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Research Article

QUALITY CONTROL CHARTS FOR MONITORING PERFORMANCE OF HOSPITAL CALL CENTER

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ABSTRACT

As a first contact point of a company with customers, call centers are important to keep customers happy and satisfied. There are key performance metrics and other minimum requirements that a Call Center has to meet. In order to improve service quality, performance metrics are monitored by routine daily calls. In this study, the performance metrics of an inbound hospital call center located in Samsun were studied to measure and understand the variability in performance metrics. The control charts were used to detect assignable causes of variability in average speed of answer, abandonment rate and service level so that necessary precautions can be taken to improve process. Since autocorrelation was recognized in data, Autoregressive Integrated Moving Average (ARIMA) model was used to model correlative structure and then control chart were applied to the independent and identically distributed stream of residuals. ARIMA (6,1,1) for all performance metrics was determined as the best time series model to eliminate autocorrelation. The results showed that the call center process was not under statistical control and sources of variability should be investigated and eliminated.
Keywords: ARIMA, autocorrelation, hospital call center, special cause control chart.

1. INTRODUCTION

A call center is a centralized location that handles phone calls between organizations and customers. The main places that have call centers are banking and finance companies, airline companies, public service agencies, hotels, hospitals, cargo companies, etc. Call centers can handle both inbound and outbound calls [1-3].

Inbound call centers deal with calls from customers who want to communicate with an organization. Calls may relate to complaints, technical support, purchase, queries about services or products, requests etc. Usually, calls are examined and then allocated to an agent who can deal with the customer's request. This process can be done manually or automated with the IVR (Interactive Voice Response) system. Outbound call centers are the exact opposite of inbound call centers. These call centers make phone calls to the customers. They have typical tasks such as collecting customer satisfaction data and determination of sales forecasts with customer surveys. Calling customers process can be automated with an automatic dialler. These connect agents only when calls are answered, which increases the number of calls that can be made per hour and saves

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time. Blended call centers are capable of both inbound and outbound calls. Big companies that have a call center will need to meet both inbound and outbound tasks.

People are an integ ral part of the call center process. Since no two people have exactly the same skills, the same attitude and the same behavior then interactions between the customer making a contact and the agent receiving the contact are not the same. Therefore, regardless of how well designed or carefully maintained it is, there will be always certain amount of variability in any call center process. Control charts are used to detect such variations caused by unusual occurrences in a process.

The control chart, one of the quality tools, is a graphical display of a quality characteristic such as average speed of answer that has been computed from a sample. The chart contains a center line that represents the average value of the quality characteristic and three-sigma control limits (Upper Control Limit- UCL and Lower control limit- LCL). These control limits are computed so that if the process is in control, 99.73% of the sample points will fall between them [4]. By comparing current data to these limits, whether the process variation is stable (in control) or is unpredictable (out of control) can be drawn. As long as the points plot within the control limits and there is no evidence of unusual behavior between the limits such as trends and cycles, the process is assumed to be stable/in control (common cause variation) and no action is taken. However, a point outside of the control limits indicates that the process is out of control (affected by special/assignable causes of variation) and corrective actions are needed to find and eliminate the assignable causes responsible for this situation.

Control charts are useful to analyze and control repetitive processes such as call centers. By displaying running records of performance, they help to determine when corrective actions are needed. Advantages of control charts are as follows:

1. Pinpointing the unpredictable processes,
2. Evaluating process consistency over time,
3. Separating common and special cause variations,
4. Providing a common language for decision makers to discuss and improve processes.

The managers of call center operations have been interested in increasing call center performance to improve customer satisfaction and reduce costs. There are some studies about call center performance such as Evensen, Frei [5], Staples, Dalrymple [6], Dawson [7], Jaiswal [8], Budak [9], Baraka, Baraka [10], Flagg [24], Karakus and Aydin [11]. In these studies, tools such as simulation and mathematical modeling were used to assess the call center performance. Budak [9] was modeled call center network with queuing network and simulation approaches. Different models were developed with different divert, return rates and number of agents being multi-tasking or dedicated to give service to a specific call type. These models were compared in terms of systems performance metrics and reported. The modeling and simulation techniques have been used to examine the effect of different call centers parameters and to predict the performance of the system [5, 7, 8]. Staples, Dalrymple [6] used the SERVQUAL model to evaluate service quality at the call center. Baraka, Baraka [10] offered a model based on the Delone and McLean Information Systems success model to evaluate the performance of call centers. A Weighted Call Center Performance Index was proposed to evaluate the call center performance. Karakus and Aydin [11] proposed a distributed call monitoring system. The system was used evaluating all recorded calls using several quality criteria. In the system, numerous call records have been analyzed using the Hadoop MapReduce framework. Text similarity algorithms such as Cosine and n-gram were used. Empirical call records were used to show the performance of proposed call monitoring system.

