ASHESI UNIVERSITY COLLEGE

EXPLORING THE USE OF PREDICTIVE ANALYTICS IN REDUCING CUSTOMER WAIT TIME IN A COLLEGE CAFETERIA

UNDERGRADUATE THESIS

B.Sc. Computer Science

Dorothy Sarpong-Kumankoma

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Exploring the Use of Predictive Analytics in Reducing Customer Wait Time in a College Cafeteria

UNDERGRADUATE THESIS

Thesis submitted to the Department of Computer Science,

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award of Bachelor of Science degree in

Computer Science

Dorothy Sarpong-Kumankoma

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Declaration

I hereby declare that this undergraduate thesis is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature:

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Candidate's Name:

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Date:

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I hereby declare that preparation and presentation of the undergraduate thesis were supervised in accordance with the guidelines on supervision of thesis laid down by Ashesi University College.

Supervisor's Signature:

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Supervisor's Name:

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Date:

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Abstract

Predictive analytics, is a practice of extracting information from existing data sets in order to predict outcome and trends in the future. Techniques of predictive analytics such as data mining, statistics, modelling and machine learning are used extensively in the hospitality industry for predicting customer frequency, wait time, crop yields among others. For the purpose of this paper, we will be exploring the influence of forecasted data in reducing wait time at a college cafeteria, using modelling as the predictive analytics technique.

Cafeterias provide meals and drinks to specific target groups of customers especially in schools, hospitals, organizations and companies at a charge. They are mainly different from the other food service providers in terms of their service styles, whereby there is no waiting staff but rather the customer serves from a buffets of meals and pays for meals by themselves. Due to this serving style, there is a challenge of preventing long queues and reducing wait time for customers to pick up food. An increase in wait time for customers could lead to customer dissatisfaction and this paper seeks to address this challenge.

The objective of this study is to assess the impact of a predictive model in reducing the wait time at a cafeteria. To achieve this objective, a mathematical model is formulated to accurately predict the number of customers likely to visit the cafeteria at various times during the day. The impact of the predictions is then assessed in its ability to reduce wait time.

Keywords: Service quality, food service establishment, customer satisfaction, technology, prediction

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Chapter 1: Introduction

1.1 Introduction

The hospitality industry is an informal but solid indicator of a country or continent's economic well-being (Eugenio-Martín, 2004). The industry's impact on the economic and social development of a country can be massive; opening it up for business, employment, trade and capital investment, as well as protecting its heritage and cultural values. Food service establishments, as the name suggests, are settings where portions of meals are served to customers usually at a charge. Customers are given the choice of sitting in to eat their meals or ordering a take-out meal. Examples of food service establishments include fast food restaurants, coffee shops, cafeterias and casual dining restaurants.

Cafeterias provide meals and drinks to specific target groups of customers especially in schools, hospitals, organizations and companies at a charge. They are mainly different from the other food service providers in terms of their service styles, whereby there is no waiting staff but rather the customers serves from a buffet of meals and pays for meals by themselves. Due to this serving style, there is a challenge of preventing long queues and reducing wait time for customers to pick up food.

This paper aims at designing a mathematical model that predicts frequency of customers at a college cafeteria. An implemented web application is used to keep track of time spent after placing an order and picking up food, before and after predicted number of customers visiting the cafeteria is made public to the college. The difference in wait time is then measured to observe an influence of the predictive model on wait time at the cafeteria.

1.2 Background

Cafeterias like other eateries provide meals and drinks to target groups of customers especially in schools, hospitals, organizations and companies at a fee. They are however different from other food service establishments in terms of their service style. In a typical cafeteria, the food is served at a counter and set up in a buffet arrangement, where the customer takes a tray to pick up food at the counter before or after paying. The menu and prices are fixed for each meal and customers sit at the tables on a first come basis. Due to the serving style of cafeterias, there is a challenge to prevent long queues and to reduce wait time for customers. Long customer wait time leads to dissatisfaction, and this paper seeks to explore how predicted customer frequency could reduce wait time at a college cafeteria.

According to Liang and Zhang (2009) in their study, food service in colleges is a big market today, competing with other mechanisms such as food vending machines. They classified current students as more sophisticated than previous years and preferring a wider variety of types of food. Most importantly, they realised that the success of cafeterias in colleges depended on the satisfaction of the students (Liang & Zhang, 2009).

Cafeterias in schools play a very important role because they provide an environment for students, faculty and staff to enjoy balanced meals along with an opportunity to socialise with other colleagues. Thus, it is important that customers can fully utilise the time spent at these cafeterias. Ashesi University College, the context of this study, is a liberal arts college in Ghana that has a total student population of about 680 students. The school runs two main cafeterias on campus but for the purpose of this study, the focus will be on the Akornor Cafeteria, the longest operating cafeteria on the campus. This cafeteria is situated on the main campus of the school and has been in operation for over five years. The cafeteria uses a card payment system as well as a cash payment system for item purchasing.

1.3 Research Problem

Service quality is an assessment of how well a delivered service conforms to the client's expectations. It is usually concerned with attributes that affect customer satisfaction. To be globally competitive, service industries must render quality service that exceeds customers' expectations. In the food service industry, service quality is influenced by attributes such as quality of food, ambience or environment of the establishment, waiting times and meal durations. Research has been conducted to assess the impact these attributes have on service quality in food service establishments. Lee and Lambert (2001) in their paper talked about how wait time is managed in the food service industry. They mentioned that while enhancing the waiting environment uses cognitive psychological disciplines to improve customer satisfaction related with perceived waiting time, a second approach uses management science and operations management disciplines to reduce actual waiting time. Scheduling, simulation, forecasting, and process design were stated as frequently used methodologies to reduce actual waiting time, since waiting time is considered to be a key factor for customer satisfaction (Lee & Lambert, 2001).

Research by Noone, Wirtz and Kimes (2010) supports the use of these psychological disciplines. In their paper, they investigated the impact perceived service encounter pace had on customer satisfaction. An empirical study conducted indicated that, as the pace of service increased, customer satisfaction also increased (Noone et al., 2010).

For the purpose of this current study; to predict customer frequency at a college cafeteria, interviews were conducted to reveal the causes of long slow moving queues at the cafeteria. Amongst them were the poor communication between the kitchen staff and the servers at the counter, and the inability of the cafeteria staff to handle large numbers of customers. The challenges above leads to long queues of customers at the counter waiting to either order their meals or pick up their food. This paper therefore seeks to add on to the existing knowledge in the field of customer satisfaction by investigating how the use of a predictive mathematical model that predicts customer frequency can influence the planning and scheduling of meal service at a college cafeteria, consequently reducing wait time of customers.

1.4 Objectives of Research

Due to the direct relationship between service quality and customer satisfaction, it is imperative that managers of food service establishments improve service quality. From the research conducted, most customers perceive long wait time and queues at the cafeteria as a form of poor service delivery and this reduces patronage. This paper is therefore motivated by the need to reduce wait time of customers at food service establishments, hence increasing customer satisfaction. To achieve these results, the following specific objectives will be addressed:

1. To learn a model that predicts daily peak periods at the Akornor cafeteria.

2. To assess how the knowledge of the predicted numbers and times affects wait time at the cafeteria.

1.5 Research Questions and Hypothesis

In addressing the identified problem in the above paragraphs, the question that would need to be answered is; can the knowledge of peak periods from a predictive model reduce wait time at the Akornor cafeteria?

The hypothesis for this study is:

There is an impact of customer frequency prediction in reducing wait time at the Akornor cafeteria.

1.6 Outline of Research

This thesis is organised into five chapters as follows:

Chapter 1: Introduction gives a general overview of the research and its relevance. It comprises the summary of the project, research questions and objectives, problem statement, motivation and scope of the research.

Chapter 2: Literature Review outlines the related work regarding various ways technologies and the application of technology as well as technological systems have improved service quality in food service establishments such as restaurants and grocery shops.

Chapter 3: Methodology describes the methods and approaches that were used in answering the research questions that this paper poses.

Chapter 4: Experimentation and Results presents how the predictive model used in the food service establishment affected the quality of service in the food service establishments.

Chapter 5: Conclusion and Recommendation presents the discussion and conclusion drawn from experimentation.

Chapter 2: Literature Review

2.1 Nature of Cafeteria in Colleges

Cafeterias in colleges play an important role in the health of the staff, faculty and students. While the importance of offering quality education is paramount for colleges, several administrators are beginning to recognize and appreciate the concept of the "total offering" in which food services can play a vital role. According to Andeleeb and Casky (2007), many colleges have begun seeking the opinions of their students regarding food services and whether such services meet students' needs. This calls for attention on ways of improving the quality of services provided by cafeterias in various colleges. This study will therefore focus on ways of improving service quality, with respect to wait times in food service establishments, using a college cafeteria as a case study.

The importance of food service quality in college cafeterias cannot be over emphasized. In critical situations for some colleges in America, dissatisfaction with food services, food type and food quality could cause students to reconsider their college enrolment decision for that particular school (Andaleeb & Casky, 2007). The authors suggested that the keen attributes students expected from cafeterias were speed, convenience and a variety of quality choices. In their study, they analysed the factors that explained satisfaction with food services in college cafeterias and also determined which ones had the greatest impact on satisfaction in order to guide policy on food service design and delivery. The factors included cleanliness, atmosphere, space, convenient hours, food quality, staff behaviour, price and responsiveness. With the use of qualitative interviews and a multiple regression model analysis, the researchers were able to make conclusions on which factors were deemed important to students concerning their level of satisfaction in the cafeterias. The results showed that the quality of food served had the greatest impact on the satisfaction of students. Responsiveness and speed with respect to taking and serving orders, which is the focus of this paper also proved to be highly important to the students. Another important element was making the checkout process quicker, especially when time between classes was limited (Andaleeb & Casky, 2007). This current study will therefore probe deeper into the influence of a predictive model in increasing speed and responsiveness at the Akornor cafeteria based on available factors such as class periods and number of enrolments per course.

2.2 Relationship between Service Quality and Response Time

According to Noone and Kimes (2005), most of the research that has been done in relation to how long a customer is in a restaurant has focused on wait time. In that regard, a lengthy wait has been shown to reduce customer satisfaction and customer evaluations of service in such diverse service businesses as restaurants, banks, and airlines (Noone & Kimes, 2005). Jones and Dent (1994) explored the relationship between service quality and response time in hospitality operations. According to them, hotels and restaurants are customer processing operations modelled as having four key stages; amongst them is response time. There is evidence from a range of industries response time, is a major area of concern to consumers. For instance, anecdotal evidence suggests that nearly two-thirds of service complaints in retail operations are time-related in terms of waiting too long to pay or too long to be served (Jones & Dent, 1994).

Having established through surveys that response times appear to directly affect customer satisfaction and spending behaviour, Jones and Dent (1994), in their study developed a number of recommendations for managers. Among these recommendations was service system redesign and modification. However the authors failed to make mention of the technical ways service systems were to be redesigned.

2.3 Technological Applications in Restaurants

Research by Ruiz-Molina, Gil-Saura and Berenguer-Contrí (2014) suggests that it is vital that food service establishments implement technological systems that meets customer needs and improves the customer experience. In the paper, the authors study the use of information and communication technologies (ICT) as a differentiation tool in restaurants and how these tools enhance customer satisfaction. They mention the need for restaurant operators to have a competitive advantage in order to increase profitability. Previous research in the context of luxury hotel restaurants and à la carte restaurants illustrates the impact of the ambience or structure of the food service location or on the experiential value of the service encounter (Ruiz-Molina et al., 2014). Through the use of questionnaires, they showed that most restaurants in the Spanish hospitality industry used ICT tools such as point of sale systems and ambient intelligence in serving and communicating with their customers and this affected patronage positively. Nonetheless there were several cases where the implementation of some technologies was done poorly and thus the effect was minimal. The literature paid little attention to the integration or comparison of other restaurant technologies besides information communication technologies and this paper, seeks to implement other tools such as web applications that will be used to measure customer wait time at the cafeteria.

In other research work, Hwang (2008) in his paper explores how a table management system can contribute to reducing customer waiting time in a restaurant. According to the writer, customers may balk when they see long queues, or may leave during their wait if they are not seated on or near the time expected. He therefore recommends that by adjusting the configuration of restaurant tables, restaurant operators can reduce customer waiting times and provide prompt service. In agreement with Hwang (2008), the food service demand is complicated because of its variability and uncertainty across many dimensions such as customer arrival time and food choice. As such, an uncertainty factor for demand was incorporated in the table management model he developed. A simulation model of table arrangements based on factors such as party size revealed that given a small number of customers and meal orders, the model was able to efficiently reduce wait time of customers. However the simulation model was not able to contribute to any significant reduction in wait times at the restaurant when there were higher demands and large groups of customers. This suggests the system reaches a point of saturation where there is no room to process incoming customers faster. This research paper therefore aims at predicting the number of customers visiting the food service establishment at any given time during the day.

