Personalized call center traffic prediction to enhance management solution with reference to call traffic jam mitigation

- A case study on Telecom New Zealand Ltd.

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A dissertation submitted to

Auckland University of Technology

In partial fulfillment of the requirements for the degree of

Master of Computer and Information Sciences (MCIS)

2008

School of Computing and Mathematical Sciences

Primary Supervisor: Dr. Paul S. Pang

Dedicated to my mother

ACKNOWLEDGEMENTS

The Research Dissertation was written under the supervision of Dr. Paul Shaoning Pang and Dr. Russel Pears. I would like to express my deep gratitude to Dr. Paul Pang for being my primary supervisor and a great facilitator. I feel privileged to have learned from this brilliant researcher and more importantly his desire to teach and to continue learning made this research both challenging and at the same time a fascinating experience. This research could not have been completed without his open-door policy and his everlasting patience; and for that I am truly grateful.

I would like to thank Dr. Russel Pears for giving me a different perspective on things. He has always provided an insightful and correct approach towards my research. I sincerely thank him for the time and effort and his willingness to contribute to this research.

I would like to thank Harya Widiputra to assist me towards my research to understand the concepts and whenever I need any help. I thank Rajul Nair and Teena Roy for assisting me to proof read my documents. In addition, I would like to thank KEDRI staff especially Prof. Nikola Kasabov, Peter Hwang, Joyce D'Mello and other staff who always there to help me to complete my research.

I also thank Chris Linden, Allan Tayles, Paul Puppyn and Kyle McFarlane at Telecom New Zealand for providing me the required data and information to complete my research.

Also I would like to thank my family for supporting and encouraging me to attain my goals.

ABSTRACT

In today's world call centers are operated as service centers and means of revenue generation. The key trade-off between customer service quality and efficiency of business operations faced by an operations manager in a call center is also the central tension that a human resource manager needs to manage (Aksin, Armony, & Mehrotra, 2007). By looking at the importance of providing efficiency at service quality, this dissertation conducts the research which describes forecasting approaches that can be applied to any call center. A case study research is conducted on Telecom New Zealand call center data which is based on a 15 minutes call interval data collected from call centers for the years 2007 and 2008 during the period of normal and abnormal (i.e. traffic jam) call distributions. Specifically, this research proposed a novel personalized call prediction method considering the importance of agent skill information for call center staff scheduling and management. Applying the proposed method, two call broker models: (1) personalized agent software broker, and (2) supervisor involved personalized software broker are further developed in this dissertation to construct a new generation call center IT solution for small size companies, and as well for large companies such as Telecom New Zealand.

In this dissertation, a problem – solution approach is implemented. An initial step for problem generalization is to analyze and perform call predictions. The existing methods for call predictions implement inductive systems and are based on global models and thus cannot generate consistently good prediction accuracy, especially when traffic jam is confronted and/or if there is an abnormal increase of call volume which in turn makes calls to be abandoned affecting the service levels in the call center. In addition, since increase in the number of agents cannot be changed at short intervals of time, a personalized approach models an intelligent broker for every individual agent in the call center. This in turn expected to improve the general working efficiency of a call center, as compared to the traditional approach that use merely one broker for a number of agents. This concept is implemented using the proposed personalized prediction method, and demonstrated while comparing with other methods on call volume prediction experiments over real data streams from Telecom New Zealand.

The proposed two broker models are both based on Personalized Prediction method. The first model uses the concept of software call broker which aims to implement the proposed prediction method as an Automatic Call Distributor (ACD). The second model, the supervised call broker is based on the concept of real time supervised observations of agent's performance and then computing predicted calls for each agent. The broker implements the assisted knowledge of supervisor to select an appropriate agent to service the customer request. The proposed call broker models will depict as IT solutions for traffic jam problem.

The Traffic Jam as addressed in the dissertation conducts the cost and return calculation as a measure for TNZ Return on Investment (ROI). While introducing the concept of traffic jam problem solving here from section 4.5.2, the non-personalized prediction method could release the traffic jam in 8.60 days with a saving in time of 1.40 days. This is in contrast to the personalized prediction method that releases the traffic jam in 8.48 days and a saving of 1.52 days. Meanwhile, the supervised call broker model can release a traffic jam in 8.04 days with a saving of 1.96 days to predict the traffic jam.

The dissertation summarizes that, the intensity of traffic jam and cost/output analysis for scheduling more agents to improve the service factors at short intervals of time will be a challenging task for any call center. As observed the benefits of savings is achieved by improvements in the level of service that couldn't outweigh the costs of hiring new agents and in addition, couldn't improve the profitability of Telecom New Zealand during the period of traffic jam. Hence, the proposed method of personalized broker with supervisor role can be an alternative to provide a better service levels to any bigger call centers like Telecom New Zealand. For any other small size call centers consisting of 2-5 agents, implementing software call broker will resolve the problem of traffic jam and as a best possible solution to maximize Return on Investment.

ABBREVIATIONS

ACD – Automatic Call Distributor

AHT – Average Handling Time

ASA – Average Speed of Answer

AWT – Average Work Time

CA – Calls Abandoned

CFT – Customer Facing Time

CSQ – Customer Service Quality

DENFIS – Dynamic Evolving Fuzzy Interface System

dpp – non-personalized prediction

Dthr – Distance threshold

DWH – Data Ware-House

EBO – Efficiency of Business Operations

EFUNN – Evolving Fuzzy Neural Networks

FCR – First Call Resolution

IB – In Bound

IT – Information Technology

IVR – Interactive Voice Response

MLP – Multi Layer Perceptron

MLR – Multiple Linear Regressions

NDEI – Non-Dimensional Error Index

NLP – Natural Language Processor

NR – Not Ready

OB – Out Bound

PCS – Post Call Survey

RMSE – Root Mean Square Error

SERVQUAL – Service Quality

SBR – Skill Based Routing

SL – Service Level

TNZ – Telecom New Zealand

TNZ Exp – Telecom New Zealand Experience

TSF – Telephone Service Factor

KEYWORDS

Traffic Jam, Calls Abandon, TSF, AWT, Service Quality, Simulation, Data Mining, Call Prediction, Agent Skills, Personalized Prediction, Non-personalized prediction, Traffic Jam Release, Modeling, ACD, Skill Based Routing, Software Call Broker, Supervised Call Broker, Planning, Service Industry

SYMBOLS

λ – Poisson call distribution

E – Erlang - Measurement of call volume

μ – Exponential distribution of service time

f – Function for prediction computing method

D – Data stream of calls

$\mathbf{s}$ – input vectors for MLP

$\mathbf{x}$ – Output vectors for MLP

$\mathbf{A}$ – Weight matrix of first layer of MLP

$\mathbf{B}$ – Weight matrix of second layer of MLP

φ – Element wise nonlinearity

φ – Non-linear activation function for MLP

Σ – Linear function of MLP

m – Fuzzy rules for DENFIS

S – Skill grade of agents

mf – Membership Functions for DENFIS

$c(i)$ – Calls at i^{th} point of time

P – Personalized data partitioning function

x – Input Variables for DENFIS

Y – Output variable for DENFIS

R – Matrix of input vectors for DENFIS

k – Number of attributes in the data set

n – Number of rows / elements in each data set

β – Regression coefficient

ε – Residual error

$\hat{Y}$ – Predicted Values

dPP – Non-personalized prediction

PP – Personalized Prediction

SP – Supervised Prediction

SCB – Supervised Call Broker Model

$r_{xy}(k)$ - Correlation coefficient for attribute series X , Y at lag k

X, Y - Sample correlation coefficient attributes

S_x - Standard deviation of series X

S_y - Standard deviation of series Y

$C_{xy}(k)$ - Sample cross variance at lag k

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Chapter 1 Introduction

1.1 Contemporary Research in Call Center Field

Call centers are the backbone of any service industry. A recent McKinsey study revealed that credit card companies generate up to 25% of new revenue from inbound calls center's (Eichfeld, Morse, & Scott, 2006). The Telecommunication industry is improving at a very high speed, as is evident from the research work of Shu-guang, Li, & Er-shi (2007) that the total number of mobile phone users has exceeded 400 million by September 2006 and this immense market growth has generated a cutthroat competition among the service providers. These scenarios have brought up the need for call centers, which can offer quality services over the phone that is necessary to survive in a competitive environment.

1.2 Call Flow in a Call Center

Consider the idea of general call flow in a call center. The calls arrive at Poisson distribution process (λ) with 'n' different types of calls, where as the calls are serviced at an exponential distribution (μ). The offered load to the call center at a point of time (t_1) would be [$\alpha_1 = \lambda_1 / \mu_1$] (Strategies, 2004).

In a call center, Erlang is the general measurement of the traffic volume. Whereby, one erlang equals to the offered load in one unit of time $[E_1 = \alpha_1]$.

The researchers Strategies (2004) clarified with an example, that with an arrival rate of 100 calls per hour, each agent required 9 minutes (0.15 hour) of service time, the traffic volume in an 8 hour day will be 100*0.15*8 =120 Call hours (Ch).

Therefore, One Erlang equals one Ch/hour=120/8= 15 E.

The following equation (1.1) represents the homogeneous Poisson call distribution

$$P(\lambda, k) = \sum_{i=0}^{k} \frac{\lambda^{x} e^{-\lambda}}{k!}, \qquad \ldots \quad (1.1)$$

where, λ is the mean arrival rate and k is the number of occurrences of an event.

A further analysis of Call Flow in a call center is shown in Figure 1 on page 15 the high level switch identifies the call and establishes an interaction with the Automatic Call Distributor (ACD) to direct the call to an agent. Interactive Voice Response (IVR) systems, initially takes up the call from the customer; In addition, to have a better understanding of the problem the IVR invites caller/customer to explain their problem. Once, the problem is identified the ACD locates the available agent to service the call. The customer hangs up and terminates the call once the service has been received. The agent finishes the post-call work and makes him/her available to take further calls. ACD records the agent availability and initiates the calls.

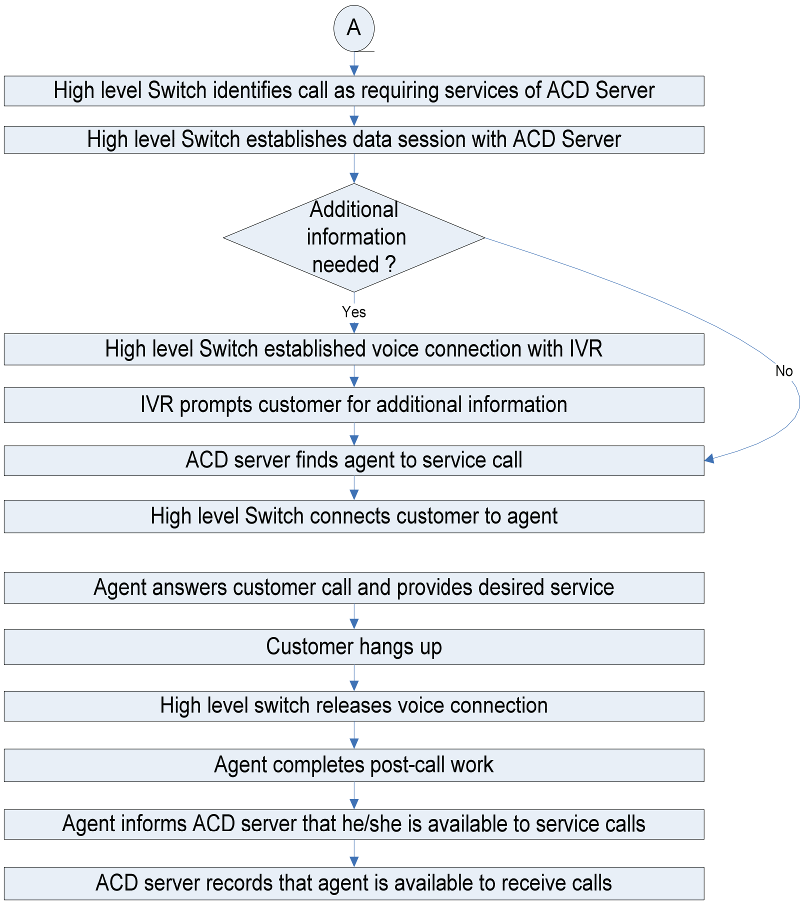


Figure 1. Call Flow Chart

1.3 Call Center in Telecom New Zealand, Status and IT Solution

This section initially gives an overview of the Telecom New Zealand call center and later focuses on the current status and IT solution for call volume prediction. The final section explains the Agent broker for call routing functionality.

1.3.1 The Telecom New Zealand Limited (TNZ)

The Faults Resolve call center handles calls from several queues and mainly consists of Residential, Mobile, Business and Broadband customers. There are some other queues that are handled specially for internal transfers. The faults call center queues operates 24x7, 365 days a year. In addition, to meet the business needs all the calls between 7am and 11pm are handled at main faults center building and the Managed Corporate Center handles the calls for faults team between 11pm and 7am. A glance of TNZ call center is pictured in Figure 2 on page 16 and Figure 3 on page 17 depicts the tools made available to mobile resolve agents to service the customer calls.

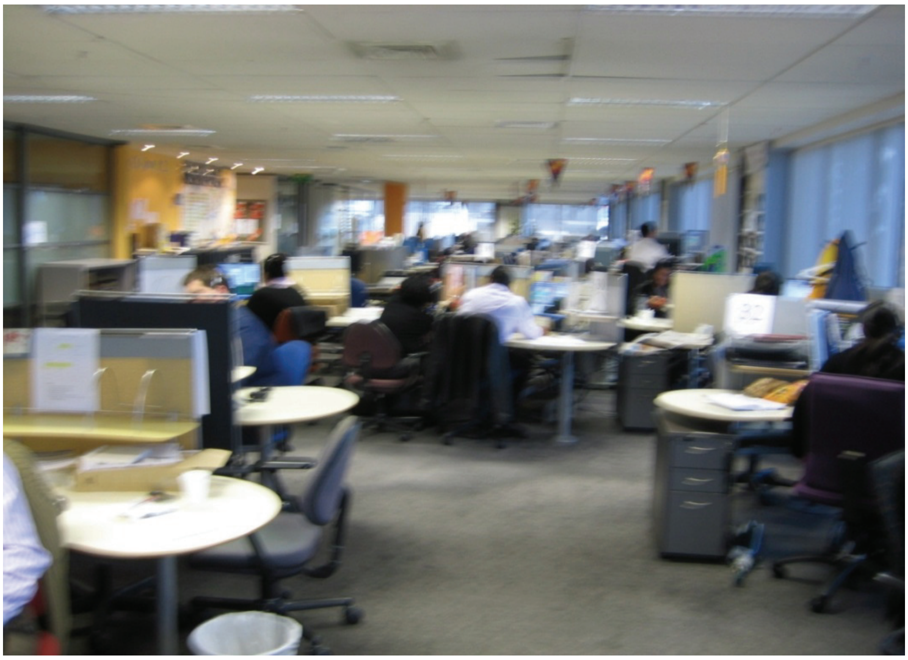


Figure 2. Telecom New Zealand Call Centre on a busy day

Figure 3. TNZ Call Center's mobile handset display to assist agents

1.3.2 TNZ Call Center Structure and Staff Management

The TNZ faults Resolve call center resolves the issues of residential, mobile and broadband customers. The center operates with 190 agents, 11 team leaders, 4 knowledge specialists, 2 mentors, and a center manager. The center always aspires to provide excellent customer service.

In a normal busy day the faults resolve call center operates with 70-80 agents, 7 Team Leaders and the evening shift operates with 30-40 agents and 4 team leaders. In addition, 3 to 4 knowledge specialists assist the agents to resolve complex issues with the customers. There is 1 mentor available especially to help newly recruited agents. Depending on business needs, the agents will be employed on the floor. The center manager takes care of the floor and ensures the availability of adequate head count (number of agents) to address customer issues. If the center manager feels that the head count is insufficient and there is a requirement for new recruits, the human resources department is contacted for recruiting new agents. All these processes needed to be within the budget of the cost center (of call center).

(1) TNZ Call Center Structure

The hierarchical structure of TNZ call center is as shown in Figure 4 on page 18 and consists of the Center Manager to ensure that the floor runs smoothly within the set standards of the call center. Team Leaders, who ensure customer issues are resolved appropriately, monitor and evaluate agents' performance and take actions accordingly. The agents answer the calls and resolve the customer issues while adhering to their assigned tasks and duties. If the customer issues are not resolved in time and customer is not happy with the service, the agents' escalate the complaint to the Team Leader who liaises with the service providers and customers to ensure that Telecom offers the right service.

The team leaders have to report daily to the center manager with regards to the performance of their team. The center manager, in turn, gives a performance report of the whole center to his/her superiors to ensure that the call center standards and benchmarks are met. The customer care manager ensures that the customer gets the correct service; performs audits as per the telecom standards and take actions accordingly. In addition, the customer care manager implements the suggestions, as received from head of broadband and resolve to improve the performance of the call center.

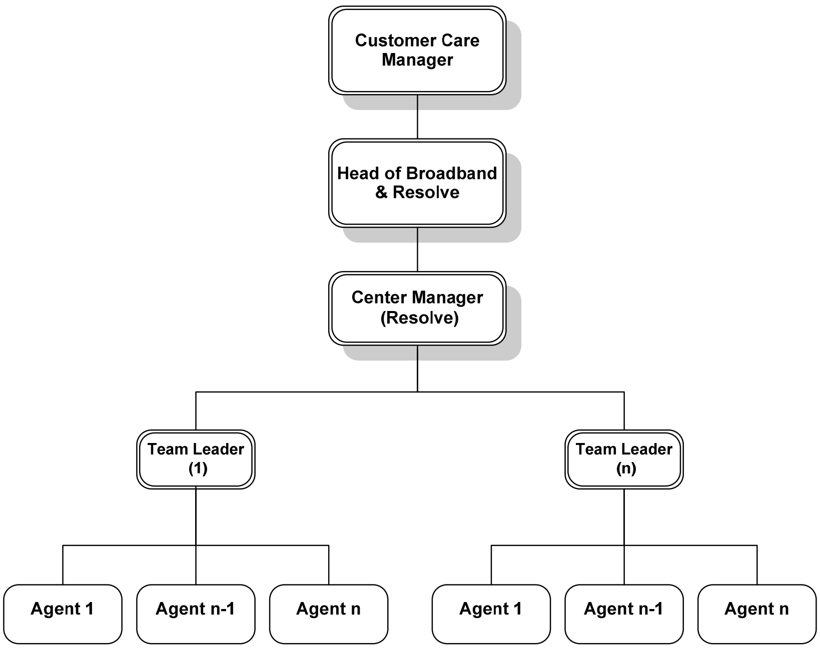


Figure 4. TNZ Call Center's hierarchical chart

(2) TNZ Call Center Staff Management

A team in the call center usually consists of 14-20 agents. The team leader manages the team with the available software and tools. The performance of the agents is as shown in Figure 5 on page 21 and depends on the following factors:

a) Adherence
b) Not Ready (NR)
c) Customer Facing Time (CFT)
d) Post Call Survey (PCS)
e) Transfers
f) Ticket Quality
g) Call Quality.

The team leader has to address their team performance to the center manager on the basis of the above factors.

a) Adherence – This is the percentage of time an agent adheres to his allocated work timings. Telecom considers adherence of 95% as a good benchmark.

b) Not ready – It is the state where the agent is not available to take the next call, by keeping him/herself to be not ready. The reasons could be performing offline tasks for completing the previous call works. The telecom call center benchmark states that not ready should be less than 15%. (Team leaders usually considers NR>20% to be an inefficient agent).

c) Customer facing time – The team leader expects the agents to face customer calls with a percentage greater than 60 of their total adhered time. This is in order to make them self available to resolve customer issues and reduce call abandonments.

d) Post call survey – The survey is based on customer satisfaction from the service received from agents. As on August 2008 out of the total calls only 10% of the customers will have a choice to do a post call survey. Telecom is planning to increase the number in future depending on the response of the survey. The survey is based on 4 questions which will give a chance to rate from 1-4 (1 being very dissatisfied and 4 being very satisfied). The questions will say

i) “Please rate the rep’s interest in you and your enquiry?”

ii) “Please rate the confidence you have in the answer or solution provided to you by the Rep.”

iii) “Please rate the following statement: The Rep listened carefully to what I was saying.”

iv) “How would you rate the overall service from this Rep?”

e) Transfers – Telecom states that the internal call transfers by an agent should be less than 10% of all the calls received. A manager looks for the percentage of calls that have been transferred to other departments. If an agent transfers more than 10% of the calls it shows a lack of ownership and training deficiency.

f) Ticket Quality – A team leader performs a ticket quality, once a week to ensure that the entire job sent by the agent is with sufficient and relevant information and within the defined standards.

g) Call Quality – A team leader usually does the call quality check of an agent once a fortnight. The procedure of call quality involves listening to agents calls on-line or off-line (recorded). The check list of call quality consists of four categories of ratings like A, B, C, D. Whereby, ‘D’ is the mandatory checklist and if the agent misses any of the ‘D’s he/she gets ‘F’ fail grade. If the agent covers all the D’s gets grade ‘D’. If he/she covers checklist for ‘C’ grade along with D will be awarded grade ‘C’. In addition, if the agent covers checklist for ‘B’ as well gets grade ‘B’. Finally if the agent covers the entire checklist for D, C, B including for ‘A’ during the conversation with the customer will be awarded as being star rated with the customer service.

In addition, the management monitor and evaluate the performance of agents using the Software “CCPulse”. As shown in Figure 6 in page 21, the software gives the online state of every agent. The state of an agent could be ‘Waiting’ for the call, “Not Ready”, kept customer on ‘Hold’, ‘Internal’ transfer, making ‘Out Bound’ call, on ‘Incoming’ call or ‘Consulting’ with other staff.

Figure 5. Agents Performance Display Chart

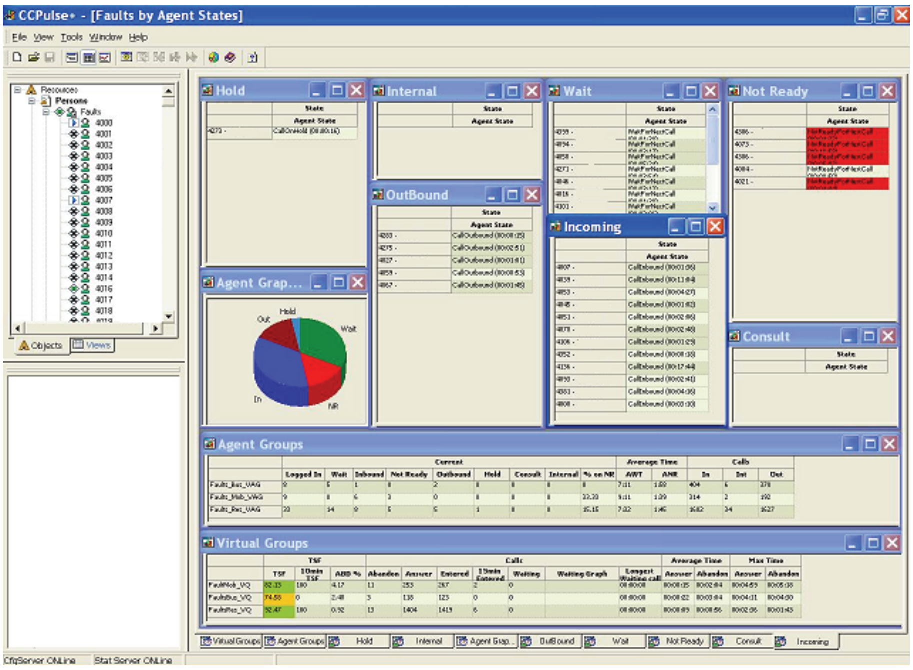


Figure 6. Agents On-line Performance

1.3.3 TNZ Call Center IT Solution

TNZ performs call predictions based on historical call forecasting approach and some estimated techniques implemented using Microsoft Excel spreadsheets. The TNZ management uses the Erlang C model for performing optimized prediction of agents. To overcome the operational service challenge of service quality to the management of a call center, TNZ uses skilled-based routing to solve the matching of agents to the customer needs. These real-time scheduling techniques and optimization models enable TNZ call center to manage capacity more efficiently, even when faced with highly fluctuating demand.

1.3.4 Agent Broker (ACD)

The automatic call distributor implements skill based routing where by calls will be routed based on the priority skills of the agents. Each agent has specialized skills like residential, mobile, mobile data, broadband, and business; thus each agent will be kept in different queues depending on the call flow and the load on the center to ensure that the calls will be handled by agents and not abandoned by the customers. TNZ call center implements skill based routing at ACD in a manner similar to that as shown in Figure 7 on page 22 which is adapted from the works of the researchers Wallace & Whitt (2005).

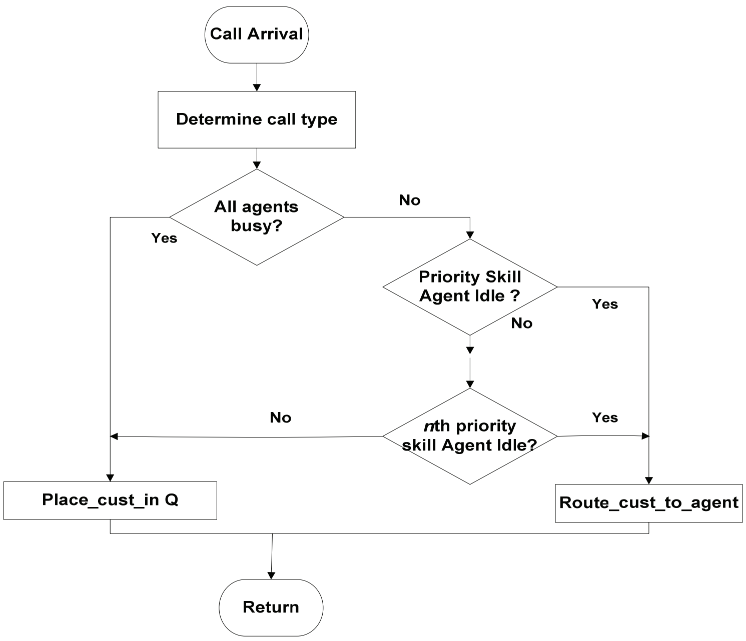


Figure 7. Skilled Based Routing functionality at ACD

1.3.5 Software for Call Volume Prediction

This section presents an overview of the prediction software's and methods used at a Telecom New Zealand call center.

(1) Prediction Software's

The TNZ forecasting team uses Microsoft Excel spreadsheets for forecasting call volume and call handling time. In addition, agent prediction is performed based on forecasted call volumes and using the Erlang C model. The required agents are scheduled using a workforce management tool called as "ResourcePro".

(2) Prediction Methods

Telecom New Zealand performs call forecasts based on call center prediction estimator for the output variable. The estimates are drawn from experience and depend largely on historical call data to forecast future values.

1.3.6 Introduction of TNZ Call Center Data

The datasets originated from The Telecom New Zealand Limited call center data. The call data consists of detailed call-by-call histories obtained from Faults Resolve department.

