

How to Write a L^AT_EX Dynamic Report

A Hi-Fi Audio DIYer

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Contents

1	TF34-100 Engine Sensor Locations	2
2	Type of Engine Compressor Stall Fault	2
3	Data Definition	3
4	Plots of ts, diff, acf and pacf	4
5	Mathmatical Equations	5
6	Four ARIMA Performance Parameters	8
6.1	Sigma2	8
6.2	Log-Likelihood	8
6.3	AIC	8
6.4	Percentage of Significant Coefficients (PSC)	9
7	Linear Regression Model Adequacy	12

1 TF34-100 Engine Sensor Locations

The locations of certain engine sensors are shown in Figure [1].

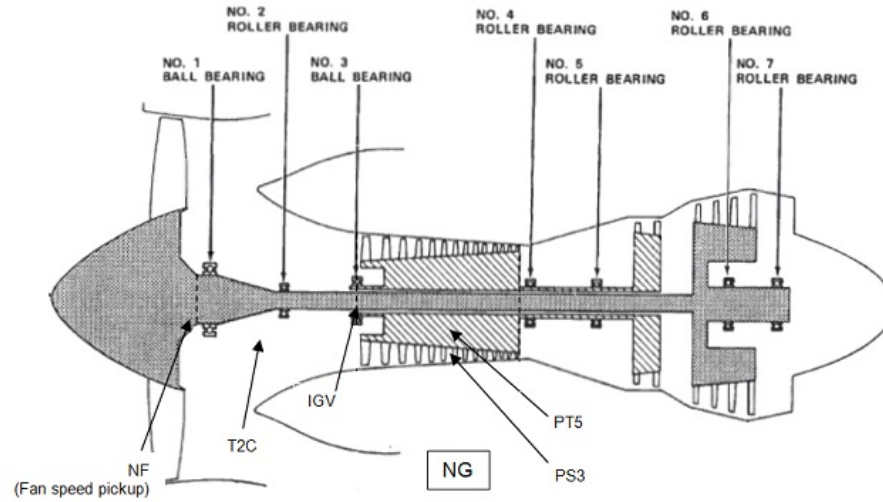


Figure 1: Locations illustrated for three interested sensors (T2C, NG and IGV)

2 Type of Engine Compressor Stall Fault

See Table [1].

Table 1: Type of compressor stalls

	WESA	AoA in Envelope
PLA	$\geq 12^\circ$	$\geq 12^\circ$
PS3(% drop over 500ms)	$>25\%$	$>50\%$
NF	7%	
AoA	in envelope for mach number	in envelope for mach number

3 Data Definition

Reference [3], Reference [2] and Reference [1]

Following is the definition for the data used in this Dynamic Report.

```
> seekData <- function ( workDir = "/home/albert/simplifiedthesis/data",  
+                          Num = 4,    ## number of flights combined  
+                          K = 3       ## the Kth data ie. the Kth Aircraft Series Number  
+ ) {  
+   pattern <- paste("comb_", Num, sep = "")  
+   filez <- list.files(path = workDir, pattern = pattern, full.names = TRUE)  
+   faultStatus <- substr(filez[K], 44, 51)  
+   Dat <- read.csv(filez[K])  
+   Dat <- Dat[which(Dat[,2] < 9.999 & Dat[,2] > -9.999), ]  
+   Dat <- ts(Dat[,2])  
+   return(Dat)  
+ }
```

Table 2: Defination code for data used for this report.