2.3.1 Customer-centred technological applications.

Chang, Kung and Tan (2008), in their research focused on the importance of technologies developed to be more customer centred. They mentioned that traditional restaurants only provide passive service where waiter can only deal with customer's order by asking customer's need and then waits for answer. However, they stated that a high quality service system should be customer-centred, i.e. customer's identity and therefore his/her favourite meals and expenditure records in past days can be immediately recognized by service system so as to provide customer-centric services (Chang et. al., 2008).

As mentioned earlier, there is a need for food service operators to employ techniques that facilitate and enhance customer satisfaction. Introducing a fast and error free system to restaurant operations upgrades the overall service quality, thereby increasing customer satisfaction. Throughout this review, it was realised that various applications of technologies have improved service quality. Most of these technologies, however, are not customer-centred, meaning, the customer's identity is not readily available to the systems. In the paper by Chang et al., (2008), they believe that high-quality service systems should be customer-centred.

Customer-centeredness is therefore, achieved by integrating radio frequency identification (RFID) and wireless local area network (WLAN) technologies to implement an e-restaurant for customer-centric service, which enables waiters to immediately identify each customer via his/her own RFID-based membership card and thereafter provide customized services. RFID has been used for years in animal identification and tracking, being a common practice in many farms. Also, it has been used in the food chain for traceability control. The implementation of sensors in tags, make possible to monitor the cold chain of perishable food products and the development of new applications in fields like environmental monitoring, irrigation, specialty crops and farm machinery (Ruiz-Garcia, & Lunadei, 2011). Introducing a system that takes advantage of the RFID technology provides an opportunity for food service establishments to reduce wait time of customers thus enhancing the customer satisfaction. Similar to the literature by Noone et al., (2012), both papers tend to address the benefits of applying a more customer centred technology in restaurants to heighten customer satisfaction.

2.4 Technologies Improving Service Quality

According to the Oxford advanced learners dictionary (2015), technology is "Scientific knowledge used in practical ways in industries or machinery" (Oxford Dictionaries, 2015). As established in a paper by Brynjolfsson and Yang (1996), technology immensely improves productivity in businesses. According to this research paper, most academic studies report positive effects of information technology on the various measures of economic performance. Information technology over the years has been applied in various sectors such as health, education, transportation, amongst others. The major benefit of applying technology is the efficiency it provides in operations. On the other hand, procurement of technology in the food service industry comes at a cost, most importantly the cost of training and maintenance.

Restaurateurs as part of their intentions to boost their restaurant businesses adopt many techniques and marketing practices. Among these is the use of technologies that seek to increase customer turnovers at restaurants and also improve service and operations. The use of technology in restaurants has become popular over the years due to the competitive advantage and efficiency it provides (Pantelidis, 2009). Technology has not only been applied to food preparation, but also to the other functions in the restaurant value chain. Examples of these technologies are the computerised point of sale system which is relatively common in fast food establishments and fine dining restaurants, pagers for table management, commonly used in fast food diners, online payments on websites, amongst others.

According to Dixon, Kimes and Verma (2009), “Technological innovations have been shown to increase market share and improve customer satisfaction and retention” (Dixon et al., 2009). The authors mentioned that, benefits restaurants receive from adopting technology included speed of service, reduced processing cost, an increase in revenue and improved service. On the other hand, technologies used may make it difficult to recover from errors or may reduce the customer’s personal interaction with the waiters or staff of the restaurant. In as much as these technological tools are utilised to enhance the restaurant business and operations, it is worthwhile to ensure that they do not tamper or obstruct the satisfaction of the customer. Restaurateurs need to assess the reaction of customers to the technology and compare the benefits to the cost of the system.

Dixon et al., (2009) in their paper chose technologies which the best-worst experimental modelling was tested on. The technologies are listed as pagers, online reservations, internet-based ordering, virtual menus, kiosk-based ordering and payment and payment via smart card and cell phone using near field communication (NFC) technology. The technologies were put under the categories queue management, internet-based, menu, kiosk and payment. The results from the experiments conducted showed that most customers were comfortable with using pagers and online reservation technologies. The authors however failed to provide reasons why the respondents in the research preferred using pagers and online reservations more than virtual menus and kiosk-based ordering and payment or the other technologies mentioned.

2.5 Predictive Analytics in Foodservice facilities

The use of predictive analytics and forecast models in foodservice establishments can improve service quality. In the paper by Zhang, Nguyen and Zhang (2013), the authors explored ways through which predictive models could be used to forecast peak demands and wait times. In the paper, they evaluated approaches for predicting the expected wait time for obtaining driver license and vehicle registration given a historical data collected from the California Department of Moto Vehicle (Zhang et al., 2013). They grouped the data set into two parts with equal sizes; the training data and the test data. The time based model, which was developed by averaging wait times for distinct periods in a day generated a prediction error of 0.5235 hours. In using the linear regression model, they used the formula $W_t = a_{t-1}*W_{t-1} + a_{t-2}* W_{t-2} + \ldots. + a_1*W_1$, where W_t is the wait time at time t that they want to predict, and W_{t-1}; $W_{t-2}..W_1$ are all the previous wait time. a_{t-1}; $a_{t-2}\ldots a_1$ are the coefficients learned from the wait time history. The average prediction error achieved with this approach was 0.1582 hour. From their results, they observed that the simple linear regression model seemed to have the least prediction error. Thus, by considering only a small number of the past wait times, linear regression produced more accurate predictions.

A review of paper by Kisang and Sanchez (2002) focuses on evaluating forecasting methods at an institutional foodservice dining facility. The objective of the paper was to identify the most appropriate forecasting method for the Texas Tech University. The writer compared different forecasting models with two data sets to forecast meal counts for a semester. The models used in the study were the naïve model, moving average, exponential smoothing, double exponential smoothing, Holt’s model, winters’ model, linear and multiple regressions. The appropriate model was determined based on accuracy and ease of use, where some of the accuracy methods used were the mean squared deviation and mean squared error. The results were based on the criterion that the lower the forecast error, the higher the accuracy of the forecast model. Multiple regression model outperformed all other forecasting methods in terms of accuracy due to the seasonality pattern. A limitation however was the type of data set used for analysis. In situations where the data is not seasonal, the multiple regression method may not be the most accurate method for prediction. In agreement with this study, a multiple regression method will be used to predict the wait time of customers at the Akornor cafeteria. This method was selected because of the negative correlation between the number of students in class and the number of students at the cafeteria. This study will further apply one of the predictive modelling methods; multiple regression discussed by Kisang and Sanchez (2002), to predict the number of customers that will be visiting a college cafeteria for each period in a day. Further studies will be conducted afterwards to assess the influence of the predictions in reducing wait time at the cafeteria.

Chapter 3: Methodology

3.1 Approach

This chapter describes the implementation process used to formulate the model and assess its impact on reducing wait time at the Akornor cafeteria. The chapter will outline the various implementation procedures as well as the processes for data collection, analyses and presentation to achieve a valid conclusion. A quantitative approach was used to analyse the data in order to understand how the information from the predictive model will affect wait time at the Akornor cafeteria and improve service quality. Ashesi University College, the context of this study, is made up of a total population of about 680 students. The school has two main cafeterias; Akornor cafeteria and BigBen cafeteria. The Akornor Cafeteria, was used as a case study for the research. The establishment was selected because it is patronised by a majority of the school population.

3.2 Hypothesis

This study seeks to assess the usefulness a predictive model will have on the quality of service provided at the Akornor cafeteria, with a focus on improving or reducing waiting times of customers at the cafeteria. The main objectives will be to

(a) Accurately predict customer frequency in a given day at the cafeteria

(b) Measure the significance of the predictive model on reducing wait time of customers at the cafeteria

Therefore, the hypotheses for this paper is:

There is an impact of customer frequency prediction in reducing wait time at the Akornor cafeteria, thus predictive analytics can be used to improve service quality in cafeterias.

3.3 Research Design

This research makes use of a quantitative research approach to investigate the research topic; the impact of predictive analytics on reducing wait time at the Akornor cafeteria. Predictive modelling, an aspect of data mining was used in the analysis of data collected. A mathematical model using regression analysis was formulated because it is a fast and simple method of forecasting the number of customers that will be visiting the cafeteria at any given time during the day. This research method suits the study because it is generally useful when a researcher seeks to study patterns of behaviour on small-scales. The study was conducted mainly in two phases. An initial correlational study was conducted to determine the variables that cause long wait times at the cafeteria. After these variables were examined, an experimental study was conducted to assess the impact of the predictive model on reducing waiting time at the cafeteria. Thereafter, conclusions were drawn on how well the research questions were answered.

3.3.1 Procedure for implementation.

The methodology was conducted in three main phases. The first phase was concerned with collection of data for the model. A web application was designed to collect the time it took for people to order food and get served at the cafeteria. The data was collected over a span of two weeks. The second phase is the model learning. This process involves the cleaning and grouping of data into inputs for the mathematical formula to be learned. The variables were inserted into the mathematical formula to build the predictive model. The last phase was the assessment of the influence of the information provided by the predictive model at the cafeteria in relation to reducing wait time.

3.3.2 Sources of Data

Data that was needed for learning the predictive model was collected from the college registry, the Akornor cafeteria database and a custom developed web application. This data includes

1. The academic timetable for the 2015/2016 fall semester
2. The sales records at Akornor cafeteria showing the date and time of sales in a day
3. The wait time of customers at the cafeteria during a day

Observational data collected from the Akornor cafeteria during the one week period includes

1. Peak times during the day
2. How long a customer waits in a queue to be served after placing an order
3. What is happening at the counter when customers are waiting in the queue to be served

3.4 Design and Implementation

3.4.1 Software created.

A web application designed in PHP language was used to collect data on the wait time of customers at the cafeteria over a period of two working weeks. The application which was hosted on a Samsung galaxy tab, recorded the time the customer placed an order and the time his or her order was served in a phpMyAdmin database system. With these two inputs, the time it took for the meal to be served after ordering was calculated. The application had two different views: the first view was to allow the user to input his/her name or initials immediately after ordering food, and the second view was to allow the user to log out of the queue after picking up his/her food from counter.

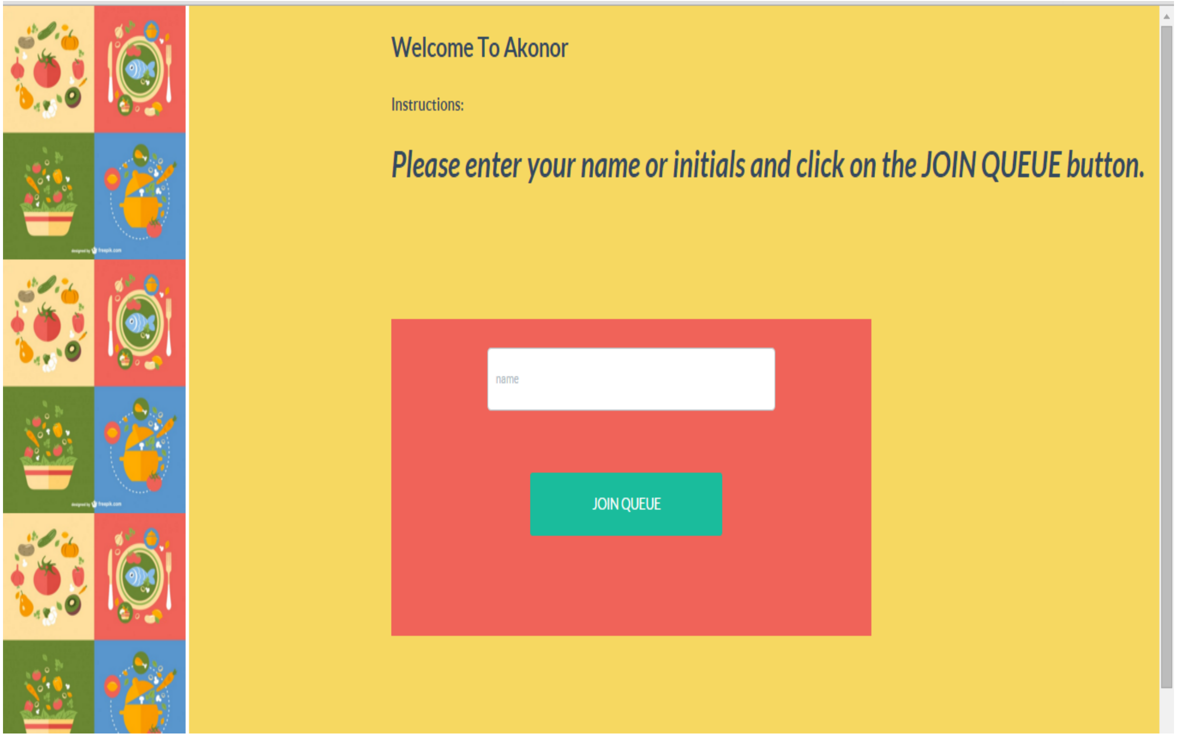


Figure 3.1: User interface to log timestamp of customers joining queue

Figure 3.1 above shows the interface for user to input name or initials. The user entering the name or initials clicks on the Join Queue button to add name into database. This web application recorded the customer’s id, name or initials and timestamp for logging in, in the database. The data collected from this application was the day and time the person placed an order to pick up food from the serving counter.

