



IE-468 Case 3 Report

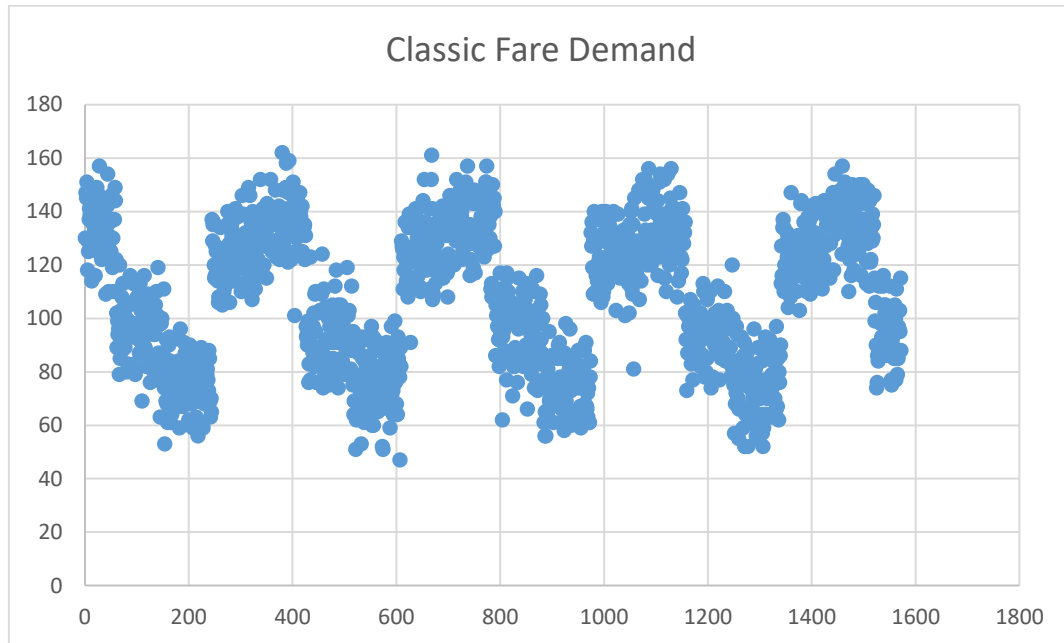
Bilgehan Güçlü Özkan 22003839

Damla Uçar 22103276

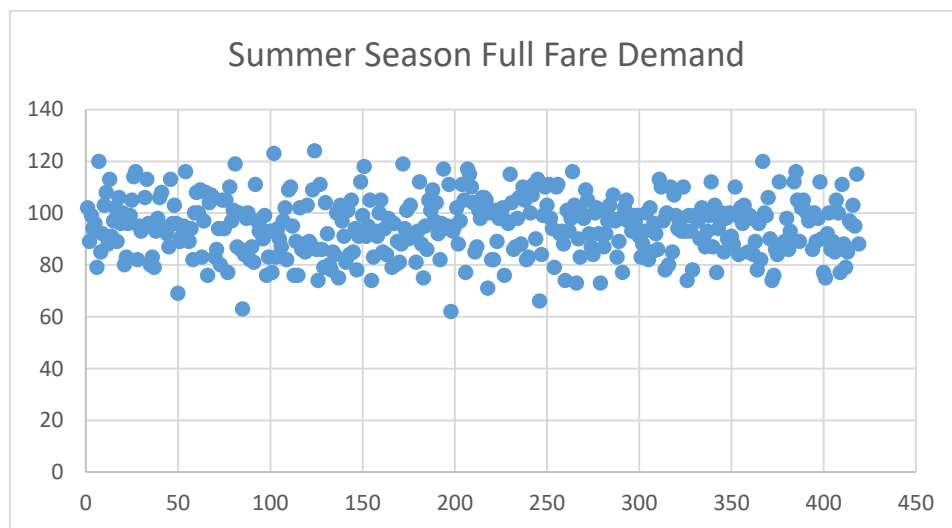
Ahmet Sayan 21903426

Q1)

To give us an initial idea on estimating a distribution for the full fare customer demand we graphed the demand. For this case we didn't estimate a distribution for discount customers as it is assumed that the demand for this class is greater than capacity.



From the graph we can see the effects of seasonality as there is a clear “on” and “off” season for this route. Investigating further there seems to be a partial “off” season in the summer; June, July and August, which is the period we’ll focus on in this question.



For each day of the week June 16-22, 2025 we estimated the parameters of its distribution using regression. So we assumed the demand for full fare tickets was normal within a few categories. Using linear regression, we determined that the month and the day-of-week are significant attributes for estimating demand.