4 Plots of ts, diff, acf and pacf

Following 2 figures (Figure 2 and Figure 3) demonstrate how the R codes would work here.

```
[1] "For 7-Combined-Flights data; Aircraft 3th in ASN."
```

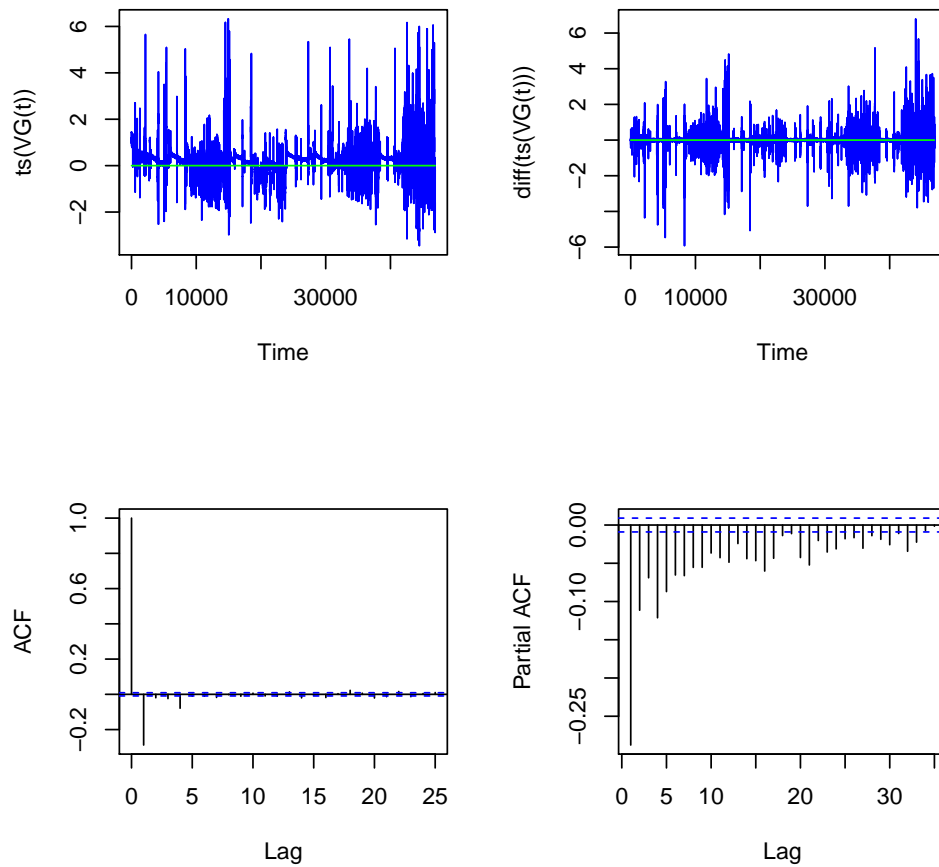


Figure 2: The $ts(VG(t))$, $diff(ts)$, $acf(diff(ts))$ and $pacf(diff(ts))$.

[1] "For 7-Combined-Flights data; Aircraft 18th in ASN."

