MEF UNIVERSITY

ORDER MANAGEMENT PERFORMANCE STUDY

Capstone Project

Vedat Güneş

İSTANBUL, 2017

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Asst. Prof. Dr. Vahid Akbari

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EXECUTIVE SUMMARY

ORDER MANAGEMENT PERFORMANCE STUDY

Vedat Güneş

Advisor: Asst. Prof. Dr. Vahid Akbari

SEPTEMBER, 2017, 27

In this project, we have aimed to understand how asynchron order management[7][8] system works at Vodafone Turkey and what is the current performance status about the orders which run between three systems; billing charging system-Kenan, CRM system-Siebel, and order management system-Tibco BPM. There are Key Performance Indicators (KPI) about the orders which they should meet and we have tried to understand the current status about order KPIs and we will try to define a model which can predict the next failure point of the order scenario that we will study. A failure can be described not meet the order completion KPIs such as CreateModifyOrder end-to-end completion KPI is less than 210 sec. If the order in the CreateModifyOrder scenario accomplishes more than 210 sec this is called failure and this situation is reported as customer compliant for IT department.

In order to identify the issues during the study we will focus on to prepare data for modelling, use the prepared data in the models listed below;

- Classification and Regression Trees (CART)
- KNN (k-Nearest Neighborhood Classifier)
- Support Vector Machines (SVM)
- Random Forest Classifier
- Linear Model

Key Words: order, order management, Siebel, Kenan, tibco, tibco bpm, random forest, tableau KNN, SVN, linear model, CART, linear regression

ÖZET

İŞ EMRİ PERFORMANS ÇALIŞMASI

Vedat Güneş

Tez Danışmanı: Asst. Prof. Dr. Vahid Akbari

EYLÜL, 2017, 27

Vodafone Türkiye'de bütün işlemler iş emirleri(order) adı verilen talepler üzerinden gerçekleştirilir. Bu iş emirleri ağırlıklı olarak müşteri ilişkileri sistemi olan Oracle Siebel ürünü üzerinden başlatılır. Daha sonra iş emirlerini koordine eden Tibco-BPM platform üzerine gelir. Bu platform bütün iş emirlerini ilgili alt sistemlere aktararak koordinasyonu sağlar. Seri bağlanmamış bu eş zamanlı olmayan iş emir yönetimi inceleyeceğimiz durumlar için Siebel ve Kenan platformları üzerinden başlatılır.

Sistemler arasında çakışan iş emirlerinin birer tamamlanma süreleri vardır.Bu süreler sistemlerin istenilen şekilde çalıştığını gösterir. Her bir iş emri tipi için bu KPI'lar farklıdır. Bu KPI'lara uyum sağlanmadığı durumunda iç müşteriler tarafından şikayet konusu olur. KPI'lar kaşılanmadığında; maliyetler artar ve son müşterilerimizin bizi tercih/tavsiye etme oranları düşerek mali zararlar meydana gelir.

Bu çalışma bizlere; bu üç ana sistem üzerinde iş emirlerinin akışını ve performans konusunda hangi noktalarda sorunlar yaşadığımızı, yaşadığımız bu sorunlar için ne gibi çözüm önerileri bulabileceğimizi gösterecektir.

Anahtar Kelimeler: iş emri, iş emri yönetimi, Siebel, Kenan, tibco, tibco bpm, random forest, tableau KNN, SVN, linear model, CART, linear regression

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1. INTRODUCTION

This study will identify the Order Performance status at Vodafone IT. Orders are very important to identify customer satisfaction because every operation is done by asynchrony orders in Vodafone applications. So any improvement on order performance this outcome will have great impacts for both Vodafone operations team and Vodafone Customers.

We can summarize this study as;

- System information which order flows. Plus, the order data details and insights for the last month period – About the Data Section
- Models information that I run on the data and tableau discovery platform details – Project definition section
- Model results and the problem definition with the help of applied data transformation and modelling steps- Methodology section
- Output of the study and main outcomes of this model execution process – Result section

2. PROJECT DEFINITON

Our project will try to find out the answer for the following question: "Is there an improvement point on order process which effects directly Vodafone order availability KPIs?"

There are KPIs which Vodafone Turkey should meet and explain any extraordinary actions if the KPI could not be met. Those KPIs are being tracked by Vodafone internal units like Customer Operations, Customer Value Management teams, Vodafone Group and *Bilişim Teknolojileri Kurumu* (BTK). If there is a problem about order performance this means a very big problem for Vodafone Turkey and BTK can define punishments based on customer complaints.

The scope of the project is;

- To focus on an order dataset for a month
- To identify the status of the performance KPIs
- To create a dashboard portal for daily tracking with Tableau
- To identify the potential problems
- To define a solution statement

I have also run different machine learning algorithms on this analyses process. I have listed these algorithms below:

- Classification and Regression Trees (CART)
- KNN (k-Nearest Neighborhood Classifier)
- Support Vector Machines (SVM)
- Random Forest Classifier
- Linear Model

Additionally, I will present the outputs to the related departments in the company and they are valuable we will take actions based on this research and improve the KPI values on orders.

Within the scope I will not study other order types except **Service.Mobile.ModifyOptions.** Other scenarios do not have valuable effect on KPIs. Plus they do not affect components. One month of data has more than 17 million of records and this amount of data will be available for daily routine controls via dashboard which I will deliver.

3. ABOUT THE DATA

In order to explain this study very well, we want to share information about the systems those order flows on; Amdocs Kenan, Oracle Siebel CRM, and Tibco OSM.

3.1. Amdocs Kenan

Amdocs Kenan[8] skillfully handles complex revenue management for customers by delivering any combination of voice, video, messaging, content or Internet Protocol (IP) for complex B2B customers or traditional B2C services.

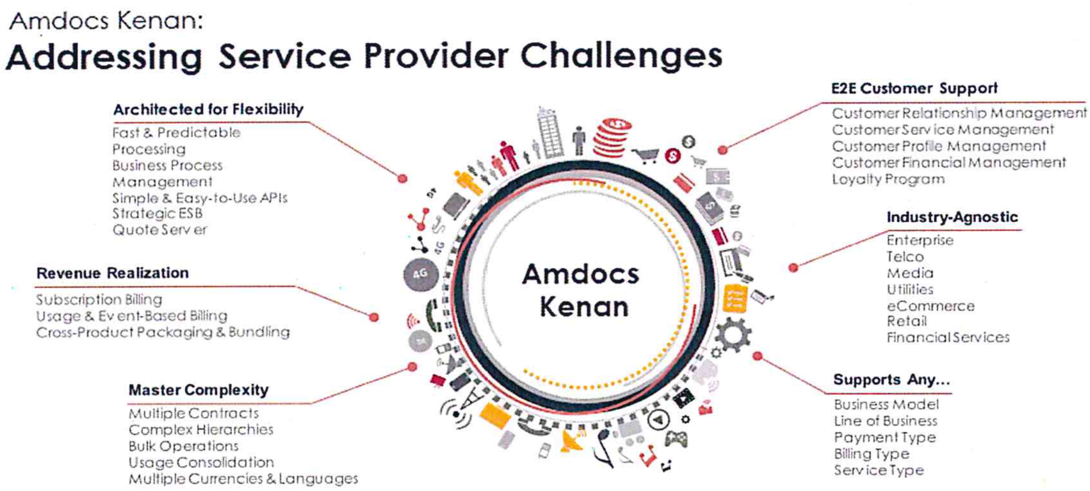

Figure 1 - Amdocs Kenan specifications

3.2. Oracle Siebel CRM

Oracle's Siebel Customer Relationship Management[1] (CRM), the world's most complete CRM solution, helps organizations achieve maximum top- and bottom-line growth and deliver great customer experiences across all channels, touchpoints, and devices[2]. Siebel CRM plays an important role within the Oracle Customer Experience (CX) portfolio, delivering customer experience across mobile, in-store, and field service, and leveraging a wide range of Oracle foundation tools.

