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A NOVEL CALL ROUTING OPTIMIZATION IN AN IN-DIRECT SALES ENVIRONMENT

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Chronicle

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Abstract

In today's competitive business landscape, call centers are crucial in optimizing direct and indirect sales. While traditional call routing systems assign calls randomly, an intelligent call routing algorithm can significantly enhance sales and customer satisfaction. This research proposes a skill-based routing (SBR) algorithm that prioritizes calls based on past data and assigns them to agents with the highest likelihood of converting inquiries into sales. This approach enhances call center efficiency by reducing call waiting time and ensuring skill-based call distribution. The study includes data analysis, algorithm design, testing, and evaluation through simulated and real-world call center environments. Results indicate that SBR improves sales optimization and resource utilization compared to first-come-first-serve (FCFS) and shortest processing time (SPT) models. The findings highlight the importance of intelligent call routing in boosting indirect sales and reducing average handling time in call centers.

Keywords: Call routing, sales optimization, call handling time, machine learning, customer service, resource utilization, and heuristic algorithms.

INTRODUCTION

With a world awash in competition, every business seeks to boost revenue through all means possible. Direct and indirect sales are the two most common strategies for generating revenue. Indirect sales are described as the handling of a product or service created by your company but sold by a third party, such as an affiliate or reseller. Indirect sales help to reduce sales workload while also increasing the efficacy of the marketing network [1]. On the other hand, direct selling is a type of retail in which items and services are sold directly to consumers. Direct selling is typically done one-on-one, in a group, while sitting, or online. Put another way; if a company engages a brand ambassador to introduce and sell a product so that customers will buy it, the ambassador will enhance sales. On the other hand, the same method is used at call centers when customers phone the helpline department, and the representative tries to hang up when the customer is satisfied with the product. Most call centers contain a sales department, which allows them to persuade clients to buy a product rather than sell it or answer their questions.

On the other hand, call centers have a helpline department whose primary goal is to resolve consumer questions about the product [2]. Furthermore, there are some industries where indirect sales outnumber direct sales. The Education Industry is the most prominent example of this type of industry, in which parents/students call the college to obtain information and subsequently visit the campus to get admission. When compared to the helpline department, call centers are more focused on sales. When a call is received in the sales department, it is routed through a call routing system, where practically every call center uses an algorithm to assign the call to the best possible agent based on the incoming call. Therefore, companies can ensure sales with this approach rather than assigning calls to agents randomly [3]. On the other hand, the helpline agents are an add-on to the sales done on campus. Therefore, introducing an algorithm for the helpline department will benefit the company's sales; even a slight rise in sales can make a significant difference in earnings. The customer interaction plan includes call center optimization. It uses digital, automated, and advanced techniques to update call center platforms and workforce management systems. Even before the firm can start looking into ways to increase sales at the call center level, it must first guarantee that calls are handled as efficiently and effectively as possible. The customer experience must be high enough to keep the consumer delighted and engaged, from the auto-attendant greeting and instructions to the length of time the customer waits in an on-hold queue. A potential sale is lost if a consumer becomes annoyed by an overly sophisticated IVR system or while the customer is on hold for 10 minutes [4]. The objective of this study is to optimize in-direct sales in call centers. Furthermore, it will also identify how we can reduce average call handling time with the help of call routing using algorithms. It will help to collect data and allow call centers to do skill-based routing. Using past data, agents can be ranked according to their performance and can be divided agents into different groups. Calls will be assigned to them according to their skills and expertise. This study is novel research for a call routing system that will show how calls may be directed to optimize sales, which will be significantly beneficial for the call center industry.

BACKGROUND STUDY

In a call Centre, there are two types of departments. One is outbound, which is primarily focused on sales and whose goal is to make phone calls to various people to sell their products. One of the most notable examples is when credit cards were first introduced, practically every one of us received a call from someone trying to sell us a credit card. These outbound call Centres are sometimes used for more than just selling new products; they are also utilized for customer service when they phone customers at random and ask for feedback on their service. The other sort of department is inbound, which occurs when a consumer calls the company's helpline and is connected to an agent who can provide better support [5]. In such call Centres, a customer calls with a question, and the agent determines how far he or she can assist the caller. A call center agent in a cable net provider or a network-based organization can be of great assistance to the customer, allowing for immediate remedies to small problems and glitches.

An author [6] invented a system that optimizes the sales in the store as shown in Figure 1. This includes a store database (20) where details of the store are stored which includes data of sales representatives, store merchandise, special offers/promotions, the layout of the store and its department, etc. Moreover, it also stores the rules that a sales representative has to follow to contact a customer. This database is connected image database (26), which stores biometric images and other information about customers. It is further connected to the customer identification engine (24), which identifies customers by their biometrics. The identified customers' data is entered into the visitor's log (28). The business rules engine (30) in the system links the identified customer to a sales representation according to past experiences/data and also will apply rules that are set by the store. The business rules engine (30) is connected to the Sales representative's individual terminals (32), which receive instructions from the engine (30). Then that sales representative will deal with the customer and again that data will be stored in the database.