Using the coefficients from our model we estimated the means for each day. We then utilized our residual sum of squares to estimate the standard error of regression as our standard deviation for all days.

$$\text{Standard Error} = \frac{\sqrt{\text{Residual Sum of Squares}}}{\# \text{ of Data Points} - \# \text{ of Model Parameters}}$$

So we estimated the parameters for the normal distribution of demand for these days as:

Date	Predicted_Mean	Standard Error
6/16/2025	70.37712937	10.05733202
6/17/2025	71.34806194	
6/18/2025	71.01319372	
6/19/2025	77.47891231	
6/20/2025	78.87460995	
6/21/2025	78.87538835	
6/22/2025	70.61417632	

The full results of our regression model:

OLS Regression Results						
Dep. Variable:	Classic	R-squared:	0.853			
Model:	OLS	Adj. R-squared:	0.852			
Method:	Least Squares	F-statistic:	531.0			
Date:	Thu, 24 Apr 2025	Prob (F-statistic):	0.00			
Time:	12:53:43	Log-Likelihood:	-5846.1			
No. Observations:	1572	AIC:	1.173e+04			
Df Residuals:	1554	BIC:	1.182e+04			
Df Model:	17					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	87.4156	0.207	421.830	0.000	87.009	87.822
day_Friday	17.2795	0.620	27.870	0.000	16.063	18.496
day_Monday	8.7820	0.621	14.137	0.000	7.563	10.001
day_Saturday	17.2803	0.620	27.872	0.000	16.064	18.496
day_Sunday	9.0191	0.620	14.547	0.000	7.803	10.235
day_Thursday	15.8838	0.620	25.619	0.000	14.668	17.100
day_Tuesday	9.7529	0.621	15.700	0.000	8.534	10.971
day_Wednesday	9.4181	0.621	15.161	0.000	8.200	10.637
month_1	35.7131	0.778	45.933	0.000	34.188	37.238
month_2	33.7887	0.812	41.625	0.000	32.196	35.381
month_3	-4.5224	0.777	-5.817	0.000	-6.047	-2.997
month_4	-5.5990	0.814	-6.875	0.000	-7.196	-4.001
month_5	-5.6803	0.861	-6.596	0.000	-7.369	-3.991
month_6	-25.8205	0.874	-29.531	0.000	-27.535	-24.105
month_7	-24.9293	0.861	-28.948	0.000	-26.619	-23.240
month_8	-24.7515	0.861	-28.741	0.000	-26.441	-23.062
month_9	23.0638	0.874	26.378	0.000	21.349	24.779
month_10	26.0609	0.861	30.261	0.000	24.372	27.750
month_11	24.8493	0.874	28.420	0.000	23.134	26.564
month_12	35.2429	0.858	41.075	0.000	33.560	36.926
Omnibus:	3.983	Durbin-Watson:	2.040			
Prob(Omnibus):	0.136	Jarque-Bera (JB):	3.935			
Skew:	-0.097	Prob(JB):	0.140			
Kurtosis:	2.850	Cond. No.	5.21e+15			

a)

To determine the protection and booking levels we utilized Littlewood's rule, since our goal is to maximise profit rather than revenue we first deducted the 4 € cost for food from prices.

$$p_f P(D_f \geq C - b^*) = p_d$$

$$P(D_f \leq 161 - b^*) = 0.34266$$

Meaning our z value will be -0.40522, so we calculated the booking limit with the cdf of the normal distribution using the parameters we estimated previously for each day:

$$C - b^* = \sigma_f z^* + \mu_f$$

Our rounded protection and booking limits are:

	b	y
6/16/2025	95	66
6/17/2025	94	67
6/18/2025	94	67
6/19/2025	88	73
6/20/2025	86	75
6/21/2025	86	75
6/22/2025	94	67

b)

To calculate the expected load factor, we first calculated the expected number of empty seats using our previous protection levels and booking limits. As this number can't be negative we used the expectation of a max function.

$$\begin{aligned} E(\max\{y^* - D_f, 0\}) &= \sigma_f E(\max\{w - z^*, 0\}) - \mu_f + y^* \\ &= \sigma_f L(z^*) - \mu_f + y^* \end{aligned}$$

Where w is the standard normal and L(z) is the standardized loss function. Using the previously calculated z value for the value of the standardised loss function we get:

$$L(-0.40522) = 0.63387$$

Using the previously found formula we calculated the expected number of non-empty seats which is the same for all days since the probability of having empty seats is the same for all days with their respective protection levels.

$$158.7005 = 161 - 2.2995$$

And the expected load factor as:

$$98.572\% = 158.7005/161$$

c)

We calculated the Revenue Per Available Seat Kilometer (RASK) by utilizing both the yields and changing load factor contributions of full fare and discount customers. Using revenue rather than profit, the yields are:

0.04047 €/km for full fare tickets

0.02703 €/km for discount tickets

And their contributions towards the load factor change day by day, so we found each day's values with their respective booking limits. Multiplying load factors and yields within their ticket classes finally gave us the daily RASK as can be seen below.