The call data to the system arrives regularly at 15 minutes intervals and for the entire day. However, the TNZ forecast the calls between 7 AM and 11PM as the queues are busy mostly during this time. In order to bring a legitimate comparison and while considering the business need, data from 07:00 to 23:00 hours will be considered for data analysis and practical investigation.

(1) Analysis of Interval Resolution

Referring to the ideas of Aldor-Noiman (2006), in order to maintain homogeneity with the data, the theoreticians suggest that the considered interval should be as small as possible. In addition, from the practitioner's perspective the interval should match with the time interval of new agent's addition to the queue. Since, TNZ schedule agents with a minimum time resolution of 15 minutes. Moreover, even the call data arrives once for every 15 minute to the system; the analysis of interval resolution has been set for 15 minutes. In addition, 64 quarter hourly arrival intervals between 07 AM and 11 PM are considered for call arrival pattern analysis.

While considering the inter-day call arrival pattern at TNZ call center as shown in Figure 8 on page 24, the trend analysis of call arrival for 30 days (between dates of 22/01/2008 and 20/02/2008) the graph has shown a sort of low-high fluctuation at the middle of the day. Consider the data values, 398 at point 1 which is an average of 13 calls between interval (07:00-07:15). This reaches the peak at point 11 which is an average of 73 calls at an interval (09:45-10:00) and remains steady at point 32 which is 50 calls for (14:45-15:00). A gradual raise at point 39 for time interval (16.30-16.45) drops to a dead level of 174, which is an average of 6 calls at point 64 for the time interval (10:45-11:00).

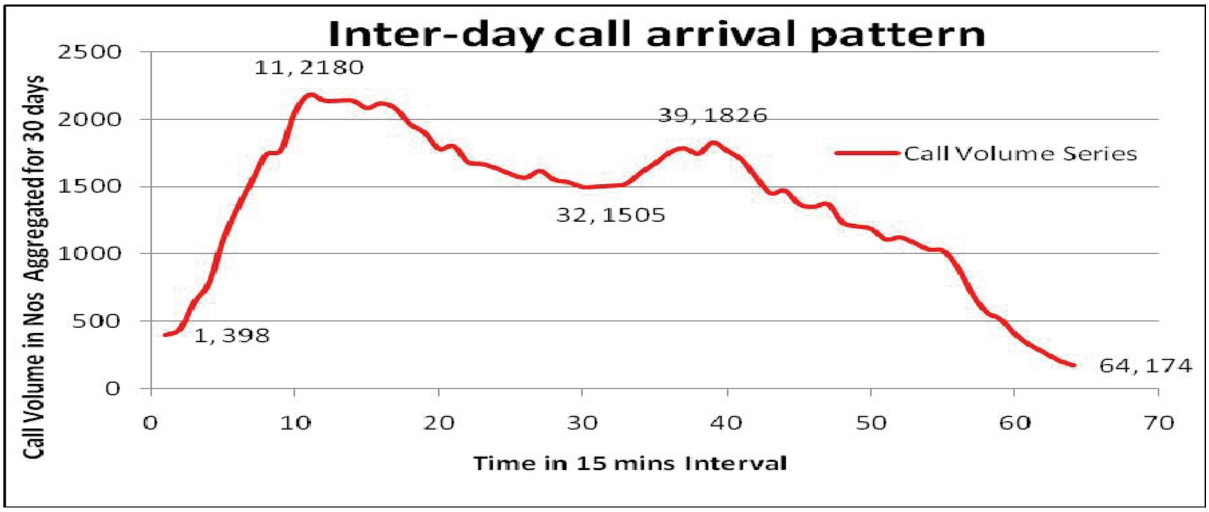


Figure 8. A 30 day Inter-day call arrival pattern

So, in order to have a better analysis of the call arrival a two 32 quarter hourly intervals; one between 7 am and 3 pm and other between 3 pm till 11 pm will be considered in the practical investigation and experimental analysis. In addition, the calls which are handled at the faults calls center between 7am and 11pm will be investigated.

(2) Analysis of Calls Distribution

While analyzing the distribution of data, an interesting pattern has been discovered for 10 days during the periods of 21/02/2008 till 01/03/2008. As shown in the Figure

9, on page 25, the call arrival pattern for these 10 days period depicts an unusual distribution of calls while comparing with the normal call pattern which is represented as an average of 10 days for a 30 day period (between 22/01/2008 till 20/02/2008).

These 10 days recorded an abnormal distribution of calls. While analyzing the facts for these unusual distributions of calls; it was observed that a major Telecom exchange system was down and it caused an increase in the number of calls coming in to the call center.

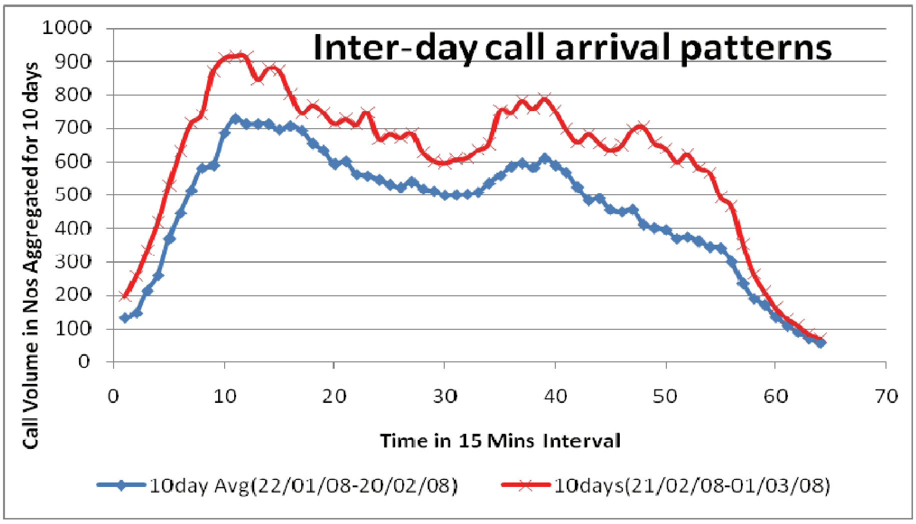


Figure 9. Comparison of Normal vs. Traffic Jam Inter-day call arrival pattern

1.4 Motivation of the Presented Research

The primary motivation of conducting this research is to analyze the Telecom New Zealand call center performance, and the main focus would be to analyse:

1) Call Center Traffic Jam
2) Importance of Agent Skill Information

1.4.1 Call Center Traffic Jam

The huge variation of calls in the queue system as observed at section 1.3.6 has raised a research interest to analyze the impact of the so-called occurrence of "Traffic Jam" on the performance of the center. It was also interesting to analyze how well the call predictions could be improved to avoid future traffic jams. The traffic jam will surely affect the service factors in the call center and simultaneously have an adverse impact on the call predictions. A further analysis of the problem will be presented in Chapter 3 “Personalized call center traffic prediction”. A detailed analysis of traffic jam problem solving and ideas that focus on call center management solutions will be put forward in Chapter 4.

1.4.2 Importance of Agent Skill Information

While observing the skill based routing in section 1.3.4, it was noted that the calls are routed based on the availability of the skilled agent for which the call was made for. If the primary skilled agent is not available, the call will be routed to the secondary skilled agent. However, if ‘m’ number of primary skilled or ‘n’, number of secondary skilled agents are available to answer the calls; the ACD will allocate the calls giving priority to the agents who have been waiting for the longest time. Obviously, this is not an efficient approach because the skill of each agent is different from one another; as is evidenced at section C of the appendix where a sample of 10 agents’ skill information is pictured.

In addition, given a call center with ‘m’ agents, most traditional software brokers maintain a single general call volume prediction, and distribute calls equally to ‘m’ agents. The analysis of the call center problem investigation, as described in section 3.3.4 and data analysis in section 3.4, further raised the interest to investigate the importance of the agent information (for example, the skill grade of agent in a call center), and develop an agent personalized predication models which can enhance the capability of call broker software and boosts the performance of service factors predictions within a call center.

1.5 Organization of Dissertation

This research study is organized into the following chapters:

Chapter 2 provides a literature review of several call center prediction methods, including inductive, transductive fuzzy inference method (for personalized prediction), local and global models with the consistency of call predictions. In addition, provides a review of call broker models, SBR (Skilled Based Routing for multiple skills).

Chapter 3 presents the proposed Personalized Prediction method and describes the approach to handle traffic jams in the call center. The analysis of experiments draws the attention of the Telecom New Zealand management to consider inclusion of agent skills while performing call prediction for improvement of service factors in the call center.

Chapter 4 provides traffic jam problem solving with call broker models. An analysis of intensity of traffic jam and cost/output analysis for scheduling more agents to improve the service factors at short intervals of time will be shown as a challenging task for the call center management. The proposed method of personalized broker with supervisor role is an alternative to provide a better service levels to the call center.

Finally, Chapter 5 reviews the summary and conclusion of the presented research and as well gives recommendations for the future work.

Chapter 2 Literature Review of Call Center Research

2.1 Introduction

The ultimate goal of call center forecasting would be to predict the call arrivals to the center such that it will assist management to perform agent scheduling and service factors prediction. This chapter initially describes the call center predictions methods and reviews the prediction methods for computational intelligence. Later, this chapter brings a review of call center IT solutions and different computational models for call center predictions. Finally, it describes the importance of simulation and personalized models for call predictions.

2.2 Review of call-center IT solutions

According to Jack, Bedics, & McCary (2006) researchers develop several types of optimization, queuing and simulations models, heuristics and algorithms to help decrease customer wait times, increase throughput, and increase customer satisfaction. Such research efforts have led to several real-time scheduling techniques and optimization models that enable call centers to manage capacity more efficiently, even when faced with highly fluctuating demand.

2.2.1 Call Center Software

This section reviews the existing call prediction software's for call centers. Finally, it compares and contrasts the TNZ approach towards call predictions and agent scheduling in their call centers. The following list gives the five different types of software technologies used in call center predictions.

1) Erlang C
2) Erlang A
3) Erlang B
4) Data Ware Housing (DWH)
5) Data Mining

1) Erlang C: This queuing model M/M/n assumes calls arrive at Poisson arrival rate. The service time is exponentially distributed and there are ‘n’ agents with identical statistical details. According to Ernst, Jiang, Krishnamoorthy, & Sier (2004) the Erlang-C queuing model is preferred in most call centers for predictions. However, it is deficient as an accurate depiction of a call center in some major respects. It does not include priorities of customers and it assumes that skills of agents and their service-time distributions are identical. Finally, it ignores customers' recalls, etc. (Mandelbaum & Zeltyn, 2004). In addition, Erlang C ignores call abandonments (Zeltyn & Mandelbaum, 2006).

2. Erlang A: Focusing on the ambiguities of Erlang C model for ignoring call abandonment's, the researchers Garnet, Mandelbaum & Reiman (2002) analyzed the simplest abandonment model M/M/n+M (Erlang-A). In this model, customers' patience is exponentially distributed; such that customer satisfaction and call abandonments are calculated. In addition, "Rules of thumb" for the design and staffing of medium to large call centers were then derived (Mandelbaum & Zeltyn, 2004).

3. Erlang B: It is widely used to determine the number of trunks required to handle a known calling load during a one-hour period. The equation assumes that if callers get busy signals, they go away forever, never to retry (lost calls cleared). Since some callers retry, Erlang B can underestimate the trunks required. However, Erlang B is generally accurate in such situations with few busy signals as it incorporates blocking of customers (Aksin et al. 2007).

4. Data Ware Housing (DWH): Looking at the works of researcher Shu-guang et al. (2007) use of OLAP (On-Line Analytical Processing) and data mining manage to mine service quality metrics such as Average Speed of Answer (ASA), recall, Interactive Voice Response (IVR) system optimization to improve the service quality. However, if we include agent database within the DWH it is possible to monitor and evaluate the performance of agents to improve call quality and customer service satisfaction.

5. Data Mining: With predictive modeling such as decision-tree or neural network based techniques, it is possible to predict customer behavior. Furthermore, the analysis of customer behavior with data mining aims to improve customer satisfaction (Paprzycki, Abraham & Guo, 2004).

The Telecom New Zealand management uses the Erlang C model for performing optimized prediction of agents. According to Shu-guang et al., (2007) telecommunication call center often uses the queuing model like Erlang A & Erlang C for the operations of optimization. However, Erlang C model might not be a right approach for forecasting calls and agent prediction during the period of traffic jams as evidenced with the high call abandonments at TNZ call center. Furthermore, researchers Zeltyn & Mandelbaum (2006) advise that Erlang C exclude abandonments during call predictions.

An alternative solution to perform agent predictions would be to perform simulations. As suggested by researchers Koole (2006) simulation models can assist management to perform agent predictions especially when it comes to multi-skilled operations, as no simple equation such as Erlang C are appropriate. In addition, simulation can consider many practical factors and compute real world simplifications with call predictions and staff requirements (Ernst et al., 2004).

2.2.2 Call volume prediction and Staff Scheduling

As more than 70 % of all customer-business interactions are handled in call centers, call center forecasting is critical for telecommunication industry (Shen & Huang, 2008). A recent McKinsey study revealed that credit card companies generate up to 25% of new revenue from inbound calls centers (Eichfeld et al. 2006). Hence, accurate forecasting of call arrivals is critical for call center operations, so that adequate amount of staff can be deployed for answering the calls. For performing agent prediction, both inter-day (day-to-day) and intra-day (with-in day) forecasting would be critical (Shen & Huang, 2008). In addition, to forecast the workload accurately, the first and critical step is to provide an accurate forecast of future call volumes. Moreover, there is a considerable demand and interest for demand forecasting in telecommunications (Abidogun, 2005).

Forecasting call arrivals is based on time series prediction, which implies to ascertain the predicted calls at any single point of time. Calls arrive at non-homogeneous interval of time measured by Poisson process. Hence, prediction of future arrival rates will be a crucial step for staffing decisions and will draw attention for complicated statistical task to the management (Zeltyn & Mandelbaum, 2006).In addition, since the calls arrive at a random rate there should be some scope to adjust for the variations and a predefined error rate on predicted call volumes should be applied (Robbins, Medeiros & Dum, 2006). The researchers Robbins et al., (2006) claim that only a limited amount of research has been carried out so far to investigate the cause-effect relationship with the uncertainty of call arrivals. The uncertainty with calls subsequently results in a highly variable demand of resources generally expressed in terms of call forecasts. These are typically comprised of varied call arrival distributions and service time distribution. This in turn requires forecasting and queuing models to play an important role in modeling resource deployment decision (Aksin et al., 2007).

The researchers Aksin et al. (2007) presented the ideas of Weinberg, Brown, and Stroud (2007) who had proposed a multiplicative effects model using Monte Carlo Markov Chain (MCMC) methods for forecasting Poisson arrival rates for short intervals of time during intraday forecasting. The researchers claimed that their multiplicative effects model is quite valuable from an operational perspective and is able to forecast Poisson arrival rates in conjunction with agent scheduling and performance enhancement models. In addition, the researchers analysed the Singular Value Decomposition model from the works of Shen & Huang (2008) that would be able to forecast more accurately and less computationally intensive than the multiplicative effects model of Weinberg et al. (2007). They further claim that MCMC method is computationally complicated for calculating call forecasting.

According to Aksin et al., (2007) in call centers' there is an increasing expectation from managers to deliver both low operating costs and high service quality. To achieve a balance between cost and quality, the call center demands for a right schedule of agents and it seems to be a challenging task. In addition, determining an optimal (or near-optimal) schedule of agents has raised a significant combinatorial complexity (Aksin et al., 2007).

2.3 Prediction Methods

This section brings out five different ranges of predictions methods.

1) Multivariable Regression
2) Multi-layer Perceptrons
3) Dynamic Evolving Neural-Fuzzy Inference System (DENFIS)
4) Transductive Fuzzy Inference
5) Global and Local Inference Method

2.3.1 Multivariable Regression

Multiple Linear Regressions is one of the methods of multivariate prediction methods. MLR performs least squares fit on multivariate data. The method takes a data set that has several input variables and one output variable (from a continuous time series values) and finds an equation that approximates the data samples that can fit in linear regression. The generated regression equation will be used as a prediction model for new input vectors. The mathematical description of MLR is given in Chapter 3.

2.3.2 Multi-layer Perceptrons

Multi-layer Perceptrons (MLP) is a network of simple neurons called perceptrons, and are standard neural network models for learning from data at a non-linear function that discriminates (or approximates) data according to the output labels (values).

MLPs are trained with the use of the back-propagation algorithm developed by Rumelhart and it assists to solve supervised learning problems (Kasabov, 1996). According to the researcher Honkela (2001), the MLP algorithm consists of two steps. In the forward pass, the predicted outputs corresponding to the given inputs are evaluated as shown in Equation 2.1, which implements the single hidden layer.

In the backward pass, partial derivatives of the cost function with respect to the different parameters, which are propagated back through the network.

The signal flow graph of MLP as shown in Figure 10 on page 33, (as adapted from researcher Honkela (2001) who referred works of Haykin (1998)) represents MLP implementing the single hidden layer. The perceptron computes a single output from multiple real-valued inputs by forming a linear combination according to its input weights. It uses one or more hidden layers of computation nodes, and then possibly puts the output through some nonlinear activation function (Retrieved from sub-section "Multilayer Perceptrons" from the thesis work of researcher Honkela (2001)). The whole process of MLP is iterated until the weights have converged (Haykin, 1998).

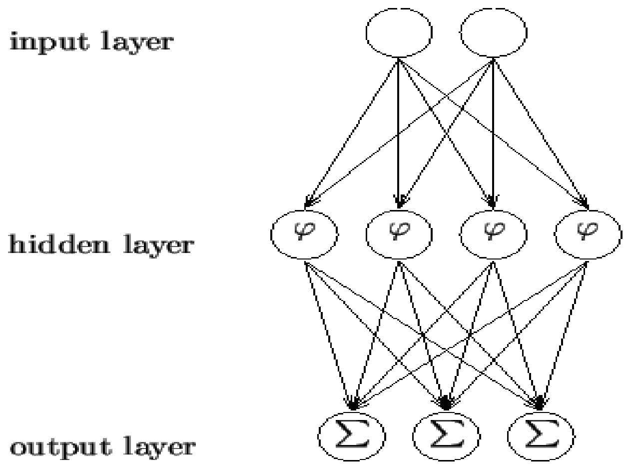


Figure 10. Signal flow graph of MLP

$$x = f(s) = B\varphi(As + a) + b \qquad \ldots (2.1)$$

where,

s=input vectors

x=output vectors

A= weight matrix of first layer

B=weight matrix of second layer

φ= element wise nonlinearity

a=bias vector of first layer

b=bias vector of second layer

φ Non-linear activation function

Σ Linear function

2.3.3 Dynamic evolving neural-fuzzy inference system (DENFIS)

The dynamic evolving fuzzy interface system is a local method used for adaptive on-line and offline learning, and its application for dynamic time series prediction (Kasabov & Song, 2002) uses Takagi-Sugeno type of fuzzy inference method (Kasabov, 2003, pg 107-109). The inference engine of Takagi & Sugeno (1985) is based on '*m*' fuzzy rules as shown in equation (2.2),

$$\begin{cases} if\ x_1\ is\ R_{11}\ and\ x_2\ is\ R_{12}\ and ... and\ x_q\ is\ R_{1q}, then\ y\ is\ f_1(x_1, x_2, ..., x_q) \\ if\ x_1\ is\ R_{21}\ and\ x_2\ is\ R_{22}\ and ... and\ x_q\ is\ R_{2q}, then\ y\ is\ f_2(x_1, x_2, ..., x_q) \\ ... \\ if\ x_1\ is\ R_{m1}\ and\ x_2\ is\ R_{m2}\ and ... and\ x_q\ is\ R_{mq}, then\ y\ is\ f_m(x_1, x_2, ..., x_q) \end{cases}, \quad \text{… (2.2)}$$

where, "*xj* is R*ij*", *i* = 1, 2 … *m*; *j* = 1, 2 … *q*, are *m* × *q* fuzzy propositions as *m* antecedents form *m* fuzzy rules respectively.

In addition, all fuzzy membership functions in on-line and off-line DENFIS models depend on the three parameters, a, b, c, as given in equation (2.3)

$$\mu(x) = mf(x, a, b, c) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{cases} \quad \text{… (2.3)}$$

where,

x – Input Variables

Y – Output variable

R – Matrix of input vectors

b – Value of cluster centre on the variable x dimension

$a = b - d$ x Dthr (distance threshold of clustering parameter)

$c = b + d$ x Dthr

d =1.2 ~ 2

There are three kinds of fuzzy inference systems as generated by output functions. If the generated function values are constants, $f_i(x_1, x_2, ..., x_q) = c_i$, $i = 1,2,...m$ we call such as system as Zero-order Takagi-Sugeno type fuzzy inference system. If the consequent function values are linear then the system is called as first-order Takagi-Sugeno type fuzzy inference system. In addition, if the functions are non-linear, it is called high-order Takagi-Sugeno fuzzy inference system (Kasabov & Song, 2002).

For an input vector $x^{\circ} = [x_1^{\circ}, x_2^{\circ}, ..., x_q^{\circ}]$, the results of inference y° (the output of the system) is the weighted average of each rule's output indicated in equation (2.4) & (2.5) as follows:

$$y^{\circ} = \frac{\sum_{i=1}^{m} \omega_i f_i (x_1^{\circ}, x_2^{\circ}, ..., x_q^{\circ})}{\sum_{i=1}^{m} \omega_i} \qquad \dots (2.4)$$

$$where, \omega_i = \prod_{j=1}^{q} \mu Rij(x_j^{\circ}); i = 1,2,...m; j = 1,2,...,q. \qquad \dots (2.5)$$

DENFIS incorporates the process of continuous learning in order to adapt to the new features from the dynamic change of data so that it can forecast the dynamic time series prediction efficiently. DENFIS can effectively learn complex temporal sequences in an adaptive way and outperform some well-known, existing models (Kasabov & Song, 2002).

2.3.4 Transductive Fuzzy Inference

In transductive systems, a local model is developed for every new input vector, based on a certain number of data that are selected from the training data set and the closest to this vector. The TWNFI method not only results in a "personalized" model with a better accuracy of prediction for a single new sample, but also depicts the most significant input variables (features) for the model that may be used for a personalized medicine (Song & Kasabov, 2006).

According to Vapnik (1998) the transductive fuzzy inference models overcome the drawbacks with inductive reasoning models, rather than making approximates of the whole data space they concentrate on single point of space creating personalized models.

In addition, the individual (personalized) model represents a single point (vector, patient record) of problem space using transductive reasoning. The personalized models have the capability to add new variables if there is a data for them (Kasabov, 2007).

Bringing the concept of Transductive inference from the works of researchers Song & kasabov (2006, pg 1). "For every new input vector x_i that needs to be processed for a prognostic task, the N_i nearest neighbours, which form a sub-data set D_i, is derived from an existing data set D. If necessary, some data in D_i can also be generated by an existing model M. A new model M_i is dynamically created based on these samples as shown at Figure 11 in page 36. This new model is then used to calculate the output value y_i for the input vector x_i".

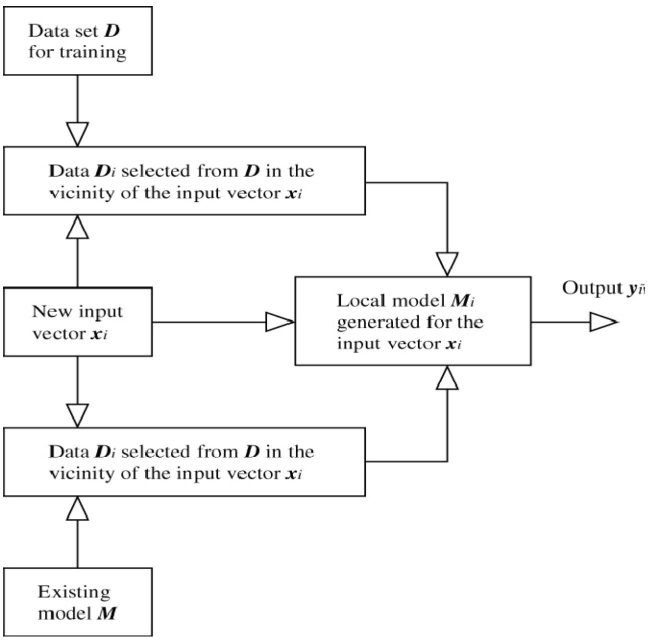


Figure 11. A block diagram of a transductive reasoning system

The problems such as predicting time series or a target day for share market index, or predicting individual data vectors in medical applications (e.g. individual patient's medical conditions in a certain point of time), all need the application of transductive fuzzy inference model, which in turn creates personalized models for each individual data vectors (Song & kasabov, 2006).

2.3.5 Global and Local Inference Method

According to researcher Kasabov (2007), there are three approaches to classify the call prediction models

1) Global Modelling
2) Local Modelling
3) Personalized Modelling

(1) Global Modeling

A global model is an approach, which covers the whole problem space and is represented as a single function for the entire data set, e.g. a Multiple Linear Regression (MLR), a neural network of Multi Layer Perceptron (MLP) etc. (Kasabov, 2007). However, according to Song & Kasabov (2006) the inductive learning approaches and inference approaches are useful when a global model of the problem is needed even in its approximate form.

(2) Local Modeling

A local model represents a sub-space of the data set (e.g. a cluster) of the problem space. For example, dynamic evolving fuzzy interfaces system (DENFIS) (Kasabov, 2007), and Evolving Fuzzy Neural Networks (EFuNN) (Kasabov, 2001) models can used to represent local modeling approach.

The local models allow for adding new inputs and/or outputs at any time of the system operation (Kasabov, 2001). The local models are derived through continuous learning processes and knowledge accumulated through evolving approaches. The local learning procedure and the local normalized fuzzy distance using Euclidean distance method and Gaussian membership function will derive evolving learning in EFuNN (kasabov, 2003). This way of learning is typical for humans who always use new sources of information and add new input variables, classes, and concepts in a continuous manner (Kasabov, 2001).

(3) Personalized Modeling

While looking at the concept of transductive inference and works of researchers Song & kasabov (2006), Kasabov (2007) and Vapnik (1998) the personalized model can be applied to call centers as time series prediction. This concept generates strength to perform personalized call prediction to each individual data vectors (agents) in the call center.

In a call center as the number of agents increases it will bring in an increase in skills, availability and other constraints. This kind of events leads to combinatorial nature type of problem (Voudouris, Dorne, Lesaint & Liret, 1926). In addition, according to these researchers Heuristic search methods are efficient for solving optimisation and NP-Hard problems where near-optimal solutions are acceptable. However, according to Ernst, Jiang, Krishnamoorthy & Sier (2004) Metaheuristics, is rather a better approach, to solve the problems that cannot be solved by Heuristic search methods. Metaheauristics combines the goodness of all flavors of methods such as machine learning, neural networks, genetic algorithms, greedy random adaptive search procedure (GRASP) etc. under one roof.