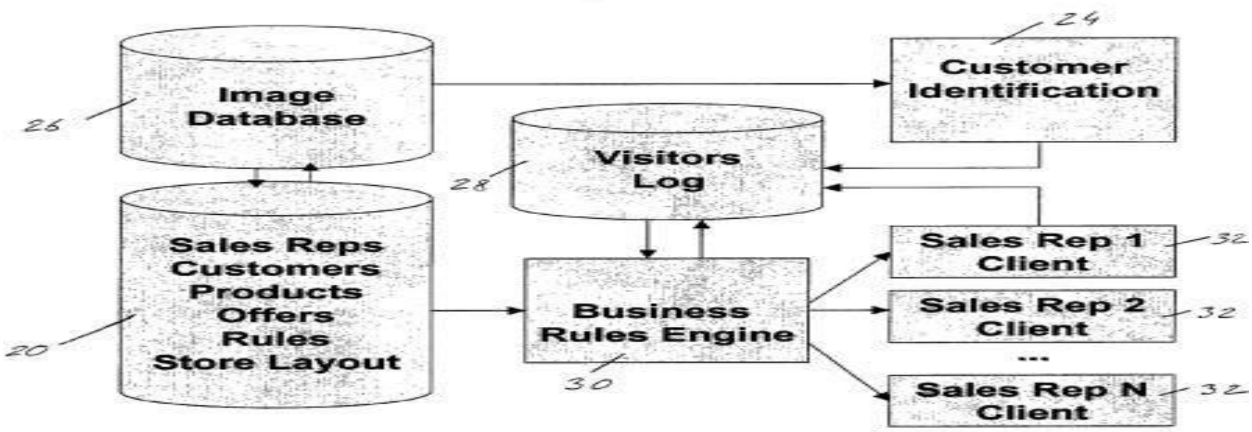


Figure 1.
Data Store

Another author [7] conducted surveys in multiple Call Centres in Australia, along with six in-depth semi-structured interviews with the managers to investigate Call Centre management from their perspective. According to the survey, half of Call Centre managers had listed formal KPIs the same as preferred KPIs. While the rest of the Call Centre managers' formal KPIs differ from preferred KPIs. During interviews it was observed that the Call Centres were a hive of activity with large numbers of staff. The managers were in pressure roles but appeared energetic and focused. They considered themselves as a part of the organization, which led to cooperation and working together. In every interview, the common issue that the manager raised was the restricted budget given to them, which the major obstacle to fulfilling their management responsibilities. During the interview, the managers pointed out, that they face difficulty in getting approval for the budget to fulfill the requirement as it is senior management's mindset that high productivity should be achieved with a low/assigned budget. Moreover, the KPIs in the survey weren't that well understood, in an interview it was told that the number of calls attended or the number of seconds the call was entertained gets the highest KPI [8]. The focus for KPI is more quantitative rather than measuring the quality of service provided by the agent.

In other words, the managers are concentrating on the call itself instead of focusing and analyzing the outcome of the call from the organization's view. Author [9] made a study on how knowledge is and can be managed in a Call Centre. She says that these days organizations know the worth of having proper knowledge about their Product, Services, and Customers. Proper knowledge management in a Call Centre can reduce agent training time and speed up new employee ramp-up. It will also make an agent more confident and competitive. In this paper, the author has studied and surveyed two companies namely, Irankhodro and SAIPA. She digs into the company's information and gives a conclusion as to how to manage the knowledge. She concludes; that both companies realize that knowledge management is as important as training. Both companies use experts to solve practical issues and are aware of the benefits of applying advisor's knowledge in the area of customer services, but no strategic view has been set in order to apply the process of putting the knowledge into action. The companies that have been studied seem to have problems in knowledge adaptation. They do not find any other way of adapting customer's information to their requirements without their advisor's opinion. There is no trust developed among managers and staff in Call Centres to let and motivate them to act freely to customize their services. There are no strict rules for monitoring the Call Centres activities. The controls are all bound to the reports of management information software. Keeping a log and documentation is a normal way in both companies to keep the history of activities in Call Centres but there is no proper way to share the information through the groups. Both the companies agree to the significance of gathering knowledge to enhance the Call Centres performance. Moreover, both monitor the recruitment and training process to help new staff gain the necessary knowledge. Both companies have a few difficulties regarding the cultural issue of generating the generation. Due to this issue, the staff is not directly involved in knowledge generation. For inbound Call Centres, the main objective is to reduce the waiting time for incoming calls. He explains the traditional way of handling inbound calls as well as how modern Call Centres are dealing with so [11]. When a call arrives, it is handed over to the available agent. However, having an available agent without a customer has to wait for has a very low probability. Therefore, there is a waiting queue in the Call Centres where the call is transferred to wait till any agent gets free. Traditionally this situation is handled by analyzing past data and hiring agents as per customers.

In this way, the waiting time for customers is reduced compared to the previous one. This problem arises for selecting the number of agents to be hired. The number of customers cannot be determined leads to either understaffing or overstaffing. Under-staffing is a temporary issue but over-staffing may prevent certain quantitative targets from being met, due to the lack of a sufficient number of calls per employee. Numerous studies show that customers are the highest priority for the Call Centres. They have applied techniques to reduce the waiting time of the customer. Moreover, call routing has been done where calls are handed over to the agents according to their skills. This call routing is done using the past data of both customers and agents. However, there is a need for an effective model for predicting which call should be routed to which agent. Moreover, there is a need to work on agents' behavioral issues that influence Call Centres' operations. In a real-time environment, numerous calls are received by the call management system. The author presents [12] a mathematical model of scheduling the calls that are waiting to achieve customer satisfaction and to deal with the calls efficiently rather than making them random and leaving the most important calls unattended. Moreover, the paper says the call should be handled in a way that an agent should make the most out of his time, he is available in the Call Centre.

Another factor that they have catered to is an agent's skill. Most CSRs are specialized in certain types of calls, and hence have faster service rates for those calls, while only minimally trained on others, and hence have slower service rates on those calls. The model caters to any number of calls, as the number of calls varies according to the time. In the daytime a different number of calls were observed compared to the evening ones. He concludes that it is very important to optimize the calls along with having skilled agents. The model that they have presented is applicable to almost all the Call Centres. There is a drawback that the model is slow to be employed in a real-time environment. Besides agents to be trained, calls to be scheduled and teams to be managed to maximize sales and quality, another presented [13] an architecture of a call routing system and applied three different machine learning algorithms to test the results of three different datasets from different industries. He emphasizes that agents and customer interaction are the key point where you a Call Centre will gain customer satisfaction and eventually the sales will increase. It further says Call Centres have been following numerous processes to enhance Call Centre's processes such as agent training to increase sales, call recording for quality monitoring, acquiring customer feedback, and many similar processes. The main component that is the call routing system throws calls to the agents randomly, as if you flip a coin. This system should be intelligent enough to decide which incoming call should be given to whom to handle the customer. Hence, the paper presents a basic architecture of a call routing system that works intelligently. The main component of the architecture is ‘Mapper’ which receives data from the switch and uses artificial intelligence that has been fed into it and maps the calls to the agents according to the algorithm. The algorithm is modelled using the past data, in other words, it is trained over the past data [14]. The training is done offline and uses five factors that are extension of the CSR who received the call, the BTN of the customer who dialed the call, and the outcome of the revenue, talk time, and satisfaction level outcome marked by the customer based on the services CSR provided. The CSRs are scored and mapped according to the mentioned five factors. Whenever a customer call is arrived in real-time environment, the two features’ extensions of available CSRs and updated list of customer BTN communicate with the offline training process. In this process the new data is entered into the trained model, this model updates itself on monthly basis. On the other hand, the received call is given to the agent according to the trained model’s outcome. To check how efficient did the model worked a mathematical work is done that compares outcome of the calls that were routed using the algorithm and calls that routed randomly as shown in Figure 2.

