, the study encouraged researchers not to use only one metric but a combination of metrics in assessing the performances of the non-dominated sets produced by multi objectives scheduling algorithms.

Service Quality Assessment

Mr. Vice Chancellor Sir, in today's competitive environment, delivering high quality service is the key to a sustainable competitive advantage, hence the reason for my interest in the assessment of service quality of organizations that provide services. Services are activities that require personal contact. They are also commodities that disappear in use, thus they cannot be stored. Every service has manufactured tangible elements. For example, banks provide statements, airlines provide tickets, and restaurants provide foods. Services usually have more intangible elements than manufactured goods. Other qualities of service include:

(a) Intangibility: There is no physical product

(b) Perishability: Since service is produced and consumed at the same time, it cannot be stored for later usage. This, however, does not hold for every service industry.

(c) Heterogeneity: Services range from simple to complex, from high-contact to low-contact, from fully customized to fully standardized, from personal to business services, etc.

(d) *Inseparability:* Production and consumption usually take place at the same time.

The service quality assessment has become a major area of interest to practitioners, managers and researchers because of its impact on customer satisfaction, customer loyalty, and, of course, company profitability. Many different models have been developed to measure service quality delivered by firms in many businesses. The SERVQUAL (Fig. 9) conceptual model serves as a concise framework for understanding, measuring and improving service quality. The SERVQUAL model does not only help in learning the factors that play an important role to customer satisfaction, but also, provides directions for improvement. It is a simplified description of the actual situations. The SERVQUAL conceptual model helps managers to identify problems with service quality as well as help them improve the efficiency, profitability and overall performance of their firm.

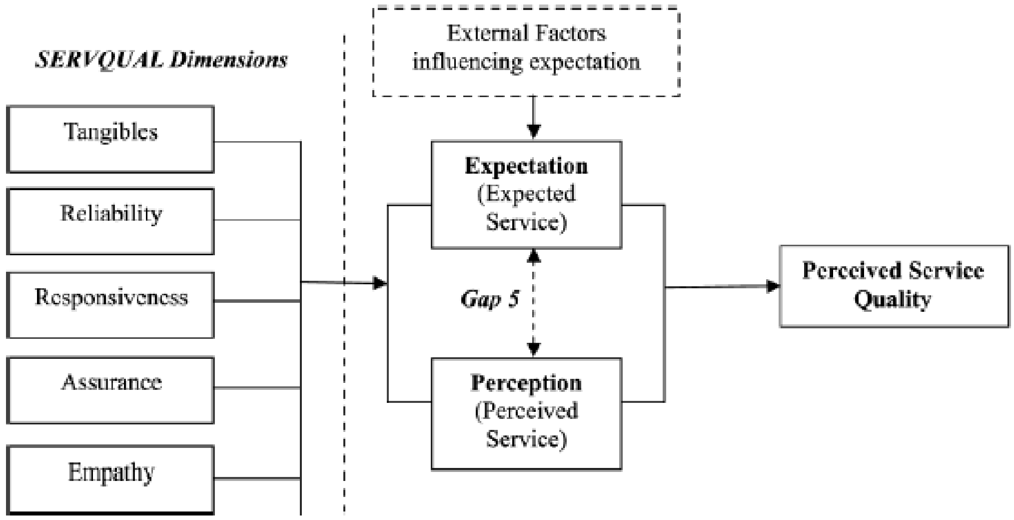

Fig. 9. The SERVQUAL model (Source: Kumar et al, 2009)

The SERVQUAL model consists of five dimensions which can be defined as follows:

1. **Reliability:** The ability to provide the promised service dependably and accurately. Reliability is the customer expectation that the service is accomplished on time every time, in the same manner, and without errors.
2. **Responsiveness:** The willingness to help customers and provide prompt service. Keeping customers waiting, particularly for no apparent reason, creates negative perceptions of quality. In the event of a service failure, the ability to recover quickly with professionalism can create very positive perceptions of quality.
3. **Assurance**: The knowledge and courtesy of employees and their ability to inspire trust and confidence. The assurance dimension includes competence to perform the service, politeness and respect for the customer, and effective communication with the customer.
4. **Empathy**: The provision of caring, individualized attention the organization provides its customers. Empathy includes approachability, sense of security, and the effort to understand the customer’s needs.
5. **Tangibility**: Appearance of physical facilities, equipment, personnel and written materials.