While the researchers Zeltyn & Mandelbaum (2006) suggest that to overcome the operational service challenge of service quality to the management of a call center, the Skills-Based Routing (SBR) decisions can solve the matching of agents to the customer needs. In addition, according to Koole (2006) complex problems such as multi-skill based routing is trivial for any call center; and the models available are (1) Monte Carlo simulation, whereby the uncertainty problem is solved by repeatedly performing an input and output and taking an average for the solution based on the mathematical equation and will give an appropriate solution. (2) Discrete event simulation, to simulate a system that evolves over time and the visual tools can show the happening of an event and will be focused on driving towards taking corrective actions.

Considering the trivial problem experienced because of multi skill based routing, and to deal with computational effort of the resource-scheduling problem, the current research proposes the personalized prediction method. The personalized prediction method is based on predicting calls based on personalized streams for each available agent/s. The researchers Ernst et al. (2004) suggest that in a call center, all the agents will have different call-handling skills and the modern call centers should consider the agents skills to assist staff scheduling solutions. The personalized prediction method proposed in this research considers the specialized skills of agents for call predictions. The proposed method will later concentrate on two models (1) The software call broker and (2) The supervised call broker model that assist brokers to perform intelligent search strategy for call routing and to solve the problem. Additionally, the personalized prediction will complement the efforts to solve the matching of appropriate agents to the customer needs and simultaneously improve the service quality of the call center.

2.4 Summary

2.4.1 Importance of agent selection

According to Andrews & Parsons (1993), understaffing can lead to excessive queue times, which cause trunk-connect charges to increase dramatically. Overstaffing incurs the obvious extra penalty of increased direct labour costs for the underutilized pool of telephone agents on duty. To improve the service quality, the next best option available to the manager is to employ new agents to the call center. According to researchers, it costs $6,300.65 to recruit a new agent (Anton, 2001) and a total cost of $21,551 if an agent leaves his job (Hillmer, S., Hillmer, B., & McRoberts, 2004). Therefore, it is quite important to best utilize the available agent. For an arriving call that finds one or more appropriately skilled agents free, one must decide to which agent the call should be routed if any. Often these are dubbed call-selection and agent-selection problems (Gans, Koole & Mandelbaum, 2003).

2.4.2 Proposed- Supervisor involvements

In a real time scenario, the agent information is highly volatile and dynamic as staffs come in and go at regular intervals of time. The involvement of supervisor can increase the efficiency of the system by adding real time data. The supervisor will monitor and evaluate the performance of the agent and update the system frequently. This will help the system to perform heuristic search efficiently to allocate an agent to the customer. Constant monitoring by call center supervisors and continuous feedback from customers regarding perceptions of the service and the Customer Service Representatives' (CSR) are recommended to aid in ensuring the most appropriate service level for the firm's customers (Froehle, 2006).

In addition, the performance evaluation by a supervisor actually works. From the observations of Fujitsu Service, valuing the expertise and skills of an agent coupled with the support of their managers helped them to perform higher level of tasks and enabled them to release the energy and potential of the whole organization (Marr & Parry, 2004). From these observations, supervisor involvement could be able to increase customer satisfaction by 20%, employee satisfaction by 40% and reduced operating costs by 20%.

Through a querying interface, a call center supervisor with no statistical expertise can ask "what if?" questions of call center data to identify hidden patterns that can point to operational and customer service problems. Once these patterns are identified, the supervisor can immediately listen to the associated voice recordings to drill down to the source of the problems (Dilauro, 2000).

The supervisor with his performance evaluation - while monitoring the calls on live and while liaising with the customer can estimate the performance of an agent. The realisation will provide a solution for selecting an agent who is efficient and smart enough to take the calls in any circumstances. The front line staffs actually do the work, and a chosen agent is able to accept the challenges and perform the task better.

According to Froehle (2006) the supervisor will look for the quality measurement factors with the service of agents. The following list gives the service criteria and measures of customer satisfaction.

$X1$ – Courteous-How courteous was the agent?
$X2$ – Professional-How professional was the agent?
$X3$ – Attentiveness- How well did the agent “listen” to you?
$X4$ – Knowledgeable-How knowledgeable was the agent regarding your Issue?
$X5$ – Prepared-How informed and prepared was the agent regarding you, your account, and your previous communication [with the firm] (if any)?
$X6$ – Thorough- How thorough was the agent in addressing your needs?

Y – Customer Satisfaction- How well did your customer service experience match your expectations?

Solution quality: This is based on the weighted historic customer solutions provided by an agent, Telephone Service Factor (TSF) and the actual solution date as compared to the original commit time given by the system. The solution quality scores as proposed by Paprzycki et al. (2004) can be used for converting the scores into final evaluations.

Not met score < 2
Met some score >= 2 and score < 3
Met score >= 3 and score < 4
Exceeded score >= 4 and score < 4.75
Far exceeded score >= 4.75

Chapter 3 Personalized Call Center Traffic Predictions

3.1 Introduction

The occurrence of traffic jam in Telecom New Zealand was observed in chapter 1.This chapter brings out an analysis of “Traffic jam call volume and approaches to call center prediction”.

The analysis of raw data has shown some interesting patterns with the distribution of calls during the period of traffic jam. Examination of 10 days of data has shown a major shift on the call flow into the call center and is considered as an abnormal distribution of data. The severity of the abnormal call volume has generated a problem to understand and further analyze the impact of abnormal distribution of calls on the service factors and performance of a call center. Section 3.3 explains the problem definition and the approaches to model experiments for traffic jam call predictions.

The elements of research involves use of case study, statistical analysis and sampling methods and experimental research methodology for performing research which will focus on critically analyzing data through rigorous research which will ultimately benefit the management of call centers and especially to Telecom New Zealand Limited.

Analysis of traffic jam data using valid modeling techniques (e.g. Multiple Linear Regressions, Dynamic Evolving Neuro Fuzzy Interface System, and Multi-Layer Perceptron), sampling methods (sequential and random) and Normalization methods presented dissimilar results. To investigate this abnormality in the outcomes and to discover its cause and effect relationship was a motivation for performing a “constructive research” as a process of knowledge creation. A multivariate model has been applied to forecasting the data. This idea is backed up by Vlahogianni, Golias & Karlaftis (2004) who used the multivariate approach for simultaneous forecasting of more than one variable. In addition, researchers Whittaker, Garside &

Lindeveld (1997) focused on the importance of multivariate model approach using neural network approach when using more than one variable as input.

The research outcome will measure the performance of the proposed methods. The prediction accuracy is defined as the accuracy of forecasted values to the actual values. The Root Mean Square Error (RMSE) of predicted values is used as a statistical comparison and as a means to measure prediction accuracy.

This chapter is organized in the following manner. It initially brings out the importance of agent skills information to generate a personalized model. Then it describes how the analysis of traffic jam was performed and articulates the problem. It introduces the Personalized Prediction method for call prediction during traffic jam period and finally explains the importance of introducing personalized prediction method to the normal traffic period.

3.2 The Importance of Agent Information and Personalized Broker modeling

The analysis of call forecast at Telecom New Zealand call center during the 10 days period of traffic jam, as shown in Table 1 at page 44, reveals that the TNZ is able to predict 3717 calls as compared to the 4474 actual calls on the first day of traffic jam. This observation implies that 757 calls went unpredicted. In addition, 976, 1459, 1474 and 1176 calls were not predicted on 2^{nd}, 3^{rd}, 4^{th} and 5^{th} day of traffic jam; and this unpredicted calls brought an immense pressure on the agents and to the management of call center. Since, the available number of agents cannot be altered in a short period of time; it will be a challenging task for the management to utilize the available agents in a better way. This is required so as to handle the unpredicted calls with maximum efficiency which, in turn increases customer satisfaction.

The consideration of agent skills will be a key factor which can handle the happening of traffic jam event. So, while performing call predictions, introducing a personalized model that includes agent skills information can boost the performance of a call center. “The Proposed Prediction Method” in section 3.5 presents a further analysis of the personalized model.

Traffic Jam Days	1	2	3	4	5	6	7	8	9	10
TNZ forecast For 24hrs	3753	3617	2148	1676	3959	3784	3838	3734	3616	2131
TNZ forecast for 7am-11pm	3717	3493	2107	1648	3935	3767	3789	3701	3583	2108
Actual calls for 7am-11pm	4474	4469	3566	3122	5111	4196	3871	3613	3284	3264

Table 1. Comparison of TNZ forecasted Vs Actual call Values

3.3 Traffic Jam Problem

For a better analysis of traffic jam and its impact on service quality and efficiency of agent's performance, the problem investigation will focus on service factors prediction as an approach to defining problem of traffic jam.

The experiments will forecast the following service factors - Average Work Time (AWT), calls abandon and Telephone Service Factor (TSF). These forecasts will be generated using the following methods: Multiple Linear Regressions (MLR), Multi-Layer Perceptrons (MLP), Dynamic Evolving Fuzzy Interface Systems (DENFIS), and TNZ experience (TNZ Exp).

The problem under investigation is how well the experiments can forecast service factors during the period of traffic jam for Telecom New Zealand call prediction. As a part of analysis of the problem investigation, the performance of predicted values will be compared with actual values, analyzed and evaluated with the benchmarks of TNZ call center's service factors. The analysis will indicate a summary of statistics of RMSE of forecasted service factors.

The approach of building solutions will highlight:

1) The importance of Agent skill information in the proposed Personalized Model
2) Traffic Jam call predictions

3.3.1 Traffic Jam Relevant Datasets

To investigate the problem of traffic jam; this section explores the approach, methods and experimental set up for the study of traffic jam occurrences in a call center.

To understand a shift pattern analysis of normal to traffic jam call volume, the training dataset consists of 10 days of call interval data prior to traffic jam period and the test dataset consists of first 2 days of traffic jam call interval data. i/puts and o/puts for prediction.A legitimate comparison data from 07:00 am and until 23:00 pm with 15 minutes interval is considered for practical investigation. The attributes (V3-V12) as shown in Table 2 on page 45 were initially selected for performing experimental analysis of problem definition.

Date	Interval	Calls Entered	Calls Answered	Calls Abandon	Avg Agents	ASA	AWT (IB&OB)	AWT IB	AWT OB	Avg NR	TSF
V1	V2	V 3	V 4	V 5	V 6	V 7	V 8	V 9	V 10	V 11	V 12

Table 2. Attributes in data set

The experimental results at section 3.3.4 will bring out the analysis of attributes and the impact of V5, V9 and V12 attributes on service factors of TNZ call center. For predicting Calls Abandon (V5) the inputs would be V3,V4,V6,V7,V8,V9,V10,V11 and V12; and for predicting V9 the inputs would be V3,V4,V5,V6,V7,V8,V10,V11 and V12; and for predicting V12 the inputs would be V3,V4,V5,V6,V7,V8,V9,V10 and V11. Section 3.4 discusses about a further data analysis with cross-correlation of attributes to highlight the strength of attributes during normal and traffic jam call distribution of data. The strength of attributes will later emphasize the importance of feature selection and their role in assisting call volume prediction and building solutions for traffic jam problem.

3.3.2 Handling Missing Values

To preserve the features of missing values the researchers Saar-Tsechansky & Provost (2007) proposed several alternative methods for further analysis such as

1) Acquire missing values
2) Discard Instances
3) Imputation

For Telecom New Zealand, all the call volume data comes from an online queue system and if there is a missing value it is not possible to re-acquire the original data from the source. A better approach would be to perform a missing value treatment.

There are some missing values in the Traffic Jam data and discarding those instances will cause an adverse affect on the strength of factors which in turn will impact the effects of traffic jam. Hence, in order to preserve the features of attributes the method of Predictive Value Imputation is considered, whereby the mean values of three days of call data prior to the missing day value and at the same interval of time are considered to replace the missing values in the data sets.

3.3.3 Parameter set up for Existing Prediction methods

The following section gives a parameter set up for different prediction methods to conduct an investigation of the traffic jam problem.

Multi Layer Perceptron(MLP)	No of Hidden Nodes	Iterations	Output value precision	Output function precision
Calls Abandon	600	1000	0	0
AWT	600	1000	0	0
TSF	500	1000	0	0

Table 3. Parameter Selection for Training data set (1)

DENFIS	Distance threshold (Dthr)	MofN	Epochs
Calls Abandon	0.1	4	20
AWT	0.2	4	20
TSF	0.1	4	20

Table 4. Parameter Selection for Training data set (2)

where,

a) Distance Threshold (Dthr): determines the maximum radius of the rule nodes in the network
b) M-of-N: determines the number of nodes which are referenced to estimate the output of the current sample

c) Epochs: is the number of iterations used to train or retrain the network originally.

The selected parameters as shown in Table 3 and Table 4 on page 46 have given good prediction accuracy and lower root mean square error values on the training data set.

3.3.4 Traffic Jam Prediction using Existing Methods

This section will perform experiments which will predict values for calls abandon, average work time and telephone service factors during the traffic jam period and will help in problem definition. According to Koole (2006) considering calls abandon, TSF, AWT as service factors will help evaluate the Service Level (SL) in a call center. In addition these factors will generate a psychological perception in the minds of customers on how bad the call center is managed.

(1) Calls Abandon Prediction

The experimental results for calls abandon prediction from Figure 12 on page 48 and Table 12 in the appendix reveals that the methods DENFIS, MLR, MLP and TNZ Exp would be able to predict 392, 286, 203, and 188 calls respectively for the actual value of 744 calls on day one of traffic jam, with an accuracy of 52.69 %, 38.44 %, 27.28 % and 25.27 % respectively. The evolutionary approach of DENFIS has shown some good prediction at the beginning followed by MLR with respect to dynamically changing of data as the calls abandoned jumped from 92 to 744. MLP and TNZ Exp couldn't react with the same proportion of prediction. Additionally, if the values for 24 hours were considered, the actual values of calls abandon are 760 and 775 for the 11th and 12th day respectively. While looking at the overall calls abandon prediction for first two days of traffic jam none of the methods could be considered as a strong winner to predict correctly.

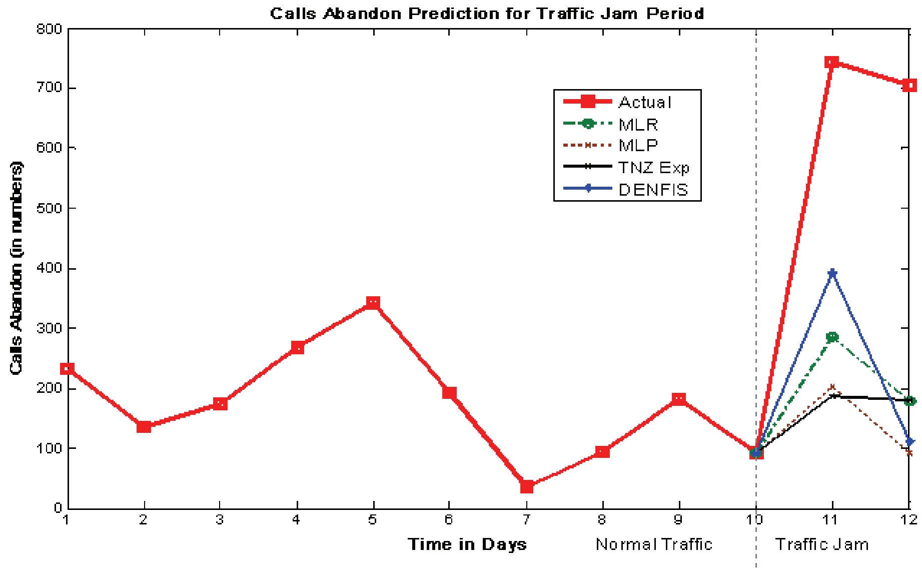


Figure 12. Calls abandon prediction during Traffic Jam

(2) Average Work Time Prediction

A comparative study of AWT predictions from Figure 13 on page 49 and Table 12 in the appendix has shown predicted values of 442, 433, 450 and 472 calls using the methods of MLR, DENFIS, TNZ Exp, and MLP respectively for the actual value of 441 calls. The performance analysis shows that MLR has an approximate forecast accuracy of 100%, while TNZ estimate has one of 97.96% which is well within the service threshold of TNZ. However, if the AWT values for the total day (of 24 hours) are considered, the actual values are 426 and 394 for the 11th and 12th day respectively of the traffic jam period. Using TNZ the obtained forecasted to an actual value percentage are 94.37% and 91.12 % which is well below the threshold value of (95%) of TNZ impacting the service factors of call center. DENFIS and MLP made an accuracy of 98.19 and 92.97% for the predicted outputs

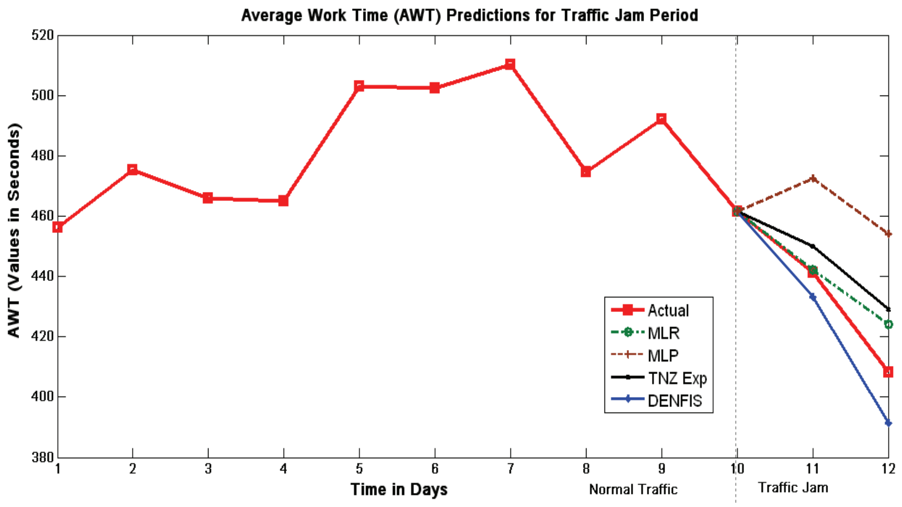


Figure 13. Average Work Time predictions

(3) Telephone Service Factor Prediction

The results of telephone service factor prediction experiments from Figure 14 on page 49 and Table 12 in the appendix, shows that MLR, DENFIS, TNZ Experience and MLP methods have predicted TSF values of 0.68, 0.77, 0.80 and 0.81 respectively for the first day of traffic jam period as compared to the actual value of 0.70 with an accuracy of 97 %, 90 %, 86 % and 84 % respectively.

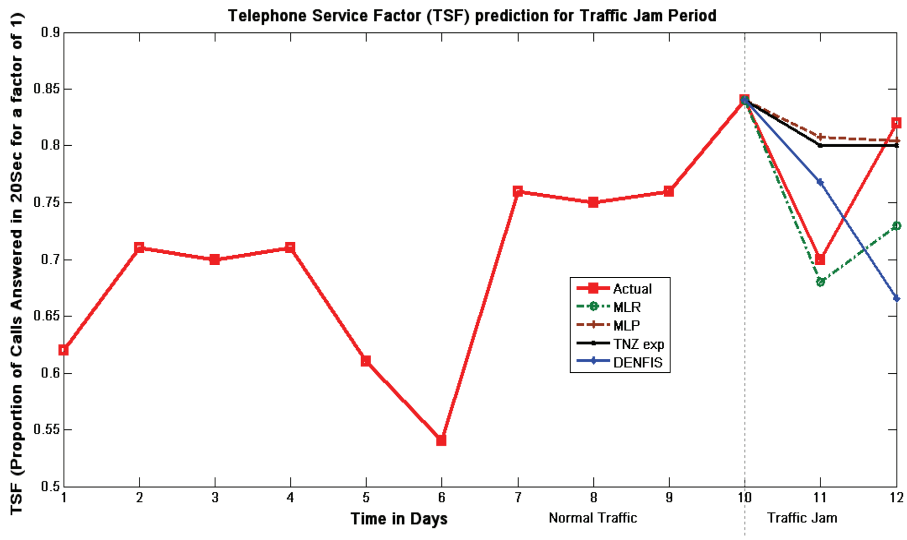


Figure 14. Telephone Service Factor predictions

While analyzing the data sets, it is observed that the attributes have varied data ranges and the RMSE comparison is done for each output series individually. The TSF has a data range between (0 & 1), whereas AWT has (390-473) and Calls Abandon ranges between (92- 744). A comparative study from Table 17 in appendix shows that DENFIS has a lower RMSE of 12.60 when compared to forecast calls abandon where as MLR has lower RMSE of 57.44 with regards to forecast AWT and MLP has lower RMSE of 0.19 to forecast TSF. The analysis shows the performance of methods with respect to service value forecasts while dealing with abnormal trend of data.

From the analysis of experimental results it is summarized that the service factors of TNZ were badly affected by the occurrence of the traffic jam event, and the company's expectation has not correlated with the actual values as it is evidenced with one of highest RMSE values for prediction of service factors. It is evident from the investigation that none of the methods has actually brought good prediction with regards to the actual values. Hence, it can be concluded from the analysis that even powerful software's and good prediction methods cannot accurately predict the occurrence of traffic jam events or abnormal distribution of data.

3.4 Data Analysis and feature selection

This section will bring in a comprehensive data analysis and will evaluate the correlation among the attributes, distribution of data and analyze the factors for traffic jam. As evidenced in section 3.3.4, predictions of service factors during the period of traffic jam has brought up an analysis of how the attributes, calls abandon, average work time and telephone service factor has made an impact on the abnormal calls during the traffic jam. The following sections initially focus on a comparative analysis of attributes using coefficient of cross-correlated attributes; which will enhance the strength of factors affecting traffic jam. Later, it examines a comparison with the strength of correlated attributes during events of normal and traffic jam period.

3.4.1 Comparative analysis of coefficient of Cross Correlated attributes during Traffic Jam

This section examines an analysis of attributes during the period of traffic jam, the tables and figures are found in section B of the appendix and a summary of the values are shown at Table 5 on page 54. Analyzing the attributes calls entered and calls answered has shown a strongest correlated value of 0.868 at Lag 0 which is at current period of time and it has a least strength of correlation (0.327) at Lag 7 which is 105 minutes (7x15) interval ahead to the current period of time. These figures imply that there could be only 0.327 calls which can be answered at Lag 7. The attributes calls entered and calls abandoned have a strong correlation of 0.555 at Lag 0, and the next strongest correlation is at Lag 1 (0.527) which is 15 minutes ahead of current period of time.

Definition of Lag: A Lag is based on transformation, whereby it brings the past values of a series into the current case. The case prior to the current case is a lag of -1; two cases prior to the current case is a lag of -2; and so on. The lag order is the number of cases prior to the current case from which the value is obtained. The number of cases with the system-missing value at the beginning of the series is equal to the order value.

The cross-correlation between average agents and the calls entered was strongest at Lag 1 (0.541) which is 15 minutes prior to the current period of time whereas at Lag 0 the correlation is reduced to 0.538. The analysis shows that even though the call volume is increasing at an alarming rate there is comparatively a lesser number of agents to handle the calls at the current period of time.

The agents are performing better to maintain a strong correlation with calls answered as observed with a strong correlation of 0.760 at Lag 0. However, while considering the correlation of average agents to telephone service factor (V12), the correlation is quite weak as is evidenced from 0.415 at current period of time (Lag 0). This implies that 58 % of the total calls were answered beyond the service benchmark of TSF as it says 80% of calls were to be answered in a period of 20 seconds. In addition, the correlated strength was higher at Lag 7 which was 0.570. The reason for this is due to higher calls abandon which can be evidenced with -0.535 correlations between calls abandon and TSF at the current period of time (Lag 0). Due to a decreasing strength of correlation between average agents to calls entered eventually brought the correlation of average agents to TSF quite low, however while comparing with 7 lags prior (Lag 7) the strength of correlation of TSF to average agents is better among all the lags and stands at 0.418.

One more reason of higher calls abandon (V5) is due to a longer average speed of answer (V7) by Interactive Voice Response (IVR) system at the Automatic Call Distributor (ACD) queue. It can be evidenced with 0.731 as higher strength of correlation at Lag 0. The correlation between average agents and ASA (V6 and V7) showed almost a constant correlation as can be evidenced with -0.339 (Lag 0) and -0.333 at Lag 1. This implies that the strength of ASA is increasing for current period of time while the number of available average agents is constant which eventually ends up with more calls to be abandoned and finally affects TSF. In addition, it can be evidenced from a weaker correlation of average agents to TSF. 0.415 at Lag 0 as compared to 0.570 at Lag 7 causes ASA to increase and generate a strong correlation of -0.802 with TSF at the current period of time.

During the traffic jam period an increase in calls entered by a factor of 1 will need an increase of average agents by a factor of 0.538 otherwise calls abandon might increase by 0.555; which in turn will increase ASA by a factor of 0.225 and will eventually end up causing customers to have a longer waiting time in the queue than getting answered by an agent and thus cause TSF to decline by a factor of -0.221. In addition, an increase in call volume will make an agent to go in a not ready state (as agents will be stressed) and will eventually decrease the calls to be answered by a factor of -0.179 and finally, the efficiency of the call center will be adversely affected.

The cross correlation analysis brought a comparative analysis of main attributes which are calls abandon, telephone service factor, average work time and other correlated factors which impact customer service levels during the period of Traffic Jam.

To summarize, an increase in number of calls (V1) by a factor of 1 has an adverse impact factor of 0.555 on calls to be abandoned (V3); while calls abandon has a negative impact on telephone service factor (V12) as an increase by 1 factor will eventually decrease TSF by a factor of -0.535. In addition, if average speed of answer increases by a factor of 1, it will shoot calls to be abandoned with a factor of 0.731 and decrease TSF by a factor of -0.802. As a shorter ASA by IVR system at ACD queue represents a higher service quality and eventually leads to a higher customer satisfaction. If not ready (V11) of agents increases by a factor of 1 will increase Average Work Time-In Bound (AWT-IB) by a factor of 0.621, and in addition if number of agents (V6) increase by a factor of 1 will enhance TSF by a factor of 0.415. In addition, according to SPSS (2008) cross correlation brings a good analysis among the attributes in a data set.

3.4.2 Analysis on strength of correlated attributes

This section discusses a comparative analysis with the strength of correlated attributes during normal and traffic jam period.

An increase of calls entered by a factor of 1 will increase calls abandon and the strength of correlation from 0.311 (during normal period) to 0.555 (during traffic jam period). This increase of strength in correlation has an impact on correlation among calls entered and the calls answered; as evidenced with a weaker strength of correlation value of 0.868 as compared to 0.944 during the normal period of time.

The strength of number of agents to calls entered has dropped from 0.748 (normal period) to 0.538 (traffic jam period) which actually reveals the lesser number of agents to answer the calls; as can be evidenced with a decrease in strength from 0.837 to 0.760 during traffic jam period. This shift of strength has eventually increased the negative relationship (Feinberg, A. R., Kim, I., Hokama, L., Ruyter, K., & Keen, C. (2000) among agents to ASA from -0.198 to -0.339 and finally leads to more calls to be abandoned; as can be evidenced with an increased strength of correlation between calls answered to calls abandoned from 0.063 to 0.159 and eventually decreases TSF by a factor of -0.221 during traffic jam as compared to -0.158 during normal period.