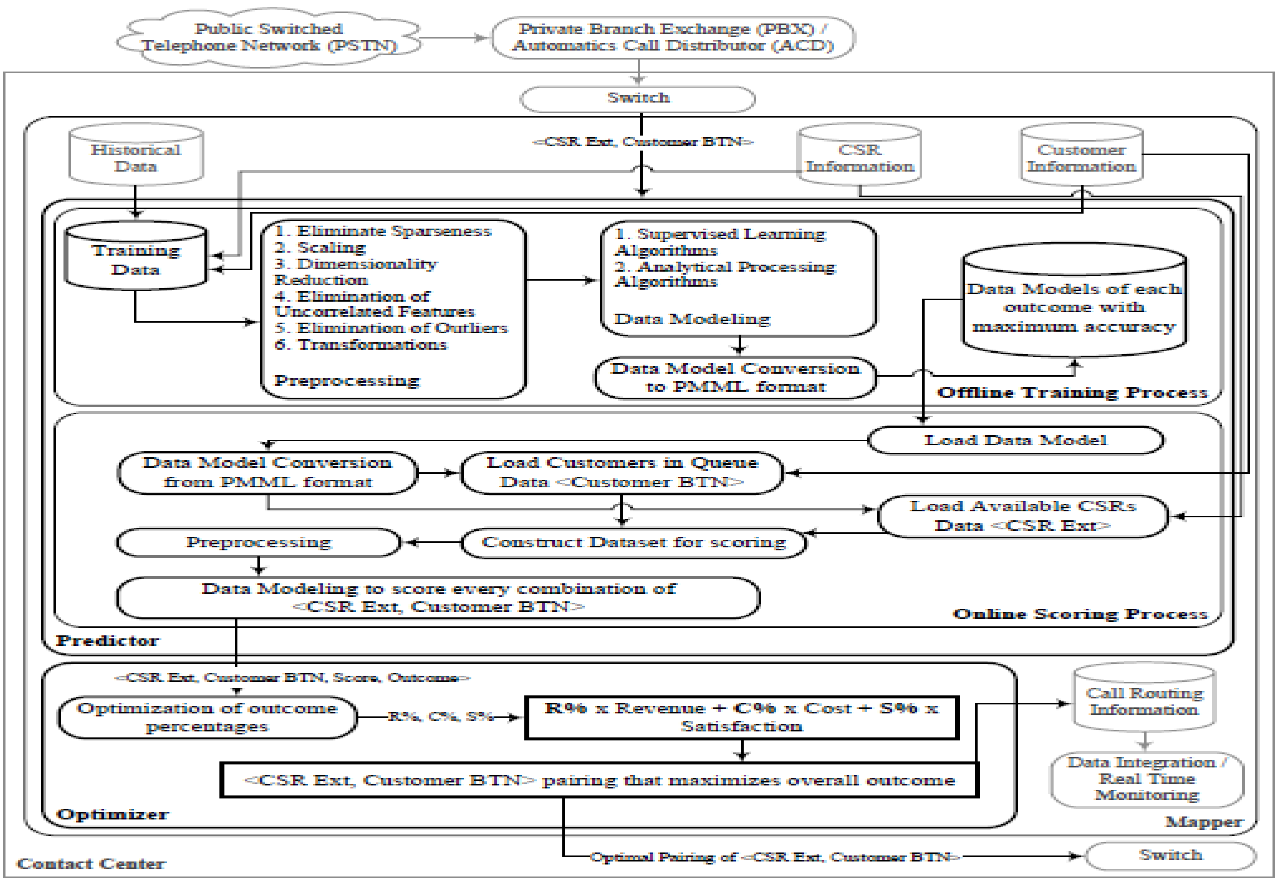


Figure 2.
Detailed architecture of call routing system

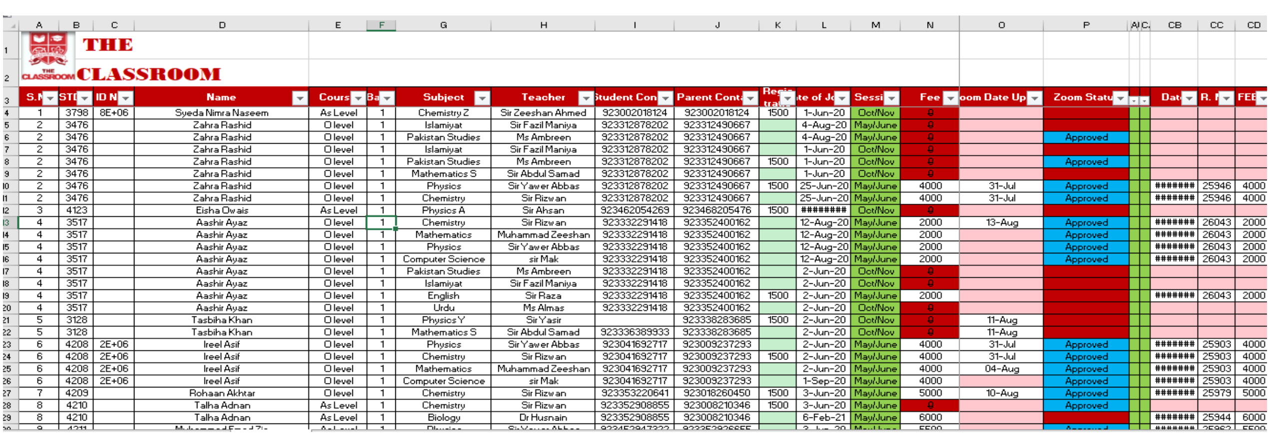
As per the study, the previous studies have provided different techniques to optimize call Centre call routing to make customer dealing efficient. The solutions are either mathematical or theoretically explained. None of the papers present a solution that shows results from the real environment. The papers that explain the architecture of a call routing system have explained which module is responsible for call routing but no algorithm has been presented to optimize the call routing. Also, the research so far fails to explain that besides agents' training and management, it is very important to train call routers in a way that should perform call routing that will add to in optimization of sales.

METHODOLOGY

In a traditional call routing system, the process follows a straightforward approach. When an incoming call is received, the system checks for an available agent and assigns the call accordingly. If no agent is available, the call is placed in a waiting queue, which it follows a first-come, first-served (FCFS) mechanism or prioritizes calls that have been waiting for the longest. To enhance call routing efficiency, rather than assigning calls randomly and relying on FCFS, an improved approach is proposed based on offline and online learning techniques. Offline learning, operating in a static environment, involves ranking both agents and calls using past data [15]. Agents are categorized based on factors such as the number of successful sales, their expertise in specific skills, customer satisfaction levels, and efficiency in handling calls. Similarly, customers are ranked based on their history, including whether they are regular or new customers, call duration, satisfaction levels, and prior interactions. Online learning, functioning in a dynamic environment, processes incoming calls by prioritizing them according to predefined rules derived from past data. The system first determines the priority level of the call and checks for an available agent [16]. Instead of assigning calls randomly, the system identifies the most relevant skilled agent among those available. If an appropriate agent is free, the call is assigned immediately; otherwise, it is placed in a waiting queue. Unlike traditional methods, this queue does not operate solely on an FCFS basis; instead, calls are prioritized based on predefined rules, ensuring that high-priority calls are handled first. This approach optimizes call routing, improves customer service, and enhances overall sales performance in call centers.