In view of the fact that the SERVQUAL model has been widely accepted as a concise framework for measuring and improving service quality, it was adopted to assess the service quality delivered by a telecommunication firm (located in Navrongo, the Upper East Region of Ghana) to its customers (Oyetunji and Bae, 2013). To this end, a questionnaire based on the SERVQUAL model was used to collect data from the subscribers of the telecommunication firm. The data were analyzed and the results of the analysis (Table 15) show that the telecommunication firm's service quality is deficient (poor) in all the twenty two items and in all the five dimensions of SERVQUAL considered. Generally, the customers of the telecommunication firm are not satisfied with the quality of service delivered to them by the firm. The results further show that the dimension that required the most urgent attention is reliability while the item that requires the most urgent attention is "Telecommunication service provider staff tells you exactly when services will be performed" (under responsiveness dimension). The study recommended to the management of the telecommunication firm to make efforts to improve their service quality in the areas identified above. They should consider providing services at the time they promise to do, so that the promised deadlines can be truly met.

Table 15. Summary of service quality with respect to the five dimensions of SERVQUAL

		EXPECTATION						PERCEPTION						(P – E)
		Frequency of Response					Average	Frequency of Response					Average	
		1	2	3	4	5		1	2	3	4	5		
TANGIBILITY	1	2	7	21	21	45	4.041	3	10	34	18	31	3.667	-0.375
	2	2	8	27	32	27	3.771	4	5	28	37	22	3.708	-0.063
	3	4	3	21	26	42	4.031	1	4	35	31	25	3.781	-0.250
	4	0	14	16	32	34	3.896	4	12	26	27	27	3.635	-0.260
	Average tangibility													**-0.237**
RELIABILITY	5	8	8	14	24	42	3.875	5	13	16	41	21	3.625	-0.250
	6	7	11	23	21	34	3.667	10	9	27	30	20	3.437	-0.240
	7	4	12	22	25	33	3.740	7	10	39	26	14	3.312	-0.427
	8	4	9	22	21	40	3.875	6	12	30	30	18	3.438	-0.438
	9	7	9	25	23	32	3.667	1	24	23	25	23	3.469	-0.198
	Average reliability													**-0.310**
RESPONSIVENES S	10	5	9	22	19	41	3.854	11	8	31	26	20	3.375	-0.479
	11	6	6	18	32	34	3.854	4	8	23	35	26	3.739	-0.115
	12	0	8	21	32	35	3.979	2	9	28	30	27	3.739	-0.240
	13	6	7	21	33	29	3.750	13	10	25	25	23	3.365	-0.385
	Average responsiveness													**-0.305**
ASSURANCE	14	8	8	17	19	44	3.864	6	10	24	40	16	3.520	-0.344
	15	5	19	14	2	38	3.698	7	15	33	20	21	3.343	-0.354
	16	5	6	30	22	33	3.750	2	5	37	36	16	3.615	-0.135
	17	5	3	7	3	46	4.188	4	9	21	27	35	3.883	-0.354
	Average assurance													**-0.297**
EMPATHY	18	5	10	14	24	43	3.938	4	11	21	28	32	3.760	-0.177
	19	8	12	17	17	42	3.760	8	15	22	20	32	3.531	-0.229
	20	6	5	26	26	33	3.781	3	15	37	19	22	3.437	-0.344
	21	10	3	28	19	36	3.708	8	17	22	23	26	3.437	-0.271
	22	5	3	30	25	33	3.812	4	8	30	28	26	3.667	-0.146
	Average empathy													**-0.233**
	Overall average = -0.276													

Mr. Vice Chancellor Sir, as the quest for the assessment of service quality continues, the SERVQUAL model was also used to assess and compare the service quality delivered by two notable commercial banks operating in Bolgatanga, Upper East Region of Ghana (Oyetunji. Baguri, and Otis, 2014). A total of one hundred (100) customers who have bank accounts in the two banks under study were conveniently sampled. The results of the analysis show that the customers rated the two banks poorly (negative values of service quality were recorded) on all the five dimensions of service quality. In order to stay competitive, both Banks need to improve service quality especially in the identified areas. Bank B needs to be more responsive to its customers (Table 17) while Bank A needs to train its staff on how to show empathy to their customers (Table 16). The overall service quality obtained show that, although the customers are not satisfied with the two banks, they prefer Bank A to Bank B. However, a further examination of the possible ways in which service quality can be improved revolves around technology, human dynamics and technology management. These in turn devolve on scheduling both human and technological resources to leverage on the custom offered by the consumers. In a nutshell, the problem solving riddle is essentially a decision making problem encapsulated in a virtuous cycle.