3.3. Tiboc ActiveMatrix

Tibco Active Matrix[3] is a technology-neutral platform for composite business process management (BPM) and service-oriented architecture (SOA) applications. The platform includes products for service creation and integration, distributed service and data grids, packaged applications, BPM and governance.

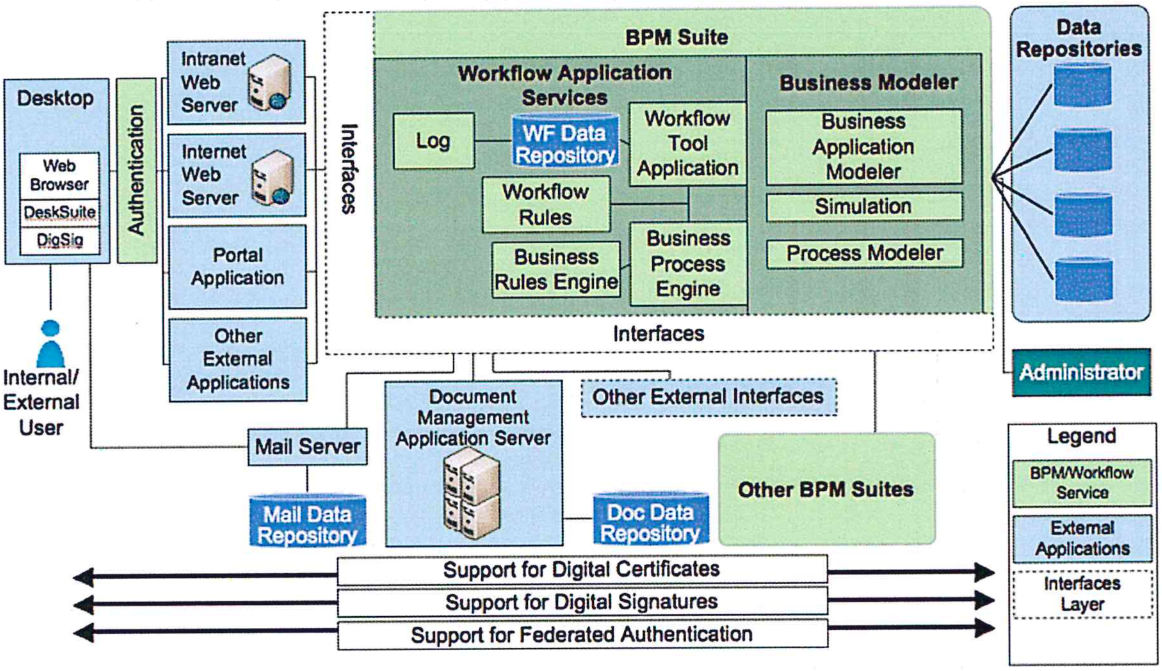

Figure 2 Workflow/Business Process Management (BPM) Service Pattern [4]

In case of good orchestration these three systems should run perfectly with each other.

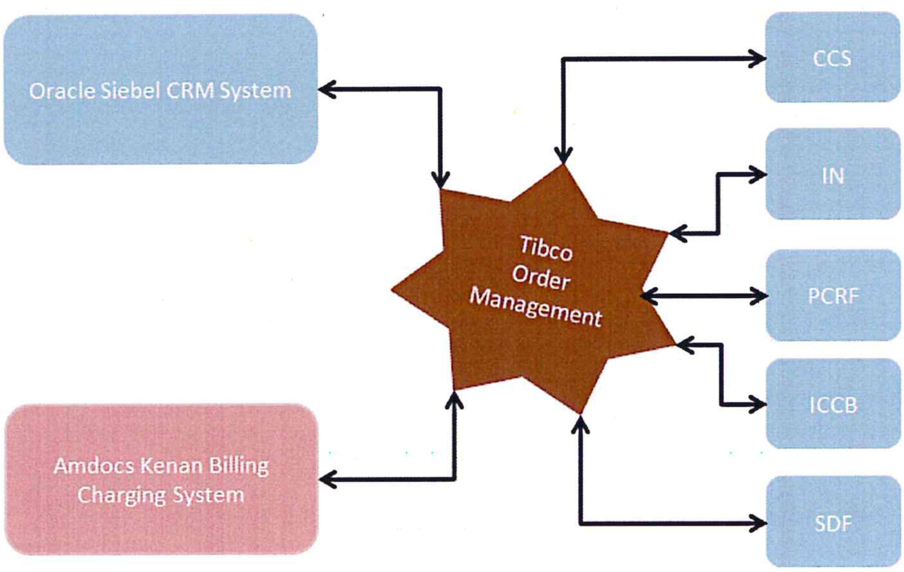

Figure 3 Order flow

We will study the orders those run between these three systems and identify if there is a performance issue. Then we will try to predict the next failure point (order completion time increases dramatically) in order to plan actions not to reflect the problems to our end users, customers.

3.4. Data Specifications

The data, we studied on, is related with last month July 31 – August 29. There are two source systems (Orders initiated);

1- Kenan Billing & Charging System
2- Oracle Siebel CRM system

There are fifteen components which the orders go thorough within their lifecycle

1- Billing.CSS
2- Billing.Kenan
3- CustomerCare.ICCB
4- CustomerCare.M2M
5- CustomerCare.PMS
6- CustomerCare.Siebel
7- External.Duman
8- InventoryManagement.CDRDispatcher
9- InventoryManagement..ICCB
10- Network.IN
11- Network.MTT
12- Network.SDF
13- ProvisioningManagement.ExternalTable
14- ProvisioningManagement.MPBX
15- ProvisioningManagement.PRF

These components are different systems which run standalone in Vodafone application architecture. On each component orders do different activities and these activities are called scenarios. The list of scenarios created on the components is listed below;

Service.Mobile.ActivateNewLine

Service.Mobile.BackwardMigration

Service.Mobile.ChangeMSISDN

Service.Mobile.ChangeSIMCard

Service.Mobile.Deactivate

Service.Mobile.ForwardMigration

Service.Mobile.ModifyOption

Service.Mobile.ResumeSIM

Service.Mobile.SuspendSIM

It is created a Tableau Dashboard in order to serve the data to the operational system owners for identifying the performance issues easily. The general views of the orders are shared below;

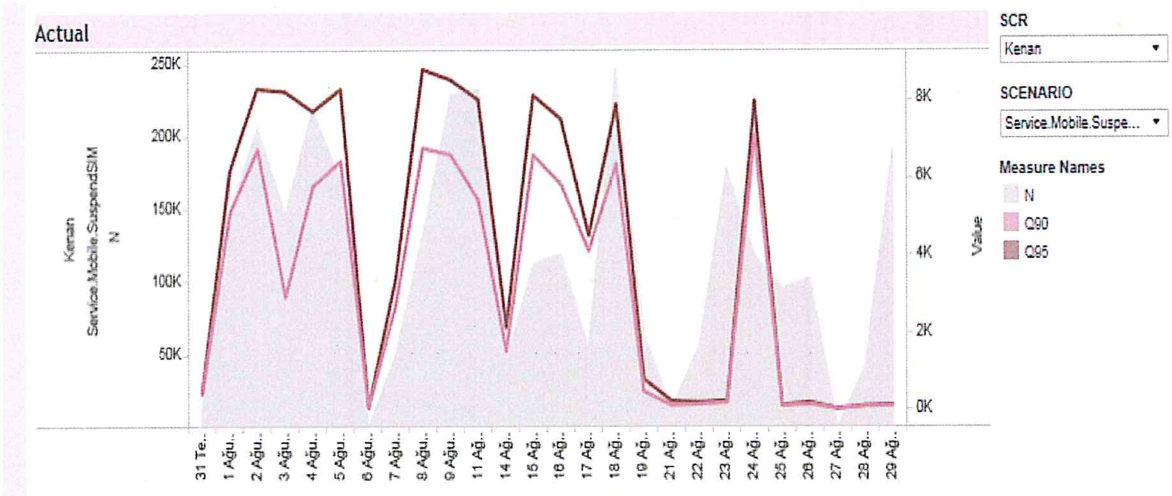

Figure 4 Order Discovery Tableau Platform Main View

This dashboard is live on vodafone tableau server now and used for order performance analysis on related components and source systems.