DATA COLLECTION

To begin this research, we approached many institutes and found THE CLASSROOM that fit best to our requirements. There were universities, colleges, schools but due to confidentiality they were providing limited data. We required data which could show the variability in sales. The universities sales are made twice a year while schools and colleges make once a year, therefore we couldn't rank calls and agents with limited data having such low sales. Therefore, we chose a coaching center whose sales take place on a daily basis as shown in Figure 3.



THE CLASSROOM

S.N	STD	ID N	Name	Cours	Ba	Subject	Teacher	Student Con	Parent Conta	Regis tra	ate of Jo	Sessi	Fee	oom Date Up	Zoom Statu	Dat	R. N	FEE
1	3798	8E+06	Syeda Nimra Naseem	As Level	1	Chemistry Z	Sir Zeeshan Ahmed	923002018124	923002018124	1500	1-Jun-20	Oct/Nov	0					
2	3476		Zahra Rashid	O level	1	Islamiyat	Sir Fazil Maniya	923312878202	923312490667		4-Aug-20	May/June	0					
2	3476		Zahra Rashid	O level	1	Pakistan Studies	Ms Ambreen	923312878202	923312490667		4-Aug-20	May/June	0		Approved			
2	3476		Zahra Rashid	O level	1	Islamiyat	Sir Fazil Maniya	923312878202	923312490667		1-Jun-20	Oct/Nov	0					
2	3476		Zahra Rashid	O level	1	Pakistan Studies	Ms Ambreen	923312878202	923312490667	1500	1-Jun-20	Oct/Nov	0		Approved			
2	3476		Zahra Rashid	O level	1	Mathematics S	Sir Abdul Samad	923312878202	923312490667		1-Jun-20	Oct/Nov	0					
2	3476		Zahra Rashid	O level	1	Physics	Sir Yawer Abbas	923312878202	923312490667	1500	25-Jun-20	May/June	4000	31-Jul	Approved	#######	25946	4000
2	3476		Zahra Rashid	O level	1	Chemistry	Sir Rizwan	923312878202	923312490667		25-Jun-20	May/June	4000	31-Jul	Approved	#######	25946	4000
3	4123		Eisha Owais	As Level	1	Physics A	Sir Ahsan	923462054269	923468205476	1500	########	Oct/Nov	0					
4	3517		Aashir Ayaz	O level	1	Chemistry	Sir Rizwan	923332291418	923352400162		12-Aug-20	May/June	2000	13-Aug	Approved	#######	26043	2000
4	3517		Aashir Ayaz	O level	1	Mathematics	Muhammad Zeeshan	923332291418	923352400162		12-Aug-20	May/June	2000		Approved	#######	26043	2000
4	3517		Aashir Ayaz	O level	1	Physics	Sir Yawer Abbas	923332291418	923352400162		12-Aug-20	May/June	2000		Approved	#######	26043	2000
4	3517		Aashir Ayaz	O level	1	Computer Science	sir Mak	923332291418	923352400162		12-Aug-20	May/June	2000		Approved	#######	26043	2000
4	3517		Aashir Ayaz	O level	1	Pakistan Studies	Ms Ambreen	923332291418	923352400162		2-Jun-20	Oct/Nov	0					
4	3517		Aashir Ayaz	O level	1	Islamiyat	Sir Fazil Maniya	923332291418	923352400162		2-Jun-20	Oct/Nov	0					
4	3517		Aashir Ayaz	O level	1	English	Sir Raza	923332291418	923352400162	1500	2-Jun-20	May/June	2000			#######	26043	2000
4	3517		Aashir Ayaz	O level	1	Urdu	Ms Almas	923332291418	923352400162		2-Jun-20	Oct/Nov	0					
5	3128		Tasbiha Khan	O level	1	Physics Y	Sir Yasir		923338283685	1500	2-Jun-20	Oct/Nov	0	11-Aug				
5	3128		Tasbiha Khan	O level	1	Mathematics S	Sir Abdul Samad	923336389933	923338283685		2-Jun-20	Oct/Nov	0	11-Aug				
6	4208	2E+06	Ireel Asif	O level	1	Physics	Sir Yawer Abbas	923041692717	923009237293		2-Jun-20	May/June	4000	31-Jul	Approved	#######	25903	4000
6	4208	2E+06	Ireel Asif	O level	1	Chemistry	Sir Rizwan	923041692717	923009237293	1500	2-Jun-20	May/June	4000	31-Jul	Approved	#######	25903	4000
6	4208	2E+06	Ireel Asif	O level	1	Mathematics	Muhammad Zeeshan	923041692717	923009237293		2-Jun-20	May/June	4000	04-Aug	Approved	#######	25903	4000
6	4208	2E+06	Ireel Asif	O level	1	Computer Science	sir Mak	923041692717	923009237293		1-Sep-20	May/June	4000		Approved	#######	25903	4000
7	4209		Rohaan Akhtar	O level	1	Chemistry	Sir Rizwan	923353220641	923018260450	1500	3-Jun-20	May/June	5000	10-Aug	Approved	#######	25979	5000
8	4210		Talha Adnan	As Level	1	Chemistry	Sir Rizwan	923352908855	923008210346	1500	3-Jun-20	May/June	0		Approved			
8	4210		Talha Adnan	As Level	1	Biology	Dr Husnain	923352908855	923008210346		6-Feb-21	May/June	6000			#######	25944	6000

Figure 3.
Dataset of Classroom

From the above-given data by the classroom, which is admissions data, we extracted our admissions table for our use. We didn't extract student data because it wasn't required for our algorithm. So, the following is the data and the columns that were created, and these are the columns that were required, and we extracted out from the above table. We extracted only admissions data along with the admission ID that we assigned it ourselves as shown in Figure 4. This admission data is basically sales that were made in-person in the institute, so this is basically sales data in other words, and admission data as per institute.