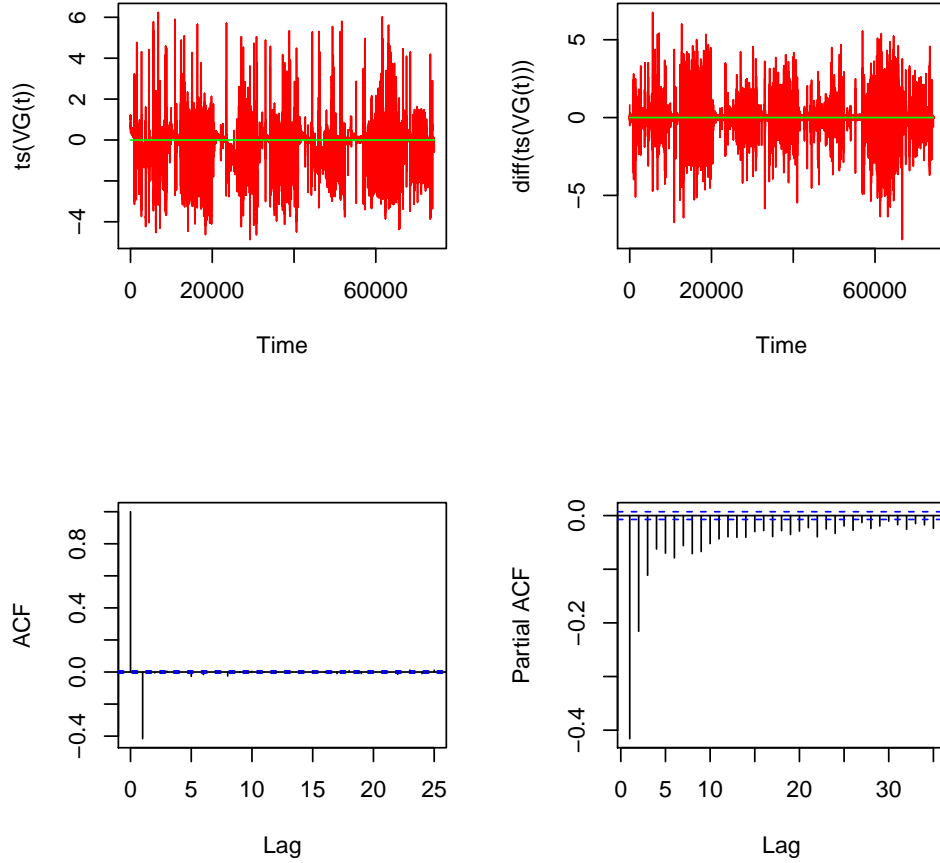


Figure 3: The $ts(VG(t))$, $diff(ts)$, $acf(diff(ts))$ and $pacf(diff(ts))$.

5 Mathematical Equations

$$X_t = \delta + AR_1 X_{t-1} + AR_2 X_{t-2} + \cdots + AR_p X_{t-p} + A_t - MA_1 A_{t-1} - MA_2 A_{t-2} - \cdots - MA_q A_{t-q} \quad (1)$$

Where $X_t = X(t) = diff(ts(VG(t)))$ is the first order differenced value of the ts transformed VG data at the time , AR_i is the AutoRegression (AR) coefficient, and MA_j is the Moving Average (MA) coefficient. This model is denoted as $arima(p, 0, q)$.

$$p(\text{CompressorStall}|N_{\text{CombinedFlights}}) = \beta_0 + \sum_{i=1}^p \beta_i * AR_i + \sum_{j=1}^q \beta_{j+p} * MA_j + \epsilon \quad (2)$$

Where N indicates number of flights data used, currently, $N = 1, 2, \dots, 7$. AR_i is the AR coefficients ($i = 1, 2, \dots, p$) and MA_j is the MA coefficients ($j = 1, 2, \dots, q$). This Probability Model of Compressor Stall Fault Event is based on the data as described below:

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \\ y_{m+1} \\ \vdots \\ y_n \end{pmatrix} \sim \begin{pmatrix} AR_{1_1} & AR_{2_1} & \dots & AR_{p_1} & MA_{1_1} & MA_{2_1} & \dots & MA_{q_1} \\ AR_{1_2} & AR_{2_2} & \dots & AR_{p_2} & MA_{1_2} & MA_{2_2} & \dots & MA_{q_2} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ AR_{1_n} & AR_{2_n} & \dots & AR_{p_n} & MA_{1_n} & MA_{2_n} & \dots & MA_{q_n} \end{pmatrix} \quad (3)$$

Where the response variable (independent variable) (y_1, y_2, \dots, y_m) indicates compressor stall fault event DID NOT happen for engine 1 to engine m , and (y_{m+1}, \dots, y_n) indicates compressor stall fault event DID happen for engine $(m+1)$ to engine n ; $AR_{i,k}$ ($i = 1, 2, \dots, p; k = 1, 2, \dots, n$) and $MA_{j,k}$ ($j = 1, 2, \dots, q; k = 1, 2, \dots, n$) are the regressor variables (explanatory variables) which are AutoRegression (AR) coefficients and Moving Average (MA) coefficients of the fitted $arima(p, 0, q)$ model from each set of first-order differenced VG data. Currently $m = 22$ and $n = 28$. This reflects that the data consists of 14 aircraft (equipped with a total of 28 engines), and that 6 of the engines have compressor stall fault events.