As it is seen in the picture I shared there are SRC and SCENARIO filters which can be used for detail analysis and the graphic shows the trend on full value with grey, quantile 90 with purple and quantile95 with brown.

3.5. Data Transformation Step: Creation of new attributes

I created a subset form OSM data set; Order List. This data set has the attributes below;

Order_ID:	The unique id for each order
Total_Duration:	The total time passed when the order complete
Actual_Duration:	The actual time for the order completion. Actual time is less than total duration because parallelism is used here to decrease the order time in database level.
Start_dt:	Order start date
End_dt:	Order end Date
Component_Count:	The number of components for the order.
Component:	It is the steps (Vodafone applications) for the order.
Scenario:	The action that the order does in single process by passing components on its lifecycle.
Report_day:	Order report date.

Order; is the atomic process, defined as a web service. Each order manages a single action between the systems.

3.6. Data Collection Step: Extracting the data

The initial data set is shared at the table below;
Initial view of the data extracted from OSM. P/L SQL programming language was used to prepare the data on source system and via database links the data extracted to file and loaded to the R processing environment. You can see the sample of the extracted data;

	I..REFERENCE_NUMBER	ORDER_SEQ_ID	SCENARIO	ORDER_COMPONENT	END_DATE	START_DATE	DURATION	INSERT_DATE
1	1-383265870504	272763312	Service.Mobile.ActivateNewLine	Billing.Kenan.AddProduct	01.05.2017 06:26:01	01.05.2017 06:25:54	7	02.05.2017 04:00:01
2	1-388357207525	272992102	Service.Mobile.ActivateNewLine	Billing.CCS.ChangeSubscriberInformation	01.05.2017 13:18:41	01.05.2017 13:18:39	2	02.05.2017 04:00:01
3	1-388357207525	272992102	Service.Mobile.ActivateNewLine	CustomerCare.Siebel.UpdateItemsDates	01.05.2017 13:19:41	01.05.2017 13:19:38	3	02.05.2017 04:00:01
4	1-384364641513	272773245	Service.Mobile.ActivateNewLine	ProvisioningManagement.PRF.UpdateProvisioningOrder	01.05.2017 06:28:17	01.05.2017 06:24:58	199	02.05.2017 04:00:01
5	1-382872519373	272775213	Service.Mobile.ActivateNewLine	Billing.Kenan.AddProduct	01.05.2017 06:30:48	01.05.2017 06:30:31	17	02.05.2017 04:00:01

Figure 5 Sample View of Studied Data

Then we started to transform the data in order to processing. Main KPI is to finalize this order type in 210 secs. Our discovery steps will identify on which days this KPI did not met and what is the overall status of this web service performance. Plus, adding a prediction model at the end of the process in order to have an idea that there would be a problem for the next day on processing orders.

We transformed the date attributes to day-hour-min-sec set for both insert_date and start_date

Transformed BPM data set view is added below;

component	eday	emonth	eyear	ehour	emin	esec	sday	smonth	syear	shour	smin	ssec	duration	insert_date	end_dt	start_dt
Billing.Kenan.AddProduct	01	05	2017	06	26	01	01	05	2017	06	25	54	7	02.05.2017 04:00:01	2017-05-01 06:26:01	2017-05-01 06:25:54
Billing.CCS.ChangeSubscriberInformation	01	05	2017	13	18	41	01	05	2017	13	18	39	2	02.05.2017 04:00:01	2017-05-01 13:18:41	2017-05-01 13:18:39
CustomerCare.Siebel.UpdateItemsDates	01	05	2017	13	19	41	01	05	2017	13	19	38	3	02.05.2017 04:00:01	2017-05-01 13:19:41	2017-05-01 13:19:38
ProvisioningManagement.PRF.UpdateProvisioningOrder	01	05	2017	06	28	17	01	05	2017	06	24	58	199	02.05.2017 04:00:01	2017-05-01 06:28:17	2017-05-01 06:24:58
Billing.Kenan.AddProduct	01	05	2017	06	30	48	01	05	2017	06	30	31	17	02.05.2017 04:00:01	2017-05-01 06:30:48	2017-05-01 06:30:31
Billing.Kenan.CreateSubscriber	01	05	2017	07	08	55	01	05	2017	07	08	52	3	02.05.2017 04:00:01	2017-05-01 07:08:55	2017-05-01 07:08:52

Figure 6 Transformed view of studied data

Nearly 85% of the data is related with the scenario Service.Mobile.ModifyOptions. There are 17683403 orders related with this scenario. We created a subset contains only Service.Mobile.ModifyOptions. This subset is created for two main reasons;

The data is composed of mainly this Service.Mobile.ModifyOptions

There are performance issues on running the code on full data. Although this data has all attributes and I can do my study with this scenario.

Data Transformation Step: Creation of new attributes

I split the two attributes into pieces;

End_date: c("eday", "emonth", "eyear", "ehour", "emin", "esec"))

Start_date: c("sday", "smonth", "syear", "shour", "smin", "ssec"))

We will study the performance issues on orders so we need atomic pieces of time values.

We created new variables and set 0 instead of null values;

- ehour[is.na(osm$ehour)] <- "0"
- emin[is.na(osm$emin)] <- "0"
- esec[is.na(osm$esec)] <- "0"
- shour[is.na(osm$shour)] <- "0"
- smin[is.na(osm$smin)] <- "0"
- ssec[is.na(osm$ssec)] <- "0"

Summary of the osm data set;

```
            ref_no                order_id                                scenario
1-693191114076:     243   420892503:       15   Service.Mobile.ModifyOptions:17683403
1-696549303433:      64   421334272:       15
1-694190272374:      35   421565088:       15
1-693225818104:      25   425141313:       15
1-649823785240:      17   425377517:       15
1-556697533275:      15   425572028:       15
(Other)        :17683004   (Other)   :17683313
                              component                               end_date
CustomerCare.Siebel.UpdateItemsDates    :3227140   16.08.2017 00:18:28:      545
NotificationCenter.SendNotification     :3150003   16.08.2017 00:18:27:      505
ProvisioningManagement.PRF.CreateOrder:2849303   16.08.2017 00:18:29:      503
Network.SDF.SynchronizeEntities         :2596986   16.08.2017 00:18:30:      501
Billing.CCS.ModifyOptionalOffer         :2419354   16.08.2017 00:23:05:      481
Network.SDF.UpdatePromoterScore         : 986014   07.08.2017 00:27:14:      474
(Other)                                 :2454603   (Other)               :17680394
              start_date           duration
22.08.2017 00:01:38:    1008   Min.   :    1.00
22.08.2017 00:02:14:     998   1st Qu.:    2.00
22.08.2017 00:02:01:     995   Median :    2.00
22.08.2017 00:02:06:     966   Mean   :   82.63
22.08.2017 00:01:41:     962   3rd Qu.:    6.00
22.08.2017 00:02:07:     953   Max.   :90746.00
(Other)             :17677521
```

Figure 7 Summary information of the ModifyOption Dataset

3.7. Discovery Step: Understanding the data

We continued to review data after creating new attributes on date attributes. I looked into the dataset to provide a general view on it. I have provided a daily base order distribution view. We are trying to catch an anomaly and will go detail on that detail. Our main driver is to understand the performance problems on studied orders.