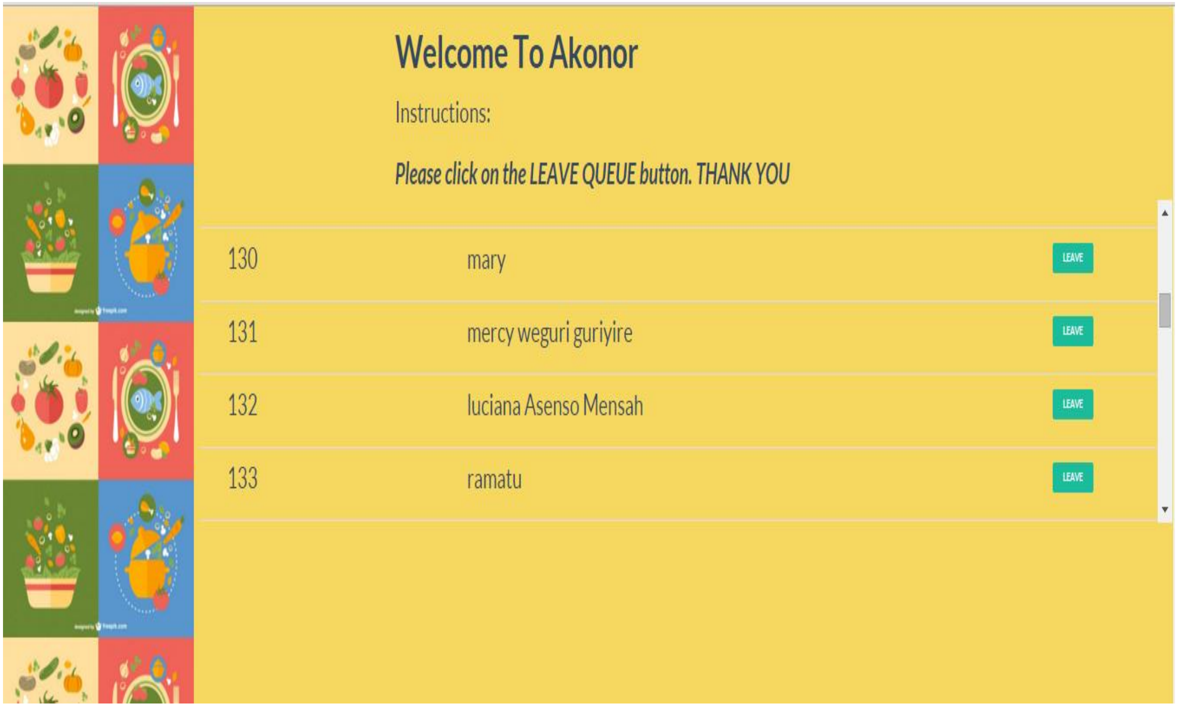
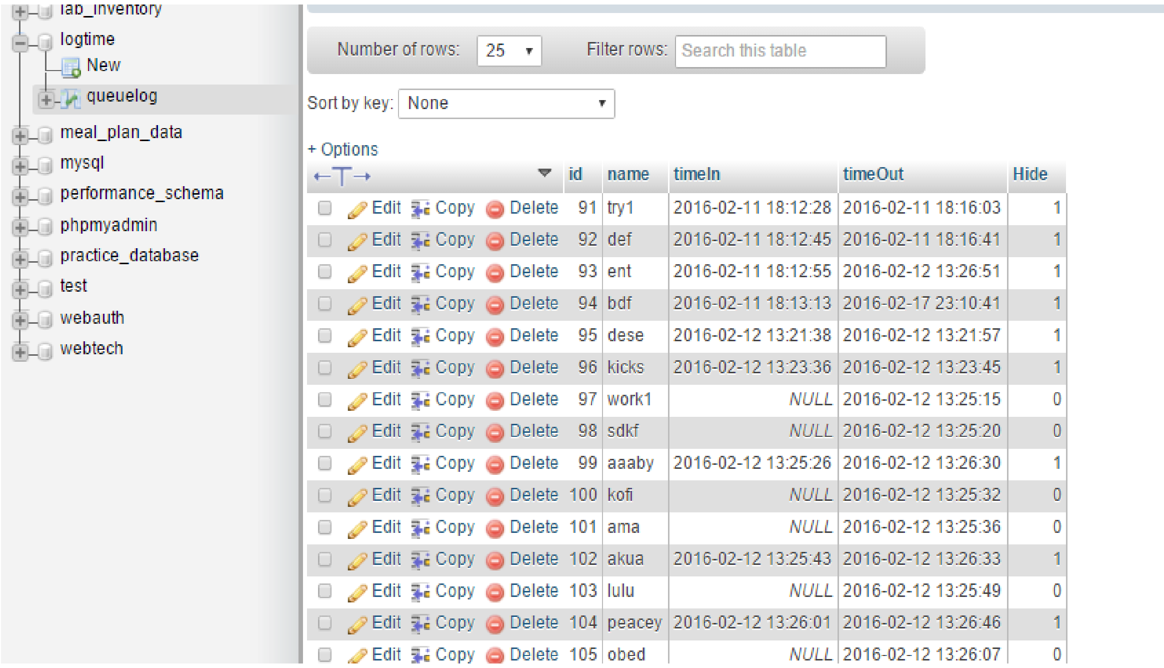


Figure 3.2: User interface to log timestamp of customers leaving queue

Figure 3.2 above shows the interface for the user to log out of the queue. The user must scroll up or down for his/ her name and click on the "Leave button" by the name. Immediately the Leave button was clicked, the timestamp of the user was updated in the database. The id, day and time the customer received food after placing order was also recorded in the database.



				id	name	timeIn	timeOut	Hide
	Edit	Copy	Delete	91	try1	2016-02-11 18:12:28	2016-02-11 18:16:03	1
	Edit	Copy	Delete	92	def	2016-02-11 18:12:45	2016-02-11 18:16:41	1
	Edit	Copy	Delete	93	ent	2016-02-11 18:12:55	2016-02-12 13:26:51	1
	Edit	Copy	Delete	94	bdf	2016-02-11 18:13:13	2016-02-17 23:10:41	1
	Edit	Copy	Delete	95	dese	2016-02-12 13:21:38	2016-02-12 13:21:57	1
	Edit	Copy	Delete	96	kicks	2016-02-12 13:23:36	2016-02-12 13:23:45	1
	Edit	Copy	Delete	97	work1	NULL	2016-02-12 13:25:15	0
	Edit	Copy	Delete	98	sdkf	NULL	2016-02-12 13:25:20	0
	Edit	Copy	Delete	99	aaaby	2016-02-12 13:25:26	2016-02-12 13:26:30	1
	Edit	Copy	Delete	100	kofi	NULL	2016-02-12 13:25:32	0
	Edit	Copy	Delete	101	ama	NULL	2016-02-12 13:25:36	0
	Edit	Copy	Delete	102	akua	2016-02-12 13:25:43	2016-02-12 13:26:33	1
	Edit	Copy	Delete	103	lulu	NULL	2016-02-12 13:25:49	0
	Edit	Copy	Delete	104	peacey	2016-02-12 13:26:01	2016-02-12 13:26:46	1
	Edit	Copy	Delete	105	obed	NULL	2016-02-12 13:26:07	0

Figure 3.3: Customer logs displayed in the database

Figure 3.3 above shows the records in the database. A timestamp for the inputted name was recorded in the database, as shown in Figure 3.3 immediately the user clicked the input button, to record the time the user joined the queue. This timestamp was recorded in the timeIn column. When the user clicked on the leave button, the timestamp was updated in the timeOut column to show the exact time the user left the queue. From the timestamp records, the total time it took the user to pick food from counter after ordering for a meal was calculated to find wait time using the equation

timeOut – timeIn = wait time.

The wait time collected using the web application was compared to the wait time collected after the information of the predicted number and wait time at the cafeteria during the day was made public to the school. This allowed an assessment of the impact of the predicted data in reducing wait time at the cafeteria.

3.5 Regression Models

Due to the cyclical nature of the data collected, the mathematical formula was designed using a polynomial equation, to forecast the number of people who will be at the cafeteria at a given time during the day. A curvilinear regression was used to determine the curve of best fit and the intercept of the data. Every value of the independent variable x was associated with a value of the dependent variable y. For each day of the week beginning from Monday to Friday, the number of people who visited the cafeteria was recorded for each period of the day. The daily periods grouped at an interval of 30 mins started at 7:00 am till 5: 00pm. Daily sales records collected from the cafeteria was for a span of three weeks; the first two weeks as the training data set and the third week as the testing data set. This testing data set was used in calculating the root mean square error of the predicted values.

3.5.1 Model 1

To increase the accuracy of predicted number of customers and wait time at the cafeteria, four mathematical models were formulated. The first model had one dependent variable as the number of people at the cafeteria for a given period in the day represented in the formula as (N_a), and one independent variable as the period of day represented in the formula as (t). This model was generated for each day of the week from Monday to Friday. A sixth order polynomial line of the input t was generated because it showed the line of best fit for the independent variables. The polynomial equation generated as the line of best fit was in the form

$$\mathbf{N_a = at^6 + bt^5 - ct^4 + dt^3 - et^2 + ft + i}$$

Where $\mathbf{N_a}$ = predicted number of people at the cafeteria

a = coefficient of the sixth order of the period in the day

b = coefficient of the fifth order of the period in the day

c = coefficient of the fourth order of the period in the day

d = coefficient of the third order of the period in the day

e = coefficient of the second order of the period in the day

f = coefficient of the first order of the period in the day

i = intercept of line of best fit

t = period of day

3.5.2 Model 2

The second model took in the number of students in class at each period in a day, represented as N_c in the formula and the period of the day, represented as t, as the independent variables. The dependent variable was the predicted number of people at the cafeteria at a given period in the day, represented as N_c in the formula. This model was generated for any day of the week from Monday to Friday. The polynomial equation generated as the line of best fit was in the form

$$\mathbf{N_a = N_c + at^6 + bt^5 - ct^4 + dt^3 - et^2 + ft + i}$$

Where $\mathbf{N_a}$ = predicted number of people at the cafeteria

$\mathbf{N_c}$ = number of students in class at each period in the day

a = coefficient of the sixth order of the period in the day

b = coefficient of the fifth order of the period in the day

c = coefficient of the fourth order of the period in the day

d = coefficient of the third order of the period in the day

e = coefficient of the second order of the period in the day

f = coefficient of the first order of the period in the day

i = intercept of line of best fit

t = period of day

3.5.3 Model 3

The third model took in the period of day (t) as the independent variable and the number of people at the cafeteria (Na) as the dependent variable. This model was generated for each day of the week starting from Monday to Friday. A sine, cosine, first and second order polynomial for the independent variable was calculated to formulate an equation for the model. The equation formulated as the line of best fit was in the form

$$\mathbf{N_a = at + bt^2 - \sin(t) + \cos(t) + i}$$

Where $\mathbf{N_a}$ = predicted number of people at Akornor

a = coefficient of the first order of the period in the day

b = coefficient of the second order of the period in the day

sin = sine value of period of day

cos = cosine value of period of day

i = intercept of line of best fit

t = period of day

3.5.4 Model 4

The fourth model, similar to the second model took in the number of students in class N_c and the period of day (t) as the independent variables predicting the dependent variable which was the number of people at the cafeteria represented as N_a. This model was generated for any day of the week from Monday to Friday. The equation generated as the line of best fit was in the form

$$\mathbf{N_a = at + bt^2 - \sin(t) + \cos(t) + N_c + i}$$

Where $\mathbf{N_a}$ = predicted number of people at Akornor

$\mathbf{N_c}$ = number of students in class at each period in the day

a = coefficient of the first order of the period in the day

b = coefficient of the second order of the period in the day

sin = sine value of period of day

cos = cosine value of period of day

i = intercept of line of best fit

t = period of day

3.6 Data Analysis Tool

The tool mainly used for analysing data collected was the Microsoft Excel software. This powerful software was selected due to its wide-ranging presentation of solutions as well as its efficiency in designing predictive models with small data using regression and its gentle learning curve. Functions such as VLOOKUP, LINEST, AVG, STDEV, t-TEST were used in data analysis to design the mathematical models. Analysis of data was simple and easy to plot using charts such as the scatter plot graphs and bar charts.