AdmissionID	STD ID	Name	Course	Student Contact	Parent Contact	Date of Joining	Session
AD0001	3798	Syeda Nimra Naseem	As-Level	923002018124	923002018124	2020-06-01	Oct/Nov
AD0002	3476	Zahra Rashid	O-Level	923312878202	923312490667	2020-06-02	May/June
AD0003	4123	Eisha Owais	As-Level	923462054269	923468205476	2020-06-03	Oct/Nov
AD0004	3517	Aashir Ayaz	O-Level	923332291418	923352400162	2020-06-04	May/June
AD0005	3128	Tasbiha Khan	O-Level		923338283685	2020-06-05	Oct/Nov
AD0006	4208	Ireel Asif	O-Level	923041692717	923009237293	2020-06-06	May/June
AD0007	4209	Rohaan Akhtar	O-Level	923353220641	923018260450	2020-06-07	May/June
AD0008	4210	Talha Adnan	As-Level	923352908855	923008210346	2020-06-08	May/June
AD0009	4211	Muhammad Emad Zia	As-Level	923452947322	923352926655	2020-06-09	May/June

Figure 4.
Admission Data

As mentioned above, the CLASSROOM doesn't record their call data which is why we conducted some meetings in which we asked them some questions. For instance:

Feature Extraction

As mentioned earlier, from the admission data given by the CLASSROOM, we created an admissions table from it and extracted columns, in other words, features, that we require, and the dummy data was already generated by us in a way so that we can extract features from the columns and don't have to do any additional work for it [17]. The main feature that we require is the sales column because it is the most important column to rank agents and to analyse which call lie in which category [18]. That is why we worked on sales column as sale in this industry is indirect so we had to connect sales with calls in a way that we could check which agent has satisfied the customer and made him to visit the institute for admission. To extract the sales feature what we did is that we connected the student's admissions data with the recent call he made. So, this is how we marked sale on that day in a way that particularly which agent convinced him that is why he came and get the admission in person on the next day. This is how we marked sales for each agent.

Building the Algorithm

Input and Output Values: The input to this algorithm will be past data of the calls, past records of the agents, and the call activity. The output will be the average time that the system has taken to deal with the given calls.

Main Frame: When the SBR algorithm begins to process calls, the ranks of the agents and calls will be calculated. After that the leads will be loaded into the system by reading the list of contact numbers from the file; they will be used in the system for depicting incoming calls [19] [20]. When this all is loaded in the system, it will be passed to the function optimize-total-time to process further functionalities. The output of the function will be an integer value that will tell total time taken to deal all the leads. The pseudocode of the main function is as below:

Skill-Based Routing Algorithm: Main()

```
1: SET call-ranks = calculate-call-ranks()
2: SET agent-ranks = calculate-agent-ranks()
3: SET leads = read contacts from file
4: SET totaltime = optimize-total-time(leads, call-ranks, agent-ranks)
5: OUTPUT totaltime
```

Function: optimize-total-time(leads, call-ranks, agent-ranks)

```
DECLARE waiting list, sum
LOOP for 1 to N leads
    SET incoming-calls = select random 10 elements from leads
    SET prioritized-calls = prioritize-incoming-calls(incoming-calls, call-ranks)
    LOOP 1 to N elements of prioritized-calls
        SET matched-agent = find-skill-based-agent(prioritized-calls, agent-ranks)
         IF matched-agent is NULL
        THEN
          SET matched-agent = find-agent-with-lowest-current-job(prioritized-calls, agent-ranks)
           IF matched-agent is NULL
                      THEN
                                ADD prioritized-calls -> incoming-calls
             ELSE
                      ADD (CONCATENATE matched-agent+','+prioritized-calls) -> waiting-list
         ELSE
         ADD assigncalls(matched-agent, prioritized-calls, agent-ranks)
    END LOOP
    sum += hangup(agent-ranks)
    check-waiting-list(waiting-list)
END LOOP
RETURN sum
```

During the phase of data collection we had generated data with the help of interview conducted to understand how the call centre of The Classroom works. The points noted from queries showed a drawback in their way of handling calls, that they do not utilize all their agents at a time for some reason [21]. That means the utilization of resources which are agents was not taking place properly. For instance, if they had 75 agents present not all of them were engaged in handling calls. Hence, the first feature from which we began to develop the algorithm is utilizing all the agents that are present [22]. Initially we developed an algorithm that deals with calls with a first come first serve rule. It receives calls and assigns to the idle agent which are arranged alphabetically by their names. When all the calls are assigned to all the agents present at the moment, the remaining calls are sent to the waiting queue till any of the agent gets free. The waiting queue is dealt with first come first serve rule as well, as soon as any of the agent gets free the first call in the waiting queue will be assigned to that agent [23] [24]. To test FCFS algorithm, we plotted a graph and used the original data of the CLASSROOM based on their own rules. Initially, we took 100 calls and plot it on graph and calculated how much time agents take on calls. Following the same sequence of calls, we passed it through the FCFS algorithm and analysed that if we used all the agents what effect comes on the time and how the calls are distributed among the agents. The results and graphs are given below. The total time taken to deal 100 calls by THE CLASSROOM took 25 minutes. While, the FCFS algorithm took 15 minutes to deal 100 calls by 75 agents as shown in Figure 5 and 6.