VG time series data is generated by combining flights 1 (one) through 7 (seven). Following equations have been used to explain how the N-Combined-Flight Data constructed.

For example, for 1-Flight Data:

$$VG(t)_{\text{aircraft}_i, 1\text{Flight}} = f(T2C(t)_{\text{aircraft}_i, \text{flight}_j} + NG(t)_{\text{aircraft}_i, \text{flight}_j} + IGV(t)_{\text{aircraft}_i, \text{flight}_j}) \quad (4)$$

Where this is aircraft i , the j is the highest flight number in our selection of this aircraft.

For 2-Combined-Flights Data:

$$VG(t)_{\text{aircraft}_i, 2\text{CombinedFlights}} = VG(t)_{\text{aircraft}_i, 1\text{Flight}_j} + VG(t)_{\text{aircraft}_i, 1\text{Flight}_{(j-1)}} \quad (5)$$

Where this is aircraft i , the $(j - 1)$ is the second highest flight number in our selection of this aircraft.

For N-Combined-Flight Data: ($N = 2, 3, \dots, 7$)

$$VG(t)_{aircraft_i, NCombinedFlights} = VG(t)_{aircraft_i, 1Flight_j} + VG(t)_{aircraft_i, 1Flight_{(j-1)}} + \dots + VG(t)_{aircraft_i, 1Flight_{(j-N+1)}} \quad (6)$$

Where this is aircraft i , the $(j-1)$ is the second highest flight number in our selection of data for this aircraft, the $(j-N+1)$ is the $(N-1)^{th}$ lower than the highest flight number in our selection of data for this aircraft.

The first order differenced VG time series data was constructed as following equations shown.

$$diff\{VG(t)_{aircraft_i, NCombinedFlights}\} = VG(t)_{aircraft_i, NCombinedFlights} - VG(t-1)_{aircraft_i, NCombinedFlights} \quad (7)$$

Thereafter, the constructed first order differenced VG time series data was used to develop an $arima(p, 0, q)$ model in R. This process can be mathematically expressed as

$$X(t) = diff\{VG(t)_{aircraft_i, NCombinedFlights}\} \quad (8)$$

$$x.fit <- arima(X(t), order = c(p, 0, q), optim.method = "Nelder - Mead") \quad (9)$$

$$AR_i = x.fit$coef[i] \text{ where } i = 1, 2, \dots, p \quad (10)$$

$$MA_j = x.fit$coef[j + p] \text{ where } j = 1, 2, \dots, q \quad (11)$$

6 Four ARIMA Performance Parameters

6.1 Sigma2

A first order difference was formed from the VG data files for the sampled 28 engines, including the 6 engines with compressor stall faults using the flight data immediately prior to the fault flight for that particular aircraft. The aircraft serial number (ASN) and engine ID were checked for consistency to ensure that this was the case. Then 1 to 7 combined-flights-data were formed for the specified ASN aircraft. The reason to form a multiple flight-combined- data is to attempt to achieve an “early alert”.

An R script was developed to check a specified ARIMA(p,0,q) model’s performance based on 4 (four) parameters.

First, check the sigma2 parameter by using the R code:

$$\text{sigma2} = \text{arima}(x, \text{order} = c(p, 0, q), \text{optim.method} = "Nelder - Mead")\$sigma2 \quad (12)$$

Where “sigma2” stands for the maximum likelihood estimate (MLE) of the innovations variance. The difference between the expected mean at time t, given the time series prior to t, and the actual value is called the innovation. Measuring the variance of the innovation will give you a better idea of how “noisy” the process is.