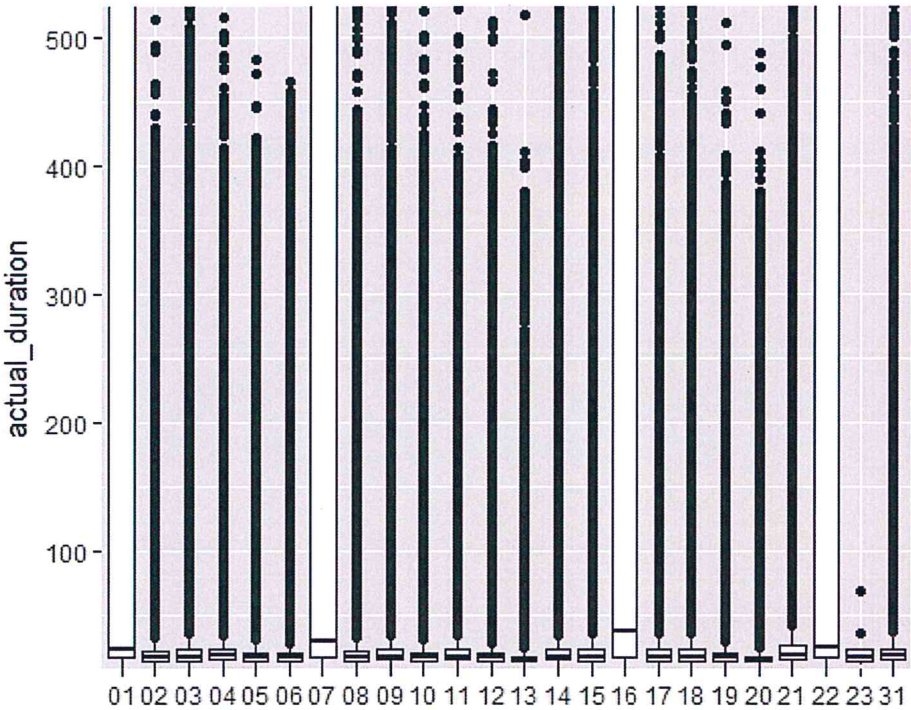

Figure 8 Daily distribution of the orders on plot

Daily distribution of orders (Figure 8) is saying that there are some problems on several days; 01,07,16,22. On the other hand there may be problematic hours which have same issues. If I can catch this kind of problem I will have direct effect on order KPIs. Let's create an hourly distribution of the orders and keep going detail for the project.

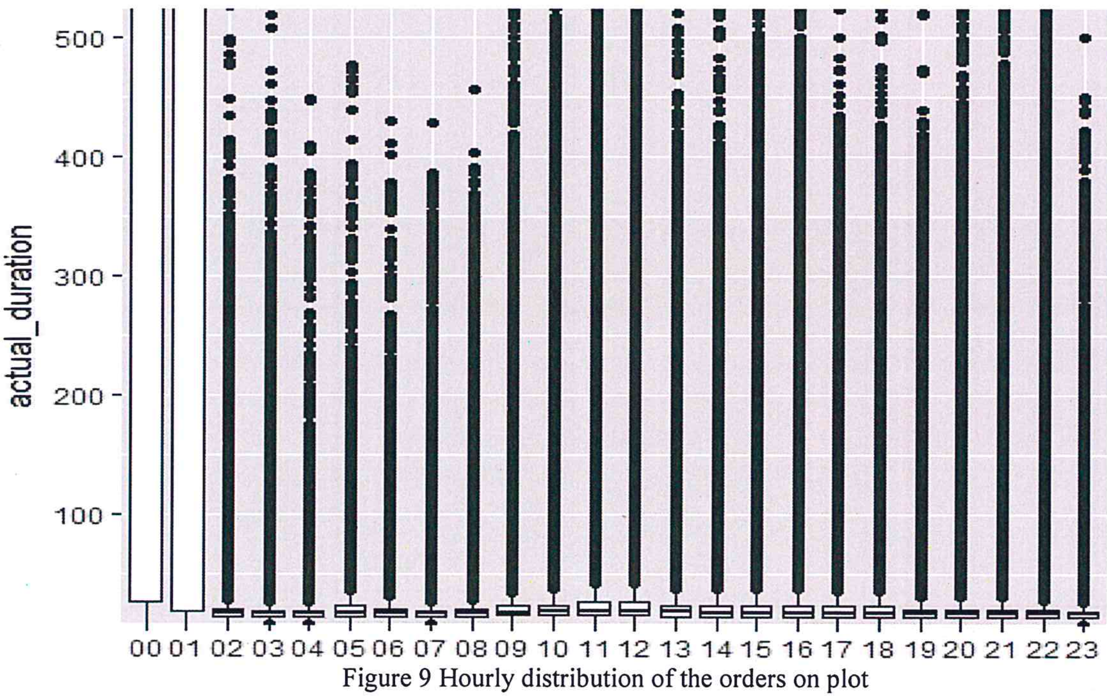

Figure 9 Hourly distribution of the orders on plot

4. METHODOLOGY

I study on the data with R programming language and have insights by using related transformations, create plots and charts to catch anomalies, and store the data to serve related users make them capable to see the problems is occurs.

I prepared the data daily base and hourly base and created visuals. There is something on hourly distribution of the orders;

Between 00 and 02 the orders are not finalized.