Despite the usage of many areas, control charts were only used by Flagg [24] to monitor the performance of call centers so that corrective actions can be initiated on time. In this study, the Resolved on Call metric was chosen and control charts were recommended as a process improvement and development tool for all processes in the call center.

In this study, appropriate control chart based on the data structure was used to monitor call center performance. The examined performance metrics are average speed of answer, abandonment rate and service level.

2. PERFORMANCE METRICS USED IN STUDY

Customer satisfaction and loyalty are closely connected to the quality of service provided. Primary customer expectations from a call center are given in below [25]:

1. Be accessible
2. Treat me courteously
3. Be responsive to what I need and want
4. Do what I ask promptly
5. Provide well-trained and informed employees
6. Tell me what to expect
7. Meet your commitments; keep your promises
8. Do it right the first time
9. Be socially responsible and ethical
10. Follow up

Call center performance criteria can be examined under three headings. These headings are called Accessibility Criteria (service level, abandonment rate, average speed of answer), Productivity Criteria (average talk time, after call work time, schedule adherence and compliance, occupancy) and Quality Criteria (call control / call listening, first call resolution, error / repeat rate, customer satisfaction survey, shadow customer research, exam / quiz). The main objective in determining the performance of a call center is to be accessible. The most important performance criteria is the accessibility criteria. In this study, accessibility criteria were used to monitor call center performance.

Average Speed of Answer (ASA), Service Level (SL), and Abandoned Calls/ Abandonment Rate (AC/AR) are Accessibility Measures of Call Centers related to the customer expectations numbered 1, 3 and 7. These metrics should be monitored over the long term to identify patterns of variability in call center that can be fixed through staffing or technical solutions. Automatic Call Distribution (ACD) is based on first-in, first-answered rule. Also it routes a call to groups of agents, also called queue. The caller who has been waiting for the longest time will be directed to the next available agent. ASA is the timing for answering the call starts when the call is queued for the ACD queue and ends when an agent answers the call. Average speed of answer is calculated by total delay divided by total number of calls. The global metric for ASA is 28 seconds in a call center [26]. Service Level is the percentage of contacts answered within a predefined duration. The global metric for SL in the call center is that 80% of the calls are answered in 20 seconds (i.e., 80/20) [12, 13]. However, goal for this metric becomes 100/0 for emergency services. Abandonment Rate is the percentage of calls that are hang up by the customer before an agent answers. The global metric for AR in the call center is between 5–8% [26]. The longer the time that callers have to wait before an agent answers, the higher the abandonment rate is likely to be as people get tired of waiting.

3. CONTROL CHARTS

Variation is a measure of the difference between the values of particular characteristic describing a product/service. Common/random variation is inherent in any process that is unable to produce every good/services the same way every time. A good example for common variation in call centers is the variation that exists in the average handle time among the call center agents. Same customer or same query will be handled in different durations by two different call center agents. On the other hand, special/assignable cause of variation is a source of variation that is unpredictable. Underlying causes of this type of variation could be a new untrained operator, system problems, power problems, telephone line problems, poorly written procedure, etc.

Control charts are used to detect nonrandom sources of variation in the data by separating variation due to common causes from variation due to special causes. Control charts are based on sampling which is subject to two kinds of error:

- Type I error (α): "False Alarm" – probability that an in-control value would appear as out-of-control.
- Type II error (β): "Failure to detect" – probability that a shift causing an out-of-control situation would be mis-reported as in-control.

One of the assumptions in designing any control chart for monitoring a process is that the process from which the data is being taken is stable (i.e. that the data are independent of each other and identically distributed in each subgroup). The second assumption is that the data is well-approximated by the normal distribution. Before implementation of control charts, it is necessary to verify the assumptions of normality and independence to prevent the above errors.

Wheeler and Chambers [14] and Wheeler [15] proposed that it is not necessary to correct nonnormality unless the data are highly skewed. However, the existence of autocorrelation in data cause problems of detecting "assignable causes" that do not exist implying a high probability of false alarms. These false alarms can cause unnecessary interventions, which can cost a business money. The effect of autocorrelation on control charts has been studied by many researchers such as Young and Winistorfer [16], Elevli, Uzgören [17], Noskievičová [18], Wang, Yu [19], Karaoglan and Bayhan [20], Kandananond [21], Perzyk and Rodziewicz [22] and Elevli, Uzgören [23]. In all these studies, it is found that autocorrelation causes an increase in the number of out-of-control signals on control chart.