Agents' not ready time has shown a marginal rise from 0.049 to 0.052 which eventually increases the strength of correlation between (AWT-IB) with NR from 0.568 (normal period) to 0.621 (during traffic jam period). In addition, a higher increase in number of calls reduces the proportion of agents to answer the calls which lead to more calls being abandoned and dropping TSF to a further 6.3%.

Attributes name	Attributes	Normal at Lag0	Abnormal at Lag0
Calls Entered - Calls Answered	V3-V4	0.944	0.868
Calls Entered - Calls Abandon	V3-V5	0.311	0.555
Calls Entered - Average Agents	V3-V6	0.748	0.538
Calls Entered - ASA	V3-V7	0.194	0.225
Calls Entered - Average NR	V3-V11	-0.007	-0.179
Calls Entered - TSF	V3-V12	-0.158	-0.221
Calls Answered - Calls Abandon	V4-V5	0.063	0.159
Calls Answered - Avg. Agents	V4-V6	0.837	0.760
Calls Answered - ASA	V4-V7	-0.021	-0.101
Calls Answered - Average NR	V4-V11	-0.027	-0.164
Calls Answered -TSF	V4-V12	-0.044	0.086
Calls Abandon - Avg. Agents	V5-V6	-0.096	-0.144
Calls Abandon - ASA	V5-V7	0.861	0.731
Calls Abandon - TSF	V5-V12	-0.680	-0.535
Average Agents - ASA	V6-V7	-0.198	-0.339
Average Agents - Average NR	V6-V11	0.049	0.052
Average Agents - TSF	V6-V12	0.232	0.415
ASA - TSF	V7-V12	-0.810	-0.802
AWT(IB) - Average NR	V9-V11	0.568	0.621
Average NR - TSF	V11-V12	-0.073	-0.012

Table 5. A comparative analysis of attributes during normal and traffic jam period

The Cross-Correlations procedure is appropriate only for time series data and it plots the cross correlation function of two or more series for positive, negative and zero lags. According to SPSS (2008), 7 lags are considered to provide enough information for the system to calculate correlation coefficient and to have enough historical data to kind of conclude how a variable is related to another variable. The cross correlation can be derived from equation (3.16) as represented in chapter 3.

3.5 The Proposed Prediction Method

The analysis of the call center problem investigation in section 3.3.4 and data analysis in section 3.4 has raised the interest to further investigate the importance of the agent information (e.g. skill grade of agent in a call center), and develop an agent personalized predication models which can enhance the capability of call broker software and boosts the performance of service factors predictions within a call center.

3.5.1 Personalized Prediction Method

Given a call center with 'm' agents, most traditional software brokers maintain one general call volume prediction, and distribute calls equally to m agents. Obviously, this is not an efficient approach because the skill of each agent is different from one another; as can be evidenced at section C of the appendix where a sample of 10 agent's skill information is pictured.

Given a data stream D , $\{c(i), c(i+1), \cdots, c(i+t)\}$ representing a certain period of historical call volume confronted by the call center, the traditional non-personalized method for call volume prediction is described as

$$c(i+t+1) = f(c(i), c(i+1), \cdots, c(i+t)), \qquad \text{… (3.1)}$$

where $c(i)$ is the number of calls at a certain time point i , f is a prediction computing method, which could be a Multiple Linear Regressions (MLR), Support Vector Machine, or any type of Neural Network for prediction. The generalized equation for function f is referred at equation (3.6).

As mentioned above, existing call centers normally run with a number of agents. The staff scheduling for call center agents is entirely based on the prediction of call volume at the next time point. In addition, the work of every agent is thus determined exclusively by the call broker software, which normally distributes calls equivalently to every agent staff.

The concept of personalized prediction constructs a personalized call prediction for every agent, such that the skill grade or the historical performance of each is considered. As an advantage, the work (i.e. calls to be answered) can be distributed to each agent in a personalized way. In addition, the entire call center is expected to have a better work efficiency since calls have been distributed according to the skill grade of every individual agent.

Suppose $S = \{S_1, S_2, \cdots, S_m\}$ represents the skill grade of m agents; S is considered as a prior knowledge of prediction, so that the above call volume is decomposed into m data streams according to S. The decomposition of data stream is modeled as,

$$d_j(t) = P(c(t), S_j, S),\ 1 \le j \le m \quad , \qquad \text{... (3.2)}$$

where, $d_j(t)$ represents calls for agent 'j'. In practice, the partitioning function P needs to consider broad skill information for every agent staff. For instance, the average daily treated calls, the average time for call treatment, and the specialized call treatment by each agent are important. In the experiments, the partitioning function P is modelled as a data partitioning model based on the skill grade of agent. The computed values of partitioning function P can be referred at Table 20 in the appendix. The personalized data stream of calls is derived as (3.3) below

$$d_j(t) = \frac{c(t) * S_j}{\sum_{i=1}^{m} S_i}. \qquad \text{... (3.3)}$$

Consider an example, on how the personalized model is generated and applied in a real time scenario. While drawing attention to section 'C' of appendix, which brings the reports on agent performance and their utilization for a sample of 10 agents at Telecom New Zealand call center. The agents' skills such as average work time, login time, their availability, not ready time and total number of calls answered were taken into consideration to calculate prioritized calls distribution to the agents. Finally, for simulated experiments the distribution of calls to 10 agents was made at priorities of 9.31%, 7.52%, 14.96%, 6.99%, 14.04%, 18.45%, 7.47%, 6.64%, 9.03%, and 5.59% respectively.

Using equation (3.3) for data partitioning and equation (3.1) for non-personalized call prediction, data stream can be treated in a personalized way as,

$$d_1(i+t+1) = f_1(d_1(i), d_1(i+1), \cdots, d_1(i+t))$$
$$d_2(i+t+1) = f_2(d_2(i), d_2(i+1), \cdots, d_2(i+t))$$
$$\cdots\cdots\cdots$$
$$d_m(i+t+1) = f_m(d_m(i), d_m(i+1), \cdots, d_m(i+t)), \quad \ldots (3.4)$$

then m data streams partitioned for f_m personalized prediction functions will initiate the personalized prediction method to be modelled as,

$$c(i+t+1) = \Omega(f_1, f_2, \cdots, f_m, S) = \frac{1}{m}\sum_{j=1}^{m} d_j(i+t+1)\frac{\sum_{l=1}^{m} S_l}{S_j}, \quad \ldots (3.5)$$

where, Ω represents a constant for f_m personalized prediction functions and equalizes to function f values as at equation (3.1)

While generating the equation for non-personalized predictions method (dPP), the equation (3.6) represents for multiple linear regressions. The generated equation using MLR will replace function f at (3.1) for performing call predictions. In addition, the equation (3.7) gives attribute values to represent (3.6)

$$Y_{dPP} = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_n + \varepsilon, \quad \ldots (3.6)$$

where:

k - Number of attributes in the data set

n - Number of rows / elements in each data set

α - Intercept (value of Y when β=0)

β - Regression coefficient

Y - Dependent variable

X - Independent variable

ε - Residual error

$\hat{Y}$ - Predicted Values

dPP – Non-personalized prediction

PP - Personalized Prediction

SP - Supervised Prediction

SCB - Supervised Call Broker Model

$$Y = \begin{pmatrix} y1 \\ . \\ . \\ . \\ . \\ yn \end{pmatrix} X = \begin{pmatrix} \propto x1,1 & x1,2 \dots x1,k \\ \propto x2,1 & x2,2 \dots x2,k \\ & . \\ & . \\ & . \\ \propto xn,1 & xn,2 \dots xn,k \end{pmatrix} \beta = \begin{pmatrix} \beta 0 \\ . \\ . \\ . \\ \beta k \end{pmatrix} \varepsilon = \begin{pmatrix} \varepsilon 1 \\ . \\ . \\ . \\ \varepsilon n \end{pmatrix} \quad \dots (3.7)$$

Assuming, the actual call values with personalized prediction and non-personalized prediction method remains the same. The equation is represented as (3.8)

$$\sum_{i=1}^{m} Y_{PP} = Y_{dPP}. \quad \dots (3.8)$$

In addition, the Personalized Prediction method gives a lower variance of predicted values with actual values as compared to non-personalized prediction method; the equation becomes,

$$(\sum_{i=1}^{m}(Y_{PP} - \hat{Y}_{PP})) < (Y_{dPP} - \hat{Y}_{dPP}) \quad \dots (3.9)$$

Using equation (3.9) the mathematical notation of residual value is derived as,

$$\varepsilon_{PP} < \varepsilon_{dPP}, \quad \dots (3.10)$$

During the experimental analysis, Root Mean Square Error (RMSE) as at equation (3.15) will be used as a method for measuring prediction accuracy and as a substitute for residual error value as shown at equation (3.10).

While generating the equation for Personalized Prediction (PP) 'm' personalized models will be generated. Hence, the function f for non-personalized predictions method (dPP) at equation (3.6) is modified as,

$$Y_{PP(i)} = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_k X_{ni} + \varepsilon, 0 < i \le m, \quad \dots (3.11)$$

the combined equation for personalized prediction method is represented as (3.12) below, which is a summation for m agents as shown in the above equation (3.11)

$$\sum_{i=1}^{m} Y_{PP(i)} = \sum_{i=1}^{m} (\alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_k X_{ni} + \varepsilon_{(i)}) \quad \dots (3.12)$$

The Supervised Call Broker Model (SCB) used at chapter 4, performs call forecasts while considering the generated equation for personalized prediction method at (3.12) and supervised predicted values represented as $\hat{Y}_{SP}$ for each agent i of total m agents. The equation is shown as,

$$\sum_{i=1}^{m} \hat{Y}_{SCB(i)t} = (\hat{Y}_{PP(i)t} + \hat{Y}_{SP(i)t})/2, \qquad \ldots\ (3.13)$$

the combined equation for personalized prediction method is represented as (3.14) below, which is a summation for m agents as shown in the above equation (3.13)

$$\sum_{i=1}^{m} Y_{SCB(i)t} = \sum_{i=1}^{m}((\alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ni} + \varepsilon_{(i)}) + \hat{Y}_{SP(i)t})/2 \; . \qquad \ldots\ (3.14)$$

The RMSE for each method of PP and dpp is performed using the equation as represented in (3.15). The mean squared error gives an average of predicted and observed values. The comparison between different forecasting models is performed over the entire set of ‘n’ observations and the subscript j = 1...n denotes the jth day in the predicted data set. Where θ_j - represents predicted values on the jth day and θ - represents actual call values. The square root of mean squared error gives the equation for RMSE as,

$$RMSE(\hat{\theta}) = \sqrt{\frac{1}{n}\sum_{j=1}^{n} (\theta_j - \theta)^2} \; . \qquad \ldots\ (3.15)$$

The cross correlation coefficient between attributes can be derived using the equation as represented as (3.16) below. The formula has been retrieved from (SPSS, 2008) .The sample correlation coefficient for attributes X , Y at lag k can be represented as,

$$r_{xy}(k) = \frac{C_{xy}(k)}{S_x S_y}, \qquad \ldots\ (3.16)$$

Where,

X, Y Sample correlation coefficient at lag n ,

S_X Standard deviation of series X ,

S_y Standard deviation of series Y,

$C_{xy}(k)$ is the sample cross variance at lag k and can be derived as (3.17) below,

$$C_{xy}(k) = \begin{cases} \frac{1}{n}\sum_{t=1}^{n-k}(x_t - \bar{x})(y_{t+k} - \bar{y}), & k = 0,\ 1,\ 2,... \\ \frac{1}{n}\sum_{t=1}^{n+k}(y_t - \bar{y})(x_{t-k} - \bar{x}), & k = -1,\ -2,... \end{cases} \quad ... (3.17)$$

3.6 Experiments and Discussion

The following sections will perform experiments of call volume predictions during traffic jam and normal traffic periods with the methods of normal prediction which will be considered as non-personalized prediction method and with the proposed personalized prediction method. A comparative study on their prediction accuracy will be subsequently analyzed.

3.6.1 Experimental Setup

The following section describes an experimental set up for traffic jam and normal call predictions.

(a) Traffic Jam call predictions setup

The traffic jam experimental set up will be given as (1) Data Sets (2) Data Normalization and (3) Experimental Approach

(1) Data Sets: The data sets consist of 40 days of call volume data between dates of 22/01/2008 till 01/03/2008. The first 30 days have a normal distribution and the last 10 days have abnormal distribution (traffic jam) data. As clarified at chapter 3, two individual data sets are created one for the first half and other for second half of the day to compute homogeneous and smooth predictions. The training data set consists of 30 days of call volume data as 30 attributes and each attribute has 32 records which consist of 15 minutes interval of call details. The testing data set consists of 29 days of call volume which is used to predict the next day's call volume. Each attribute has a similar number of records as training data set.

(2) Data Normalization: While performing call predictions, the experiments were generating some predicted values which seem to be unrealistic. In order to generate a realistic predicted value during traffic jam period, several approaches of normalization techniques were performed during the experimental analysis.

1. Normalizing the whole data set with common scaling and de-normalizes the predicted values with similar scaling approach
2. Normalize while separating the data set into two parts one for the normal distribution of data and the other for abnormal distribution of data. De-normalize the predicted value with its relevant normalized values.
3. Normalize each attribute individually with unique scaling and de-normalize the predicted values with its original normalized attribute values.

While analyzing the above three methods, the last method which is normalizing each attribute with unique scaling has given good predicted values. The other two methods experienced a drawback of incorrect scaling, as attributes which got a higher value placed an adverse impact on the attributes which has lower values.

(3) Experimental Approach: A sliding window approach is implemented to predict the next day's call volume, whereby for each subsequent day of prediction the window will be moved one day ahead. This approach will predict the call volume for 10 days of traffic jam period.

Multiple linear regressions are applied on the training data set whereby the first 29 attributes are considered as inputs and 30th attribute as output. MLR computes an equation to predict output based on 29 input attributes. For example, the application of this method works out in the following manner. If we want to predict the 31st day's call volume, the actual call volumes for 30 days prior to the predicted day will be used to train the system. The generated equation, considers the first 29 attributes as input values to predict the last attribute (30th) which is considered as the output value. Now reapplying the equation on 2nd to 30th attributes actual values will predict a value for the next day. This process of prediction continues with the approach of sliding window whereby for predicting the 40th attribute the attribute values from 9th to 39th will be inputs which will predict call volume for 10th day of traffic jam.

(b) Normal Traffic call predictions Setup

The normal traffic experimental set up will be given as (1) Data Sets and (2) Experimental Approach

(1) Data Sets: The data sets consist of 40 days of call volume data between dates of 21/01/2007 till 01/03/2007. The first 30 days will be the training data set and the last 10 days will be used as test data set. The similar period of last year's call volume data is selected as with traffic jam period to bring an appropriate comparison of normal call predictions with traffic jam call prediction.

(2) Experimental Approach: A similar experimental approach, as used in section 3.4.1 has been used while selecting two individual data sets one for the first half and the other for second half of the day, in order to obtain homogeneous and smooth predictions; normalizing data sets, selection of training and testing data sets, methods and approaches for call volume predictions.

The following section will bring the traffic jam call predictions with the methods of Personalized Prediction and non-personalized prediction.

3.6.2 Traffic Jam call predictions

A comparative study on normal and traffic jam call volume data distribution reveals that the average calls per normal day stands at 2844 calls where as during the traffic jam period the calls averages to 3898 per day which is 1054 calls higher than any normal day. These values are evidenced from the Figure 15 on page 63 as 1422 and 1949 (for half a day values).

3.6.2.1 Non-personalized predictions

The call predictions are performed based on the equation (3.6) generated by using multiple linear regressions method and applying the experimental approach as discussed before.

The analysis of experimental results for traffic jam call volume predictions as shown in Figure 15 on page 63 and Table 6 on page 64, the non-personalized prediction method could able to predict call volume for 10 days (20 half day values) during traffic jam period with an accuracy of 87, 50, 84, 62, 11, 0, 13, 98, 2, 24, 60, 49, 89, 67, 96, 39, 89, 36, 99 and 28 % respectively. With the predicted values and accuracy it can be evidenced that there is a lot of variance between computed and actual values.

3.6.2.2 Personalized Predictions

A simulated experiment was done based on equation (3.12) which resembles the real time queue system to follow the priorities while distributing the calls to the agents. The results of the experiments can be evidenced from the Figure 15 on page 63 and Table 6 on page 64.

The results for traffic jam call predictions shows that the personalized predictions method could able to predict the 10 days (20 half day values) of traffic jam calls with an accuracy of 94, 51, 83, 66, 40, 10, 55, 82, 12, 20, 55, 67, 90, 84, 97, 57, 92, 54, 100 and 56% respectively. With the predicted values it can be analyzed that personalized prediction method has generated better prediction accuracy as compared to non-personalized predictions as at section 3.6.2.1.

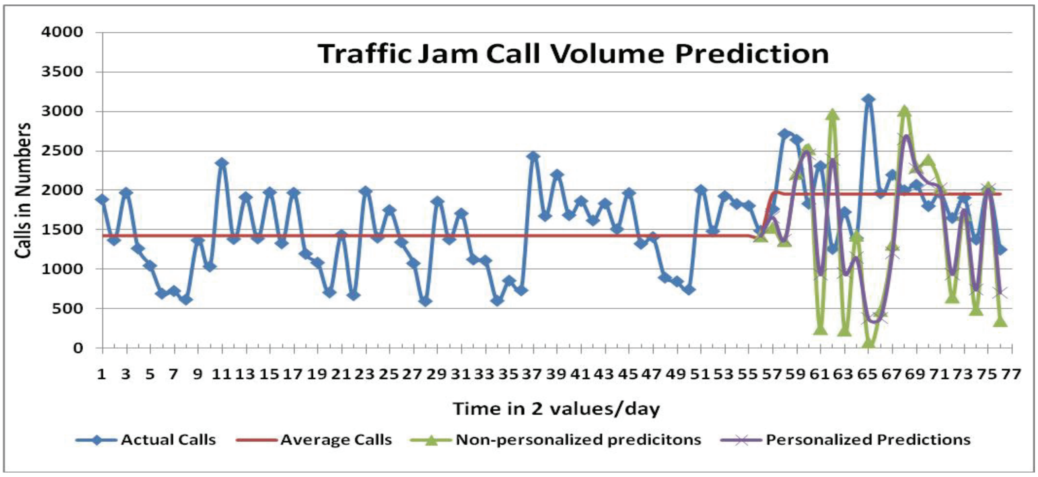


Figure 15. Traffic Jam Call Volume Predictions

Call Volume Prediction																				
Calls \ Time in Half Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Actual Calls	1763	2711	2638	1831	2305	1261	1726	1396	3149	1962	2196	2000	2070	1801	1962	1651	1906	1378	2013	1251
Average Calls	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949	1949
Non-personalized predicitons	1529	1361	2211	2522	246	2967	228	1429	77	475	1314	3011	2293	2388	2033	647	1687	490	2042	348
Personalized Predictions	1659	1374	2201	2457	933	2394	954	1148	376	383	1210	2654	2277	2096	2019	938	1755	742	2018	704

Table 6. Traffic Jam Call Prediction Values

A statistical comparison of prediction accuracy during traffic jam will be studied in the following section.

3.6.2.3 Comparison of RMSE

While bringing the RMSE as a measurement for prediction accuracy, the personalized prediction method could able to predict the call volumes with highest prediction accuracy and least variations from the actual values. Whereas non-personalized prediction method has given high variations in call volume predictions during traffic jam period.

The comparison of RMSE values as shown in Figure 16 on page 65 the personalized prediction method has an average RMSE value of 0.019 (1.9%) whereas non-personalized prediction method has 0.025(2.5%) values which show personalized prediction method is giving good prediction accuracy with low variance from the actual values.

To summarize, the proposed method of introducing agent skills information for call predictions has given good prediction accuracy with least RMSE values during traffic jam predictions. The following section will introduce the method of personalized prediction during normal call predictions and enhance the importance of introducing agent skills information for call volume predictions.

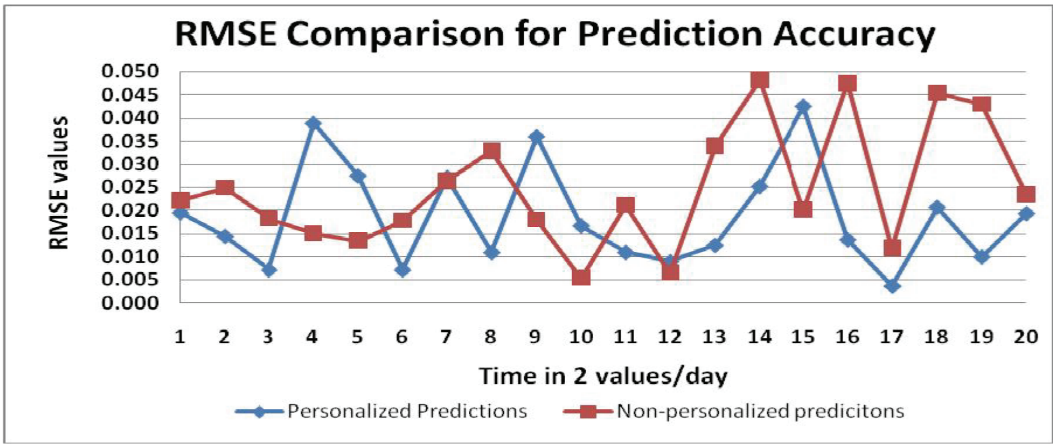


Figure 16. RMSE Comparison for Traffic Jam Predictions

3.6.3 Normal Traffic call prediction

The experiments in section 3.6.2 have emphasized the importance of agent skills during traffic jam call predictions. This section will further analyze introducing agent skills as an important factor with normal traffic call predictions. The following experiments will predict call volume data during the normal period and propose the method of personalized prediction for call forecasting.

3.6.3.1 Non-personalized predictions

The experiments are performed to predict the call volume for 10 days (20 half day values) of normal traffic period. While observing the experimental results at Figure 17 in page 66, the call predicted values using non-personalized prediction method reveals an accuracy of 48, 72, 91, 77, 90, 79, 98, 75, 31,0, 55, 99, 56, 57, 81, 96, 99, 46, 59 and 63 % respectively as compared to actual call volume.

3.6.3.2 Personalized Predictions

Simulated experiments are performed while following the strategy of real time queue system to distribute the calls based on the generated priorities. The results of the experiments to predict the call volume for 10 days (20 half day values) of normal traffic period using the method of personalized prediction can be evidenced from Figure 17 in page 66. The results show that the Personalized Prediction method could able to predict the 10 days of traffic jam calls with a prediction accuracy of 53, 72,90, 77, 90, 84,99, 77,31,0,82, 99, 57, 57,80, 93, 99, 57, 41 and 67% respectively.

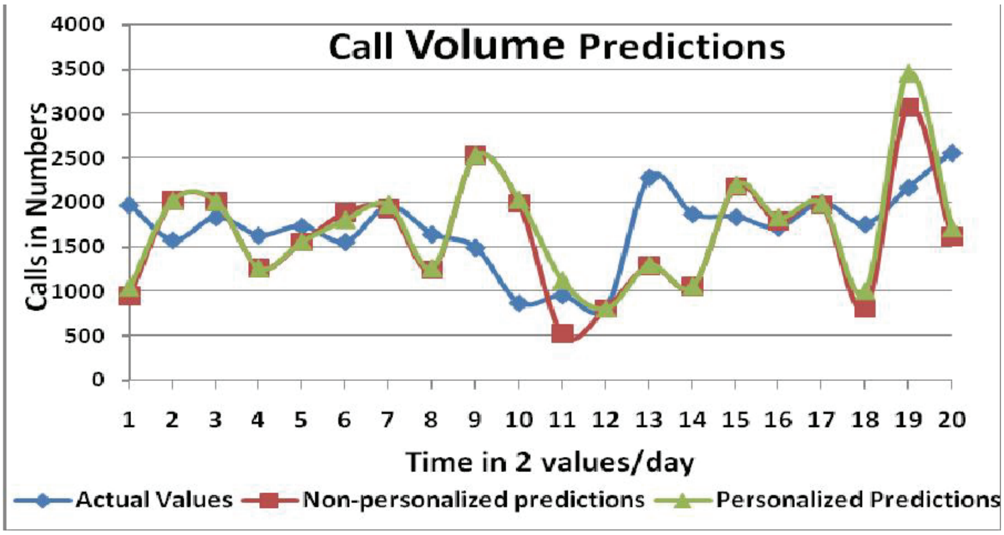


Figure 17. Normal Call Volume Predictions

3.6.4 Comparison of Personalized and non-personalized call prediction methods

While looking at the call forecasting experiments during the period of traffic jam and normal traffic periods, it is evident that introducing agent skills with the method of personalized prediction has generated a good call volume prediction with higher accuracy and lower RMSE values as compared to non-personalized prediction method.

The analysis shows that the experiments have highlighted the approaches to build a solution for traffic jam prediction and the importance of agent skill information as a personalized model for performing call prediction.

3.7 Summary

To summarize, the call volume prediction experiments have shown that the personalized prediction method has given a better prediction of calls as compared to non-personalized prediction method during normal and traffic jam period. However, the number of predicted calls has shown some variations with the actual values. The personalized prediction model can be considered as a winner for call predictions during normal and traffic jam period. The analysis of experiments draws the attention of the Telecom New Zealand management to consider inclusion of agent skills while performing call prediction for improvement of service factors in the call center.

The next chapter will bring solutions for traffic jam problem while implementing the proposed method of personalized call predictions using the following two models

1) Software Call Broker model
2) Supervised Call Broker Model

Chapter 4 Call Center Management Solutions and Traffic Jam Problem Solving

4.1 Introduction

This chapter initially examines the challenges and issues while managing a call center; and reviews the measures for service quality. Later, it discusses the solutions for traffic jam problems. Finally, a cost-return calculation with an approach towards achieving service quality as call center management solutions, especially to Telecom New Zealand call center is performed.

4.2 Call Center Management Challenges

A Call Center is a dedicated operation with employees' focusing entirely on offering customer service (Taylor & Bain, 1999). While performing business tasks a question is raised, how can we perform trade-off between customer service quality (CSQ) and efficiency of business operations (EBO)? A better customer service will bring benefits for customers such as service quality (Dean, 2002), satisfaction (Jack et al., 2006), (Gilmore & Moreland, 2000) for efficient resolutions of their problems. These will in-turn generate customer loyalty (Jack et al., 2006), (Dean, 2002), effective business solutions, revenue producer (Jack et al., 2006) and competitive market share for organization and finally bring a sort of job satisfaction (Gilmore & Moreland, 2000) to the agents for offering efficient customer solutions.