Table 16. Summary of service quality with respect to the five dimensions in Bank A

	statement	PERCEPTIONS FREQUENCY OF RESPONSES 1	2	3	4	5	Average	EXPECTATIONS FREQUENCY OF RESPONSES 1	2	3	4	5	Average	P-E
Tangibles	1	13	23	26	20	8	3.130	0	0	19	33	48	4.290	-1.160
	2	15	19	34	25	7	3.100	0	0	21	43	36	4.150	-1.050
	3	7	23	31	23	16	2.820	0	1	13	40	46	4.310	-1.490
	4	3	8	34	37	18	2.410	0	0	13	65	22	4.090	-1.680
								Average for Tangibles =						**-0.710**
Reliability	5	4	9	28	26	33	2.250	0	0	31	29	40	4.090	-1.840
	6	2	19	31	33	15	2.600	0	0	15	52	33	4.180	-1.580
	7	2	14	26	36	19	2.410	0	0	35	40	25	3.900	-1.490
	8	4	14	20	30	32	2.280	0	6	19	44	31	4.000	-1.720
	9	4	17	28	33	18	2.560	0	19	16	42	23	3.690	-1.130
								Average for Reliability =						**-0.594**
Responsiveness	10	8	18	22	30	22	2.600	0	0	8	58	34	4.260	-1.660
	11	4	13	24	40	19	2.430	0	1	10	59	30	4.180	-1.750
	12	6	15	27	41	11	2.640	0	1	23	42	34	4.080	-1.440
	13	4	10	27	34	25	2.340	0	1	30	40	29	3.970	-1.630
								Average for Responsiveness =						**-0.823**
Empathy	14	3	16	26	22	33	2.340	0	6	5	46	43	4.650	-2.310
	15	11	17	27	36	9	2.850	0	0	4	56	40	4.360	-1.510
	16	4	12	40	28	16	2.600	0	0	9	59	32	4.230	-1.630
	17	5	18	30	35	12	2.690	0	6	8	49	37	4.170	-1.480
								Average for Empathy =						**-0.948**
Assurance	18	6	14	22	28	30	2.380	0	0	21	63	16	3.950	-1.570
	19	11	21	31	28	9	2.970	0	0	20	49	26	3.960	-0.990
	20	8	9	30	30	23	2.490	0	0	9	65	26	4.170	-1.680
	21	6	16	26	30	22	2.630	0	0	17	35	48	4.310	-1.680
	22	8	18	18	38	18	2.600	0	0	3	59	38	4.350	-1.750
								Average for Assurance =						**-0.664**
	Overall Average = -0.748													

Table 17. Summary of service quality with respect to the five dimensions in Bank B

		PERCEPTION						EXPECTATION						
		Frequency of Response						Frequency of Response						
		1	2	3	4	5	Average	1	2	3	4	5	Average	(P – E)
Tangibility	1	29	28	16	19	8	2.49	3	1	8	27	61	4.42	-1.93
	2	20	37	15	23	5	2.56	2	9	9	39	41	4.08	-1.75
	3	10	22	9	37	22	3.39	1	3	9	32	55	4.37	-0.98
	4	14	33	17	30	6	2.81	3	6	8	46	37	4.08	-1.32
	Average for Tangibility =													**-1.495**
Reliability	5	43	28	8	17	4	2.11	9	11	7	29	44	3.88	-1.76
	6	33	30	7	24	6	2.40	4	7	9	29	51	4.16	-1.75
	7	35	30	8	19	8	2.35	5	15	11	43	26	3.70	-1.35
	8	28	36	13	16	7	2.38	10	8	5	32	45	3.94	-1.54
	9	24	24	13	28	11	2.78	6	13	11	33	37	3.82	-1.04
	Average for Reliability =													**-1.488**
Responsiveness	10	28	22	17	24	9	2.64	4	6	9	38	43	4.10	-1.84
	11	44	23	12	17	4	2.14	7	9	10	31	43	3.94	-1.80
	12	31	36	10	17	6	2.31	6	7	5	33	49	4.12	-1.81
	13	43	22	8	15	12	2.31	7	11	7	39	36	3.86	-1.55
	Average for Responsiveness =													**-1.750**
Assurance	14	38	32	7	17	6	2.21	3	6	12	36	43	4.10	-1.88
	15	24	13	18	28	17	3.01	2	6	6	44	42	4.18	-1.18
	16	16	37	15	25	7	2.70	4	4	16	35	41	4.05	-1.41
	17	19	26	11	31	13	2.93	5	5	4	38	48	4.19	-1.37
	Average for Assurance =													**-1.460**
Empathy	18	32	22	19	18	9	2.50	4	5	6	43	42	4.14	-1.64
	19	23	21	17	19	20	2.92	9	3	5	40	43	4.05	-1.13
	20	33	25	12	24	6	2.45	8	12	13	38	29	3.68	-1.14
	21	37	20	18	17	8	2.39	7	5	7	33	48	4.10	-1.71
	22	27	28	20	18	7	2.50	3	13	10	39	35	3.90	-1.39
	Average for Empathy =													**-1.402**
	Overall Average = -1.519													