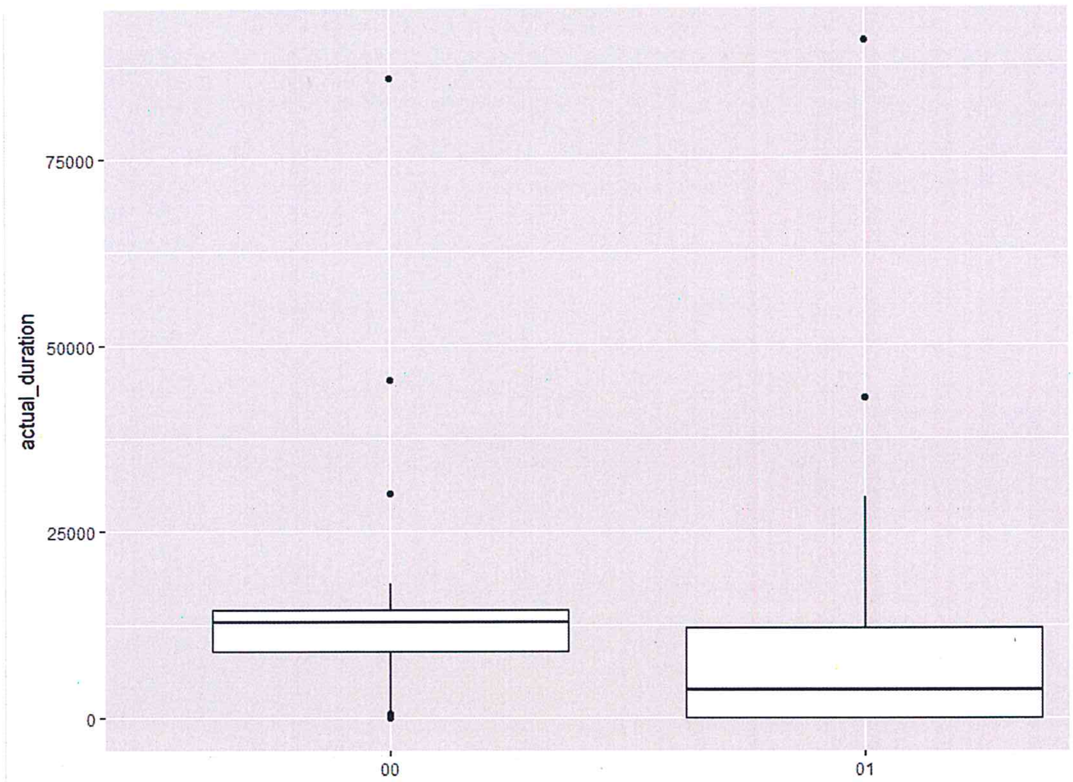

Figure 10 Problematic hours on order distribution

As it is seen in the visualisations especially 00-01 actual_duration increases to 1750 secs mean. 01-02 is a bit better than the previous hour but it is still very bad according to KPIs. The KPI is 200 secs. This is end-to-end interval that order should be finished. 1750 is pretty high and should be reviewed.

For the other hours the KPI is met and it seems it is ok for the rest of the day;

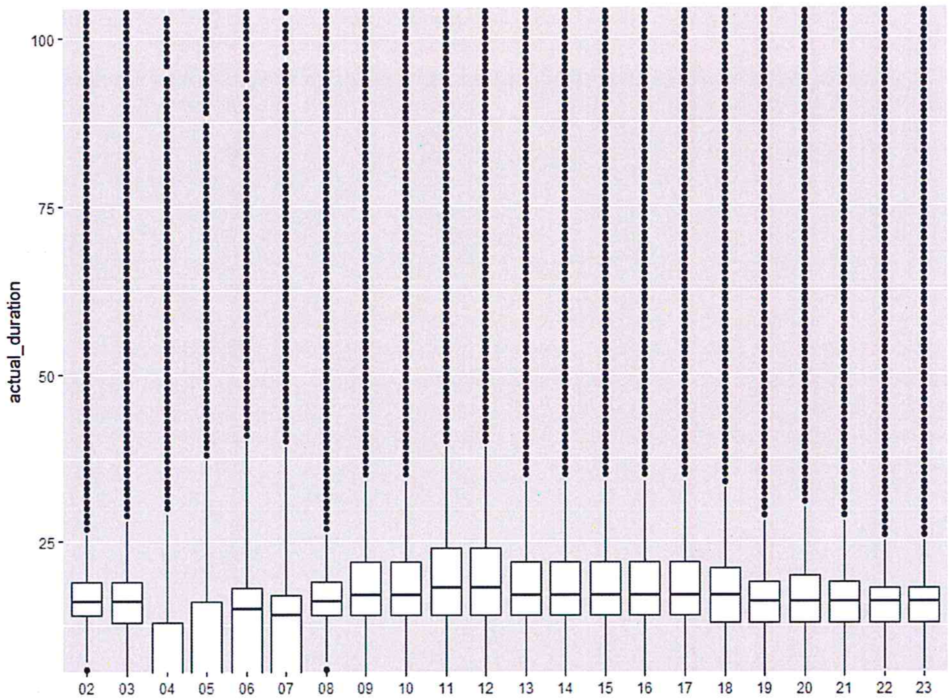

Figure 11 Order Distribution on Plot which problematic hours excluded

There are still outliers but those outliers also in the range of KPI and the mean of the orders except the ones between 00 am and 02 am is high.

On the other hand, between 04 am and 05 am the system seems that it is "idle". **Whatever occurs between 00 and 02 if it can be moved to 04 and 05 there could be significant performance gain and improvement on KPIs.**

When I apply the models listed below to my data there is not any meaningful outputs as such:

- **Linear Discriminant Analysis**

  50000 samples

  1 predictor

  24 classes: '00', '01', '02', '03', '04', '05', '06', '07', '08', '09', '10', '11', '12', '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23'

No pre-processing

Resampling: Cross-Validated (10 fold)

Summary of sample sizes: 44998, 45001, 45001, 45006, 44998, 44999

Resampling results:

Accuracy	**Kappa**
0.1603797	0.102928

- CART

50000 samples

1 predictor

24 classes: '00', '01', '02', '03', '04', '05', '06', '07', '08', '09', '10', '11', '12', '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23'

No pre-processing

Resampling: Cross-Validated (10 fold)

Summary of sample sizes: 44999, 45003, 44998, 45000, 45004, 44999

Resampling results across tuning parameters:

cp	**Accuracy**	**Kappa**
0.01113004	0.1698999	0.11370881
0.01826235	0.1558395	0.09808011
0.03270869	0.1356768	0.05284870

Accuracy was used to select the optimal model using the largest value. The final value used for the model was cp = 0.01113004.

- SVM

When this model run on the data set it raised too many warnings and did not created an output.

- Random Forest

  50000 samples

  1 predictor

  No pre-processing

  Resampling: Cross-Validated (10 fold)

  Summary of sample sizes: 44999, 45000, 45001, 44999, 45000, 45002

  Resampling results across tuning parameters:

mtry	RMSE	Rsquared
2	3985.828	0.3309647
12	2811.984	0.5977890
23	2763.905	0.6093273

It can be seen that the result of the random forest model at figure below. As it seen the values are low and the accuracy cannot be used for a prediction model

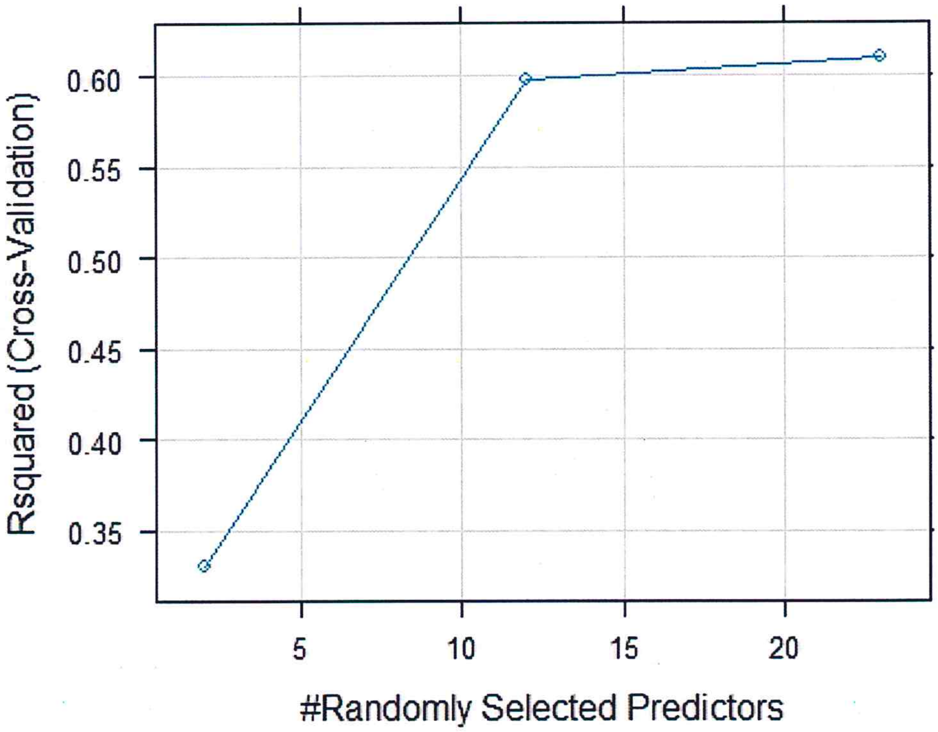

Figure 12 Random Forest model output

R-squared was used to select the optimal model using the largest value.