4.2.1 List of measurements of CSQ

1. Telephone Service Factor (TSF): It is a quality measure in a call center, which tells us the percentage of incoming calls answered or abandoned within the customer-defined threshold time. The quickness of calls answered or abandoned would be a usual measure of TSF. The customer specifies the time (in seconds) in the programming of the telephone system. The usual result would be a percentage of calls that falls within that threshold time. Considering Telecom NZ study, the organization has set 20 seconds as threshold time to answer a call and achieving

80% of TSF as a good benchmark for measuring quality of service in their call center. According to Saltzman & Mehrotra (2001) a sales call center may aim to have 80% of the callers wait for less than 20 seconds; and this a true factor for offering service level agreement with the customer to entice customers to purchase the rapid service option.

However, according to Andrews & Parsons (1993) considering the idea of benchmarking cannot always bring qualitative benefits to a call center. The researchers observed the rule-of-14 from a floor supervisor's perspective; and this rule says a service level target of TSF = 85 % can be achieved with 14 calls answered by an agent in an hour cannot always increase the efficiency of a call center. In addition, according to Anton (2001), organizations are struggling hard to get 80% of calls answered in 65.47 seconds. Furthermore, whilst managers continue to assess performance of agents by the quantity rather than the quality of the calls, employees will continue to become demoralised (Gilmore, 2001).

2. Average Speed of Answer (ASA): It is one of the measures of service quality in a call center, which tells us the speed of answer for calls received by Automatic Call Distributor (ACD) queue and ends when an agent answers the call. The timing for answering the call is an important measure for looking in to the service quality. According to Shu-guang et al. (2007), TSF and ASA are the two important service quality metrics of telecommunication call center, as a smaller ASA represents a higher service quality and leads to a higher customer satisfaction. According to Anton (2001), call centers have an ASA of 39.23 seconds based on 400 organizations data. For instance, while calculating ASA, a call center staff of 12 taking 80 calls per hour with AHT of 7 minutes can deliver an average speed of answer of 50 seconds (Strategies, 2004).

3. Average Work Time (AWT): It measures the efficiency of agent performance in a call center. AWT is computed as (Login time-wait time)/Number of calls Answered. Login time denotes the state, in which agents have signed on to a system to make their presence known, but may or may not be ready to receive calls. Wait time denotes the availability of agents to receive calls. TNZ assures AWT of 6 minutes as an effective benchmark to calculate agent's efficiency. In addition, researchers

Andrews & Parsons (1993) claimed that to obtain an optimum staffing level, an Average Work Time of 6.33 minutes can achieve the targeted TSF of 80%.

4. Recall / First call resolution (FCR): With the recall of the same customer, we can evaluate that the first agent who has taken the call to be less efficient for handling the calls. Shu-guang et al. (2007) say that the ratio of customer recall in one hour defines the service quality metric of the agents. However, TNZ measure FCR based on customer call back (recall) until the fault is resolved and it could be in an hour or in 2 days time.

5. Average Handling Time (AHT): It defines how long an agent is busy providing service to a single customer call. It is the sum of service time (talk time) plus wrap-up time based on additional activities to complete the call. According to Anton, J. (2001) call centers have an average of 13.46 seconds of AHT.

6. Calls Abandon (CA): It is one of the measures of customer service, as overall number of customers who abandon the queue before being served. According to Mehrotra & Fama (2003) this is known to be the significant indicator of customer satisfaction. CA is linked to service level parameter, TSF, as companies expect their calls to be answered with in a predefined threshold interval time.

4.2.2 List of measurements of EBO

Bringing out the experience from the case study of TNZ Call center and research study, organizations normally measure efficiency of business operations based on

a) Staff efficiency
b) Cost efficiency

Bringing out some of the approaches of organizations, according to Harris, Hoffman, & Saunders (1987) an airline industry has chosen to allow some loss of service to the customer reservations system; such that they can save large costs of staffing during heavy traffic periods and thus deviated the TSF norms deliberately in favor of economic considerations. The shift of prioritization is purely a business need of the organization such that to manage their resources efficiently while sacrificing customer service factor. Hence, the service quality thus generated is the outcome of internal organizational policies and practices (Cronin, Brady & Hult, 2000).

Looking at staff efficiency factor, the need of data analysis will bring in quality assessment and time management techniques of the agent and will evaluate efficiency of business operations. According to Paprzycki et al (2004), the basis of performance evaluation of call center agent would be

a) Customer service satisfaction
b) Business need satisfaction

4.2.3 Trade-off between CSQ and EBO

Looking at aspects for resolving trade-off between CSQ and EBO, organizations are attempting to meet both monetary and service priorities and this often leads to conflicts such as "hard versus soft goals", "intangible versus tangible outcomes" (Gilmore & Moreland, 2000), and "Taylorism versus tailorism" (Korczynski, 2001) while managing call centers.

Bringing together the views of different researchers the organization has to maintain a balance between customer service quality and efficiency of business operations, as loss of service to efficiency can influence its future. Dean (2002) has supported the idea of perceived customer loyalty to the organization that has a positive relation with service quality of the call center. The call center is no more a cost center, as a good customer service generates loyalty and revenue to the organization. Many businesses are coming out of the dilemma to consider call centers as a strategic revenue generating units rather than purely as a cost center while offering customer service (Jack et al., 2006).

4.2.4 Service Quality

The following sections bring the models and approaches to improve service quality in a call center.

1. SERVQUAL Model: Bringing out the approaches of Parasuraman, Zeithaml & Berry (1988) SERVQUAL has five dimensions of service quality from the customer's perspective.

1) Tangibles – are the appearance of the physical facilities and materials related to the service.
2) Reliability – is the ability to perform the service accurately and dependably.
3) Responsiveness – is the willingness to help customers and provide prompt service.
4) Assurance – is the competence of the system and the associated security, credibility and courtesy.
5) Empathy – is the ease of access, approachability and effort taken to understand customers' requirements.

It is possible to measure empathy, assurance and responsiveness with the agent's interaction with the customer. However, since call center works in a virtual environment, attaining physical contact and providing a perception of a reliable service would not be possible. Researchers Staples, Dalrymple & Bryar (2002) proposes SERVQUAL is not applicable in a call centre, "As a customer never comes into contact with the physical appearance of a call centre", and from the customer perspective, there is a little 'tangible' about a call center service encounter. Reliability from the customer's perception is difficult to assess for an individual service encounter.

2. Call monitoring instrument: It is a 28-point checklist to assess and evaluate agent's performance. An agent will be awarded a pass for 'quality call' if he can satisfy the 28-point checklist criterion (Staples et al. 2002). This instrument became the call centers' customer expectation benchmark and this benchmark is used by the call centre to measure its own service quality performance in between obtaining customer service feedback from external surveys.

3. Other Measures of Service Quality: Looking at some of the solutions which can evaluate performance of call centers; "eTalk and Gartner Group" integrated data mining tools in to their monitoring systems; which can actually help non-experts such as supervisors and managers who monitor agents' operations and run performance

evaluation (Paprzycki et al. 2004). They can "mine" the available data by asking "what if" questions; and with this approach, researcher Dilauro (2000) found that call transfers frustrate customers.

Looking at some of the options for modeling to see how exactly the monitoring system works, it has been determined that "iOpt optimisation toolkit" (Voudouris et al, 1926) has the ability to plug in different heuristic search algorithms from Heuristic Search Framework (HSF). HSF is a collection of standard and novel heuristic search algorithms for solving combinatorial and optimization problems.

Reviewing "eGain Adviser" software usage, a premier international bank which serves small businesses was able to increase its first call resolution from 75 % to 96 %, Average Handling Time (AHT) was reduced by 67 % and the organization was able to handle 70 % more calls without expanding the agent pool (egain*,* 2008).

While observing the service quality models in a call center all the models as mentioned above mostly concentrated on improving the efficiency of agents to improve the quality of service. However, none of above models concentrated on balancing the service quality with efficiency of business operations. The square root staffing rule of Zeltyn & Mandelbaum (2006) suggests that if the number of servers (queues) and staffing level is maintained at optimum level, then the call centers can expect to achieve improved service quality.

4.3 The Proposed IT Solution 1: Software Call Broker Modeling Solution

Referring to the Figure 18 on page 74 which brings the scenario of non-personalized broker, where by the stream of calls will be allocated by an automatic call distributor (broker) to the available agents irrespective of the skills of the agents. In addition, the model of non-personalized model could be suitable for a call center of 5-6 agents. Consider a bigger call center of TNZ where there are approximately 50 agents on floor answering the calls. In these scenarios of handling large number of agents, the alternative approach could be introducing the model of “software call broker” whereby bringing the goodness of personalized call Prediction method at the automatic call distributor (broker) software system. The idea of personalized call broker can be confirmed from Figure 19 below on page 74. With the significance of personalized prediction approach the broker virtually acts as ‘m’ personalized broker for ‘m’ agents; rather than a single generalist broker for all the agents .In addition, makes the life simpler to predict the appropriate calls to the i^{th} agent of total ‘m’ agents.

Referring to Figure 19 on page 74 and call flow diagram Figure 20 on page 75 (excluding the functionality of supervisor role) the model works like as if the broker performs personalized call predictions for each available agent with the set priorities at the software system. Implementing the strong software at ACD can improve the functionality of broker and will bring as real time approaches towards call broker modeling.

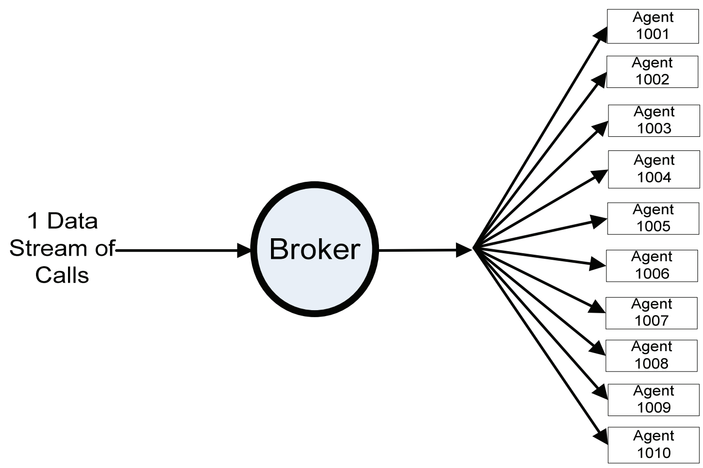


Figure 18. Non-personalized Broker

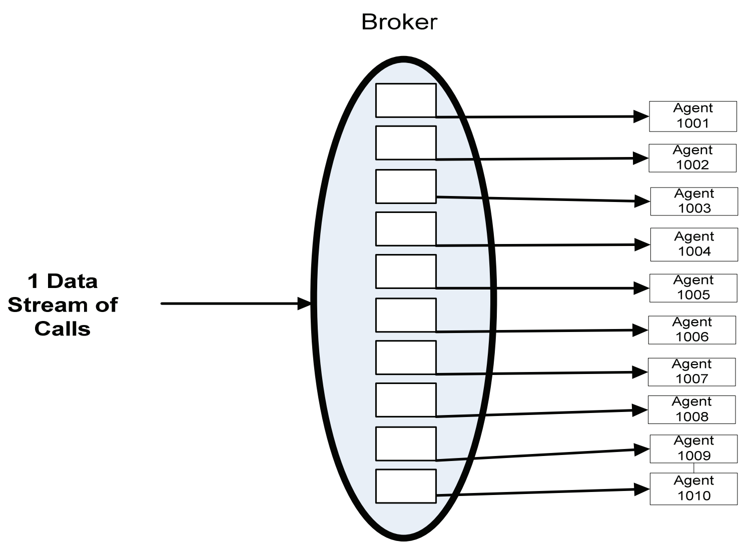


Figure 19. Significance of Personalized Broker

4.4 The Proposed IT Solution 2: Supervised Call Broker Modeling Solution

The call distribution priorities used with software call broker model implementing Personalized Prediction (PP) method are fixed and will not alter until some changes are made. While considering a real time environment this approach of fixed priorities seems to be unrealistic, since the performance of agents varies depending on the various work conditions.

Referring to the Figure 20 on page 75 (as adapted from Yang, Wang & Zhang (2003), the Supervised Call Broker (SCB) model is based on the concept of real time supervised observations of agent's performance and then computing predicted calls for each agent. The predicted call values are generated based on the priorities computed while looking into different scenarios such as perceiving the real time status of queue, agent's availability and observing how well the agent is performing with the given tasks.

The flow chart as shown in Figure 21 on page 77 (adapted from Petrunka, 2000), gives a better functionality of supervised call broker model which implements personalized prediction method. In the process of call flow, the broker requests supervisor (human) to assist in the agent selection process. The supervisor uses his knowledge to monitor and evaluate the performance of agents. The broker implements the assisted knowledge of supervisor to select an appropriate agent to service the customer request.

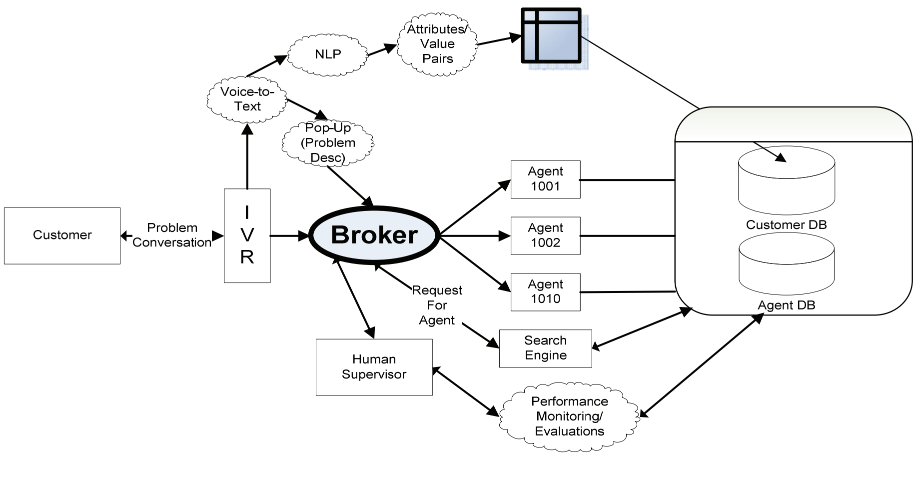


Figure 20. Call Flow Diagram of SCB modelling implementing PP method

A further analysis of Call Flow Diagram as in Figure 20 shows Interactive Voice Response (IVR) systems, initially takes up the call from the customer. In addition, to have a better understanding of the problem it invites caller/customers to explain their problem; the system with the help of voice to text converter will paraphrase and convert the problem in to an understandable description, which will "pop up" on the agent screen whoever takes the call. The pop up message will serve for better understanding of the customer problem.

Natural Language Processor (NLP) will generate appropriate values to the problem vector based on the output generated by voice to text converter and from the conversations of IVR with customer. Some attributes of the problem vector such as Problem ID, Problem date have system-generated values while others will depend on the situation of the problem.

The IVR will also perform initial diagnosis conversation of the problem with the customer, such that the problem can be resolved on-line with the process of self-check with the customer. If the problem is not resolved, it will divert the call to the software broker, which actually understands the problem by looking at the paraphrased problem description. The broker is going to request for a list of available agents to a search engine, such that it can link the path of the call to an agent queue with the help of Automatic Call Distributor (ACD). From the available list, the broker requests supervisor to assist in selection criteria. The supervisor performs monitoring of agent performance from the Agent and Customer databases (DB) and evaluates when required to select a better agent for a customer in queue. The search engine list the most appropriate agent based on Agent DB details and supervisor recommendations. ACD place the customer in the agent queue along with the pop up message.

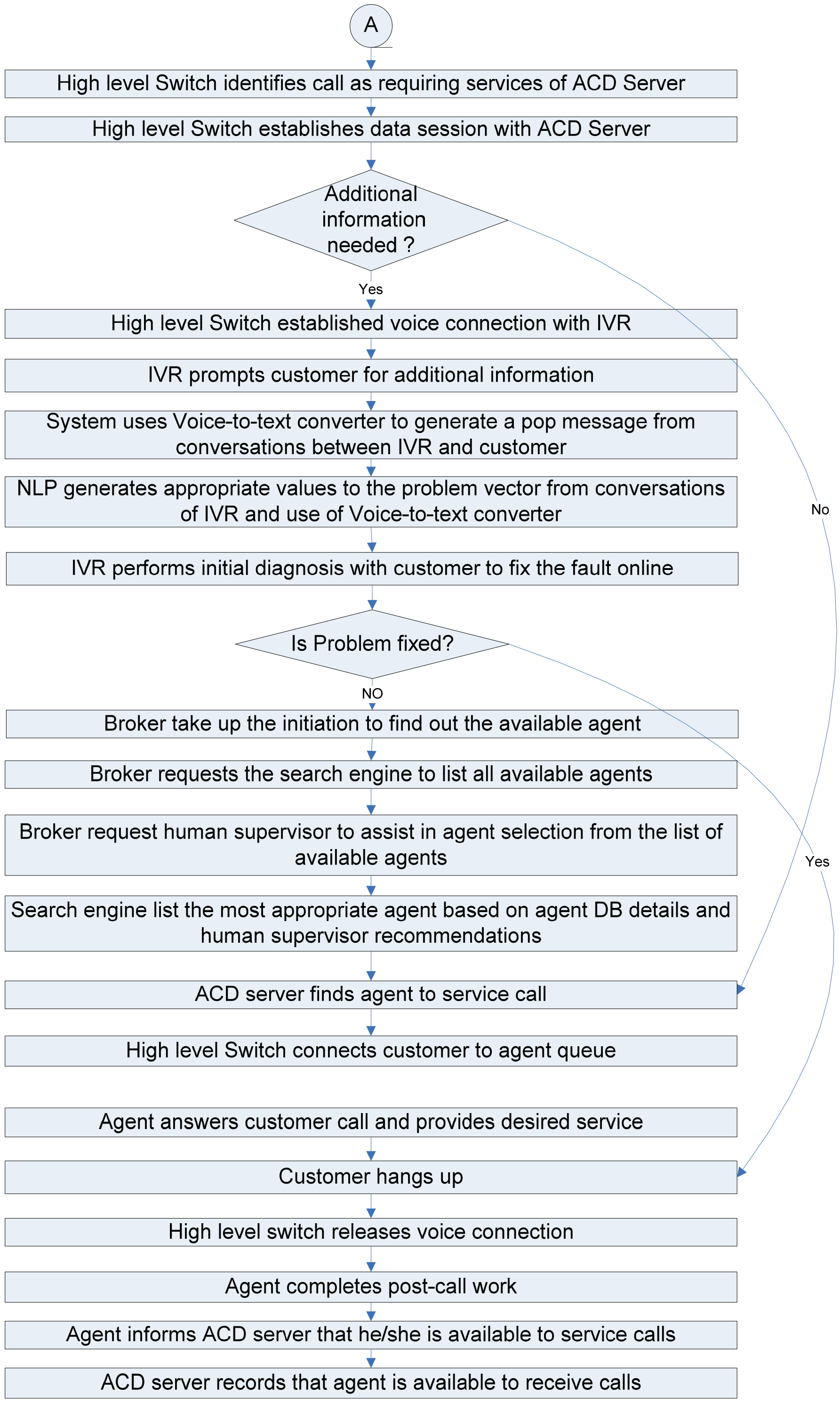


Figure 21. Flowchart for SCB modelling implementing PP method

For the simulated supervised call broker model, the computation of priorities are calculated based on previous day's actual call values (t-1) and the agents' performance on that day. An example that emphasizes this concept is that the supervised observation found at time (t) of the distribution of calls to 10 agents should be made at priorities 12%, 6%, 10%, 8%, 10%, 11%, 13%, 14%, 9% and 7% respectively rather than the fixed priorities set for software call broker model, which can generate a good call prediction and can provide better service factors to Telecom New Zealand.

The supervised predicted call values represented as $\hat{Y}_{SP(i)t}$ in equation (3.13) at chapter 3 are compared with personalized prediction method computed values as generated with the equation (3.12) in section 4.3.2.2 to compute an average of the two values. This will present a realistic computed value for the actual call values and is considered as forecasted values as at equation (3.14) for supervised call broker model.

The observation of forecasted calls by a supervised call broker model is able to estimate predict calls with an accuracy of 98 %, 53 %, 75 %, 59 %, 78 %, 32 %, 95 %, 86 %, 33 %, 45 %, 99 %, 84 %,92 %,86 %,96 %, 83 %, 98 %, 87 %, 98% and 84 % respectively. The forecasted call values can be observed from the Figure 22 on page 78. As compared with the other prediction methods the supervised call broker model could able to forecast calls with better accuracy.

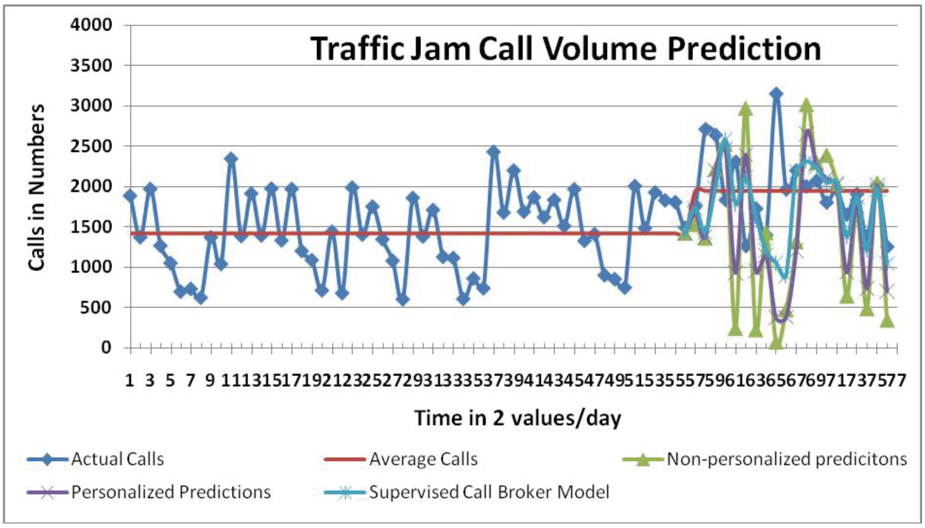


Figure 22. Traffic Jam Call Predictions with functionality of SCB model

4.5 Case Study for Telecom New Zealand

This section firstly, introduces the reasons for happening of Traffic Jam event at TNZ call center. Secondly, performing cost calculation for the fault as an approach to analyze the impact of traffic jam on the performance of a call center.

4.5.1 Disaster Analysis of Traffic Jam Events in Feb 2008

While observing the case study of Telecom New Zealand, a Telecom exchange switch was down for 10 days and this fault has affected the lines of approximately 10,000 customers. The software system could not handle this unforeseen fault event which was the cause of the traffic jam; and resulted in inappropriate prediction of call volume. In addition, this unforeseen event resulted in wrong calculation of staff required for the call center. Finally, managers had to manage the software systems with many manual adjustments to forecast the upcoming traffic and schedule the required agents accordingly in the call center.

4.5.2 Problem Solving with the Proposed IT Solution

The traffic jam problem solving is intended to observe how quickly the traffic jam can be released. In other way, the concept of release is to advice on how long the traffic jam is going to hold on using different prediction methods. The release of traffic jam is computed based on a simple calculation represented in Table 7 on page 80 and is based on values as evidenced at Figure 23 on page 81.

Bringing the concept of Gaussian distribution for 10-day period of Traffic Jam, the traffic jam reach its peak at midpoint which is at 5^{th} day and is equivalent to midpoint of normal distribution and gets released at the end point. Then, the predicted traffic jam time period (T_P)can be counted as the starting point of traffic jam plus the time cost for release the traffic jam part of calls,

$$T_P = T_S + T_r, \qquad \dots (4.1)$$

where,

T_S – Is the starting time point of traffic jam releasing, in our case study it is 5 days.

T_r – Represents the time cost for the traffic jam release.

Under the condition that different call prediction methods are used, T_r is calculated as,

$$T_r = (A - N) / P, \quad \ldots (4.2)$$

where,

A – Average Actual calls during Traffic Jam Period

N – Average Normal calls during Traffic Jam Period

P – Average daily call prediction by the used call prediction method during the traffic jam period.

Further, the saved time due to improved call predictions can be estimated by simply subtracting the predicted traffic jam time period from the original traffic jam period, which is 10 days in our case study. As a result, the Table 7 records the traffic jam release time T_r, the predicted traffic jam period T_P, and time saving estimation. From the calculation it is evident that supervised call broker model will save 1.96 days while predicting traffic jam as compared to 1.52 (using personalized) and 1.40 days using non-personalized method. The call values can be further referred at section 3.6.2.2.

Number of Customers Affected	Fault Days	Cost/Call/ 10 mins	Minimum. calls Expected @ 1 call/ Customer	Actual Traffic Jam Calls	Minimum Cost (10 mins/ Call)	Actual Cost (10mins/ Call)
10,000	10	$ 3.00	10,000	10,540	$30,000	$31,620

Table 7. Traffic Jam Release, Prediction and Saving time calculation

A further analysis of accuracy of traffic jam release call values as evidenced in Figure 23 on page 81. It depicts that the personalized broker with supervisor role (supervised call broker model) has shown very good inclination towards releasing the traffic jam. In addition, the personalized broker (Software call broker model) has shown better accuracy (refer Figure 24) than the non-personalized prediction method.

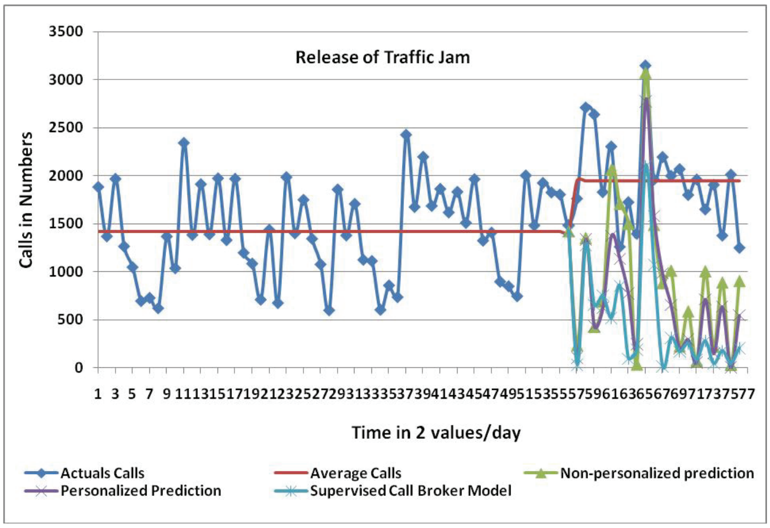


Figure 23. Representation of Traffic Jam Release

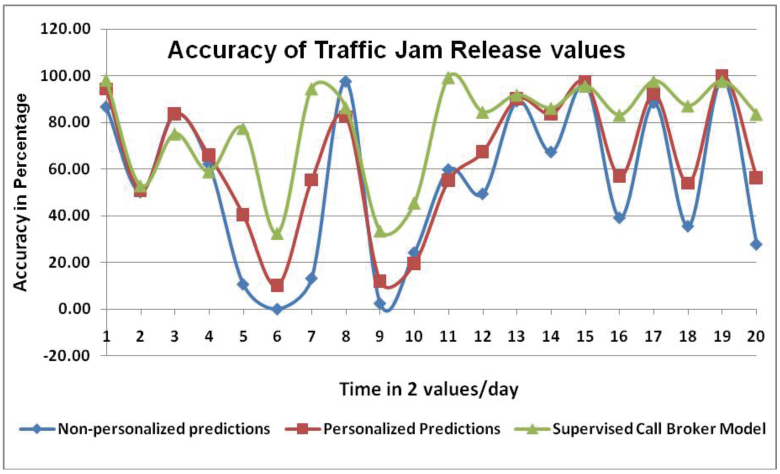


Figure 24. Accuracy with Traffic Jam Release

4.5.3 Cost & Return Evaluation

This section computes cost and returns calculation during Traffic Jam period and evaluates the best possible solutions to maximize Return on Investment (ROI).