Chapter 4: Results

4.1 Purpose of Chapter

This chapter explains the findings from the methodology used to answer the research questions of this study. The main purpose of this research was to accurately predict the number of people who will visit the Akornor cafeteria at each time period of the day, and to study the influence of the results in reducing wait time at the cafeteria. In the previous chapter, a mathematical model was successfully developed to predict the numbers at the cafeteria for the different periods. In this chapter, the findings are going to be analysed and measured to conclude on a rejection or an acceptance of the hypothesis for this study.

4.2 Observations from Results

The predicted number of people at the Akornor cafeteria from all four models will be discussed in the following chapters. The data is represented in graphs where the Y-axis is the predicted number N_a and the X-axis is the period of day represented as t. Periods on all graphs start from 07:00 to 17:00, grouped into thirty minutes intervals. On each graph, the predicted number is plotted against the testing data for each model.

4.2.1 Results of Model 1 and Model 2

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Monday using the first model. It is plotted against the actual data for testing the model. To calculate the variation of predicted data and actual data, a root mean square error of 2.43 was calculated.

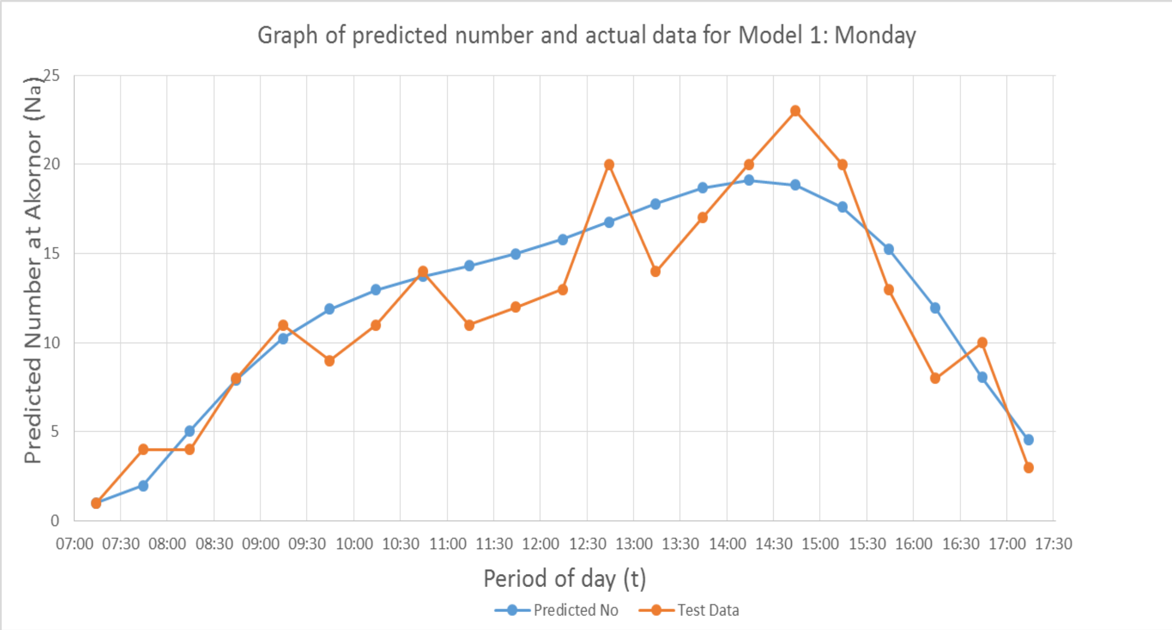


Figure 4.1: Graph of predicted and actual numbers at cafeteria at each period on Monday for Model 1

From the graph above, we see that there are a few people at the cafeteria during the early periods of the morning from 7:00 to 8:00. However, after 9:00 we can see a steady rise of numbers which peaks and stabilizes from 11:00 to 13:00. After 13:00 the numbers begin to drop slowly with an average number of 8 people during the period of 15:00 to 17:00. From the graph we realise that most people visit the cafeteria just before 12:00 and after 15:00. Comparing the actual data to the predicted data, we see a common peak period 12:45 and 14:45. Based on this prediction, the maximum and minimum number of people visiting the cafeteria at each thirty minute interval in the day is 19 and 1 respectively.

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Monday using Model 2.

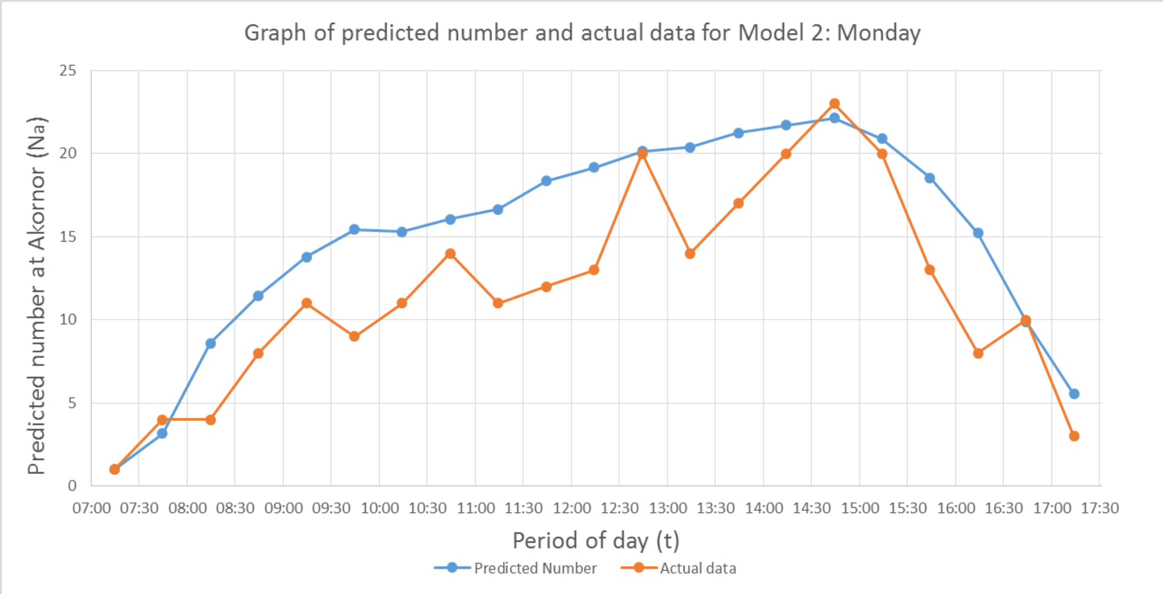


Figure 4.2: Graph of predicted and actual numbers at cafeteria at each period on Monday for Model 2

The second model has a higher peak number of 22 people at 14:45 and the lowest number as 1 person at 7:15. The root mean square error calculated for the predicted values and the actual data was 3.22, showing a higher error as compared to the first model which was 2.43. This difference can be associated to the second independent variable; number in class N_c.

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Tuesday.

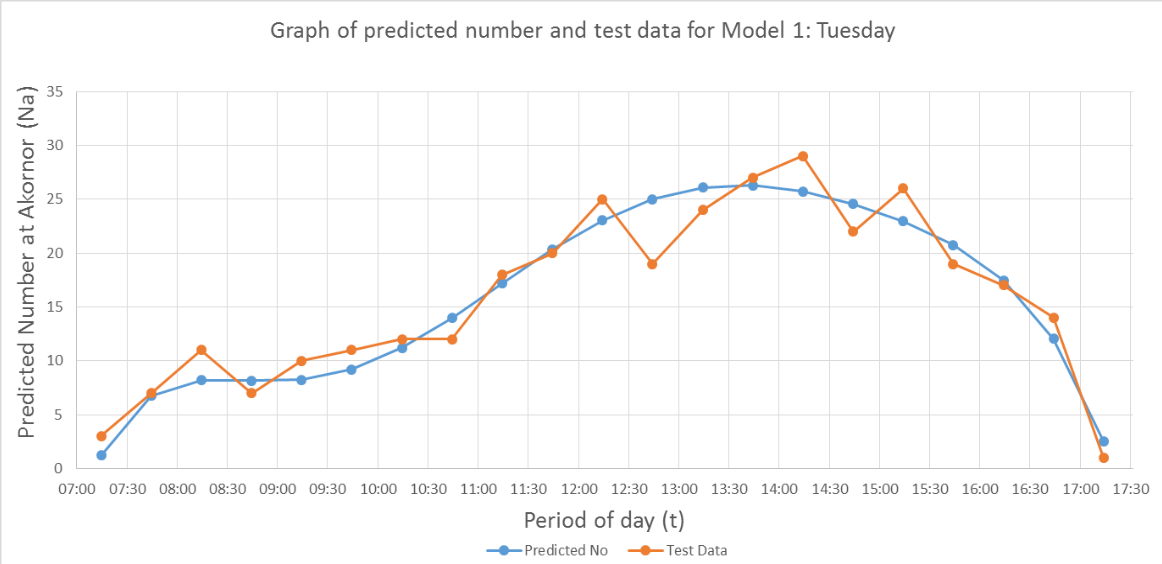


Figure 4.3: Graph of predicted and actual numbers at cafeteria at each period on Tuesday for Model 1

From the graph above, we see that there is a relatively higher number of people at the cafeteria during the early periods of the morning from 7:00 to 8:15 as compared to Monday. There is a slight decrease after 9:00 and a steady rise after 9:45. From the actual and predicted data, we see a peak period between 12:00 and 12:30 and also from 13:00 to 14:15. From the graph we realise that most people visit the cafeteria around 7:45 in the morning and also between 12:00 and 15:00 in the afternoon. The root mean square error calculated for the predicted and actual data was 2.24, accounting for the variation in values. Based on this prediction, the maximum and minimum number of people visiting the cafeteria at each thirty minute interval in the day is 27 and 1 respectively.

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Tuesday using Model 2.

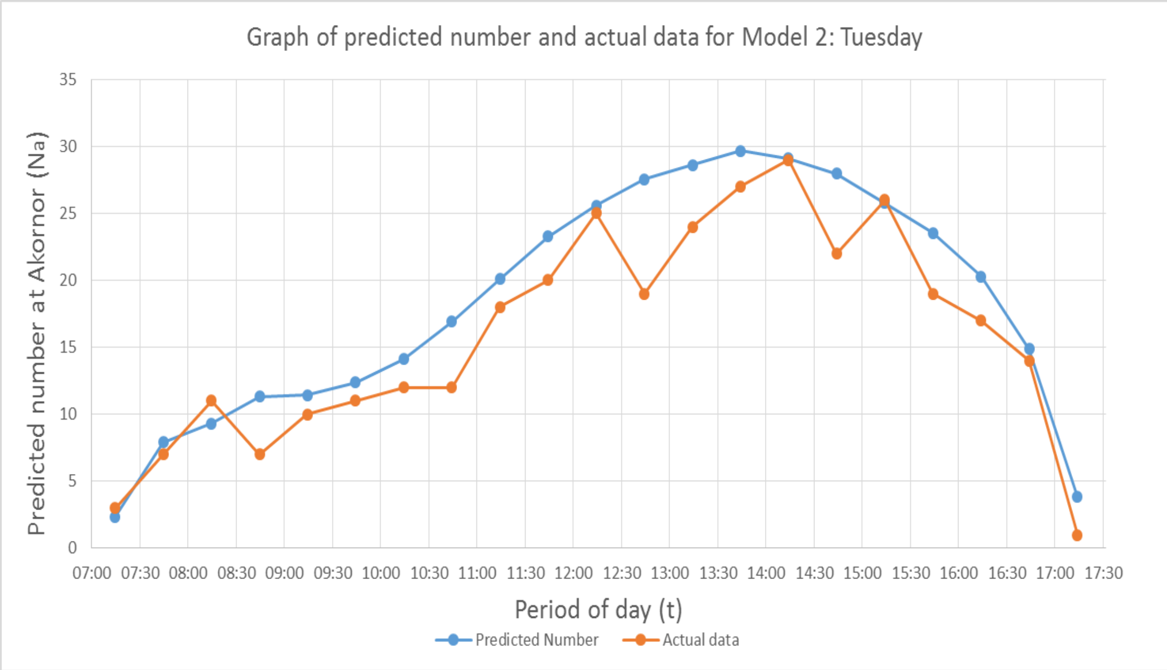


Figure 4.4: Graph of predicted and actual numbers at cafeteria at each period on Tuesday for Model 2

The second model has a higher peak number of 30 people at 13:45 and the lowest number as 2 people at 7:15. The root mean square error calculated for the predicted values and the actual data was also 2.65, as compared to the first model. This difference in peak numbers however can be associated to the second independent variable; number in class N_c.

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Wednesday.