The final value used for the model was mtry = 23.

As it seen on the results for the models we run accuracy were around 0.1. This accuracy value does not mean there can be a prediction on this set of data.

Linear Regression Model

We also run linear regression model with the data set. The model was run with subset data set for 50.000 samples and for whole date set. The outputs are added below [5];

All the plots added are important but the Residual vs Fitted view is the most important one. Residual values are the difference between actual and predicted outcome values. Fitted values are the predicted values. The shape of this graph suggests that our model is suffering from heteroscedasticity (unequal variance in error terms). Had there been constant variance, there would be no pattern visible in this graph.

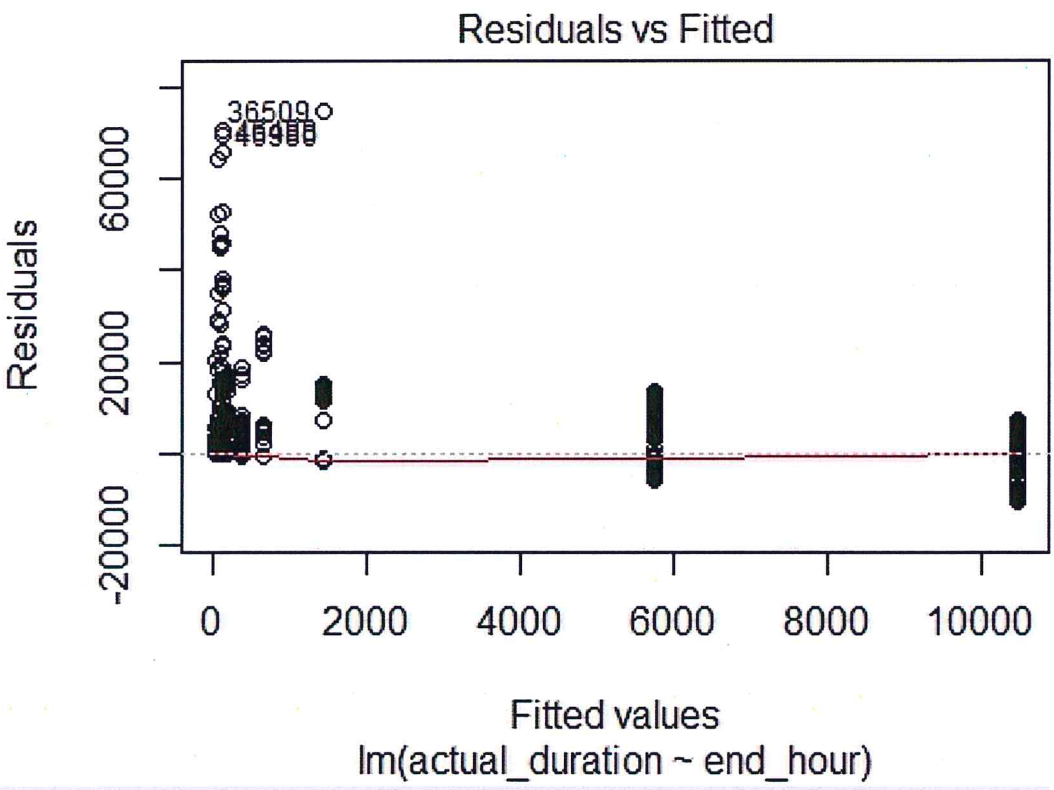

Figure 13 Linear Model Output for whole data Residual vs Fitted

As it seen in the figure below there is not recursive period on residuals and leverages:

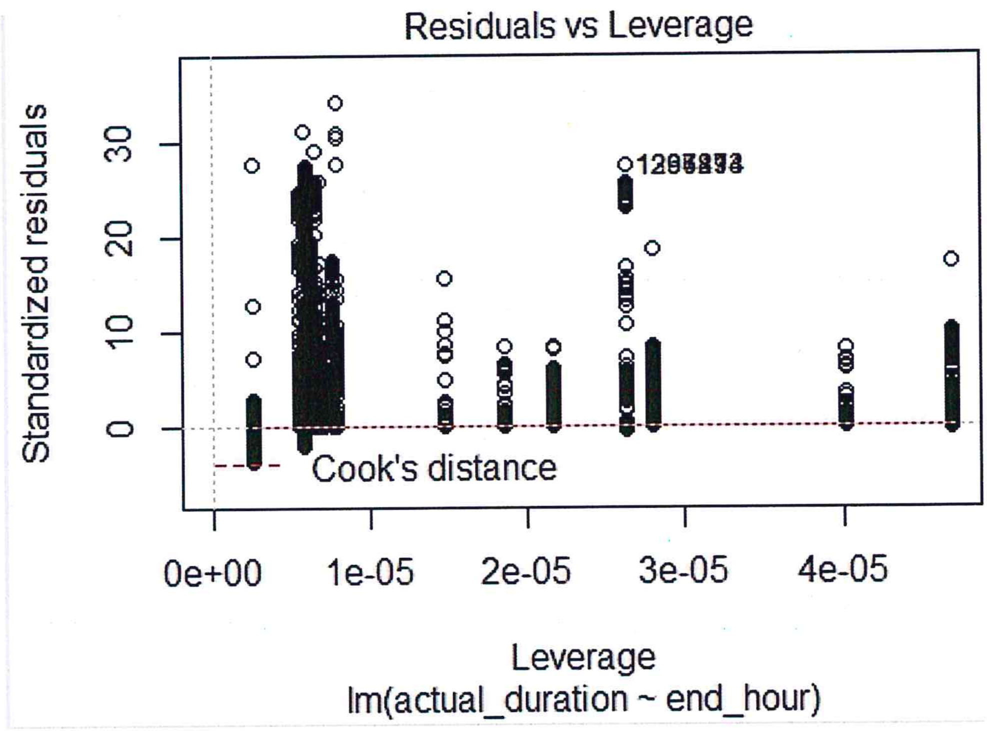

Figure 14 Linear Model Output for whole data Residual vs Leverage

5. RESULTS

Before this study there has no study on orders like this done in the company. This study will help us to identify order performance issues and then take actions based on the problem. Unfortunately, it seems that there is not a unique predictable pattern and we could not predict when the next problem occurs.

The order details have not analyzed such a way that we studied. We investigated a potential value here in the data and created a platform on tableau tool to those who want to analyze the daily data. Here are the details about the tableau platform