4. ANALYSIS

4.1. Data

In this study, the call center data of a private owned hospital in Samsun province was used. Since high quality service is an important determinant of patient satisfaction and loyalty, performance metrics such as ASA, AR and SL of this hospital call center are monitored. These metrics are used to improve the service quality of the call center. All these metrics are analyzed on a daily basis and are recorded for control of compliance with international standards. The daily data collected in this study covers January and December 2017. Descriptive statistics of ASA, SL and AR are given in Table 1. Minitab 17 and IBM SPSS V.23 (USA, Chicago) were used to analyze data.

4.2. Individuals Control (IC) Charts

An individuals control chart can be used for time-series tracking of a process to determine whether or not the process is in statistical control meaning stable [4]. It experiences only common-cause variability when a process is considered stable. Special-cause conditions can be causing non-stability when a process is out of control. This control chart type uses the moving range of two successive observations.

Individuals control charts have been established in order to analyze the variation in ASA, SL and AR. The process for all the metrics is out of statistical control according to Figure 1 because some of the data points out of the control limits.

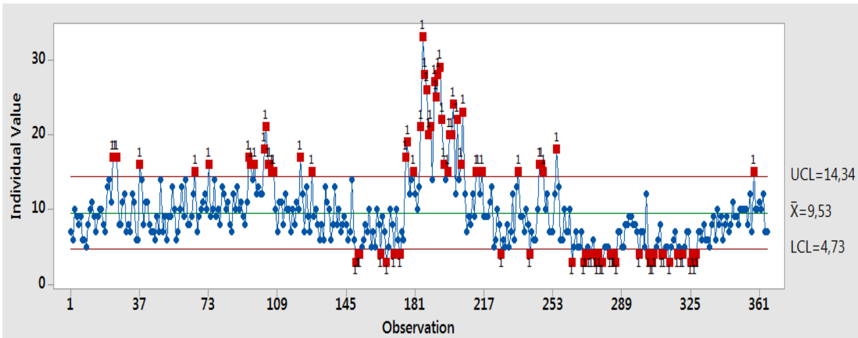
Table 1. Descriptive statistics.

Parameter	Months	Mean	Std. Dev.	Min.	Q_1	Median	Q_3	Max.	Range
Average Speed of Answer (s) Allowed limit (max 28 seconds)	Jan.	9.613	3.222	5.000	7.000	9.000	11.000	17.000	12.000
	Feb	9.250	2.876	6.000	7.000	9.000	11.000	16.000	10.000
	March	10.548	2.307	7.000	9.000	10.000	12.000	16.000	9.000
	April	12.200	3.517	7.000	10.000	11.500	15.250	21.000	14.000
	May	8.968	3.250	3.000	7.000	8.000	11.000	17.000	14.000
	June	8.233	4.049	3.000	5.000	7.000	10.000	19.000	16.000
	July	18.390	7.080	7.000	12.000	20.000	24.000	33.000	26.000
	Aug.	8.968	3.411	4.000	6.000	9.000	12.000	15.000	11.000
	Sep.	8.233	4.158	3.000	5.000	7.000	10.500	18.000	15.000
	Oct.	5.677	2.242	3.000	4.000	5.000	7.000	12.000	9.000
	Nov.	5.167	1.510	3.000	4.000	5.000	6.250	8.000	5.000
	Dec.	9.000	2.049	5.000	8.000	9.000	10.000	15.000	10.000
Abandonment Rate (%) Allowed limit (max 5-8%)	Jan.	2.753	1.101	0.949	2.092	2.751	3.291	5.659	4.709
	Feb	2.504	1.299	0.746	1.666	2.456	3.127	7.507	6.761
	March	3.374	1.273	0.565	2.396	3.438	4.044	5.930	5.365
	April	4.127	1.488	0.959	3.105	3.998	5.082	8.025	7.065
	May	2.663	1.093	0.770	1.813	2.436	3.375	6.402	5.631
	June	3.298	1.577	1.124	2.214	3.108	4.133	8.553	7.429
	July	5.575	2.742	1.363	3.132	5.579	7.523	12.743	11.380
	Aug.	2.787	0.918	1.412	2.024	2.524	3.602	4.891	3.480
	Sep.	3.706	1.702	0.793	2.475	3.526	4.681	7.368	6.576
	Oct.	3.314	2.096	0.297	1.957	2.608	4.237	9.552	9.255
	Nov.	2.412	1.087	1.120	1.503	2.155	3.000	5.534	4.414
	Dec.	2.873	1.125	0.427	2.155	2.826	3.403	6.256	5.829
Service Level (%) Allowed limit (max 80/20)	Jan.	82.505	4.889	70.730	80.090	84.210	85.700	90.410	19.680
	Feb	82.868	4.399	74.190	79.545	83.290	86.907	88.520	14.330
	March	81.073	3.747	72.080	79.320	81.770	84.070	86.240	14.160
	April	79.230	4.912	65.820	76.065	80.735	82.752	86.020	20.200
	May	83.852	5.426	70.170	80.830	84.290	87.800	92.380	22.210
	June	85.680	5.940	72.120	84.250	86.470	90.130	93.820	21.700
	July	71.560	8.830	57.280	64.170	72.410	78.220	88.630	31.550
	Aug.	83.480	5.740	72.480	78.220	84.610	88.240	91.680	19.200
	Sep.	83.420	6.920	67.020	78.590	85.340	89.110	94.600	27.580
	Oct.	88.215	4.166	74.590	85.440	89.430	91.390	93.160	18.570
	Nov.	89.457	2.973	80.950	87.580	89.910	91.555	94.310	13.360
	Dec.	83.498	3.697	74.430	80.870	83.260	85.810	91.000	16.570