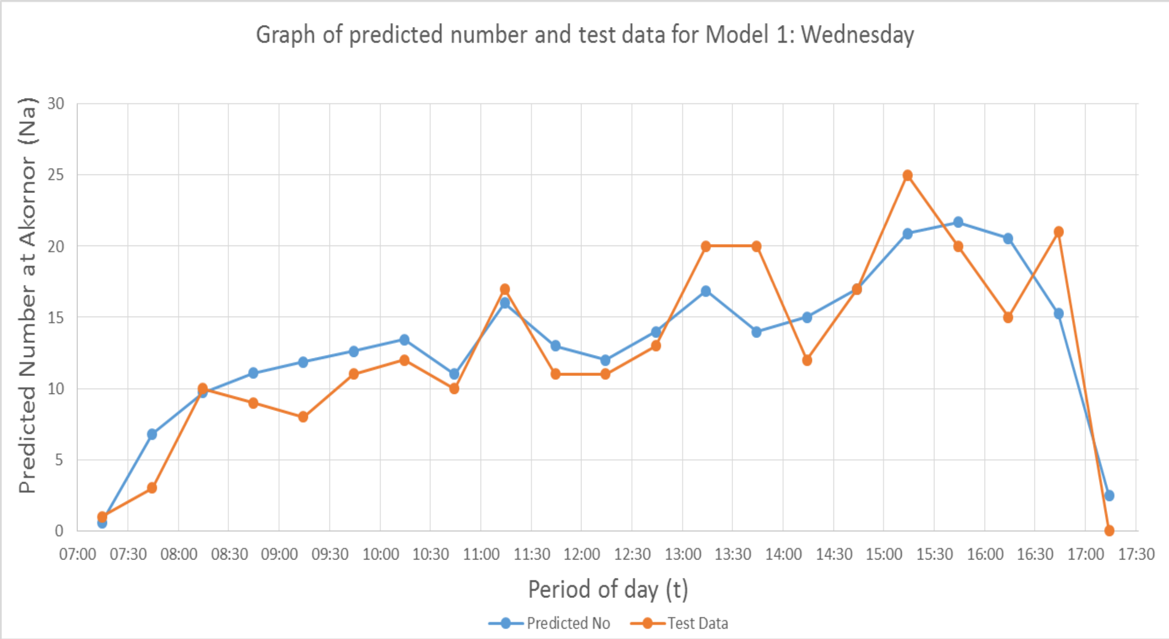


Figure 4.5: Graph of predicted and actual numbers at cafeteria at each period on Wednesday for Model 1

From the graph above, we see that there is a relatively lower number of people at the cafeteria during the day, as compared to Monday and Tuesday. We see a slight peak between 10:45 and 11:45 with a number of 17 people and another peak period between 12:45 and 14:00 with a number of 17 people. The highest peak however is between 15:15 and 16:15 with a number of 22 people. This is very different from the previous graphs that have the highest peak period between 13:00 and 15:00. The root mean square error calculated for the predicted and actual data was 3.02, accounting for the variation in values. Based on this prediction, the maximum and minimum number of people visiting the cafeteria at each thirty minute interval in the day is 22 and 1 respectively.

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Wednesday using Model 2.

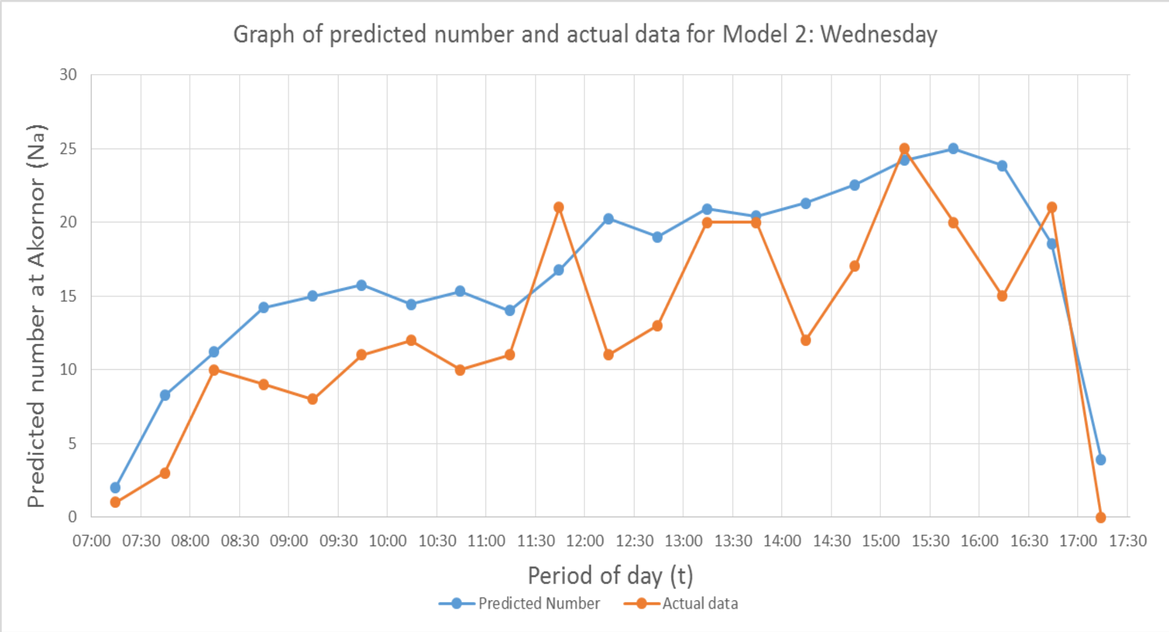


Figure 4.6: Graph of predicted and actual numbers at cafeteria at each period on Wednesday for Model 2

The second model has a higher peak number of 25 people at 15:45 and the lowest number as 2 people at 7:15. There are slight peak times between 8:15 and 10:15 as well as compared to the first model. The root mean square error calculated for the predicted values and the actual data was 4.51, accounting for the variation in predictions for both models. This difference in peak numbers however can be associated to the second independent variable; number in class N_c. The figure below shows a graph of the predicted number of people at the cafeteria at each period for Thursday.

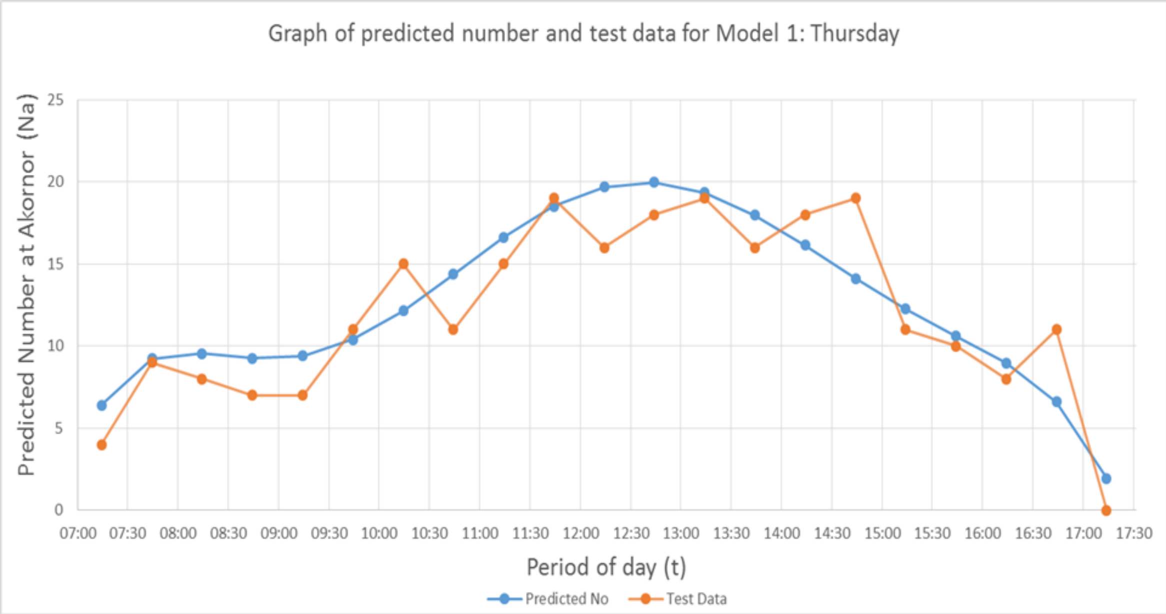


Figure 4.7: Graph of predicted and actual numbers at cafeteria at each period on Thursday; Model 1

From the graph above, we see that there is a relatively higher number of 6 people at the cafeteria 7:15, showing the highest number so far, compared to the previous days. There is a gentle rise from 10:45 which results in a peak of 20 people at 12:45. The numbers begin to reduce gently after 14:00 and peaks slightly at 16:00 with a number of 9 people. The lowest number of people at the cafeteria is predicted as 2 people at 17:15. The root mean square error calculated for the predicted and actual data was 2.36, which shows low error accounting for small variations in graphs.

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Thursday using Model 2.

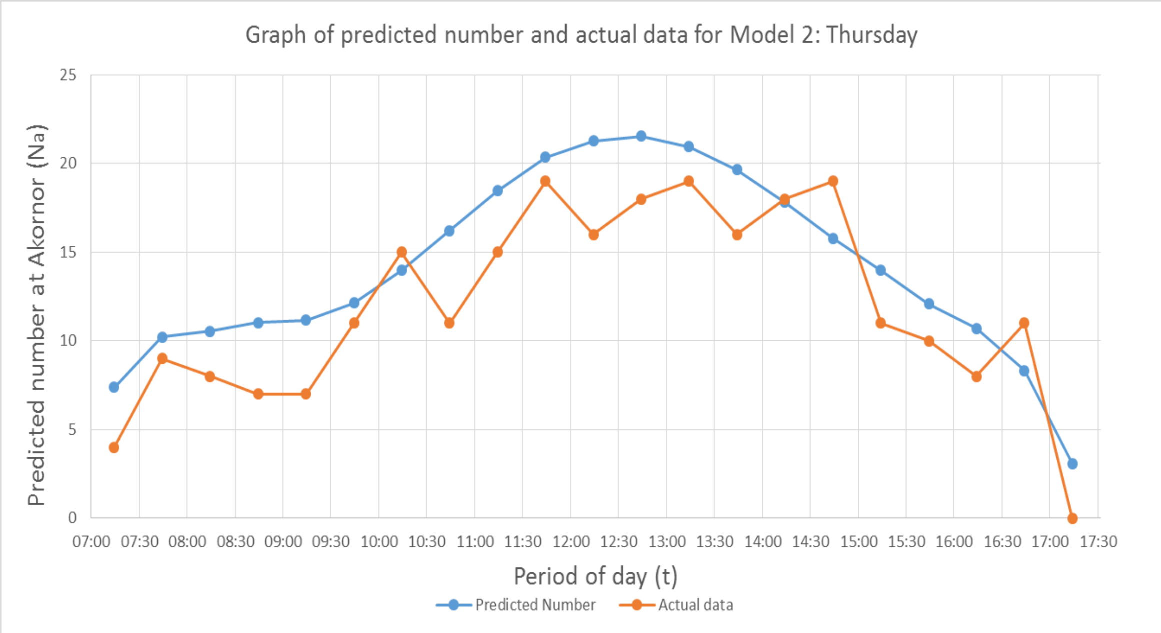


Figure 4.8: Graph of predicted and actual numbers at cafeteria at each period on Thursday for Model 2

The second model has a higher peak number of 22 people at 12:45 and the lowest number as 3 people at 17:15. There are slight peak times between 7:30 and 9:15 as well, as compared to the first model. The root mean square error calculated for the predicted values and the actual data was 3.10, accounting for the variation in predictions for both models. This difference in peak numbers however can be associated to the second independent variable; number in class N_c.

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Friday. From the graph, we see that there is no predicted value for 7:15, which shows the lowest number, compared to the previous days. There is a gentle rise from 10:45 which results in a peak of 24 people at 12:45. The numbers begin to decrease gently to a slight peak of 15 people at 16:15. The root mean square error calculated for the predicted and actual data was 2.80, which accounts for variations in graphs for predicted and actual data.