(1) Cost Calculation for the problem

According to Gans et al. (2003), the operating cost in a call center defines

1) Agents salaries
2) Network cost
3) Management cost

The agent's salaries typically account for 60 % to 70 % of the total operating costs. While observing the case study of Telecom New Zealand, the additional costs during the period of traffic jam are calculated in the following sections.

(1) Agent's Cost Calculation

Considering that TNZ pays $18/hr to an agent and, according to Duder & Rosenwein (2001) it will cost $20 per hour to hire an agent. On an average an agent has 10 minutes of Average Handling Time (AHT) per call. This figure can multiply depending on the average handling time of a call by an agent. The total calls were computed taking the difference of average normal calls and average calls during the period of traffic jam. The observation from Table 8 reveals that TNZ has spent a minimum additional cost of $31,620 for handling traffic jam event.

Number of Customers Affected	Fault Days	Cost/Call/ 10 mins	Minimum. calls Expected @ 1 call/ Customer	Actual Traffic Jam Calls	Minimum Cost (10 mins/ Call)	Actual Cost (10mins/ Call)
10,000	10	$ 3.00	10,000	10,540	$30,000	$31,620

Table 8. Agent’s Cost Calculation

(2) Network Cost calculation

The second important cost is the network or communication cost, which raises a question as how well we are using the network/ telephone lines. If we consider a call center that is open 24X7 i.e., 24 hours a day, 7 days a week, and averages 40 calls in queue will pay about $1 million per year in queuing expenses (when the cost per minute per call is $0.05) (Gans et al. 2003). In addition, according to Duder & Rosenwein (2001) the inbound telecommunication will cost $0.06 per minute per call. The observation from the Table 9 on page 83 reveals that the network cost during the period of traffic jam has shown an increase of $5270 for TNZ as the queue expenses. This figure is obtained by considering only 40 calls in the queue and an average handling time of 10 minutes per call by an agent. This figure can multiply depending on the number of customer's on hold in the queue, and will eventually affect the customer service quality.

Number of Customers Affected	Fault Days	Min. Cost/ Call	Max. Cost/ Call	Min. calls Expected @ 1 call/ Customer	Actual Traffic Jam Calls	Min Cost (10 mins/ Call @ $0.05)	Actual Cost (10mins/ Call @ $0.05)
10,000	10	$0.05	$0.06	10,000	10,540	$5000	$5,270

Table 9. Network Cost Calculation

(3) Management Cost calculation

While considering the agents' cost as 60 % of the total operating costs (Gans et al., 2003), the equation for total cost is computed as (Total cost = Agent cost + Network cost + Management cost).

Considering, total cost as X then the agent cost would be 60% of X. Since, the computed agent cost is $31,620 and this would make the total cost amount to $52,700. From the equation of total cost, the Network cost plus Management cost will be equal to the total cost minus agent cost which is $ 21,080 ($52,700- $31,620). Since, the network cost is $5,270 (as derived from Table 9 on page 83) the management cost would be $15,810 ($21,080- $5,270).

While looking at the computed total call cost of $52,700 for 10,540 additional calls received in the call center during the period of traffic jam; the cost per call is calculated as $5.00. It is reviewed that the computed call cost of $5.00 per call at a TNZ call center is a much lower cost figure as the global average call cost $7.22 in a call center (Anton, 2001). While considering the global average call cost, the TNZ might have vested an additional operating cost of $ 76,099 during the period of traffic Jam of 10 days to its inbound call center.

From the cost calculations it is evident that Telecom New Zealand could have vested a minimum additional cost of $52,700 for managing the so called "traffic jam" in the call center. However, neither the non-tangible costs such as loss of service quality and efficiency of agent's performance, and economic loss such as loss of sales revenue nor the costs involved to fix the fault has been taken into consideration while measuring the additional cost of traffic jam. The costs and return calculation are computational and based on predicted values; and in real time these values can be further enhanced. Telecom has not authorized me to publish actual figures of cost and return values during the traffic jam event and hence to protect confidentiality the values are not revealed.

(b) Return Calculation for the problem

This section initially compares opportunity cost versus quality of service, later brings the importance of personalized broker with supervisor role.

According to Duder & Rosernwein (2001) savings in costs in a call center can be achieved by improvements in the level of service; and reduction in call abandonments can improve profitability. In addition, while using the Erlang-C queuing equation suggests investment in small number of agents can increase profitability.

(1) Example representing the intensity of traffic jams

To better analyze the intensity of traffic jam on quality of service, cost and return on investment and profitability in the Telecom New Zealand call center a simple example is shown below:

The computation of cost and savings are performed using the equation adapted from the works of researchers Duder & Rosernwein (2001) whereby,

(1) Savings **(S) =qVW+ pVA (d+qh) +rRAV**

The equation is further reduced to **S=V (qW +pA (d+qh) +rRA)**

(2) Total cost associated with hiring additional agents are given by **Ct=Ca*N**

If S>Ct, the call center can hire more agents to improve profitability.

Example: A suitable sample of data is selected during the traffic jam period which has the highest value of average speed of answer (ASA). The main idea behind choosing this example is to observe the impact of lowering ASA values on cost saving and profitability in the call center. The values for the calculation as shown in the Table 11 on 85 are derived from Table 10 on page 85.

Date	Interval	Calls Entered	Calls Answered	Calls Abandon	Avg. Agents	ASA	AWT (IB&OB)	AWT IB	AWT OB	Avg NR	TSF
25-Feb-08	19:00	51	31	32	18.98	522	246.41	508	479	83	0.095
25-Feb-08	19:15	59	49	19	27.71	337	274.56	489	627	92	0.044

Table 10. Example call interval data

V	68 (49+19)
q	0.06
N	9
W	3.583
R	50
p	0.7
r	0.001
d	0.004
A	0.406
Ca	5
h	8.7

Table 11. Calculated variable values

where, C_a=cost per agent per ¼ hr

q=inbound telecommunications cost per minute

V=actual call volume (calls answered plus calls abandoned) per ¼ hour

N =number of agents required to change ASA by W

W=desired change in ASA

h=average duration of IVR experience at current interval of time

R=average revenue per customer

p=probability of customer retrial given a customer abandonment

r= probability of a customer switching to a competitor brand given inferior customer service.

d=information systems cost per IVR experience

A=change in abandonment rate

While substituting the values in the equation the values of savings and cost are derived as,

S=$26.17

C_t=$45

The analysis of the call interval data from Table 10 on page 85 shows that the drop in calls abandon from 32 to 19 is due to an increase in number of agents from 19 to 28, which in turn made ASA to drop from 522 to 337. A total savings of $ 26.17 was achieved with improvement of service; however, the TNZ call center has to incur a cost of $ 45 for hiring additional 9 agents. The benefits of savings is achieved by improvements in the level of service that couldn't outweigh the costs of hiring new agents as (S<Ct) and hence, couldn't improve the profitability of Telecom New Zealand during the period of traffic jam.

(2) Significance of Personalized Broker with Supervisor role

Considering an additional cost of $52,700 during the 10 days of traffic jam, this section will perform cost and saving calculations with the prediction methods. While introducing the concept of traffic jam problem solving here from section 4.5.2, the non-personalized Prediction method could release the traffic jam in 8.60 days with a total cost of $45,308. This is in contrast to the Personalized Prediction method that releases the traffic jam in 8.48 days with a total cost of $38,419 and a saving of $14,281. Meanwhile, the supervised call broker model can release a traffic jam in 8.04 days with a total cost of $30,883 and a saving of $21817 as compared to the non-personalized prediction method. While computing the cost of single supervisor, it will incur an additional cost of $1151 for a 10 day period to hire a new supervisor to manage the call center; as according to Hillmer et al., (2004) the cost of hiring additional supervisor amounts to $42,000 per year to manage a call center. From the cost and return calculation it is still a beneficial for any call center to implement Software Call Broker model as there is a minimum net saving of $20,666 as Return on Investment. The estimation of cost and return are performed based on certain conditions. In reality, based on Telecom New Zealand view point the costs and returns might have been higher than the calculated costs.

4.6 Summary

From the cost and return calculation it has been observed that TNZ has vested a minimum additional cost of $52,700 for maintaining Traffic Jam. Looking at the Intensity of Traffic Jam and cost/output analysis scheduling more agents to improve the service factors at short intervals of time will be a challenging task for the call center. Hence, the proposed method of personalized broker with supervisor role can be an alternative to provide a better service levels to the call center.

Chapter 5 Conclusion and Future Work

5.1 Summary

The first part of the dissertation consists of introducing the general concept of a Call Center. Later, brings the case study of Telecom New Zealand Call Center discussing the approaches of TNZ with respect to call predictions, call routing at ACD, IT solutions and staff management. Finally, brings the proposed call prediction method and call routing models which assist the performance of any call centers.

In this work, a Personalized Prediction method and call prediction models (Software Call Broker and Supervised Call Broker) were developed. The personalized prediction method introduced the importance of agent skill information for call predictions. The non-personalized prediction (normal/ existing) methods forecast call volume for the call center as a whole and predict the requirements of agents to answer the calls. In addition, the inductive systems cannot generate better prediction accuracy for single new sample, as they are meant for global model. The personalized predictions which develop a local model for every new input vector, based on a certain number of data selected from training data set and computes "personalized predictions" which generate a better accuracy of predictions. In order to be used in practice, the proposed personalized predictions method performs call predictions for each agent considering their past skill information.

While, analyzing the data some interesting patterns were found, which were later identified as Traffic Jam in the call center. There is an increase in call volume to the center which in turn caused calls to be abandoned affecting the service level in the TNZ call center. Since, increase in number of agents cannot be affected at short intervals of time; the better option is to include personalized predictions method for conducting call predictions which can enhance the service factors in the center.

The application of personalized prediction method was done on Telecom New Zealand call center data. The personalized predictions method if implemented at Automatic Call Distributor (ACD) performs as call broker to divert the calls to the agents. The ACD uses Skill Based Routing (SBR) to allocate the calls to a specific agent whose primary skill matches the required skills of the call. Additionally, if an agent is not available the call will be diverted to any other available agent with the longest waiting time irrespective of the skill level of the agent (could be primary/secondary). The proposed software call broker and Supervised Call Broker (SCB) models implement the personalized prediction method. In software call broker model the priorities of agents are loaded into the software system such that calls will be distributed to the agents accordingly. In SCB model the supervisor will monitor and evaluate the performance of the agents and assist the call broker to suggest an appropriate agent to answer the call.

The design of the model was motivated by computational efficiency and the resulting method seems successful in that sense. The personalized prediction method was able to predict the traffic jam earlier than normal method with a saving of 1.52 days in the time factor. In addition, Supervised Call Broker model implemented with personalized prediction method was about 6.5% faster than the corresponding normal prediction method and would save 1.96 days to predict traffic jam.

Looking at the Intensity of traffic jam and cost/output analysis, scheduling more agents to improve the service factors at short intervals of time will be a challenging task for the call center. The analysis of experiments is of interest to the management of Telecom New Zealand to consider inclusion of agent skills while performing call predictions and for improvement of service factors in the call center.

5.2 Contribution

The main contribution of my dissertation research project is to 1) identify the call center traffic jam and 2) highlighting the importance of agent skill information for conducting personalized calls prediction.

Additionally, this report develops two call broker models 1) Software call broker and 2) Supervised call broker which can implement the personalized prediction method to enhance the capability of call broker at ACD and have a better approach towards traffic jams. The traffic jam problem investigation with the existing methods was found not to be capable to predict the unforeseen events. The proposed method could be able to release traffic jam earlier than the normal (existing) methods. This research addresses Telecom New Zealand management while bringing awareness of traffic jam and appealing for change in prediction models to foresee and avoid future traffic jams.

5.3 Research Recommendation

There are at least two important lines of research recommendation: giving the Software Call Broker model more expressive power by implementing it at ACD making better use of the Queuing technology and optimising the speed of the Agent Selection Criteria.

5.4 Future work

The dissertation research, with extant literature and practical investigation focuses on the ideas that are actively involved in the forecasting of call center predictions. These models are used to convince Telecom New Zealand call center management to implement the proposed call broker model as a prototype in real time queue system and observe the performance of simulated results with real time environment and perform comparison analysis with the experimental results.

Appendix

Section A: The results of Traffic Jam Problem Investigation

	Calls Abandon	AWT (Seconds)	TSF %
Actual	744	441	70
TNZ Exp	188	450	80
MLR	286	442	68
MLP	203	472	81
DENFIS	392	433	77

Table 12. Comparison results for the 1st day traffic jam prediction on call abandon, AWT, and TSF

	Min	Max	mean	Std Dev
Actual	705	744	724.5	27.58
TNZ Exp	181	188	184.5	4.95
MLR	178.7	285.6	232.2	75.55
MLP	92.6	203.1	147.8	78.11
DENFIS	111	392.4	251.7	199

Table 13. Comparison results for the first 2 days traffic jam prediction on calls abandon

	Min	Max	mean	Std Dev
Actual	408.1	441.4	424.7	23.57
TNZ Exp	429	450	439.5	14.85
MLR	424.1	442.4	433.2	12.92
MLP	453.9	472.4	463.2	13.03
DENFIS	391.4	433.1	412.2	29.49

Table 14. Comparison results for the first 2 days traffic jam prediction on AWT

	Min	Max	mean	Std Dev
Actual	-88.89	1143	424.7	130.8
MLR	-210	1202	433.2	160.7
MLP	-419.3	512.5	463.2	80.41
DENFIS	-491.2	1067	412.2	172.8

Table 15. Comparison results for AWT Predictions for the period of 15mins – 2days Traffic Jam

	Min	Max	mean	Std Dev
Actual Values	0.7	0.82	0.76	0.08485
TNZ Exp	0.8	0.8	0.8	0
MLR	0.804	0.808	0.806	0.002775
MLP	0.68	0.84	0.76	0.113
DENFIS	0.768	0.84	0.804	0.05099

Table 16. Statistical Comparison of Methods for TSF Predictions (2days of Traffic Jam)

	RMSE	NDEI	Num Rn
Calls Abandon			
MLP	17.8031	0.92145	
MLR	14.6429	0.757884	
DENFIS	12.5894	0.6516	31
AWT			
MLP	123.74	0.946122	
MLR	57.4404	0.439192	
DENFIS	84.2473	0.6442	10
TSF			
MLP	0.190885	0.732795	
MLR	0.29172	1.12005	
DENFIS	0.2332	0.8953	28

Table 17. RMSE and NDEI comparison for traffic jam predictions on call abandon, AWT, and TSF

Section B: Cross Correlation Analysis on TNZ Call Center Data

	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V3	1	.868(**)	.555(**)	.538(**)	.225(**)	-.183(**)	-.217(**)	-.092(*)	-.179(**)	-.221(**)
V4	.868(**)	1	.159(**)	.760(**)	-.101(*)	-.195(**)	-.244(**)	-.120(**)	-.164(**)	.086(*)
V5	.555(**)	.159(**)	1	-.144(**)	.731(**)	-.057	-.098(*)	.063	-.149(**)	-.535(**)
V6	.538(**)	.760(**)	-.144(**)	1	-.339(**)	-.046	-.038	-.129(**)	.052	.415(**)
V7	.225(**)	-.101(*)	.731(**)	-.339(**)	1	-.010	.052	-.024	-.024	-.802(**)
V8	-.183(**)	-.195(**)	-.057	-.046	-.010	1	.823(**)	.444(**)	.421(**)	.017
V9	-.217(**)	-.244(**)	-.098(*)	-.038	.052	.823(**)	1	.162(**)	.621(**)	-.103(**)
V10	-.092(*)	-.120(**)	.063	-.129(**)	-.024	.444(**)	.162(**)	1	-.013	.094(*)
V11	-.179(**)	-.164(**)	-.149(**)	.052	-.024	.421(**)	.621(**)	-.013	1	-.012
V12	-.221(**)	.086(*)	-.535(**)	.415(**)	-.802(**)	.017	-.103(**)	.094(*)	-.012	1

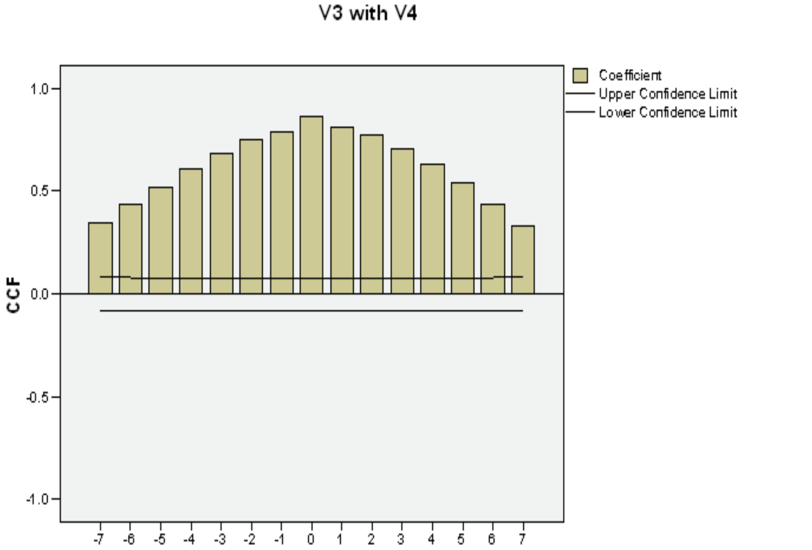
Table 18. Cross Correlation Matrix

Date	Interval	Calls Entered	Calls Answered	Calls Abandon	Avg Agents	ASA	AWT (IB&OB)	AWT IB	AWT OB	Avg NR	TSF
V1	V2	V 3	V 4	V 5	V 6	V 7	V 8	V 9	V 10	V 11	V 12

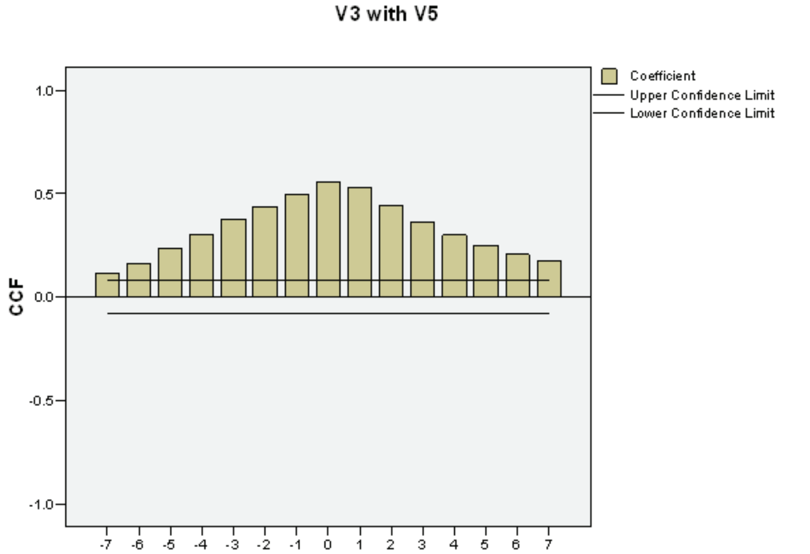
Table 19. Data Set Attributes

Traffic Jam Cross Correlations

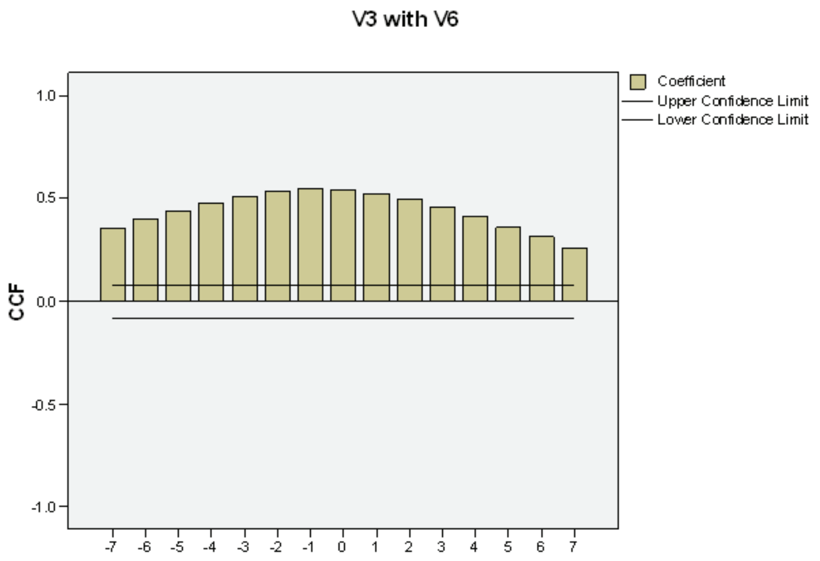
Lag	Cross Correlation	Std. Error(a)
-7	.347	.040
-6	.433	.040
-5	.515	.040
-4	.607	.040
-3	.680	.040
-2	.745	.040
-1	.787	.040
0	.868	.040
1	.812	.040
2	.771	.040
3	.706	.040
4	.631	.040
5	.541	.040
6	.434	.040
7	.327	.040



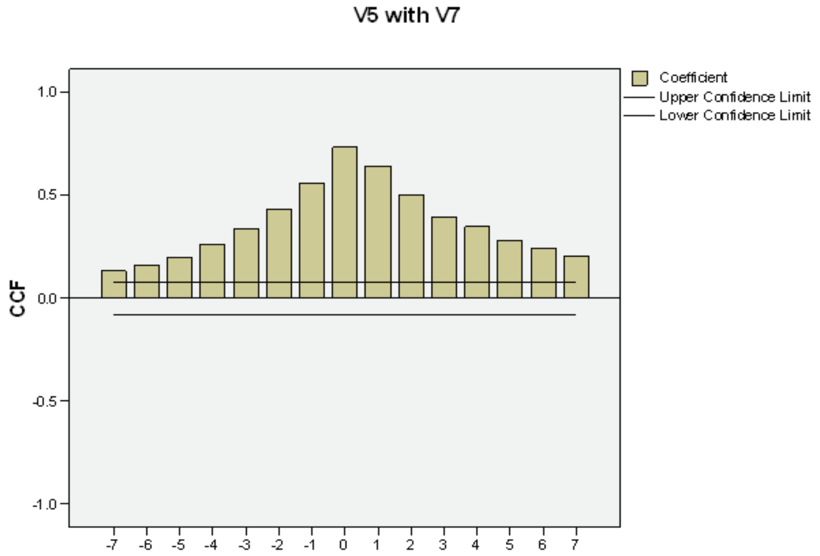
Lag	Cross Correlation	Std. Error(a)
-7	.115	.040
-6	.162	.040
-5	.233	.040
-4	.302	.040
-3	.375	.040
-2	.436	.040
-1	.496	.040
0	.555	.040
1	.527	.040
2	.441	.040
3	.364	.040
4	.300	.040
5	.248	.040
6	.205	.040
7	.174	.040



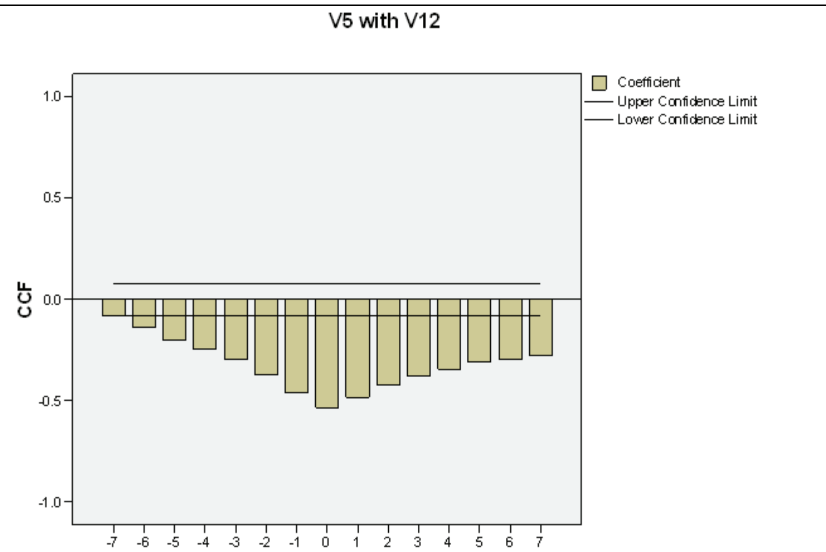
Lag	Cross Correlation	Std. Error(a)
-7	.356	.040
-6	.399	.040
-5	.438	.040
-4	.477	.040
-3	.509	.040
-2	.533	.040
-1	.541	.040
0	.538	.040
1	.520	.040
2	.495	.040
3	.453	.040
4	.411	.040
5	.359	.040
6	.308	.040
7	.254	.040



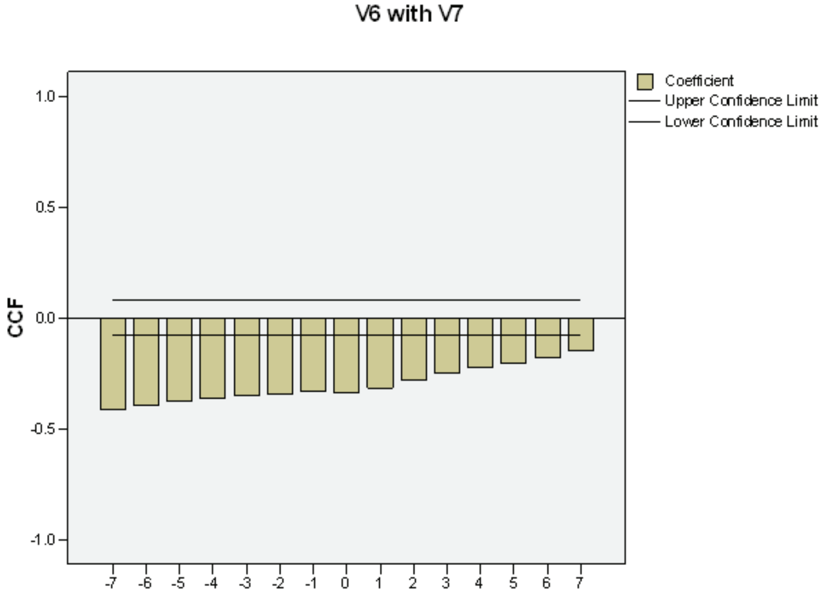
Lag	Cross Correlation	Std. Error(a)
-7	.131	.040
-6	.158	.040
-5	.195	.040
-4	.260	.040
-3	.335	.040
-2	.431	.040
-1	.558	.040
0	.731	.040
1	.642	.040
2	.500	.040
3	.395	.040
4	.346	.040
5	.279	.040
6	.244	.040
7	.202	.040