4.3. Special Cause Control Charts (ARIMA Charts)

Autocorrelation is the linear dependence of a data set with itself. In case of dependency between data, the autocorrelation structure is captured by using Auto Regressive Integrated Moving Average (ARIMA) model. ARIMA models are fitted to the time series data either to predict future points in the series. These models are shown as ARIMA(p,d,q) where p is the number of autoregressive terms, d is the number of times the series has to be differenced before it becomes stationary and q is the number of moving average terms. Autocorrelation and Partial Autocorrelation functions (ACF and PACF) are examined to identify the model parameters.

After the ARIMA model has been estimated and validated, the residuals from this model meet the independency assumption of the traditional control charts. Therefore, the problem of the autocorrelation of the original observations is overcome and the traditional control charts such as individuals control charts can be applied to the residuals. This type of control charts are called as Special Cause Control (SCC) Charts, ARIMA Charts or Forecast-Based Residual (FBR) Charts.



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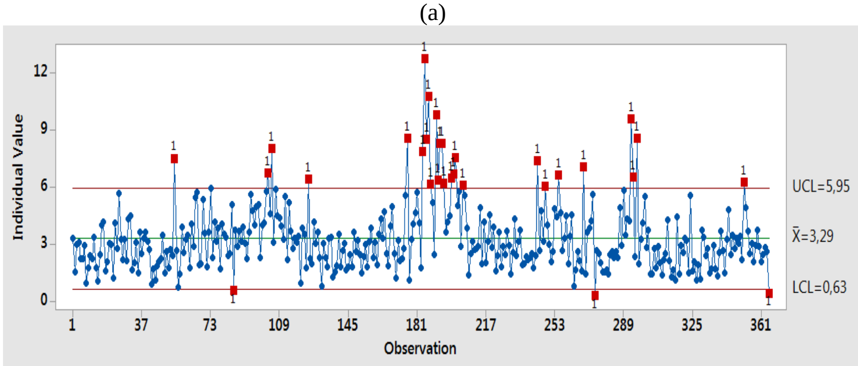

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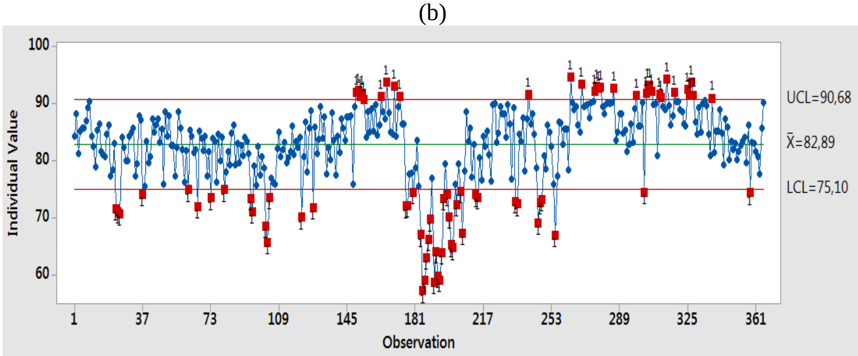

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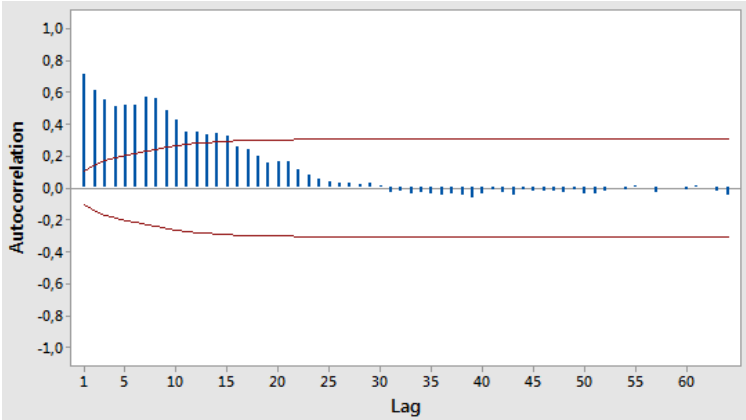
Figure 1. IC charts for average speed of answer (a), abandonment rate (b) and service level (c).