Main screen of the order dashboard

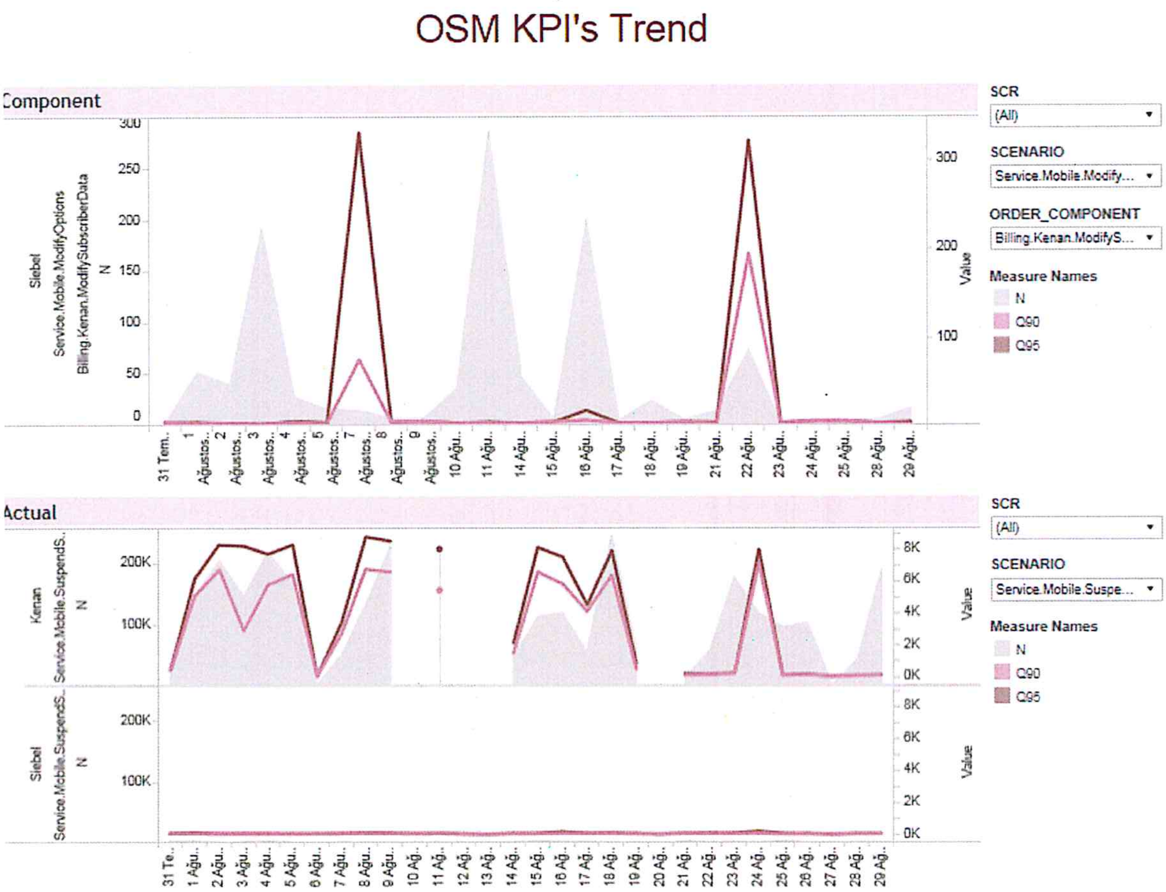

Figure 15 Daily Order Discovery Dashboard Landing Page

Components details of the Scenario

Component Detail List

Month, Day, ..	SCR	ORDER_COMPONENT	SCENARIO	MEAN	Q25	Q75	Q90	Q95	N
15 Ağustos 2017	Kenan	Billing.CCS.AddCommunityM..	Service.Mobile.ResumeSIM	94	73	124	149	160	18
		Billing.CCS.BreakCommitment	Service.Mobile.SuspendSIM	3	3	3	4	4	3.380
		Billing.CCS.DeleteSubscriber	Service.Mobile.SuspendSIM	4	2	3	3	3	8.675
		Billing.CCS.ModifyOptionalOff..	Service.Mobile.ResumeSIM	2	2	3	3	3	68.693
			Service.Mobile.SuspendSIM	4	2	3	4	5	3.383
		Billing.CCS.ModifySubscriber..	Service.Mobile.ResumeSIM	5	2	2	3	3	91.770
			Service.Mobile.SuspendSIM	3	2	3	3	4	100.663
		Billing.Kenan.AddProduct	Service.Mobile.ResumeSIM	3	3	3	4	4	1.921
		Billing.Kenan.CreateSubscriber	Service.Mobile.ResumeSIM	4	4	4	5	5	639
		Billing.Kenan.DeleteProducts	Service.Mobile.SuspendSIM	45	13	53	67	73	4.776
		Billing.Kenan.DeleteSubscriber	Service.Mobile.SuspendSIM	10	6	12	17	20	4.776
		Billing.Kenan.ResumeSubscri..	Service.Mobile.ResumeSIM	3	2	3	3	3	92.827
		Billing.Kenan.SuspendSubscri..	Service.Mobile.ResumeSIM	3	2	3	3	3	3
			Service.Mobile.SuspendSIM	4	2	3	6	13	97.419
		CustomerCare.ICCB.UpdateB..	Service.Mobile.ResumeSIM	2	2	2	3	3	94.170
			Service.Mobile.SuspendSIM	2	2	2	3	4	112.385
		CustomerCare.Siebel.Create..	Service.Mobile.ResumeSIM	16	11	16	19	31	94.170
			Service.Mobile.SuspendSIM	2.277	329	3.374	6.449	7.985	112.387
		External.Duman.NotifyDocum..	Service.Mobile.ResumeSIM	2	2	2	3	3	22.537
		InventoryManagement.CDRDi..	Service.Mobile.ResumeSIM	2	2	2	2	3	18
			Service.Mobile.SuspendSIM	2	2	2	3	3	60
		Network.IN.DeleteMultipleVP..	Service.Mobile.SuspendSIM	4	4	4	4	4	1
		Network.MTT.UpdateLocaleM..	Service.Mobile.ResumeSIM	8	2	3	49	56	19
		Network.SDF.SynchronizeEnti..	Service.Mobile.ResumeSIM	3	2	3	3	3	94.170
			Service.Mobile.SuspendSIM	3	2	3	4	5	112.387
		ProvisioningManagement.PR..	Service.Mobile.ResumeSIM	35	17	25	35	45	93.363
			Service.Mobile.SuspendSIM	92	32	100	141	182	110.730
	Siebel	Billing.CCS.AddCommunityM..	Service.Mobile.ActivateNewLi..	75	3	4	5	6	1.514
			Service.Mobile.ForwardMigrati..	4	4	4	6	6	126
			Service.Mobile.ModifyOptions	12	8	11	13	16	24.733
			Service.Mobile.ResumeSIM	115	81	157	172	203	32
		Billing.CCS.BreakCommitment	Service.Mobile.ModifyOptions	46	5	7	8	15	27.182
			Service.Mobile.SuspendSIM	3	2	3	3	3	484
		Billing.CCS.ChangeMSISDN	Service.Mobile.ChangeMSISD..	121	4	5	171	394	728

Figure 16 Daily Order Discovery Dashboard Component View

Actual Detail List

Actual Detail List

Report Date: (All)

SCR: (All)

SCENARIO: (All)