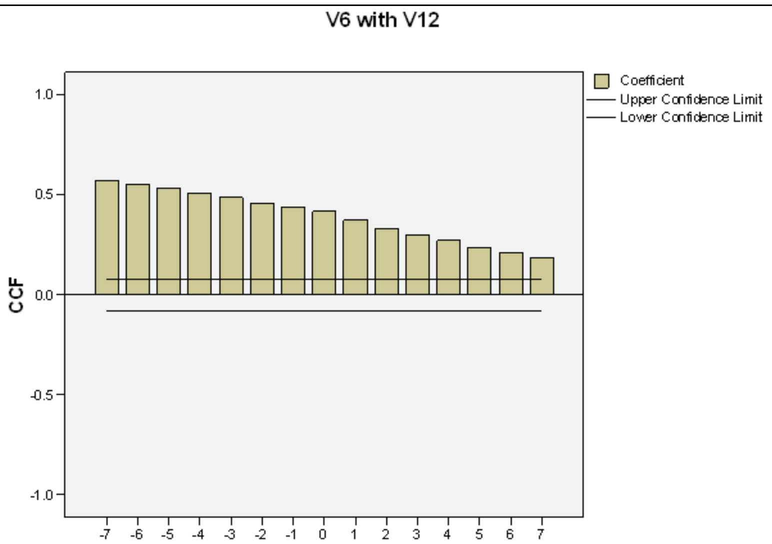
Lag	Cross Correlation	Std. Error(a)
-7	-.084	.040
-6	-.138	.040
-5	-.201	.040
-4	-.248	.040
-3	-.296	.040
-2	-.375	.040
-1	-.460	.040
0	-.535	.040
1	-.483	.040
2	-.422	.040
3	-.378	.040
4	-.345	.040
5	-.312	.040
6	-.295	.040
7	-.275	.040



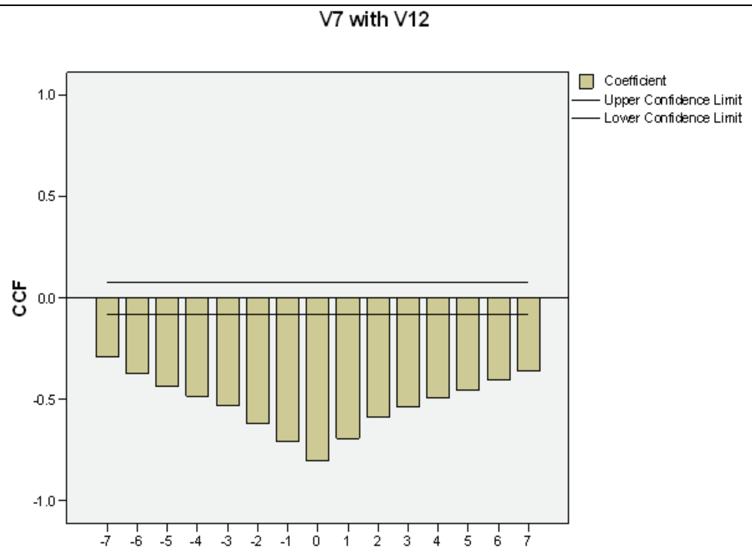
Lag	Cross Correlation	Std. Error(a)
-7	-.417	.040
-6	-.396	.040
-5	-.378	.040
-4	-.366	.040
-3	-.354	.040
-2	-.342	.040
-1	-.333	.040
0	-.339	.040
1	-.317	.040
2	-.282	.040
3	-.248	.040
4	-.226	.040
5	-.206	.040
6	-.180	.040
7	-.149	.040



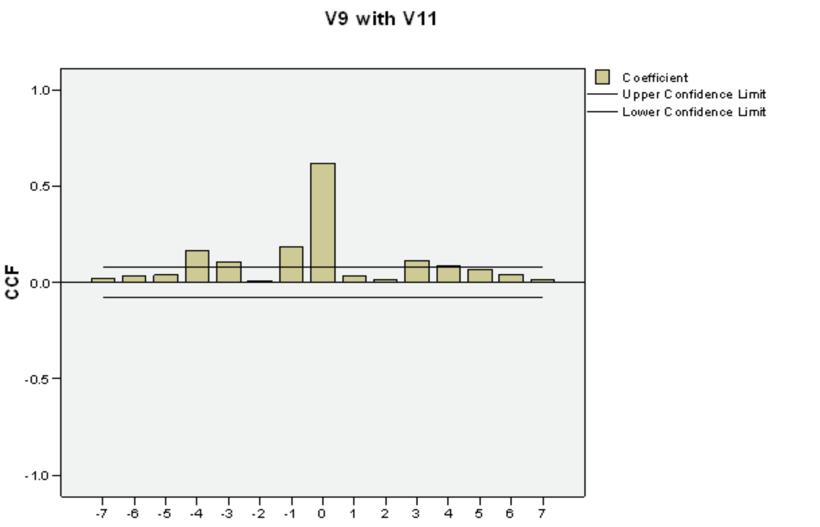
Lag	Cross Correlation	Std. Error(a)
-7	.570	.040
-6	.549	.040
-5	.530	.040
-4	.508	.040
-3	.485	.040
-2	.459	.040
-1	.436	.040
0	.415	.040
1	.373	.040
2	.330	.040
3	.296	.040
4	.269	.040
5	.237	.040
6	.211	.040
7	.186	.040



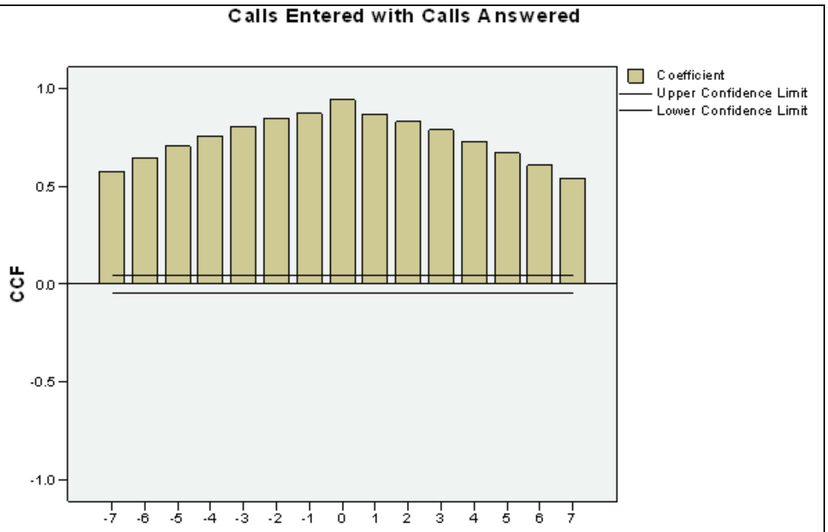
Lag	Cross Correlation	Std. Error(a)
-7	-.291	.040
-6	-.372	.040
-5	-.437	.040
-4	-.484	.040
-3	-.532	.040
-2	-.618	.040
-1	-.710	.040
0	-.802	.040
1	-.692	.040
2	-.590	.040
3	-.535	.040
4	-.494	.040
5	-.454	.040
6	-.404	.040
7	-.358	.040



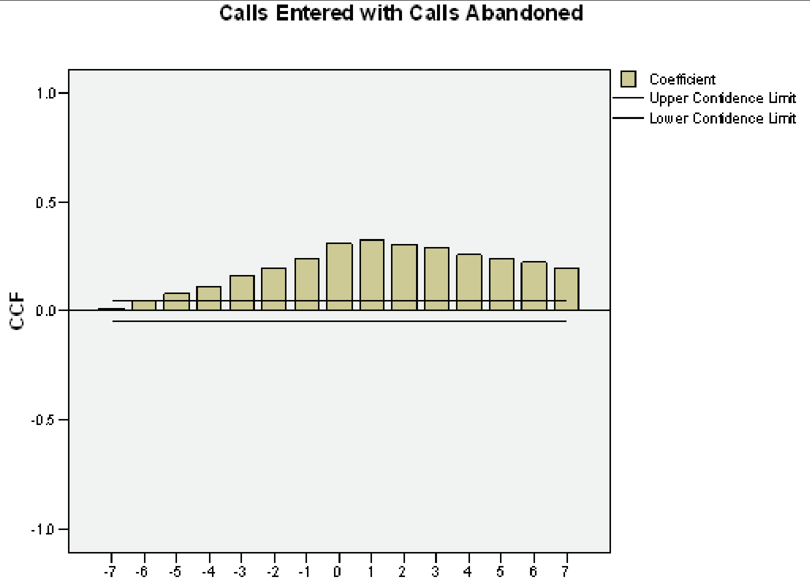
Lag	Cross Correlation	Std. Error(a)
-7	.020	.040
-6	.031	.040
-5	.039	.040
-4	.166	.040
-3	.109	.040
-2	.009	.040
-1	.187	.040
0	.621	.040
1	.031	.040
2	.015	.040
3	.112	.040
4	.088	.040
5	.069	.040
6	.044	.040
7	.014	.040



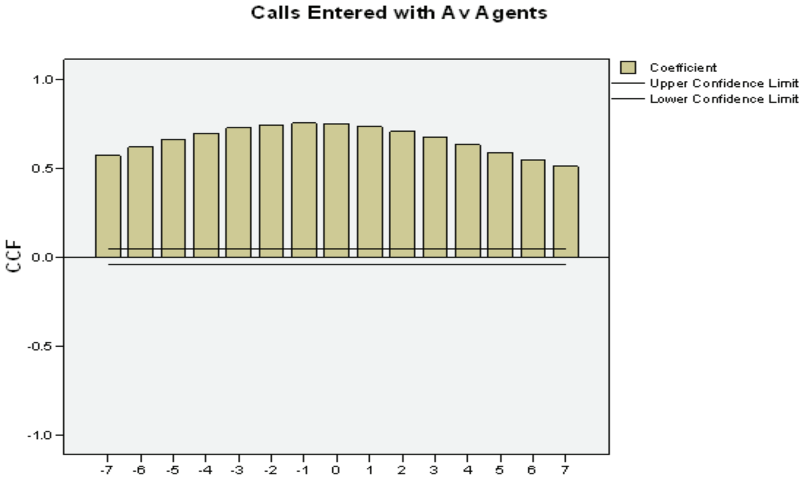
Lag	Cross Correlation	Std. Error(a)
-7	.574	.023
-6	.644	.023
-5	.706	.023
-4	.757	.023
-3	.807	.023
-2	.847	.023
-1	.874	.023
0	.944	.023
1	.870	.023
2	.830	.023
3	.789	.023
4	.729	.023
5	.672	.023
6	.608	.023
7	.540	.023



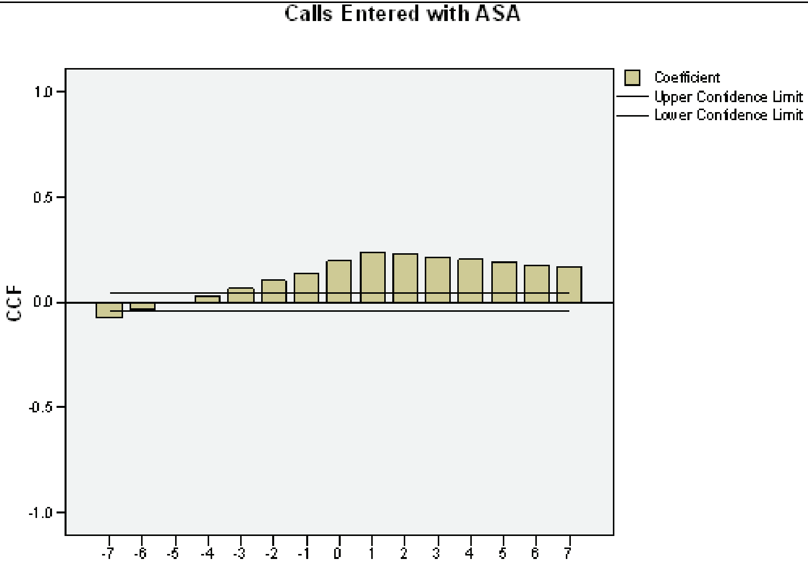
Lag	Cross Correlation	Std. Error(a)
-7	.011	.023
-6	.043	.023
-5	.080	.023
-4	.113	.023
-3	.160	.023
-2	.199	.023
-1	.238	.023
0	.311	.023
1	.328	.023
2	.308	.023
3	.289	.023
4	.261	.023
5	.238	.023
6	.223	.023
7	.199	.023



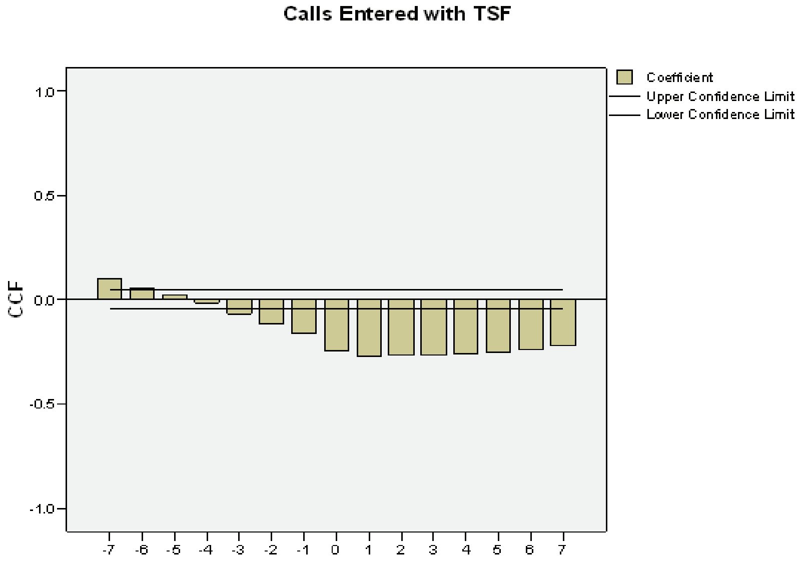
Lag	Cross Correlation	Std. Error(a)
-7	.569	.023
-6	.617	.023
-5	.661	.023
-4	.696	.023
-3	.723	.023
-2	.743	.023
-1	.751	.023
0	.748	.023
1	.732	.023
2	.703	.023
3	.671	.023
4	.631	.023
5	.586	.023
6	.546	.023
7	.508	.023



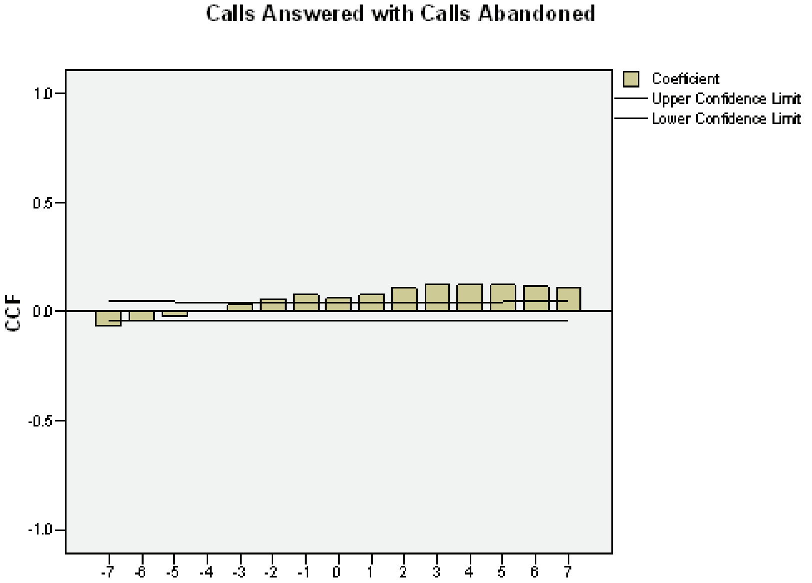
Lag	Cross Correlation	Std. Error(a)
-7	-.073	.023
-6	-.037	.023
-5	-.005	.023
-4	.027	.023
-3	.064	.023
-2	.101	.023
-1	.137	.023
0	.194	.023
1	.239	.023
2	.225	.023
3	.212	.023
4	.204	.023
5	.188	.023
6	.173	.023
7	.165	.023



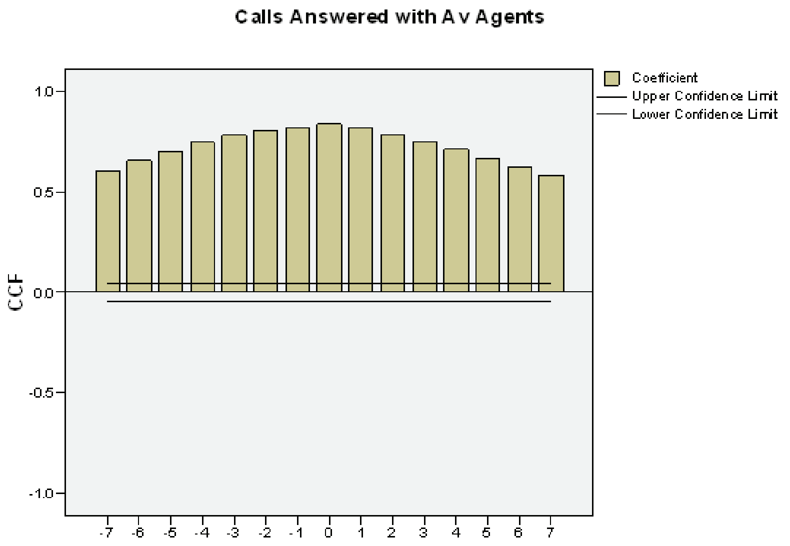
Lag	Cross Correlation	Std. Error(a)
-7	.098	.023
-6	.054	.023
-5	.021	.023
-4	-.015	.023
-3	-.068	.023
-2	-.115	.023
-1	-.158	.023
0	-.246	.023
1	-.271	.023
2	-.268	.023
3	-.266	.023
4	-.257	.023
5	-.253	.023
6	-.240	.023
7	-.219	.023



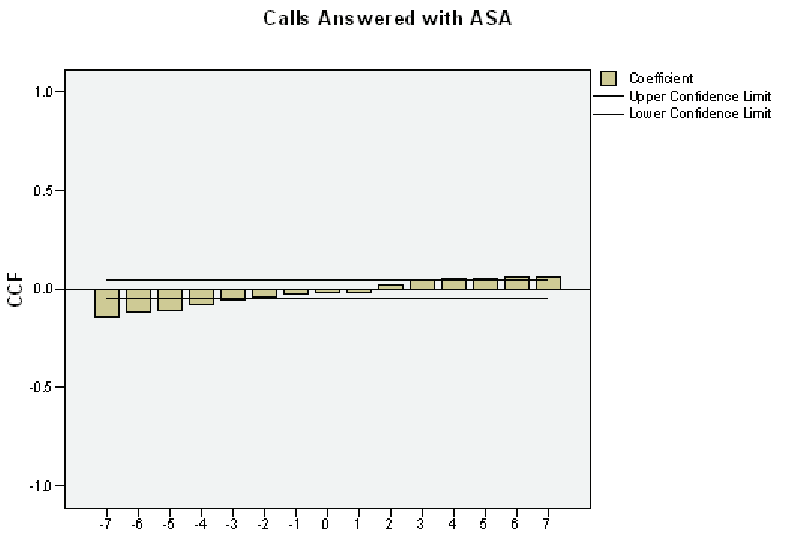
Lag	Cross Correlation	Std. Error(a)
-7	-.065	.023
-6	-.045	.023
-5	-.021	.023
-4	.006	.023
-3	.033	.023
-2	.056	.023
-1	.077	.023
0	.063	.023
1	.076	.023
2	.109	.023
3	.124	.023
4	.124	.023
5	.122	.023
6	.116	.023
7	.110	.023



Lag	Cross Correlation	Std. Error(a)
-7	.603	.023
-6	.656	.023
-5	.704	.023
-4	.746	.023
-3	.782	.023
-2	.809	.023
-1	.823	.023
0	.837	.023
1	.818	.023
2	.785	.023
3	.751	.023
4	.712	.023
5	.668	.023
6	.626	.023
7	.586	.023

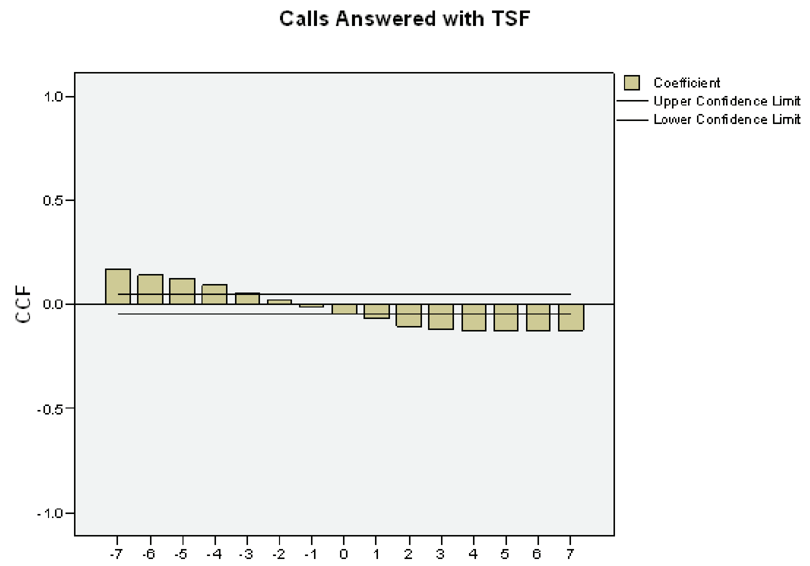


Lag	Cross Correlation	Std. Error(a)
-7	-.140	.023
-6	-.121	.023
-5	-.108	.023
-4	-.083	.023
-3	-.057	.023
-2	-.040	.023
-1	-.024	.023
0	-.021	.023
1	-.015	.023
2	.023	.023
3	.045	.023
4	.051	.023
5	.054	.023
6	.061	.023
7	.062	.023

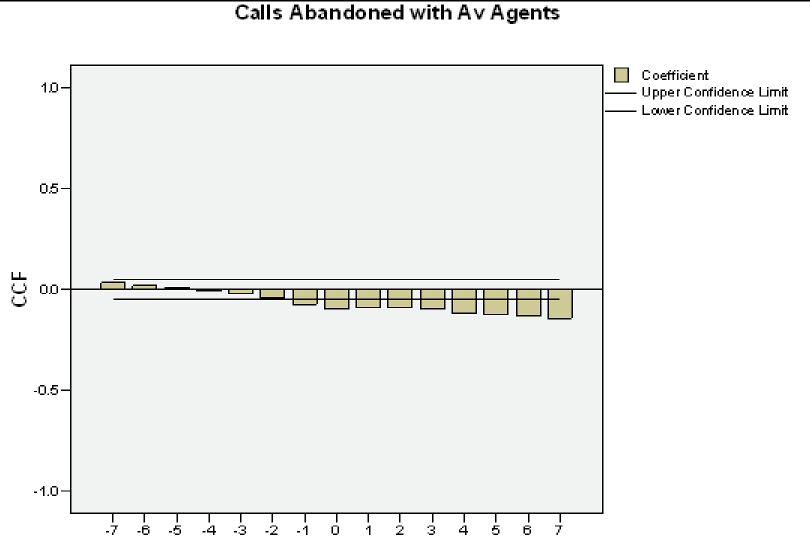


Lag	Cross Correlation	Std. Error(a)
-7	.003	.023
-6	-.011	.023
-5	-.014	.023
-4	.002	.023
-3	-.004	.023
-2	.008	.023
-1	.022	.023
0	-.027	.023
1	.060	.023
2	.089	.023
3	.100	.023
4	.115	.023
5	.132	.023
6	.133	.023
7	.146	.023

Lag	Cross Correlation	Std. Error(a)
-7	.172	.023
-6	.141	.023
-5	.124	.023
-4	.095	.023
-3	.056	.023
-2	.021	.023
-1	-.010	.023
0	-.044	.023
1	-.066	.023
2	-.104	.023
3	-.122	.023
4	-.126	.023
5	-.129	.023
6	-.130	.023
7	-.124	.023



Lag	Cross Correlation	Std. Error(a)
-7	.032	.023
-6	.019	.023
-5	.009	.023
-4	-.007	.023
-3	-.024	.023
-2	-.045	.023
-1	-.073	.023
0	-.096	.023
1	-.089	.023
2	-.090	.023
3	-.101	.023
4	-.116	.023
5	-.126	.023
6	-.134	.023
7	-.143	.023