Load-discount	Load-full	RASK
0.588188405	0.397529	0.031984
0.582157768	0.403559	0.032065
0.584237695	0.401479	0.032037
0.544077952	0.441639	0.032577
0.535409023	0.450308	0.032693
0.535404188	0.450313	0.032693
0.586716064	0.399001	0.032004

d)

Using the previously found standardized loss function value again we calculated the expected number of full fare customers denied booking as: $\sigma_f L(z^*) = 6.375$

Q2)

a)

For Question Three, we used data only from Thursday, Friday, and Saturday demand data as requested, resulting in a sample size of 675 for the Sample Average Approximation method. Next, we created our mathematical model to find booking limits and protection levels.

Parameters:

d_f^t : full fare demand for sample t $t = 1, 2, \dots, 675$

C : capacity of the vueling

p_d : discounted profit of a ticket

p_f : full fare profit of a ticket

Decision Variables:

y : protection level

x^t : number of full fare tickets we sell in sample t

Objective Function

$$\max \frac{1}{n} \left[\sum_{t=1}^{675} [p_d(C - y) + p_f x^t] \right]$$

Constraints

$$x^t \leq y$$

$$x^t \leq d_f^t$$

By solving mathematical model, we found $y = 98$ (protection level) and $b = 63$ (booking limit).

b)

Since we used only the Thursdays, Fridays, Saturdays data; We didn't include the seasonality factor in this approach resulting in higher protection level than off-season which we found in Question 1. Therefore, it is less profitable and explain worse the patterns.

c)

We used the same approach to calculate the load factor as Question 1. Then calculated the load factory with new protection level and booking limit. Except we calculated mean with simple average and standard deviation with the simple standard deviation formula as mentioned in the question.

z=	-0,5482
Loss	0,731533
Expected empty seats	4,704172
Expected non-empty	156,2958
Load Factor	0,970782

d)

Similar to first question we calculated expected denied customers by multiplying the standard deviation with standard loss function.

Expected Denied Customers	18,77083916
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Q3)

The parameters of these days' demand distributions were again calculated with the results from our regression model in Q1 and are assumed to be normal. We again deducted the costs from prices in our calculations so we used the profit margin $p_p = 205.49$ for premium tickets.

a)

Using the EMSRa heuristic, first we found the individual protection levels of premium (1) and full fare (2) tickets against discount (3) tickets. Using Littlewood's rule we calculated the z values for each days' full fare ticket distribution and found the protection levels with $y_{13} = \sigma_1 z + \mu_1$ and $y_{23} = \sigma_2 z + \mu_2$ which is calculated separately for each day as the mean changes from day to day.

Summing these values gave us y_2 which is the protection level for both class 1 and 2 against class 3. And finally we calculated $y_1 = \sigma_1 z + \mu_1$ to give us the protection level for class 1

against class 2. The final protection levels and booking limits that don't change from day to day are:

y13	14
y1	12
b2	149
b1	161

And the values that change day to day are:

	y23	y2	b3
6/17/2025	67	81	80
6/18/2025	67	81	80
6/19/2025	73	87	74
6/20/2025	75	89	72
6/21/2025	75	89	72
6/22/2025	67	81	80
6/23/2025	66	80	81

b)

Using the EMSRb heuristic we artificially create a unified class by summing the demand for class 1 and 2 tickets, D_{12} .

This class has a normal distribution with parameters $N(\mu_1 + \mu_2, \sqrt{\sigma_1^2 + \sigma_2^2})$ that change day to day due to the change in parameters for the full fare demand distribution.

D12	Mean	Std
6/17/2025	84.34806	10.49523
6/18/2025	84.01319	10.49523
6/19/2025	90.47891	10.49523
6/20/2025	91.87461	10.49523
6/21/2025	91.87539	10.49523
6/22/2025	83.61418	10.49523
6/23/2025	83.37713	10.49523

Now to use Littlewood's rule to calculate the protection levels we first came up with the prices for this unified class for each day using the formula for weighted prices.

$$\frac{\mu_1 p_1 + \mu_2 p_2}{\mu_1 + \mu_2}$$

	P12
6/17/2025	137.8199
6/18/2025	137.869
6/19/2025	136.9844
6/20/2025	136.8098
6/21/2025	136.8097
6/22/2025	137.9281
6/23/2025	137.9634

Then, using Littlewoods rule, we calculated the protection level for the artificial class y_2 as:

$$y_2 = \sigma_{12}Z + \mu_{12}$$

And using the same method we calculated the protection level $y_1 = \sigma_1 z + \mu_1 \cong 12$, which is the same for every day. We calculated the booking limits by deducting the respective protection levels from capacity such as $b_2 = C - y_1 = 149$.

The results that don't change day to day are:

y3	161
y1	12
b1	161
b2	149

And the results that change day to day are:

	y2	b3
6/17/2025	82	79
6/18/2025	81	80
6/19/2025	88	73
6/20/2025	89	72
6/21/2025	89	72
6/22/2025	81	80
6/23/2025	81	80