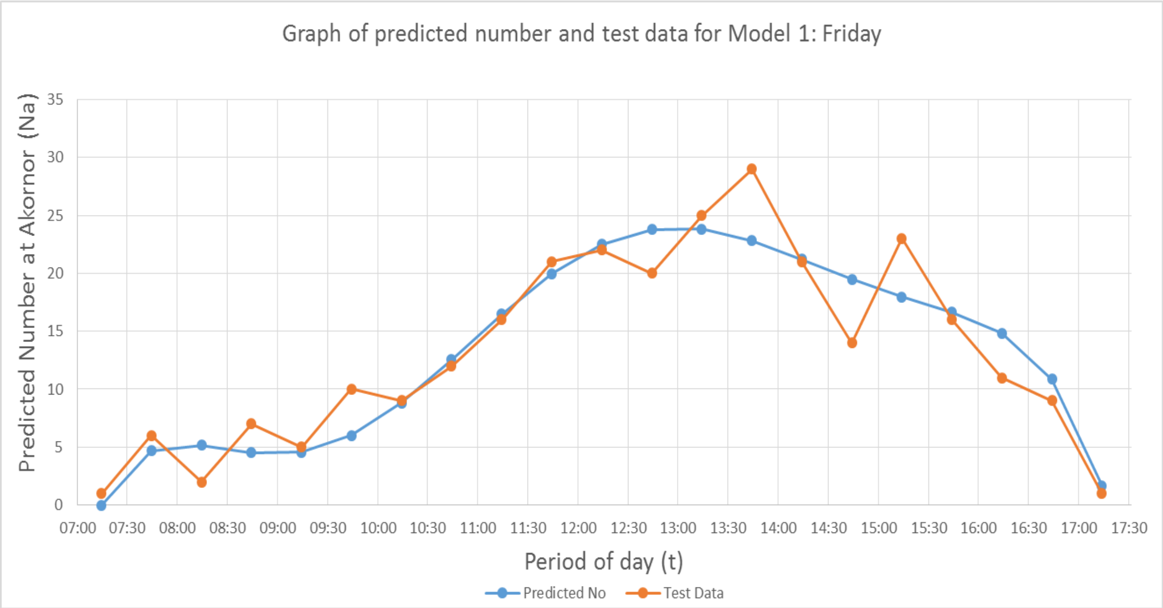


Figure 4.9: Graph of predicted and actual numbers at cafeteria at each period on Friday for Model 1

The figure below shows a graph of the predicted number of people at the cafeteria at each period for Friday using Model 2.

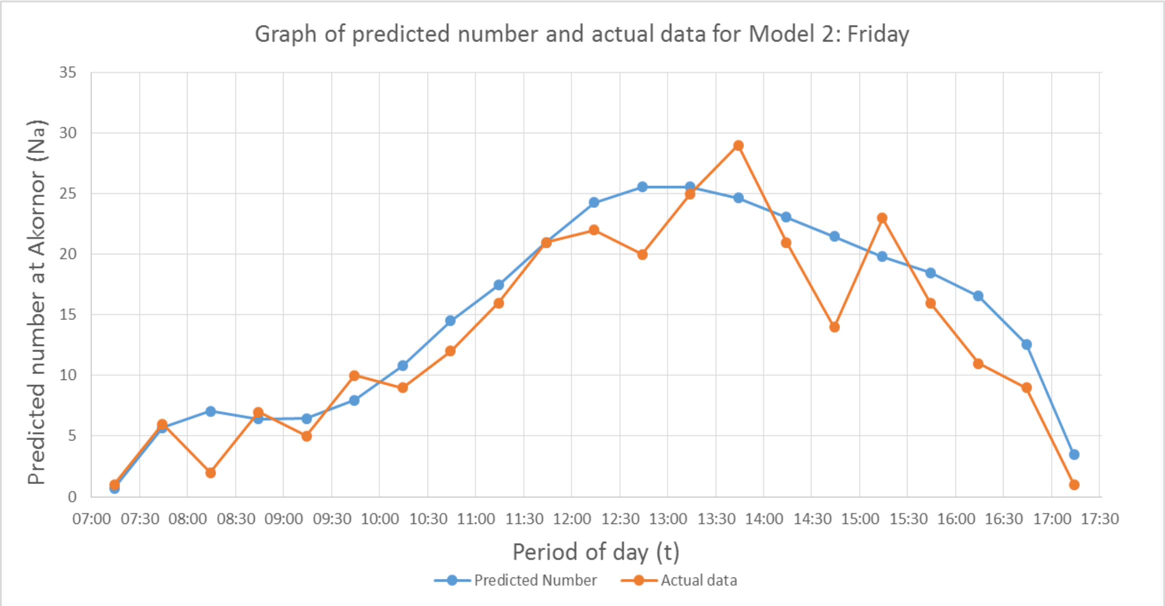


Figure 4.10: Graph of predicted and actual numbers at cafeteria at each period for Friday Model 2

The second model has a higher peak number of 25 people at 12:45 and the lowest number as 1person at 17:15. There are slight peak times between 7:30 and 9:15 as well, as compared to the first model. A second peak time is recorded between 15:00 and 16:15 with a number of 18 people. The root mean square error calculated for the predicted values and the actual data was 3.27, accounting for the variation in predictions for both models. This difference in peak numbers however can be associated to the second independent variable; number in class N_c.

The third and fourth models showed a cyclical nature as compared to the actual predicted data for model 1 and 2. This was as a result of the sine and cosine values of the independent variable t. A sample graph for Monday is shown in the figure below. The root mean square error for Model 3 and Model 4 for Monday however were 3.87 and 3.22 respectively, which shows a higher error as compared to the first and second model.

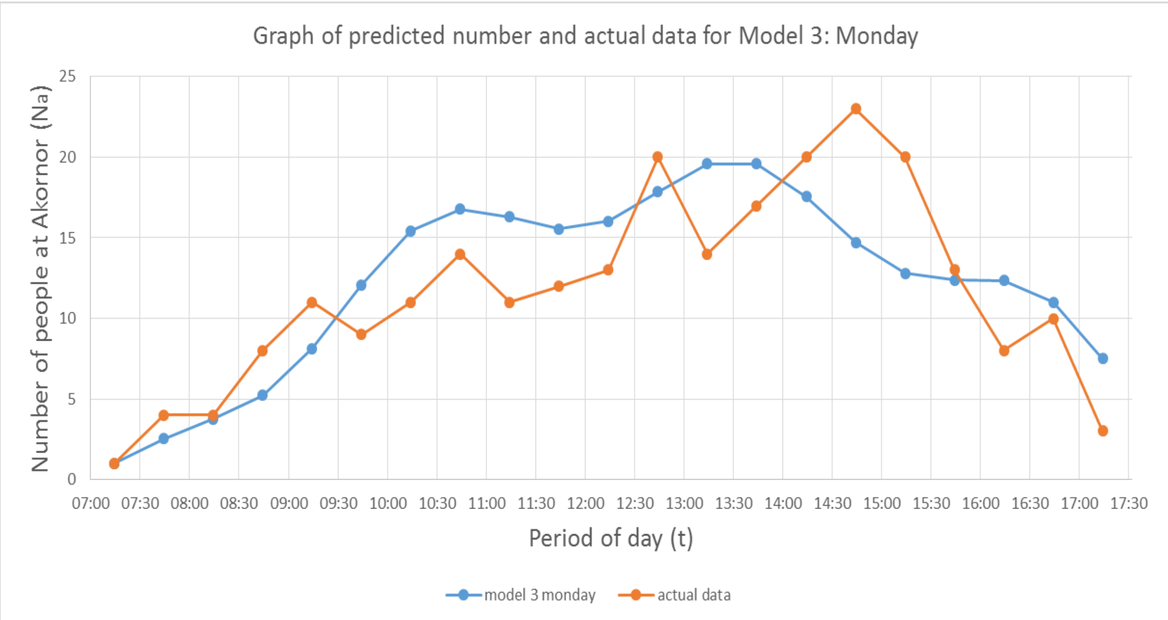


Figure 4.11: Graph of predicted and actual numbers at cafeteria at each period on Monday for Model 3

The graph below shows the predicted and actual number of people at the cafeteria at each period on Monday for Model 4.

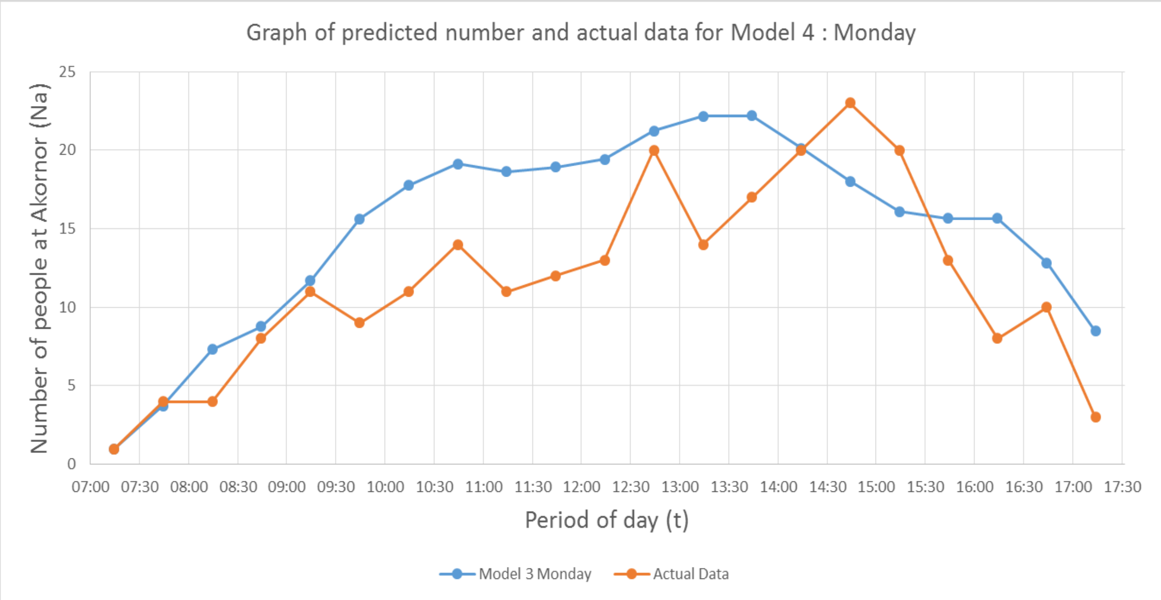


Figure 4.12: Graph of predicted and actual numbers at cafeteria at each period on Monday for Model 4

4.2.2 Results of wait time and number in class

The wait times for each day in each period of day was calculated. Figure 4.13 below shows a graph of the wait time for each day in the week with the amount of wait time converted into numbers on the Y-axis and the periods in a day for the week on the X-axis. From the graph, we see a high increase in wait time between the periods 12:15 and 13:45 and a lower wait time between the periods 7:15 and 7:45 for all graphs. Monday and Tuesday have the highest wait time of 26 and 27 respectively. This suggests more people at the cafeteria at that period in the day. Wednesday records the least average wait time compared to the other days, having its highest wait time at 12 between 12:30 and 13:15. Thursday has a slightly higher wait time of 16 between 12:45 and 13:15 whiles Friday records an average peak wait time of 17 between 13:00 and 14:00, and a high peak of 25 between 15:00 and 15:30. The increase in wait time between the periods 12:00 and 15:00 is in agreement with the graph of predicted numbers at the cafeteria. It suggests that an increase in number of people at the cafeteria between periods causes an increase in wait time for the same periods and vice versa.