Lag	Cross Correlation	Std. Error(a)
-7	.247	.023
-6	.315	.023
-5	.382	.023
-4	.428	.023
-3	.473	.023
-2	.563	.023
-1	.692	.023
0	.861	.023
1	.773	.023
2	.591	.023
3	.527	.023
4	.507	.023
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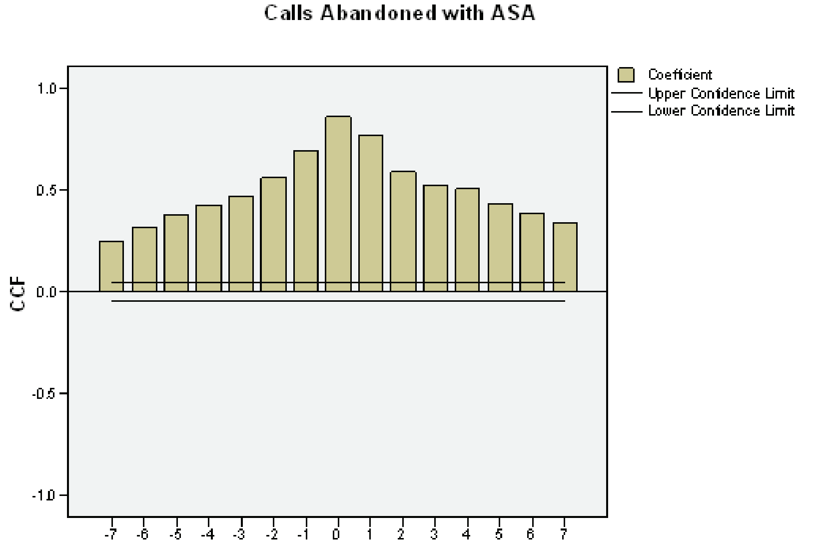
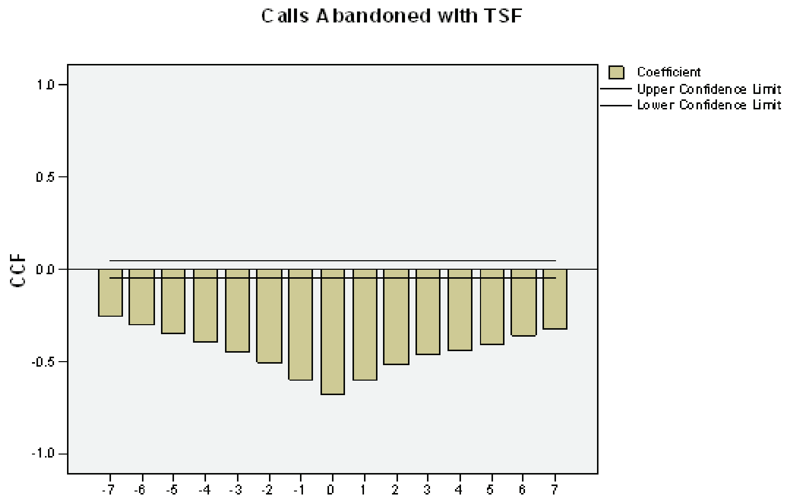
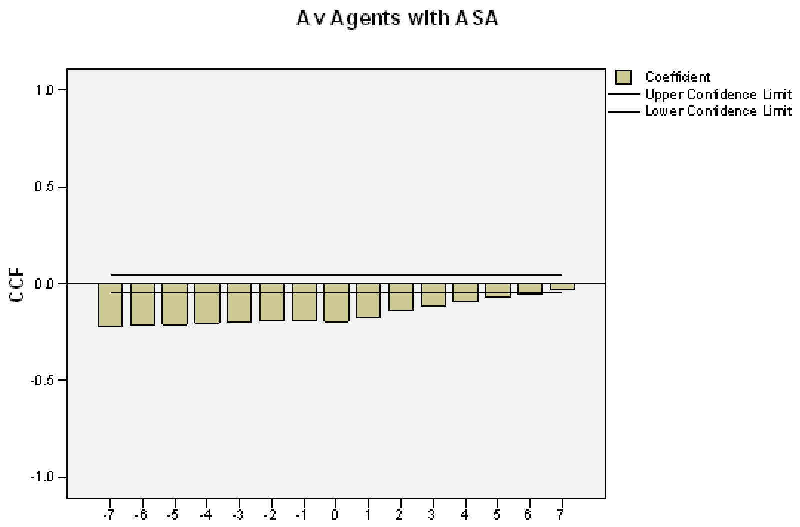
6	.386	.023
7	.343	.023



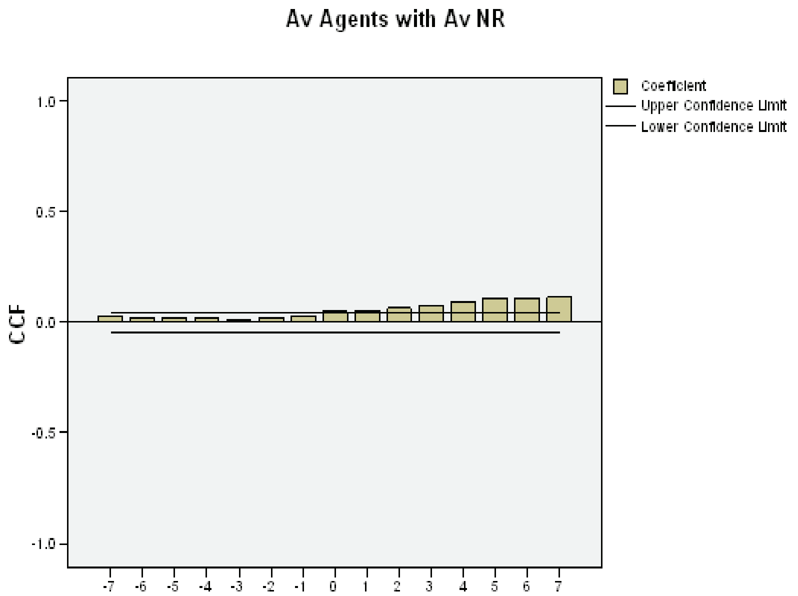
Lag	Cross Correlation	Std. Error(a)
-7	-.257	.023
-6	-.304	.023
-5	-.346	.023
-4	-.394	.023
-3	-.447	.023
-2	-.508	.023
-1	-.598	.023
0	-.680	.023
1	-.600	.023
2	-.516	.023
3	-.465	.023
4	-.442	.023
5	-.406	.023
6	-.361	.023
7	-.327	.023



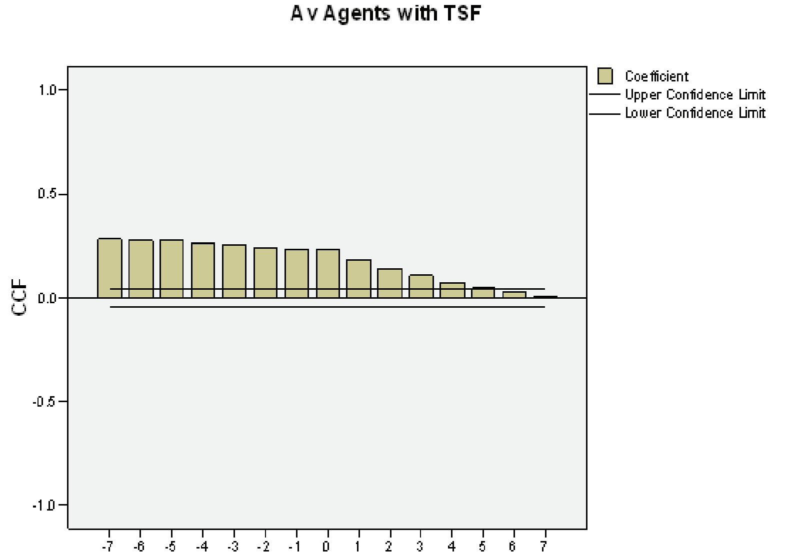
Lag	Cross Correlation	Std. Error(a)
-7	-.222	.023
-6	-.216	.023
-5	-.212	.023
-4	-.204	.023
-3	-.198	.023
-2	-.191	.023
-1	-.193	.023
0	-.198	.023
1	-.175	.023
2	-.141	.023
3	-.115	.023
4	-.093	.023
5	-.073	.023
6	-.053	.023
7	-.032	.023



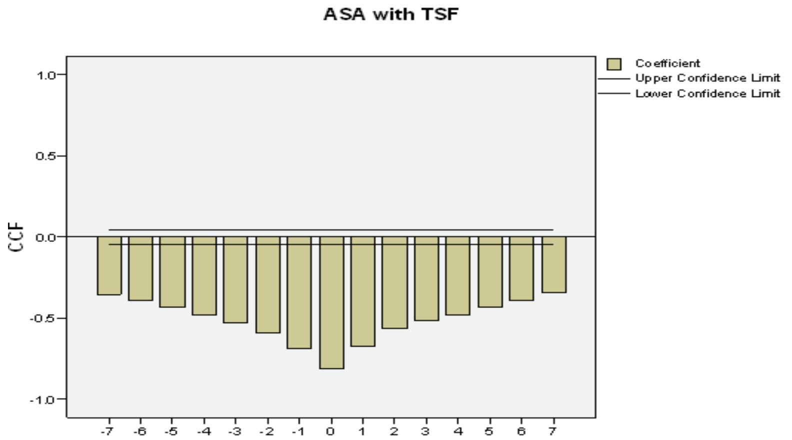
Lag	Cross Correlation	Std. Error(a)
-7	.027	.023
-6	.023	.023
-5	.022	.023
-4	.022	.023
-3	.012	.023
-2	.022	.023
-1	.030	.023
0	.049	.023
1	.053	.023
2	.064	.023
3	.080	.023
4	.091	.023
5	.107	.023
6	.112	.023
7	.114	.023



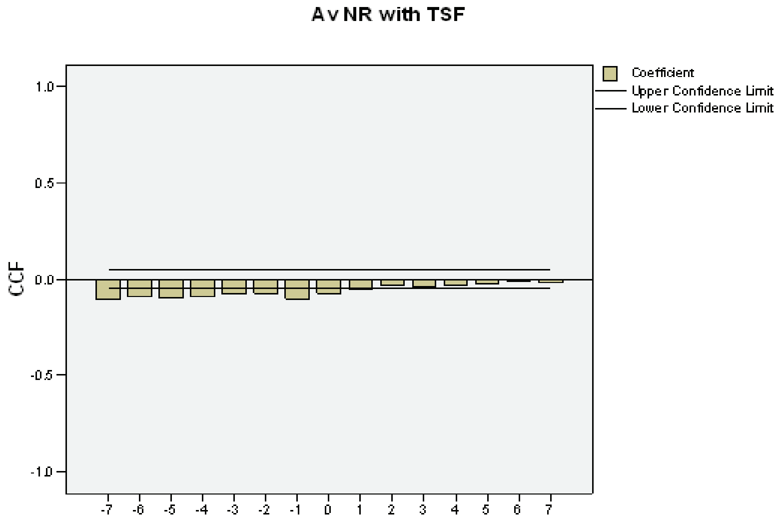
Lag	Cross Correlation	Std. Error(a)
-7	.281	.023
-6	.276	.023
-5	.275	.023
-4	.263	.023
-3	.252	.023
-2	.240	.023
-1	.236	.023
0	.232	.023
1	.184	.023
2	.138	.023
3	.107	.023
4	.073	.023
5	.047	.023
6	.027	.023
7	.006	.023



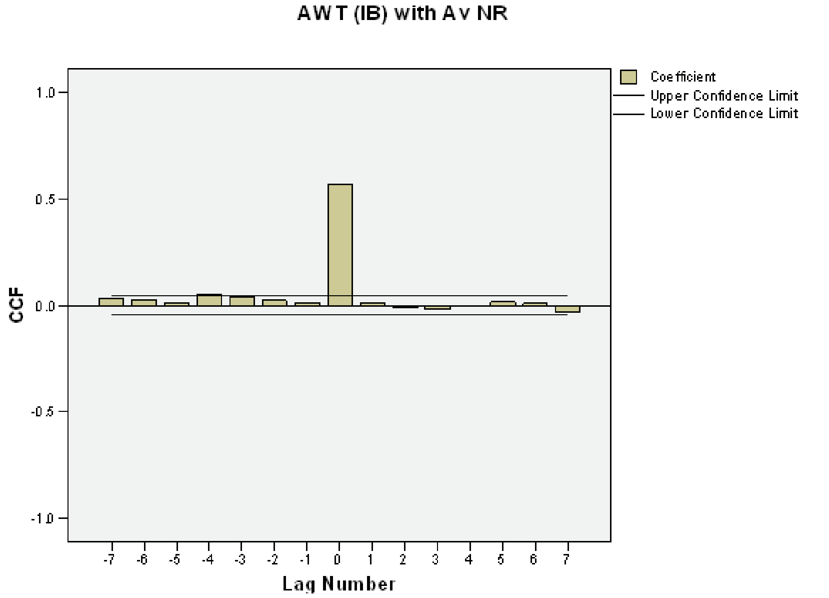
Lag	Cross Correlation	Std. Error(a)
-7	-.354	.023
-6	-.391	.023
-5	-.433	.023
-4	-.483	.023
-3	-.531	.023
-2	-.592	.023
-1	-.690	.023
0	-.810	.023
1	-.671	.023
2	-.566	.023
3	-.512	.023
4	-.480	.023
5	-.432	.023
6	-.391	.023
7	-.344	.023



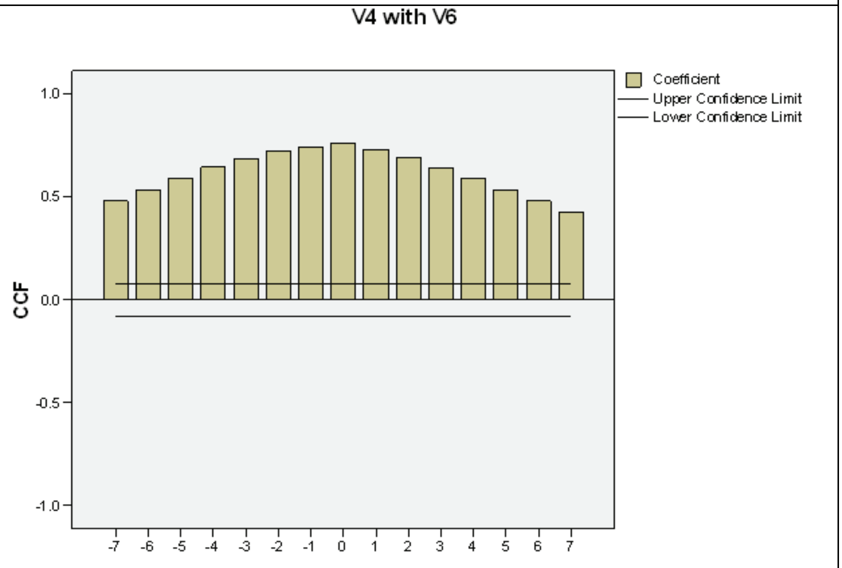
Lag	Cross Correlation	Std. Error(a)
-7	-.107	.023
-6	-.092	.023
-5	-.097	.023
-4	-.091	.023
-3	-.077	.023
-2	-.072	.023
-1	-.101	.023
0	-.073	.023
1	-.052	.023
2	-.032	.023
3	-.037	.023
4	-.032	.023
5	-.024	.023
6	-.012	.023
7	-.018	.023



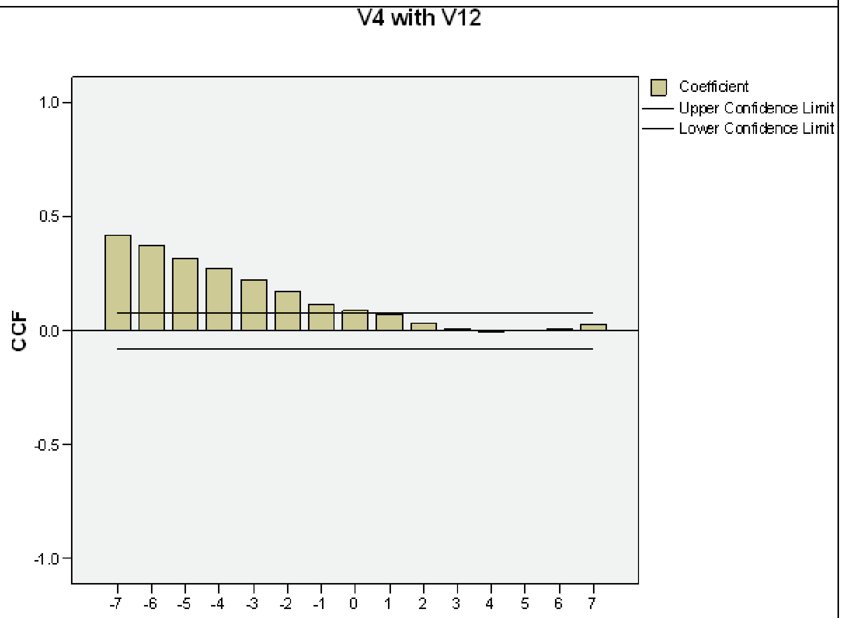
Lag	Cross Correlation	Std. Error(a)
-7	.030	.023
-6	.022	.023
-5	.013	.023
-4	.050	.023
-3	.041	.023
-2	.022	.023
-1	.011	.023
0	.568	.023
1	.011	.023
2	-.012	.023
3	-.019	.023
4	-.005	.023
5	.015	.023
6	.008	.023
7	-.031	.023



Lag	Cross Correlation	Std. Error(a)
-7	.479	.040
-6	.531	.040
-5	.587	.040
-4	.642	.040
-3	.684	.040
-2	.721	.040
-1	.741	.040
0	.760	.040
1	.730	.040
2	.692	.040
3	.641	.040
4	.591	.040
5	.533	.040
6	.478	.040
7	.424	.040



Lag	Cross Correlation	Std. Error(a)
-7	.418	.040
-6	.376	.040
-5	.317	.040
-4	.274	.040
-3	.225	.040
-2	.170	.040
-1	.117	.040
0	.086	.040
1	.071	.040
2	.032	.040
3	.010	.040
4	-.004	.040
5	-.002	.040
6	.009	.040
7	.024	.040

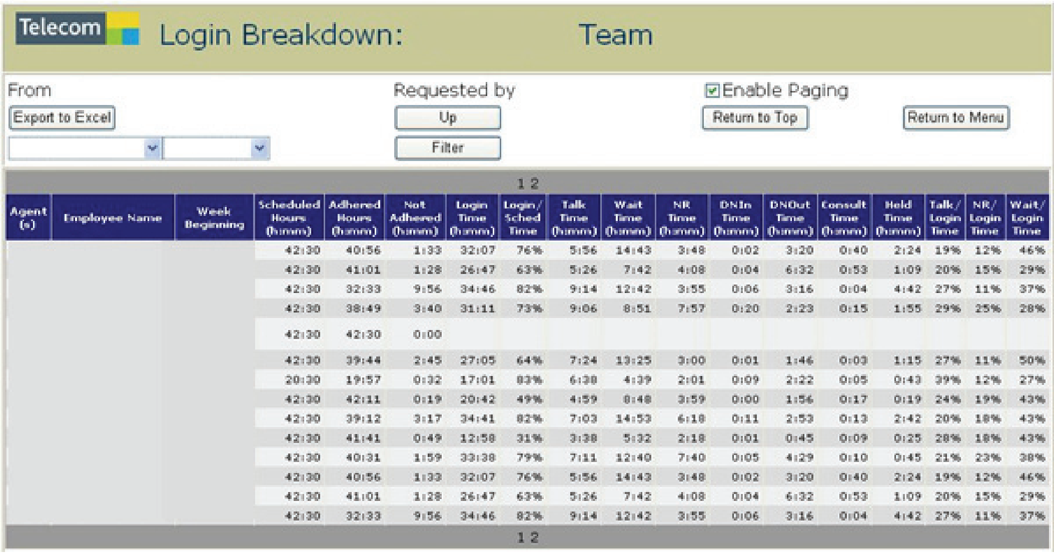


Section C: Agent Priorities Evaluation Based on Performance

The priorities of the agents are computed based on adherence and availability of statistical reports of 10 sample agents as shown in Figure 25 and Figure 26 retrieved from Telecom New Zealand. The priorities are computed based on their not ready time, talk time and calls answered by an agent. Table 20 gives computation of agent priorities. The prioritized calls distribution weights are calculated based on a priori knowledge of priority ranking.

Agent(s)	NR % of login	Talk Time % of login	NR (m)	AWT (IB)	AWT (m)	Talk Time: NR	Talk Time (m)	Calls Answered	Priority Ranking	Prioritized calls distribution
1	12	17.34	432	207.4	3.46	1.6	691	3.33	4	0.0931
2	15	19.87	540	259.2	4.32	1.29	697	2.69	6	0.0752
3	11	26.52	396	190.1	3.17	2.57	1018	5.35	2	0.1496
4	25	29.12	900	432	7.2	1.2	1080	2.5	8	0.0699
5	11	26.77	396	190.1	3.17	2.41	954	5.02	3	0.1404
6	12	37.51	432	207.4	3.46	3.17	1369	6.6	1	0.1845
7	19	22.48	684	328.3	5.47	1.28	876	2.67	7	0.0747
8	18	20.43	648	311	5.18	1.14	739	2.375	9	0.0664
9	18	26.87	648	311	5.18	1.55	1004	3.23	5	0.0903
10	23	21.3	828	397.4	6.62	0.96	795	2	10	0.0559

Table 20. Agent Priorities



Telecom Login Breakdown: Team

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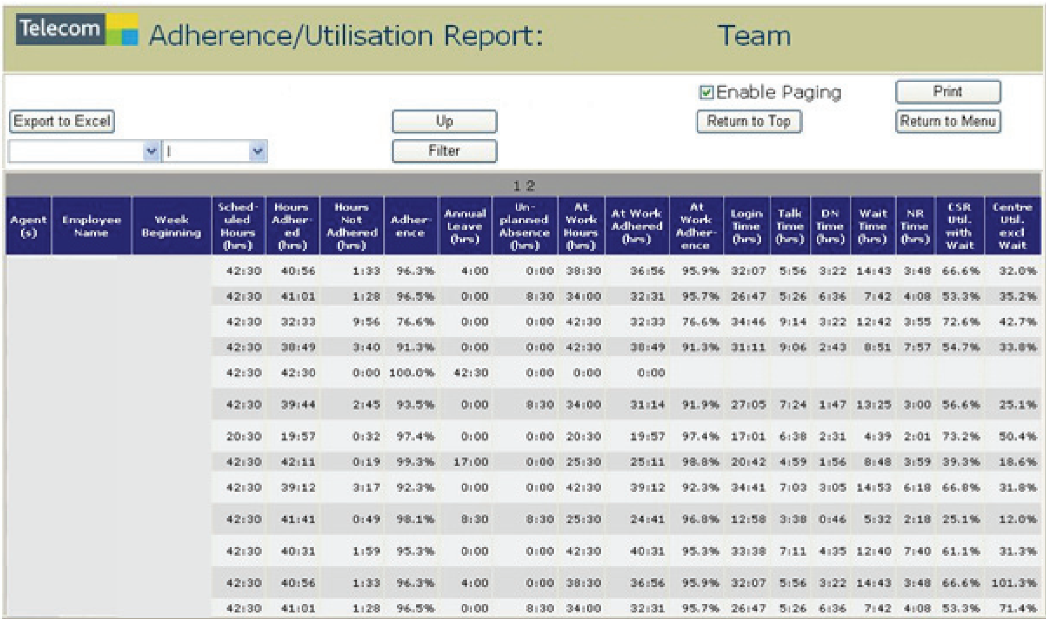
Agent (s)	Employee Name	Week Beginning	Scheduled Hours (h:mm)	Adhered Hours (h:mm)	Not Adhered (h:mm)	Login Time (h:mm)	Login/ Sched Time	Talk Time (h:mm)	Wait Time (h:mm)	NR Time (h:mm)	DNIn Time (h:mm)	DNOut Time (h:mm)	Consult Time (h:mm)	Held Time (h:mm)	Talk/ Login Time	NR/ Login Time	Wait/ Login Time
			42:30	40:56	1:33	32:07	76%	5:56	14:43	3:48	0:02	3:20	0:40	2:24	19%	12%	46%
			42:30	41:01	1:28	26:47	63%	5:26	7:42	4:08	0:04	6:32	0:53	1:09	20%	15%	29%
			42:30	32:33	9:56	34:46	82%	9:14	12:42	3:55	0:06	3:16	0:04	4:42	27%	11%	37%
			42:30	38:49	3:40	31:11	73%	9:06	8:51	7:57	0:20	2:23	0:15	1:55	29%	25%	28%
			42:30	42:30	0:00												
			42:30	39:44	2:45	27:05	64%	7:24	13:25	3:00	0:01	1:46	0:03	1:15	27%	11%	50%
			20:30	19:57	0:32	17:01	83%	6:38	4:39	2:01	0:09	2:22	0:05	0:43	39%	12%	27%
			42:30	42:11	0:19	20:42	49%	4:59	8:48	3:59	0:00	1:56	0:17	0:19	24%	19%	43%
			42:30	39:12	3:17	34:41	82%	7:03	14:53	6:18	0:11	2:53	0:13	2:42	20%	18%	43%
			42:30	41:41	0:49	12:58	31%	3:38	5:32	2:18	0:01	0:45	0:09	0:25	28%	18%	43%
			42:30	40:31	1:59	33:38	79%	7:11	12:40	7:40	0:05	4:29	0:10	0:45	21%	23%	38%
			42:30	40:56	1:33	32:07	76%	5:56	14:43	3:48	0:02	3:20	0:40	2:24	19%	12%	46%
			42:30	41:01	1:28	26:47	63%	5:26	7:42	4:08	0:04	6:32	0:53	1:09	20%	15%	29%
			42:30	32:33	9:56	34:46	82%	9:14	12:42	3:55	0:06	3:16	0:04	4:42	27%	11%	37%

1 2

Figure 25. Agent's Availability Report



Telecom Adherence/Utilisation Report: Team

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Agent (s)	Employee Name	Week Beginning	Scheduled Hours (hrs)	Hours Adhered (hrs)	Hours Not Adhered (hrs)	Adherence	Annual Leave (hrs)	Unplanned Absence (hrs)	At Work Hours (hrs)	At Work Adhered (hrs)	At Work Adherence	Login Time (hrs)	Talk Time (hrs)	DN Time (hrs)	Wait Time (hrs)	NR Time (hrs)	CSR Util. with Wait	Centre Util. excl Wait
			42:30	40:56	1:33	96.3%	4:00	0:00	38:30	36:56	95.9%	32:07	5:56	3:22	14:43	3:48	66.6%	32.0%
			42:30	41:01	1:28	96.5%	0:00	8:30	34:00	32:31	95.7%	26:47	5:26	6:36	7:42	4:08	53.3%	35.2%
			42:30	32:33	9:56	76.6%	0:00	0:00	42:30	32:33	76.6%	34:46	9:14	3:22	12:42	3:55	72.6%	42.7%
			42:30	38:49	3:40	91.3%	0:00	0:00	42:30	38:49	91.3%	31:11	9:06	2:43	8:51	7:57	54.7%	33.8%
			42:30	42:30	0:00	100.0%	42:30	0:00	0:00	0:00								
			42:30	39:44	2:45	93.5%	0:00	8:30	34:00	31:14	91.9%	27:05	7:24	1:47	13:25	3:00	56.6%	25.1%
			20:30	19:57	0:32	97.4%	0:00	0:00	20:30	19:57	97.4%	17:01	6:38	2:31	4:39	2:01	73.2%	50.4%
			42:30	42:11	0:19	99.3%	17:00	0:00	25:30	25:11	98.8%	20:42	4:59	1:56	8:48	3:59	39.3%	18.6%
			42:30	39:12	3:17	92.3%	0:00	0:00	42:30	39:12	92.3%	34:41	7:03	3:05	14:53	6:18	66.8%	31.8%
			42:30	41:41	0:49	98.1%	8:30	8:30	25:30	24:41	96.8%	12:58	3:38	0:46	5:32	2:18	25.1%	12.0%
			42:30	40:31	1:59	95.3%	0:00	0:00	42:30	40:31	95.3%	33:38	7:11	4:35	12:40	7:40	61.1%	31.3%
			42:30	40:56	1:33	96.3%	4:00	0:00	38:30	36:56	95.9%	32:07	5:56	3:22	14:43	3:48	66.6%	101.3%
			42:30	41:01	1:28	96.5%	0:00	8:30	34:00	32:31	95.7%	26:47	5:26	6:36	7:42	4:08	53.3%	71.4%

Figure 26. Agent's Adherence Report

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