Month, Day..	SCR	SCENARIO	MEAN	Q25	Q75	Q90	Q95	N
15 Ağustos 2017	Kenan	Service.Mobile.ResumeSIM	63	39	50	66	94	94.170
		Service.Mobile.SuspendSIM	2.377	408	3.471	6.570	8.119	112.387
	Siebel	Service.Mobile.ActivateNewLi..	163	62	81	109	158	10.272
		Service.Mobile.BackwardMigr..	1.249	828	1.656	1.947	1.992	7.611
		Service.Mobile.ChangeMSISD..	225	44	128	250	971	735
		Service.Mobile.ChangeSIMCa..	78	30	39	48	63	3.024
		Service.Mobile.Deactivate	16.748	16.195	19.890	20.385	20.533	4.067
		Service.Mobile.ForwardMigrati..	103	79	94	115	152	5.250
		Service.Mobile.ModifyOptions	30	14	22	33	42	135.334
		Service.Mobile.ResumeSIM	53	25	41	56	138	929
		Service.Mobile.SuspendSIM	43	23	46	63	81	2.938
16 Ağustos 2017	Kenan	Service.Mobile.ResumeSIM	235	44	137	257	445	106.147
		Service.Mobile.SuspendSIM	2.249	356	3.191	5.825	7.500	119.247
	Siebel	Service.Mobile.ActivateNewLi..	237	67	104	231	543	6.399
		Service.Mobile.BackwardMigr..	806	678	712	788	1.049	708
		Service.Mobile.ChangeMSISD..	669	46	202	1.936	4.143	728
		Service.Mobile.ChangeSIMCa..	78	32	46	74	160	2.836
		Service.Mobile.Deactivate	15.864	17.779	20.413	20.570	20.648	1.185
		Service.Mobile.ForwardMigrati..	256	87	129	278	677	4.697
		Service.Mobile.ModifyOptions	2.385	14	1.911	11.774	13.884	178.849
		Service.Mobile.ResumeSIM	86	27	51	108	191	762
		Service.Mobile.SuspendSIM	99	22	48	80	179	2.671
17 Ağustos 2017	Kenan	Service.Mobile.ResumeSIM	119	37	50	82	144	67.070
		Service.Mobile.SuspendSIM	1.737	141	3.158	4.096	4.490	54.139
	Siebel	Service.Mobile.ActivateNewLi..	170	62	85	118	177	7.358
		Service.Mobile.BackwardMigr..	800	674	706	727	818	837
		Service.Mobile.ChangeMSISD..	183	43	107	224	785	761
		Service.Mobile.ChangeSIMCa..	101	30	40	59	86	2.854
		Service.Mobile.Deactivate	14.213	10.349	20.221	20.508	20.603	2.725
		Service.Mobile.ForwardMigrati..	207	83	110	143	310	4.962
		Service.Mobile.ModifyOptions	37	13	21	33	44	115.977

Figure 17 Daily Order Discovery Dashboard Actual Detail View

Additionally, I have highlighted the problematic hours and idle hours. Now, we are trying to shift the workload which is occurring on busy hours (00-02) to idle hours (04-05). This shift will directly affect Vodafone order KPIs.

6. CONTRIBUTION

The tableau platform can be used for deeper level of analysis and be a ready-to-use platform for further research questions.

The analyses indicate that the current dataset might not be very suitable for modelling and prediction.

Order KPI improvement will be the most important output of this study. I can predict Vodafone from a possible BTK punishment and improvement on customer NPS values which is very important for Vodafone Turkey. Better performance in orders will probable influence customer satisfaction and their NPS values that stands for Net Promoter Score and very important about showing customer satisfaction [6]

APENDIX

1. Capstone_Project_Vedat_Gunes

    

    Capstone_Project_Vedat_Gunes.R

    1.1.

2. Linear Regression outpus

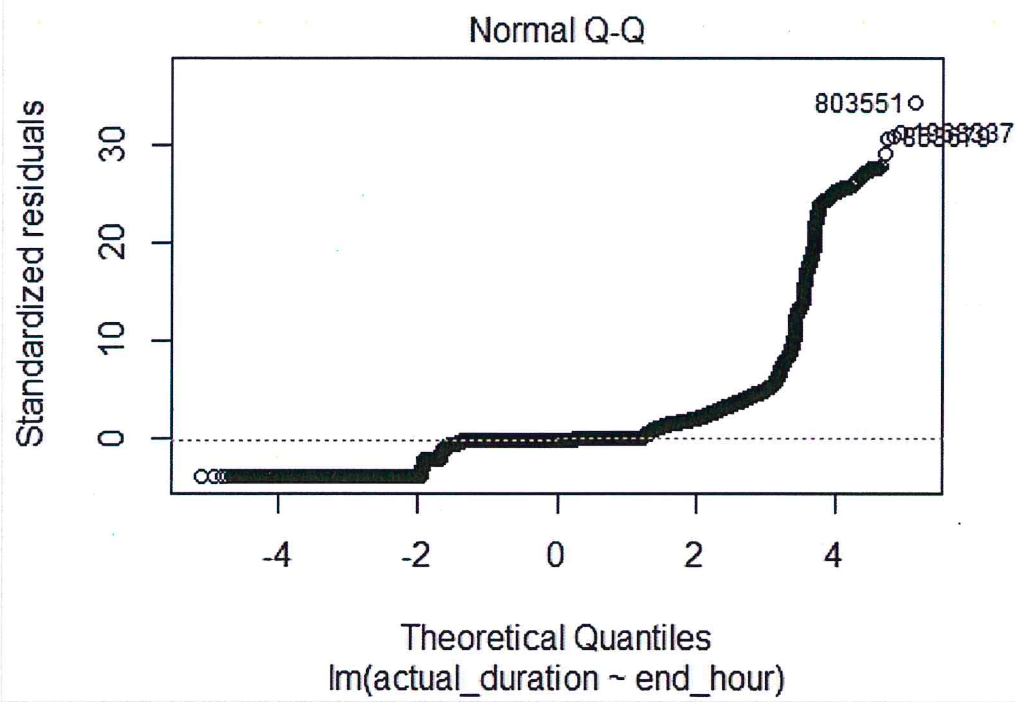

Figure 18 Linear Model Output for whole data Normal Q-Q

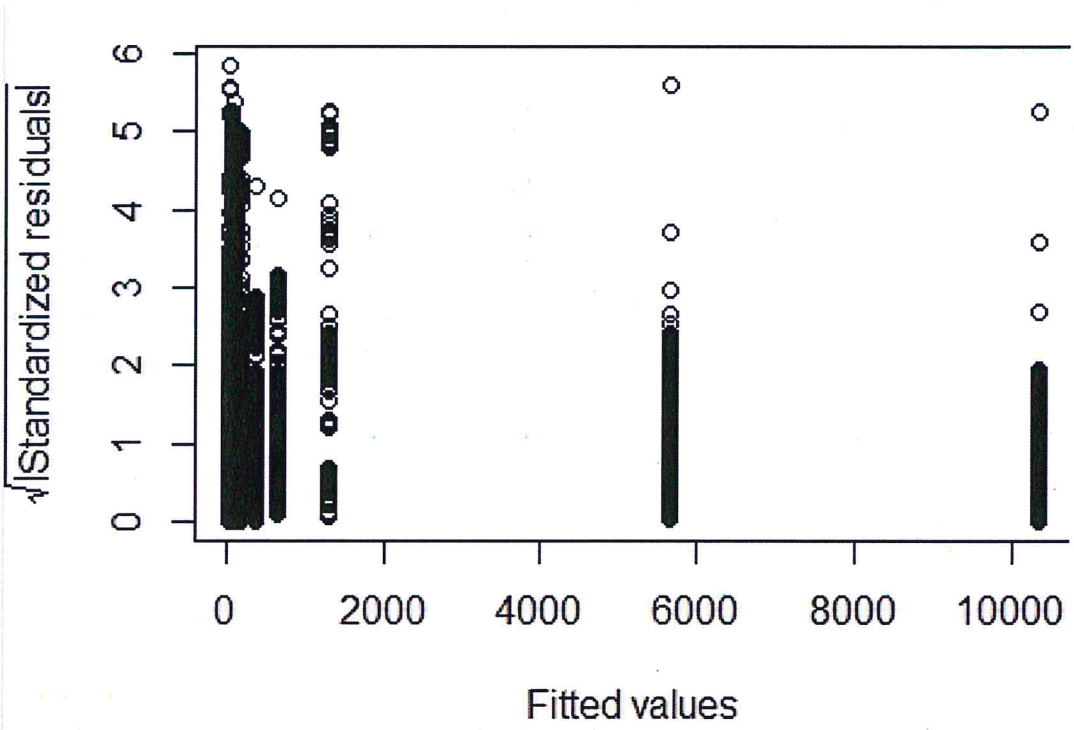

Figure 19 Linear Model Output for whole data Scale Location

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