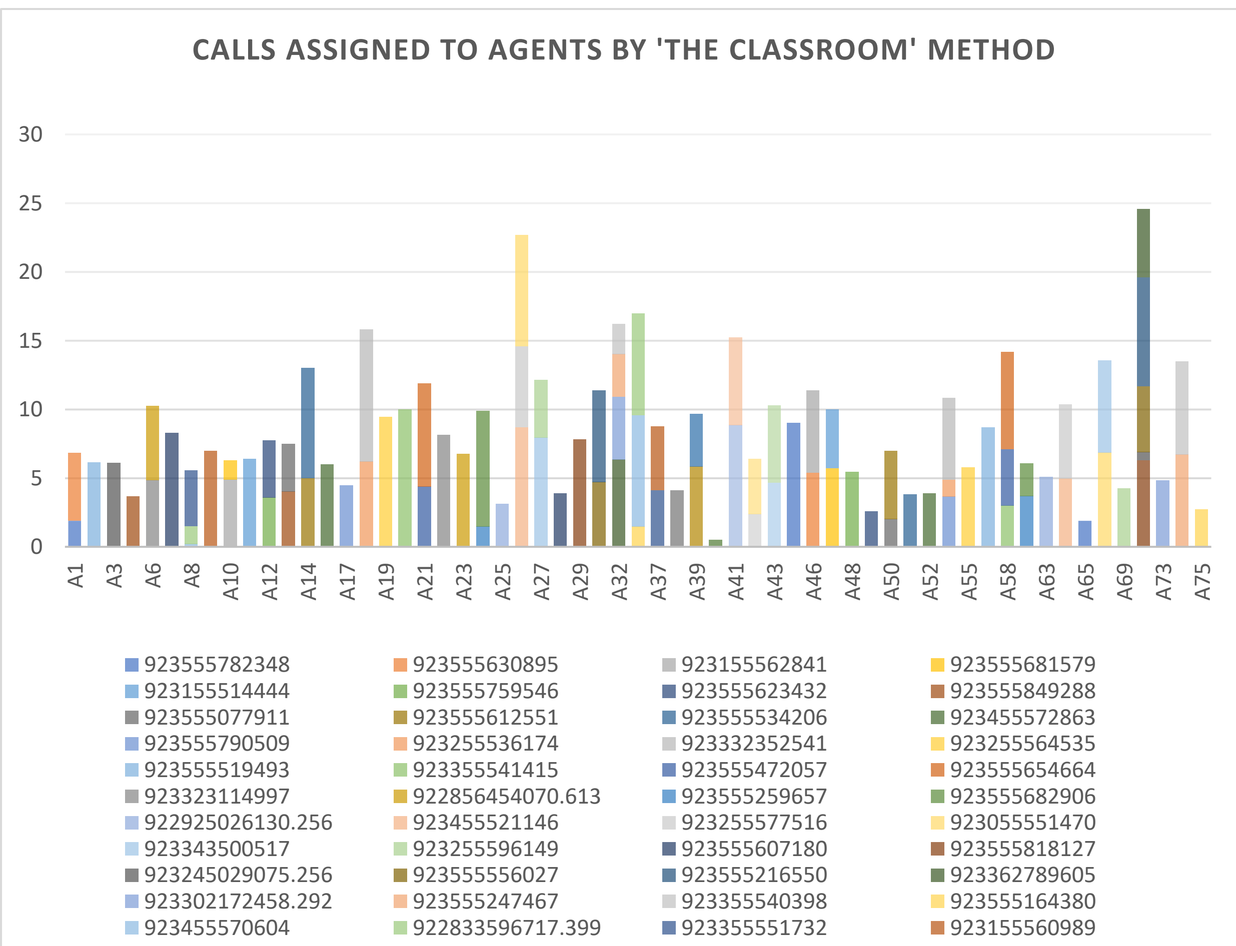


Figure 5.
Calls Assigned to Agents

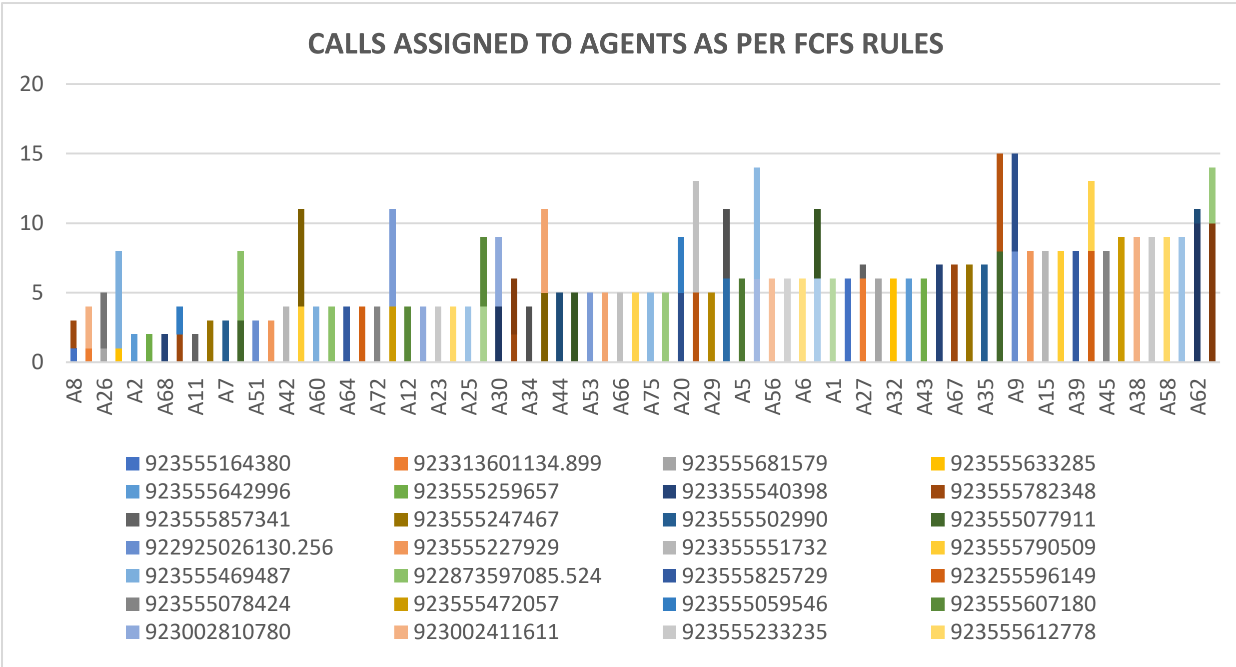


Figure 6:
Calls Assigned to Agents

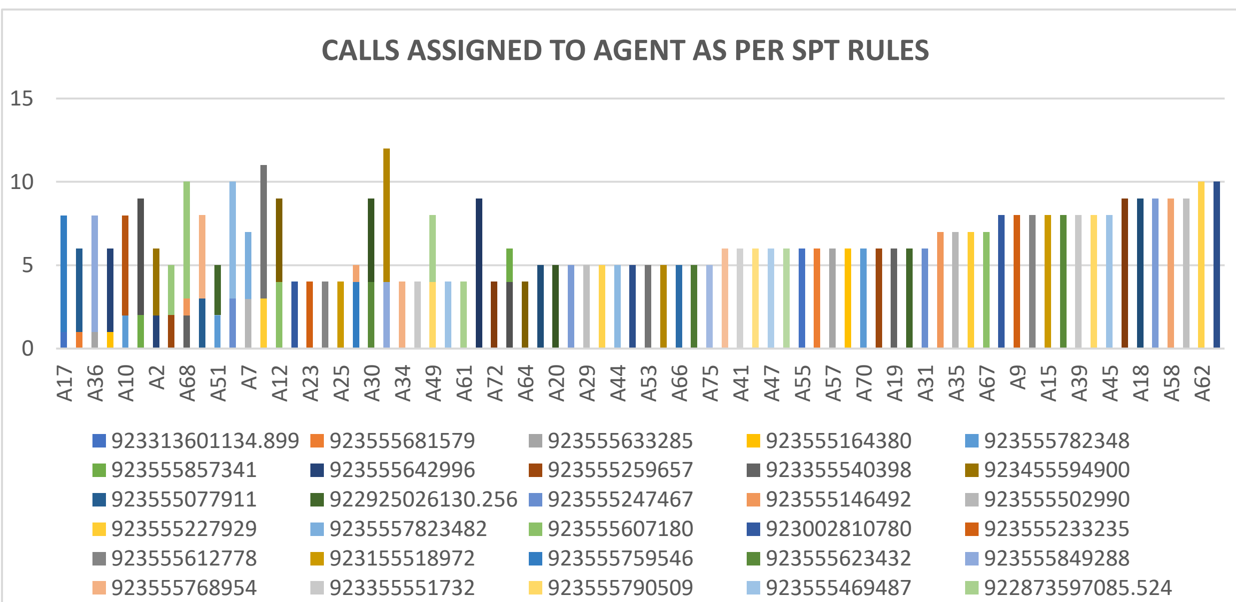


Figure 7:
Calls Assigned to Agents as Per SPT Rules

After adding the feature of first come first serve which we did resource utilization. The second feature we added to the algorithm was the Shortest Processing Time, which The Classroom was not following and it is also the objective of our research. In the SPT algorithm, all the incoming calls were added to a queue and prioritized the queue based on their shortest processing time in ascending order [25] [26]. In this way, a call with the shortest job time will be assigned and dealt with first. The next step, assigning calls to the agents is still being done randomly, no rule has been applied to this step. When no idle agent is left, the next call will be added to a waiting queue but this time before adding the call to a waiting queue the agent will be assigned to the call, who is currently dealing with the shortest process time call. The calls in the waiting queue will be entertained as soon as their assigned agent gets free. To test this algorithm, we performed the same steps that were taken to test FCFS compared to THE CLASSROOM. The SPT algorithm took 12 minutes to deal with 100 calls as shown in Figure 7. The second objective that we had to implement was skill-based routing; where the prioritization of queue and assigning calls to agents will be done based on calculated ranks. As per SPT when calls were received, they were added to the queue and prioritized as per their job time, but here we will prioritize them based on calls' ranks. The highest-ranked call will be on top, the second highest after those calls, and so on, in this way, the lowest-ranked call eventually will be on the bottom. The method of making calls wait is similar to SPT, the difference here is adding another rule that finds the same skilled agent among busy agents, and then among those agents it will find the one that is dealing with the lowest job time call. The SBR algorithm has been discussed