Control charts given in Figure 1 are based on the assumption that there is no correlation between successive observations. Since the assumption of independence of observations is questionable in practice, the existence of autocorrelation was firstly investigated (Figure 2). Bars extending beyond two standard deviation limits indicate a high degree of positive correlation for consecutive data points that do not die out quickly.



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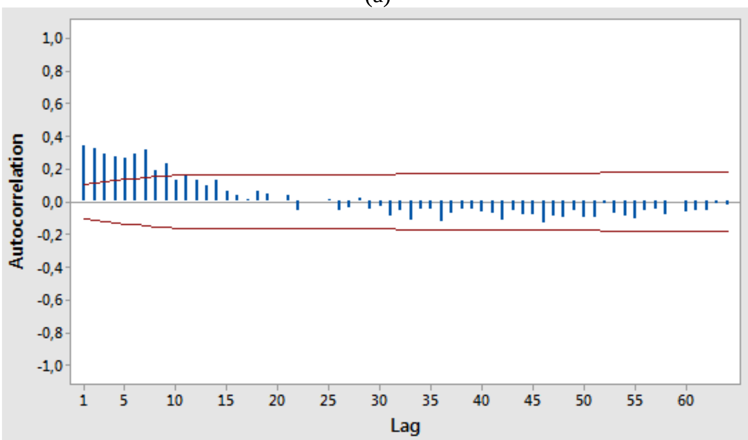

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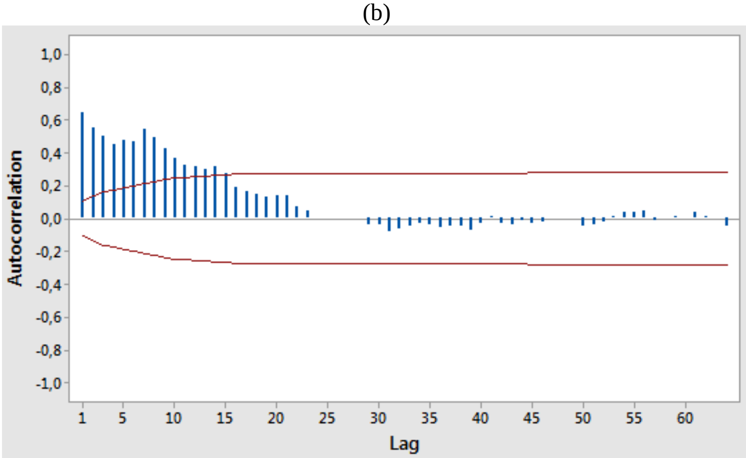


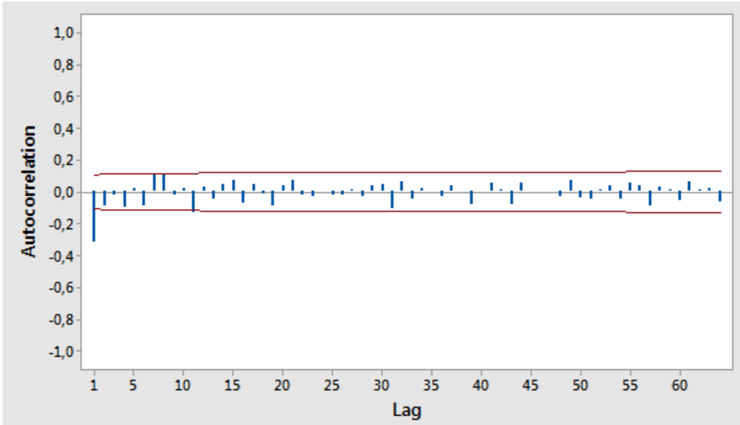
(c)

Figure 2. Estimated autocorrelations for ASA (a), AR (b) and SL (c).

The AR and MA components of the data must be identified to fit the ARIMA model. These components requires stationary series. Therefore the data were then examined for the presence of any trend. A process is considered stationary if its statistical characteristics do not change with time. ACF plots in Figure 2 indicate that the series are non-stationary, because the autocorrelations diminish very slowly. In order to overcome this problem, first order differences were taken. ACF and PACF plots in Figure 3 and 4 respectively indicated that both of the series are now stationary after first differencing and no further differencing is necessary.