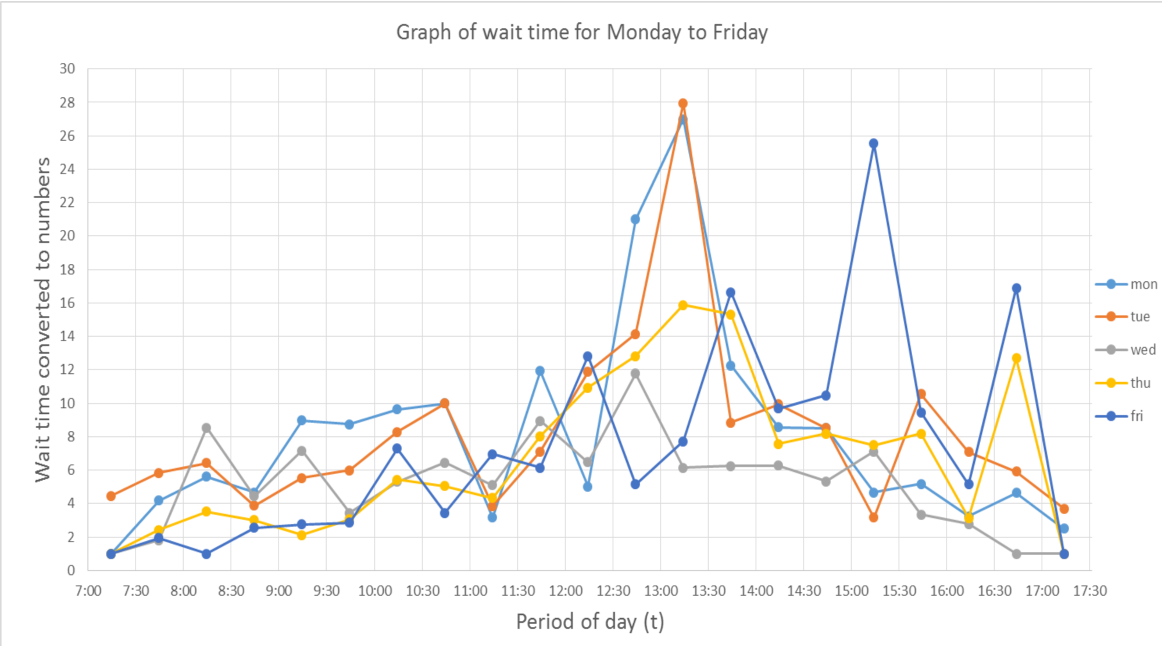


Figure 4.13: Graph showing wait times for each day in a week

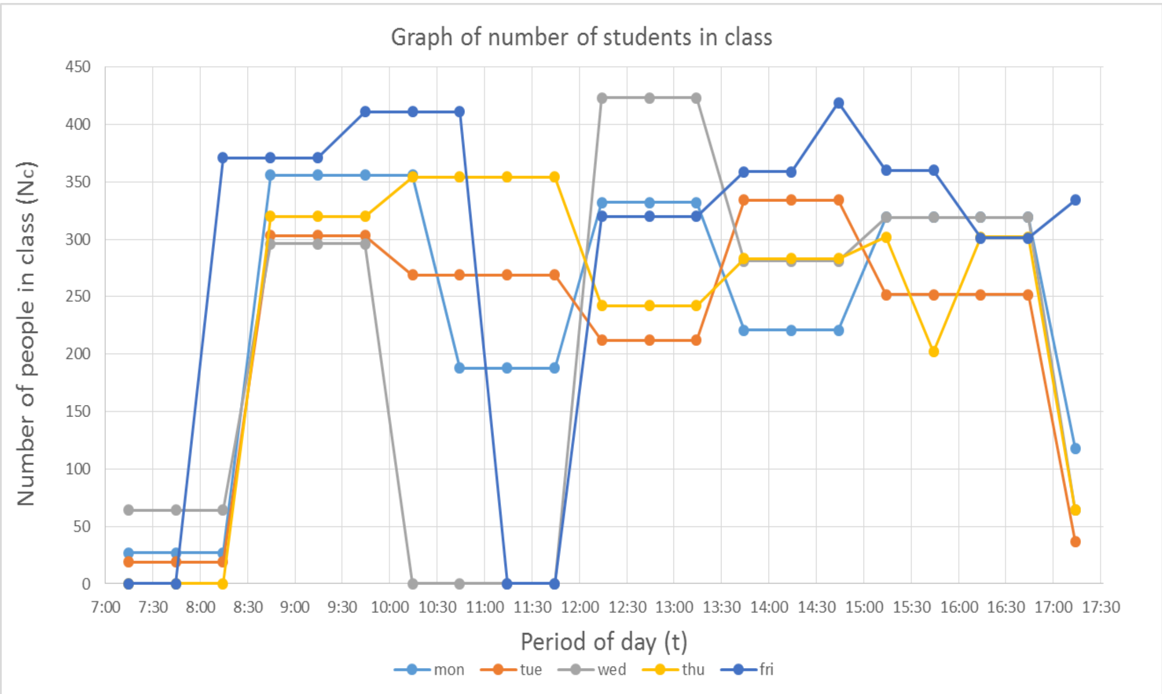


Figure 4.14: Graph of students in class from Monday to Friday

Comparing the graph of the number of students in class, Figure 4.14 and the number of students at the cafeteria for each day, we see a negative correlation between the two variables. Tuesday as represented on the graph shows the highest number of students at the cafeteria and the lowest number of students in class for the peak period between 12:00 and 14:00. Wednesday displays the lowest number of students at the cafeteria and the highest number of students in class between the hours of 12:00 and 13:30. Majority of students are in class between 8:00 and 10:00 and this accounts for the lower number of people and wait time for that period at the cafeteria. Similarly, for all the days but Wednesday, there is a relatively lower number of people in class, suggesting an increase in the number of people visiting the cafeteria during those periods. The correlation of the number of students in class and the number of people at the cafeteria, influenced the formulation of the second and fourth model already mentioned in the previous chapter.

4.2.3 Influence of prediction

The second model was used to test the impact of the knowledge of daily predictions in reducing wait time at the Akornor cafeteria. The predicted number of people visiting the cafeteria and the wait time for each period in the day was made public to the school population through daily emails. This was meant to influence the daily meal time of people in the college. In a survey conducted, out of 134 responses, 73 people stated that the information on peak times did not affect their meal time at the cafeteria, on the other hand, 61 people changed their meal time at the cafeteria due to the information on the peak period for the day at the cafeteria. The graphs below show the number of people visiting the cafeteria before and after publicizing the predictions for each period of the day from Monday to Friday.

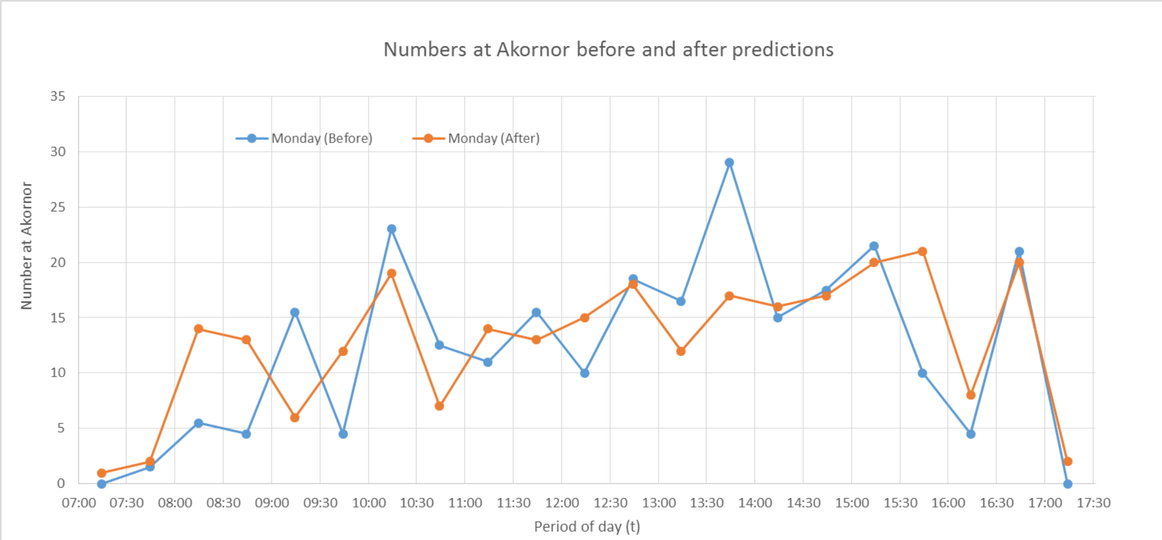


Figure 4.15: Graph of numbers at Akornor before and after publicising predictions; Monday

For Monday, the peak number of people before was recorded as 29 between 13:30 and 14:00 whereas after, the number was recorded as 17 for the same period. The peak number of people at the cafeteria on Monday after publicising the predictions was 21 recorded between 15:30 and 16:00. There was a significant change in peak period from between 13:00 to 14:00 to 15:30 to 16:00 and it suggests that more people visited the cafeteria between the period 15:30 and 16:00.

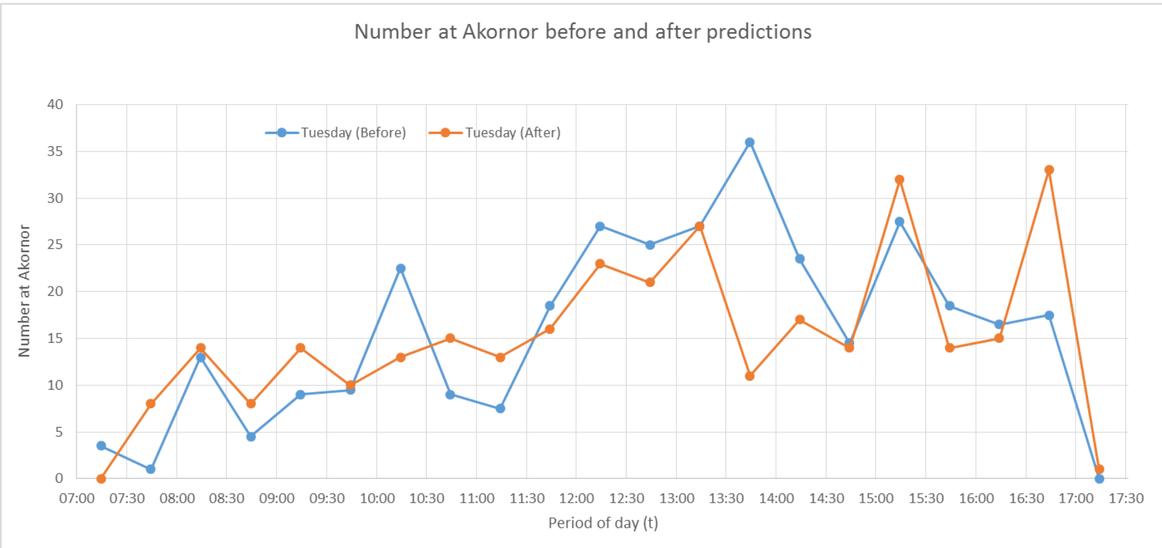


Figure 4.16: Graph of numbers at Akornor before and after publicising predictions; Tuesday

On Tuesday, the peak number of people before was recorded as 36 between 13:30 and 14:00 whereas after, the number was recorded as 11 for the same time. The peak number of people at the cafeteria on Tuesday after publicising the predictions was 33 recorded between 16:30 and 17:00. There was a significant change in peak period from between 13:30 to 14:00 to 16:30 to 17:00 and it suggests that more people visited the cafeteria between 16:30 and 17:00.

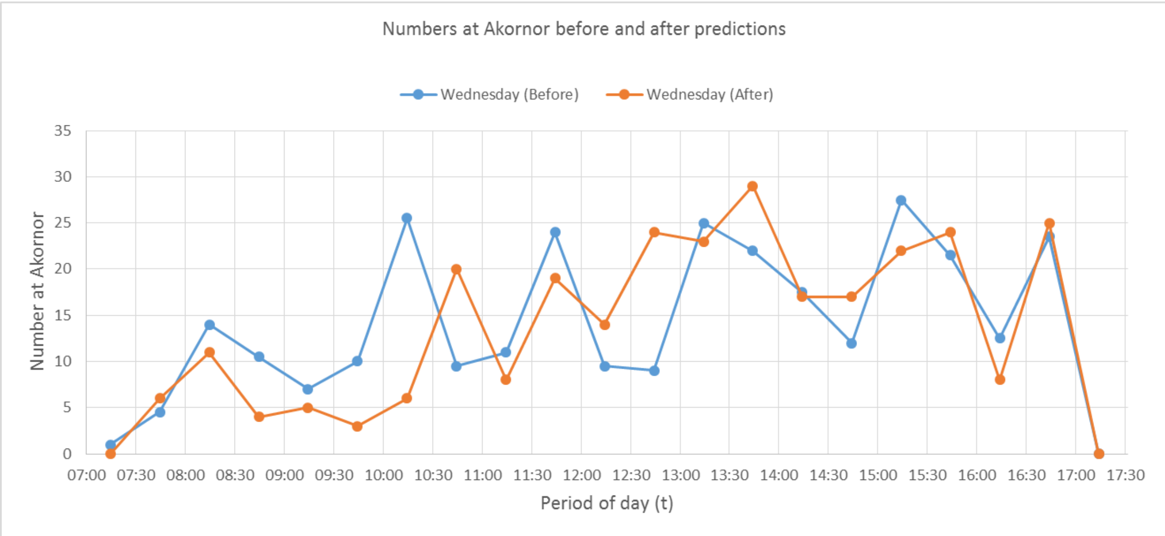


Figure 4.17: Graph of numbers at Akornor before and after publicising predictions; Wednesday

For Wednesday, the peak number of people before was recorded as 28 between 15:00 and 15:30 whereas after, the number was recorded as 22 for the same time. The peak number of people at the cafeteria on Wednesday after publicising the predictions was 29 recorded between 13:30 and 14:00. This suggest a significant change in the peak period from between 15:00 to 15:30 to 13:30 to 14:00.