in the methodology section in detail. We executed the algorithm by applying the same leads as previous algorithms. The SBR algorithm took 15 minutes to deal with 100 calls. All three algorithms were built step-wise to fulfill the objectives. If we analyze all three separately, all of these perform better than The Class Rooms in consumption of time. On comparison of these three algorithms, shows that all of these consume time and have values closer to each other. SPT is better than the other two in time consumption but our second objective is skill base routing, which is implemented in SBR as shown in Figure 8.

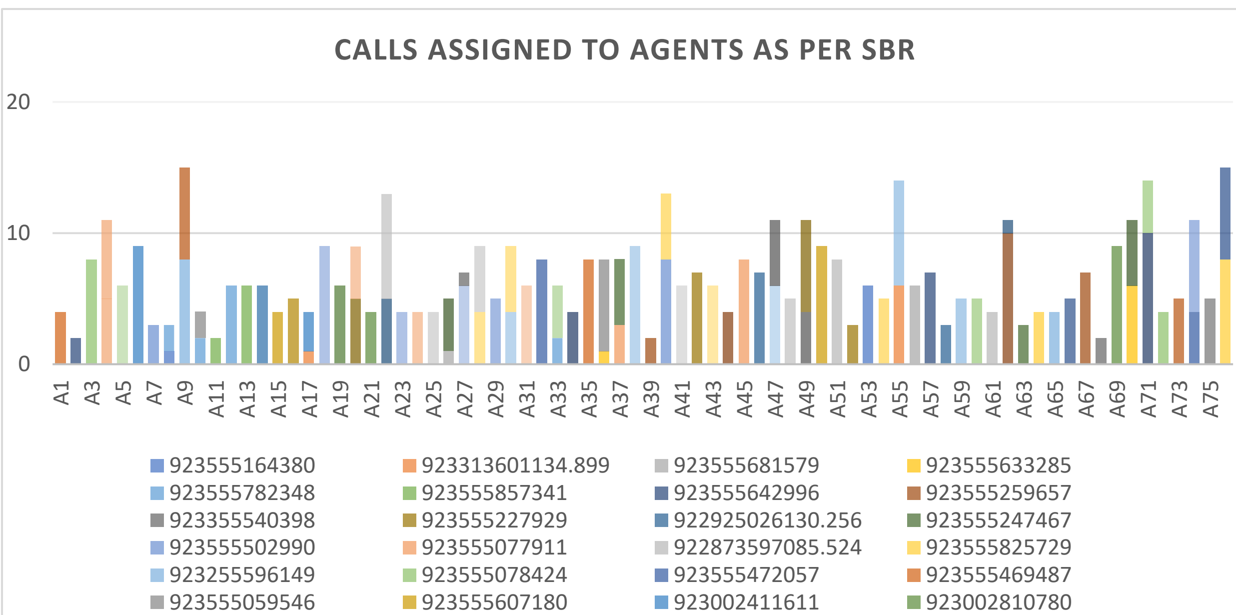


Figure 8:
Call Assigned to Agents as Per SPT Rules

RESULT AND DISCUSSION

We developed the SBR algorithm using the training data, by applying rules stepwise and eventually created three algorithms. Three of them fulfill different objectives; to test whether these algorithms would give the same results on different data sets as we gained after the evaluation or will differ. For testing the final results, we used testing data so that we would have different nature of the data. For further experiments, we created a data set so that we could experiment with different sets of data firstly we took 25 agents, then 50 agents, and then 75 agents and we assigned each set of agents three different sets of calls. First, we assigned them 50 calls, then 100 and 200. The representation of data sets is shown in Table 1.

Table 1:
Data Representation

Agents	25	25	25	50	50	50	75	75	75
Leads	50	100	200	50	100	200	50	100	200

We applied all three algorithms to each data set and initially, we executed 10 iterations of each algorithm. The average of 10 iterations from each algorithm at each data is as follows, the numeric value represents minutes Table 2.

Table 2:
Data Representation of Numeric Value Represents Minutes

Agents/Leads	FCFS	SPT	SBR
25/50	14.7	15.4	15.1
25/100	23.4	25.3	26.2
25/100	32.3	33.4	34.1
50/50	9.4	9.1	9.4
50/100	15.4	16.1	16.4
50/200	18.2	19.4	27.2
75/50	9.3	9.2	9.2
75/100	14.2	15.3	15.1
75/200	19.2	16.1	16.3

We plotted the result on a graph as shown in Figure 9.