CONCLUSION

Mr Vice Chancellor Sir, this lecture has examined the crucial roles of the analyst and decision maker in the decision making process. The role/importance of effective and efficient decision making in any organization (manufacturing or service) cannot be over emphasized. Some of these roles include:

1. Better Utilization of Resources: Proper decision making helps in utilizing the available resources towards achieving the objectives of the organization. These resources namely, Men, Money, Materials, Machines, Methods and Markets (the 6 Ms). A good manager must be able to make correct decisions in respect of the 6 Ms to result in better utilization of these resources in an organization.

2. Facing Problems and Challenges: Decision making helps an organization to face and tackle new problems and challenges. Quick and correct decisions help to solve problems and accept new challenges.

3. Business Growth: Quick and correct decision making results in better utilization of the resources. It helps the organization to face new problems and challenges. It also helps to achieve its objectives. All these result in quick business growth. It should be noted that, wrong, slow or no decisions can result in losses and industrial sickness.

4. Achieving Objectives: Rational decisions help the organization to achieve all its objectives quickly. This is because rational decisions are made after analyzing and evaluating all the alternatives. Achievement of objectives constitutes a veritable motivation for enhanced performance.

5. Increases Efficiency: Rational decisions help to increase efficiency. Efficiency is the relation between returns and cost. If the returns are high and the cost is low, then there is efficiency and vice versa. Rational decisions result in higher returns at low cost. This is concomitant for profitability.

6. Facilitate Innovation: Rational decisions facilitate innovation. This is because it helps to develop new ideas, new products, new process, etc. This results in innovation. Innovation gives a competitive advantage to the organization. Without innovations, organisations atrophy.

7. Motivates Employees: Rational decision results in motivation for the employees. This is because the employees are motivated to implement rational decisions. When the rational decisions are implemented the organization makes higher profits. Therefore, it can give financial and non-financial benefits to the employees. Who, in turn are motivated individually as well as a team for higher achievement levels.

Mr. Vice Chancellor Sir, in concluding this lecture, the followings are recommended:

1. There should be continuous interactions between the Analyst and Decision Maker: Unlike the other two methods (Priori & Posteriori) discussed in this lecture, the interactive method facilitate continuous exchange of information between the analyst and the decision maker. This process ultimately improves the quality of the final solution to the decision problem. It also builds on the human metric of participation.

2. Learning of DM is encouraged: Learning is inherently connected with the Interactive Method (IM). The DM does not know in advance what solutions constitute the “good solutions”, hence he/she needs to learn what is possible and what is not. The IM enables the Decision Maker (DM) to learn about the decision problem. It also allows the formal model to evolve in response to additional information about preferences of the DM. The quality of interactive method is very much related to what and how the DM learns in the course of the search for the most preferred solution. Therefore, the DM is encouraged to learn as much as possible about the problem.

3. Focus should be on both effectiveness and efficiency of the decision problem: **An efficient process doesn't waste any time or resources while an effective process produces a desired effect or contributes to a desired goal**. Overlap and fragmentation among government programs are indicators of unnecessary duplication and waste. By reducing or eliminating duplication, overlap and fragmentation, the governments of Nigeria (federal, state & local) can save billions of Naira annually and thus help government agencies provide more efficient and effective services. In order to attain operational efficiency, organizations (manufacturing, service, Governmental & Non-Governmental) needs to minimize redundancy and waste while leveraging the resources that contribute most to its success and utilizing the best of its workforce, technology and business processes. The reduced internal costs that result from operational efficiency enable organizations to achieve higher profit margins or be more successful in highly competitive markets. This enables the Nation to compete in perhaps the most important front, PRODUCTIVITY, which is a veritable tool for sustainable growth and accompanying societal development.

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Mr. Vice Chancellor, I end this lecture with this song "I AM SAYING THANK YOU JESUS, THANK YOU MY LORD/2x"

Thank you very much for your attention.

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