ACF and PACF for differenced data were examined to determine p and q values. In Figure 3, it is seen that one significant autocorrelation coefficient at lag 1 exists for all the performance metrics. Therefore, MA (1), having a memory of only one period, was considered for average speed of answer, abandonment rate and service level. Although it is seen that one significant autocorrelation coefficient at lag 6 exists for service level, this can be ignored. In Figure 4, sixth autocorrelation is statistically significant for ASA, AR and SL. This suggests the AR (6) model for all metrics. Therefore, ARIMA(6,1,1) was found to be suitable model for all data sets.

In Table 2, different alternative models were compared based on error statistics. ARIMA (6,1,1) with smaller root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) values was found to be suitable model for ASA, AR and SL.



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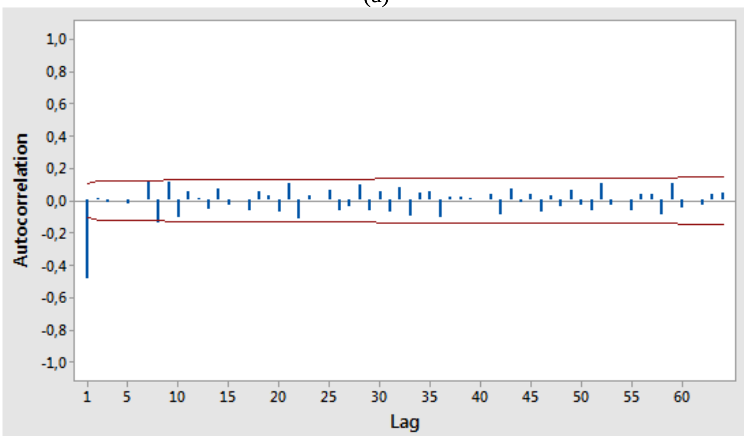

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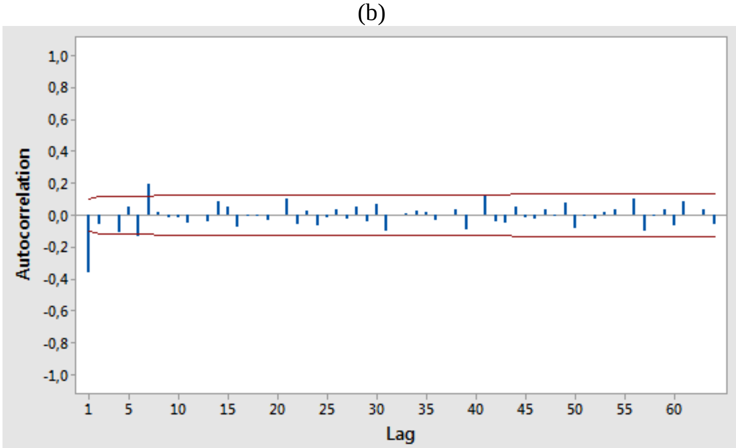

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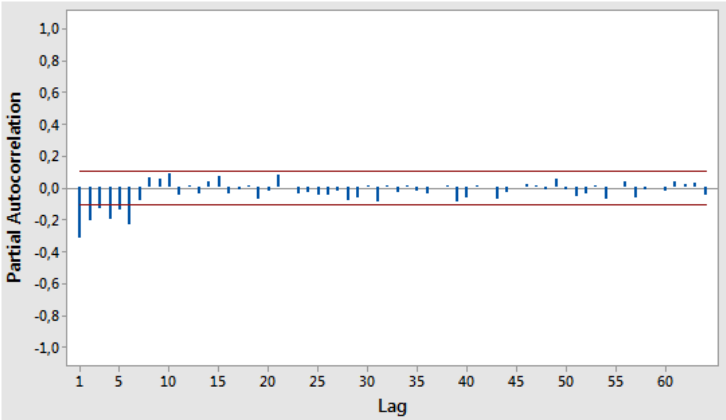
Figure 3. Estimated autocorrelations for ASA (a), AR (b) and SL (c) after first differencing.