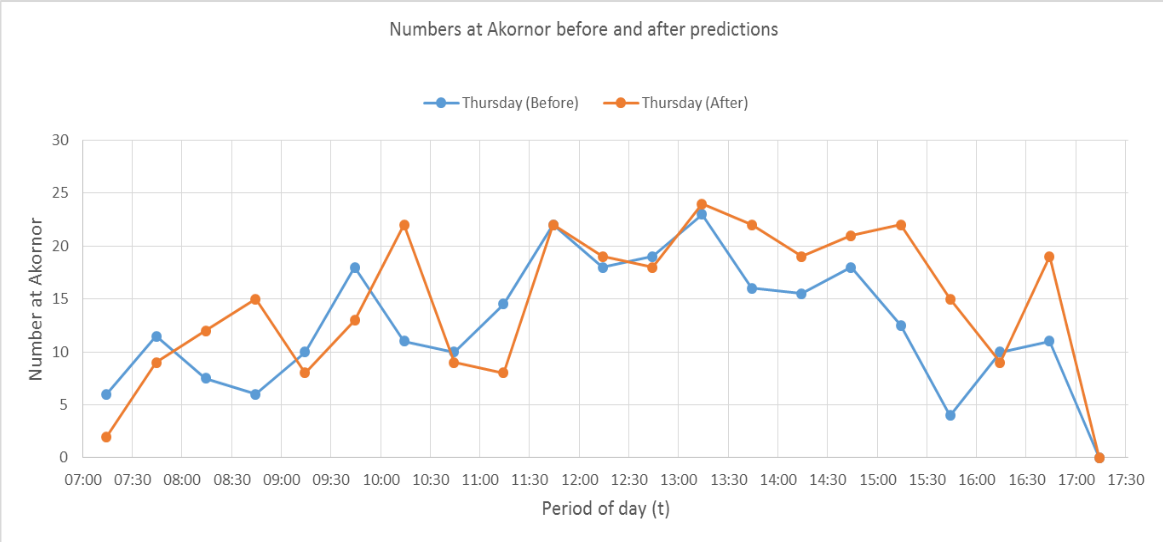


Figure 4.18: Graph of numbers at Akornor before and after publicising predictions; Thursday

On Thursday, the peak number of people before was recorded as 23 between 13:00 and 13:30, similarly the number was recorded after as 24 between same periods. The peak number of people at the cafeteria on Thursday after publicising the predictions was 24 recorded between 13:00 and 13:30. This shows an insignificant change in peak period in the day.

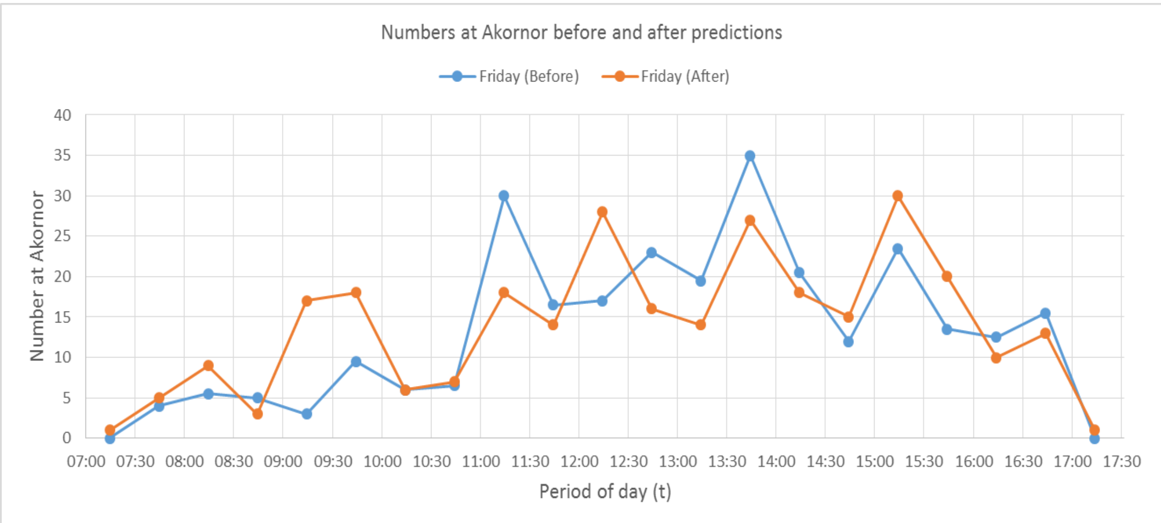


Figure 4.19: Graph of numbers at Akornor before and after publicising predictions; Friday

Lastly, on Friday, the peak number of people before was recorded as 35 between 13:30 and 14:00 whereas after, the number was recorded as 27 for the same time. The peak number of people at the cafeteria on Friday after publicising the predictions was 30 recorded between 15:00 and 15:30. This suggests a significant change in peak period from between 13:30 to 14:00 to 15:00 to 15:30.

4.3 Evaluation of Results

The findings from the generated models show a general peak period between the early hours of 8:00 and 9:00 with a maximum number of 7 people visiting the cafeteria within each thirty minutes interval for that time period. The second peak period which records the highest peak in a day begins from the period 13:00 to 14:30 with a maximum number of 29 people visiting the cafeteria between each thirty minute interval for that period. This information provides the management of the cafeteria forehand knowledge that allows them to ensure quality and fast service during those peak periods to reduce wait time.

A two tail t-Test, assuming unequal variances was conducted to measure the significance in the difference in numbers of people visiting the cafeteria before and after information on the predicted values were made public to the college population. The null hypothesis was H_0: number before – number after = 0; meaning there is no difference between the peak numbers before and after the predictions were made public. Taking the peak values for each day of the week for the before category and its corresponding after value, the t-stat value calculated was 2.7 whereas the t-critical 2 tail value was 2.3. Since t-stat was greater than the t-critical value (2.7 > 2.3), we rejected the hypothesis stating that there is no significant difference between the peak periods before and after the predictions were made public.

From the graph already shown, we see a positive correlation between the number of people at the cafeteria and the wait time for each period of the day. This suggests that, a decrease in the number of people at the cafeteria for each period will cause a decrease in the wait time. The results from the t-Test shows a significant change in the peak periods for all the days in the week hence we can conclude on an acceptance of the hypothesis for this study that, information on customer frequency at the Akornor cafeteria can influence wait time at the cafeteria.

4.4 Summary

In summary, it was proved from the mathematical model designed that the peak periods at the cafeteria were between the periods 12:30 and 15:30 and the periods with the lowest number of people at the cafeteria were between the periods 7:00 and 8:30. An increase in the number of people in class caused a decrease in the number of people at the cafeteria and this lead to decrease in wait time at the cafeteria. The predictive models designed were able to predict the number of people at the cafeteria at each period in the day with a minimum and maximum root mean square of 2.24 and 3.02 for model 1 and 2.65 and 4.5 for model 2. However, model 2 was used in testing because the equation handled two independent variables namely; number in class and period of day. Furthermore, analyses of the test data suggested a significant change in peak numbers and periods after the predicted numbers and wait times for each day was publicized.

Chapter 5: Conclusion

5.1 Significance of Study

The purpose of this study was to explore how the use of predictive analytics could reduce wait time at a college cafeteria. From the results, we can conclude that there was a significant decrease in the number of people visiting the cafeteria each day during the peak periods after the predicted frequencies of each day was publicized and this led to a reduction in wait time at the peak periods. Extending this research to other cafeterias in organisations, hospitals or colleges will be significant and feasible given that relevant dependent and independent variables are selected for the models.

Results of the predictions of number of people at the cafeteria and the wait time was presented to the management of the cafeteria, to suggest solutions to enhance service quality. Responses to the findings from the management of the cafeteria suggested

1. An increase in the number of serving staff during the peak periods.
2. A change in the service style at the cafeteria
3. An increase in serving space for serving staff at the cafeteria.

The challenges with these factors however are limitations in infrastructure and plan of cafeteria. This was because the serving area for the cafeteria could not accommodate more than four serving staff at the counter due to its small size. Another challenge with hiring more employees was an overhead cost of employee salary which was not feasible since the employer will be needed only during the peak periods and thus lead to redundancy.

5.2 Assumptions and Limitations

In the course of this study, certain limitations encountered might have reduced the accuracy of data collected and model developed. A major setback was the issue of poor network caused by power fluctuations. This disallowed customers to log in and out of the application when necessary. Another limitation was sustaining power on the tablets that hosted the web application used for the collection of data, as well as securing a location for the tablets in order for customers to use effectively.

Certain assumptions were made for the purpose of this study, and they are listed below.

1. Only students visited the Akornor cafeteria during the day
2. There is no break between the periods of classes in a day
3. Events and programs during the day does not affect the number of people at the cafeteria.
4. Customers do not wait in a queues before they place an order for a meal

5.3 Future Work

Due to the limitation in time for this study, the test results were performed only on Model 2. As part of future developments on this study, the predicted numbers from the third and fourth models can be tested to provide support to the results. The intervals between periods for each day could also be reduced to a ten minute interval, to cater for the ten minutes break between each class and also guarantee a more accurate prediction for a particular time of the day. Also, designing a mobile application in addition to the web application developed can ensure efficient collection of information on the wait time of customers at the cafeteria. This would allow people to conveniently record the time it takes to pick up food from counter after ordering or record time spent in queue to place an order without problems such as network fluctuations.

References

Andaleeb, S.S. & Caskey, A. (2007). Satisfaction with food services: Insight from a college Cafeteria. *Journal of Foodservice Business Research, 10*(2), 51-65.

doi: 10.1300/J369v10n02_04

Anderson, E.W., Fornell, C. and Lehmann, D.R. (1994). Customer satisfaction, market share and profitability: Findings from Sweden. *Journal of Marketing*, *58*(3), 53-66. doi: 10.2307/1252310

Brynjolfsson, E. & Yang, S. (1996). Information technology and productivity: A review of the literature. *Advances in Computers, Academic Press, 43*(1), 179 – 214.

doi: 10.1016/S0065-2458(08)60644-0

Chang, C., Kung, C. & Tan, T. (2008). Development and implementation of an e-restaurant for customer-centric service using WLAN and RFID technologies. In *Machine Learning and Cybernetics, 2008 International Conference on* (Vol. 6, pp. 3230-3235). IEEE. doi: 10.1109/ICMLC.2008.4620963

Dixon, M., Kimes, S. E., & Verma, R. (2009). Customer preferences for restaurant technology innovations. *Cornell Hospitality Report, 9*(7), 6-16.

Eugenio-Martín, J. L., Morales, N. M. & Scarpa, R. (2004). Tourism and economic growth in Latin American countries: A panel data approach. doi: 10.2139/ssrn.504482

Hwang, J. (2008). Restaurant table management to reduce customer waiting times. *Journal of Foodservice Business Research, 11*(4), 334-351.

doi: 10.1080/1537802519546

Iacobucci, D., Grayson, K. A. & Ostrom, A. L. (1994). The calculus of service quality and consumer satisfaction: theoretical and empirical differentiation and integration. *Advances in Services Marketing and Management, 3*(1), 1-68. doi: 10.1016/S1067-5671(94)03013-8

Jones, P. & Dent, M. (1994). Improving service: Managing response time in hospitality operations. *International Journal of Operations & Production Management*, *14*(5), 52-58. doi: 10.1177/0010880407304020

Kisang, R. & Sanchez, A. (2002). The evaluation of forecasting methods at an institutional foodservice dining facility. *The Journal of Hospitality Financial Management, 11*(1), 27-45. doi: 10.1080/10913211.2003.10653769

Lee, W. & Lambert, C. (2000). Impact of waiting time on evaluation of service quality and customer satisfaction in food service operations. *Foodservice Research International, 12*(1), 241-254. doi: 10.1111/j.1745-4506.2000.tb00021.x

Noone, B. M. & Coulter, R. C. (2012). Applying modern robotics technologies to demand prediction and production management in the quick-service restaurant sector. *Cornell Hospitality Quarterly, 53*(2), 122-133. doi: 10.1177/1938965511434112

Noone, B. M., & Kimes, S. E. (2005). Dining duration and customer satisfaction. *Cornell Hospitality Reports, 7*(2), 6-15.

Noone, B. M., Wirtz, J. & Kimes, S. E. (2010). The effect of perceived control on consumer responses to service encounter pace: A revenue management perspective. *Cornell Hospitality Quarterly, 53*(4), 295-307. doi: 10.1177/1938965512460343

Pantelidis, I.S. (2009). High Tech Foodservice; an overview of technological advancements. In *Proceedings of the Annual Research Conference*. Eastbourne: UK.

Ruiz-Garcia, L, & Lunadei, L. (2011). The role of RFID in agriculture: Applications, limitations and challenges. *Computers and Electronics in Agriculture*, *79*(1), 42-50. doi:10.1016/j.compag.2011.08.010

Ruiz-Molina, M., Gil-Saura, I. & Berenguer-Contrí, G. (2014). Information and communication technology as a differentiation tool in restaurants. *Journal of Foodservice Business Research, 17*(5), 410-428. doi:0.1080/15378020.2014.967639

Sivadas, E. & Baker-Prewitt, J. L. (2000). An examination of the relationship between service quality, customer satisfaction, and store loyalty. *International Journal of Retail &Distribution Management*, *28*(2), 73-82. doi: 10.1108/09590550010315223

Zhang, X. L. S. (2009). Investigation of customer satisfaction in student food service. *International Journal of Quality and Service Sciences, 1*(1), 113-124. doi.org/10.1108/17566690910945903

Zhang, Y., Nguyen, L. T., & Zhang, J. (2013, September). Wait time prediction: How to avoid waiting in lines? In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication* (pp. 481-490). Zurich, Switzerland. doi: 10.1145/2494091.2495980