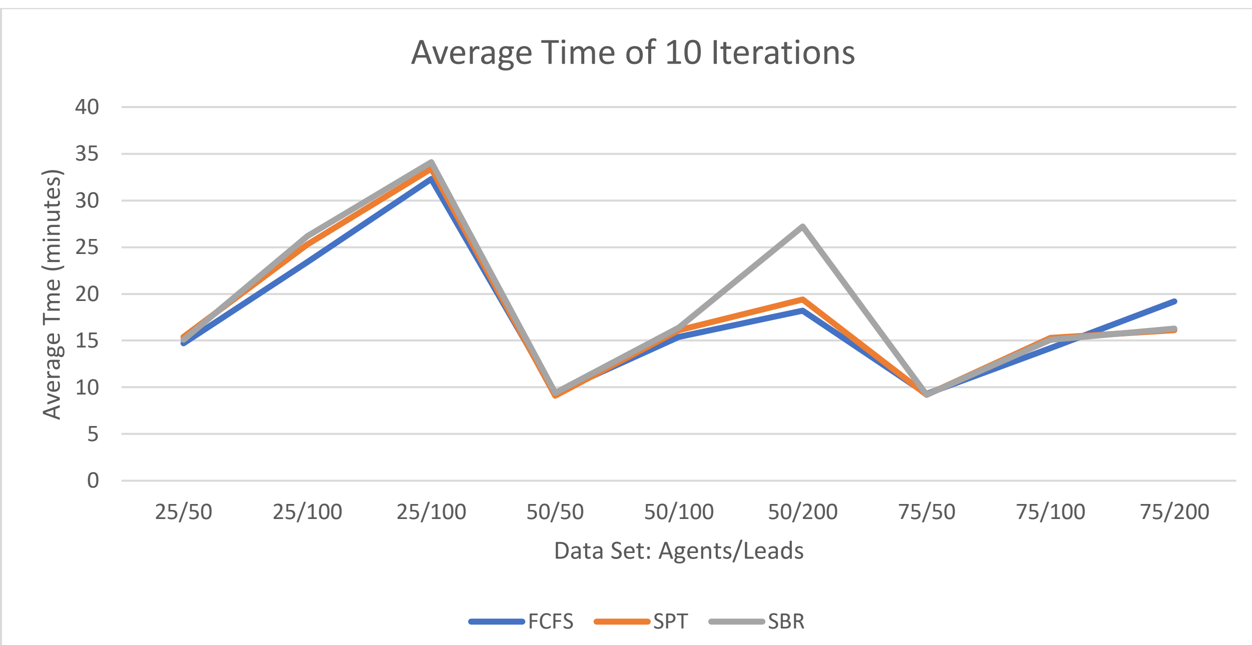


Figure 9:
Average Time of 10 Iterations.

If we look at the plot, the SPT and FCFS have similar results in each data set. The SBR's result differs at low agents with high calls – 50/200, otherwise, it is working similarly to other algorithms. To get more accuracy, we applied 51 iterations to each data for 5 times. In other words, we applied 5 experiments to each data set using all three algorithms. The average of each experiment was recorded and plotted on the graph. The graph is shown in Figure 10.

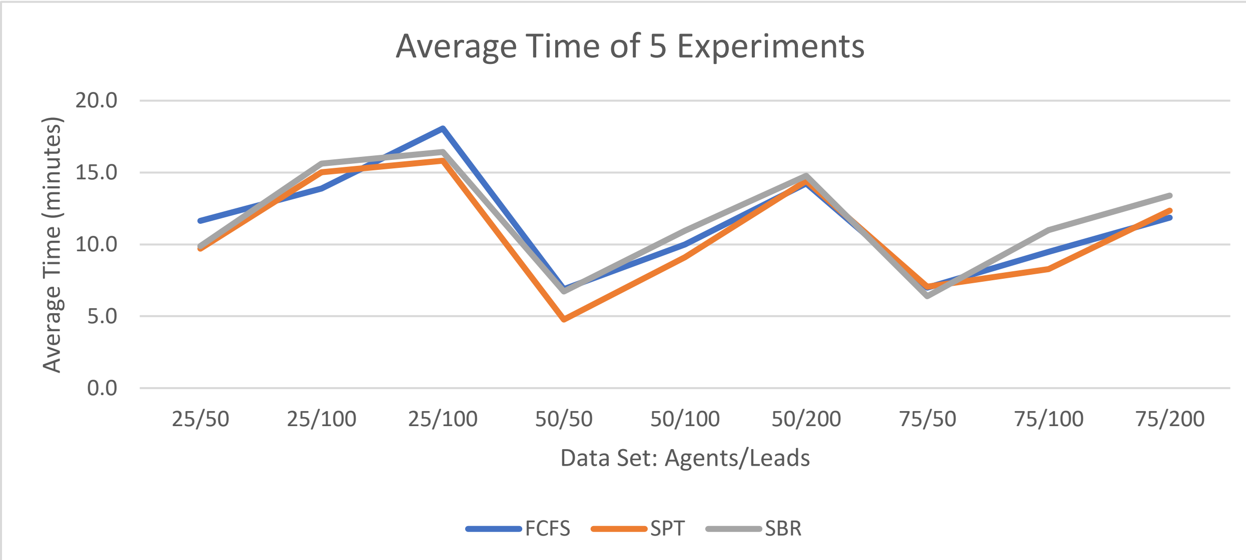


Figure 10:
Average Time of 5 Experiments.

After these experiments if we look at the graph, we can see that all three algorithms are behaving the same way as they were behaving in evaluation although there are slight differences at 25/100 FCFS time is slightly higher than others, and at 50/50 SPT is performing better, but they are not high differences due to which we may rank any algorithm over other. So, all three algorithms are behaving closely.

CONCLUSION

To conclude, if we look at the results of different data sets and for different experiments the algorithms perform nearly the same. But these algorithms have been applied to THE CLASSROOM's data set, and each of them may perform very differently for other organization's data. If we talk about each algorithm solely, each of them has better performance than the CLASSROOM. But separately FCFS only does resource utilization, it will work perfectly for the cases where all the agents are present. It is difficult to have this ideal situation at call centers where all the agents are available and present at their desks. For various reasons, the agents' presence varies. On the other hand, the SPT works well in reducing overall system time as it prioritizes the SPT rule at every process. Hence, it may optimize sales on the basis of making the total system time efficient. While the SBR includes skill-based routing where not only time but we will be selecting relevant skilled agents too. The ranking is applied to the past data which means the call center where the regular customer matters for sales, is good to go for this algorithm. But call centers where the population of the new caller is high, might lack efficiency as they will not have any record in the system and hence cannot be judged as per their rank.

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