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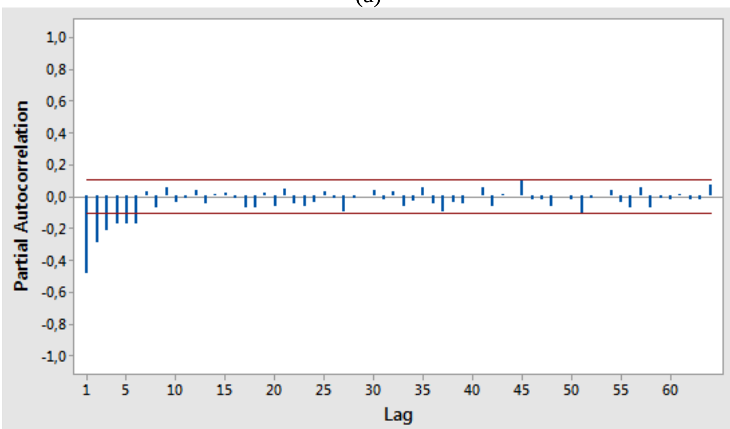

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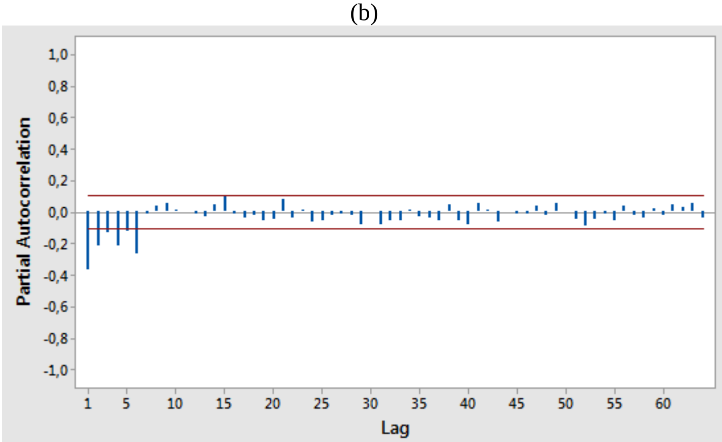

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Figure 4. Estimated partial autocorrelations for ASA (a), AR (b) and SL (c) after first differencing.

Table 2. Model comparison.

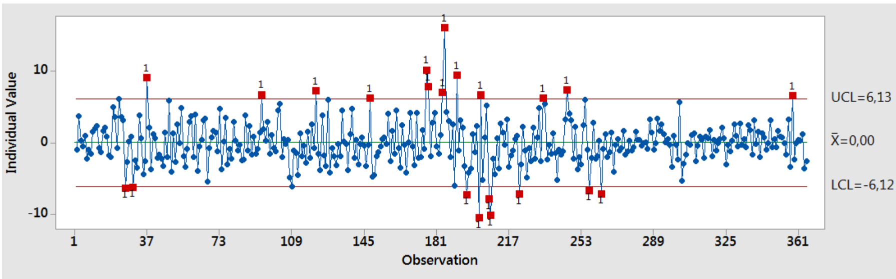
Parameter	Model	RMSE	MAE	MAPE
Average Speed of Answer	ARIMA (6,1,1)	3.173	2.347	27.845
	ARIMA (1,1,1)	3.232	2.413	28.374
	ARIMA (1,1,2)	3.236	2.412	28.341
	ARIMA (3,1,1)	3.286	2.451	29.133
Abandonment Rate	ARIMA (6,1,1)	1.564	1.136	47.910
	ARIMA (2,1,1)	1.571	1.150	48.391
	ARIMA (3,1,0)	1.633	1.195	50.043
	ARIMA (0,1,2)	1.569	1.150	48.386
Service Level	ARIMA (6,1,1)	4.853	3.687	4.589
	ARIMA (3,1,0)	5.181	3.993	4.990
	ARIMA (1,1,2)	4.990	3.841	4.799
	ARIMA (3,0,1)	4.941	3.816	4.780
RMSE: root mean squared error; MAE: mean absolute error; MAPE: mean absolute percentage error				

Table 3. Estimates of the parameters.

Parameter	Model	Model parameter	Estimate	Std. Error	t	p value
Average Speed of Answer	ARIMA (6,1,1)	Constant	0.004	0.051	0.078	0.938
		AR (1)	-0.278	0.208	-1.334	0.183
		AR (2)	-0.299	0.110	-2.720	0.007
		AR (3)	-0.245	0.089	-2.746	0.006
		AR (4)	-0.281	0.077	-3.641	0.000
		AR (5)	-0.187	0.078	-2.400	0.017
		AR (6)	-0.201	0.650	-3.101	0.020
		Difference	1.000			
		MA (1)	0.234	0.212	1.102	0.271
Abandonment Rate	ARIMA (6,1,1)	Constant	-0.002	0.023	-0.077	0.938
		AR (1)	-1.265	0.214	-5.913	0.000
		AR (2)	-0.975	0.174	-5.595	0.000
		AR (3)	-0.761	0.143	-5.330	0.000
		AR (4)	-0.595	0.119	-4.979	0.000
		AR (5)	-0.445	0.094	-4.743	0.000
		AR (6)	-0.247	0.054	-4.583	0.000
		Difference	1.000			
		MA (1)	-0.492	0.219	0.219	0.026
Service Level	ARIMA (6,1,1)	Constant	-0.002	0.076	-0.027	0.979
		AR (1)	-0.513	0.188	-2.733	0.007
		AR (2)	-0.421	0.112	-3.760	0.000
		AR (3)	-0.338	0.089	-3.780	0.000
		AR (4)	-0.367	0.078	-4.726	0.000
		AR (5)	-0.254	0.077	-3.296	0.001
		AR (6)	-0.266	0.057	-4.669	0.000
		Difference	1.000			
		MA (1)	0.059	0.195	0.301	0.764

Estimated model parameters and tests for the significance of the parameters for ARIMA(6,1,1) model are given in Table 3.

Since residuals of the ARIMA model are uncorrelated and random, the residuals of ARIMA model were then be used to create control charts. Points beyond the three-sigma control limits of special cause control charts in Figure 5 indicates out of statistical control.



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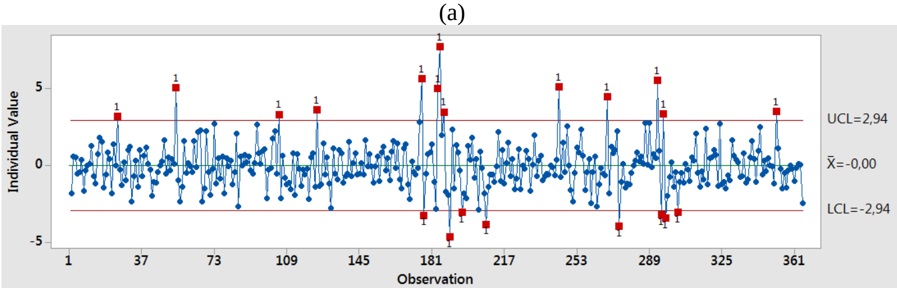

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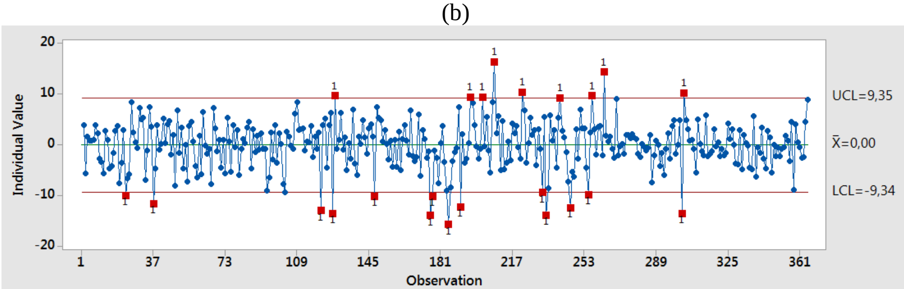

(c)

Figure 5. SCC charts for ASA (a), AR (b) and SL (c).

Number of out-of-control points in IC chart and SCC chart are given in Table 4. IC charts in Figure 1 have more out-of-control points than the SCC charts. That is, the presence of autocorrelation in the data leads to a significant increase in false alarm rate.

Table 4. Number of out of control points in IC chart and SCC chart.

	Number of points out of control limits	
Parameter	**IC Chart**	**SCC Chart**
Average Speed of Answer	86	22
Abandonment Rate	30	21
Service Level	78	23

5. RESULTS

In order to satisfy customers, Call Center Managers should measure the variation in performance metrics, understand the causes of variation and reduce the variation. Because control charts reveal what's going on in a call center, they allow managers to detect and correct variation before they cause deeper problems. This greatly reduces the need for recall or additional expenditures to fix the service offered.

When independency assumption of control charts is not met, traditional control charts lead to excessive number of false alarm or the loosing ability to detect an assignable cause of variation. SCC charts provide an improved method for examining process stability by enhancing the ability of isolating and identifying assignable causes of variation in case of autocorrelation existence.

In this study, ARIMA (6,1,1) model was found to be suitable for average speed of answer, abandonment rate and service level. Control charts based on the residuals of this model showed that the call center process is not in statistical control. Since huge variability in performance metrics was detected, all metrics should be improved.

Since call center's aim is to serve the best performance to its customers, it is necessary to investigate and eliminate the variations that occur in performance. In this scope, providing better call center training, increasing employee engagement, using better call center technology, automation powered by artificial intelligence and solutions for system problems, power problems and telephone line problems can be developed.

Technology enables customers to streamline their experience while simultaneously reducing the stress on agents. As an example, routing calls directly from certain areas of the website or having a interactive voice response system provides customers moving through system to arrive at a solution more quickly, and agents are freed up to work with more complicated customer needs.

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