6.2 Log-Likelihood

Second, check the Log-Likelihood parameter by using R code:

$$\text{Log} - \text{Likelihood} = \text{arima}(x, \text{order} = c(p, 0, q), \text{optim.method} = "Nelder - Mead")\$loglik \quad (13)$$

Where “Log-Likelihood” stands for a logarithm of likelihood function. In statistics, a Likelihoodfunction (often simply the Likelihood) is a function of the parameters of a statistical model. The likelihood of a set of parameter values, θ , given outcomes x, is equal to the probability of those observed outcomes given those parameter values, that is $\mathcal{L}(\theta|x) = \mathcal{P}(x|\theta)$.

6.3 AIC

Third, check the AIC parameter by using R code:

$$\text{AIC} = \text{arima}(x, \text{order} = c(p, 0, q), \text{optim.method} = "Nelder - Mead")\$aic \quad (14)$$

Where "AIC" stands for Akaike Information Criterion, which is a measure of the relative quality of a statistical model for a given set of data.

6.4 Percentage of Significant Coefficients (PSC)

Fourth, check the Percentage of Significant Coefficients (PSC) parameter. PSC represents the percentage of significant coefficients among the AR coefficients and MA coefficients of the fitted $\text{arima}(p,0,q)$ model. Let x be the first order differenced ts data of VG, $x.\text{fit}$ be the fitted $\text{arima}(p,0,q)$ model. That is $x.\text{fit} < -\text{arima}(X(t), \text{order} = c(p, 0, q), \text{optim.method} = "Nelder - Mead")$.

If one of the coefficients $x.\text{fit}\$coef[k]$ ($k = 1, 2, \dots, (p + q)$) of the fitted $\text{arima}(p, 0, q)$ model meets following condition, it is considered as significant.

$$\left| \frac{x.\text{fit}\$coef[k]}{x.\text{fit}\$var.coef[k]} \right| > 1.96 \quad (15)$$

In R programming environment, $x.\text{fit}\$coef[k]$ is the coefficients of the resulting $\text{arima}(p, 0, q)$ model, where $x.\text{fit}\$coef[k]$ be AR coefficients while $k = 1, 2, \dots, p$, and $x.\text{fit}\$coef[k]$ be MA coefficients while $k = (p + 1), (p + 2), \dots, (p + q)$. Correspondingly, $x.\text{fit}\$var.coef[k]$ be the estimated variances of coefficient . Therefore, the PSC is calculated as:

$$PSC = \frac{\text{Sum of the Number of Significant } x.\text{fit}\$coef[k]}{(p + q)} \quad (16)$$

The following is a demonstration of the parameter's performance for the various ARIMA models and the different sampling data:

For example, process the sample data as of Figure 4, is to fit to an $\text{arima}(12, 0, 4)$ model for the first order differenced values of ts transformed VG data. By using of an R script, the coefficients of $\text{arima}(12, 0, 4)$ is calculated as shown as Table 3.

(-0.1815, 0.0002387, 0.01500, 0.03247, 0.02954, -0.002241, 0.05759, 0.04050, 0.006447, 0.01128, 0.01244, 0.02152, -0.05026, 0.04650, 0.02096, -0.01320)

[1] "For 4-Combined-Flights data; Aircraft 3th in ASN. p=12 & q=4 in arima(p,0,q) model."

ar1	ar2	ar3	ar4	ar5	ar6
-0.181470271	0.000238739	0.015003603	0.032469898	0.029538878	-0.002240709
ar7	ar8	ar9	ar10	ar11	ar12
0.057590585	0.040496339	0.006446809	0.011284292	0.012444539	0.021522452
ma1	ma2	ma3	ma4		
-0.050258616	0.046497112	0.020957831	-0.013201263		

Table 3: Coefficients of *arima*(12, 0, 4) for a 4-Combined-Flights data.

Where the first 12 coefficients are called AR coefficients, and the last 4 coefficients are called MA coefficients, because $p = 12$ and $q = 4$ in an *arima*($p, 0, q$) model here.

And the variance of the coefficients of the *arima*(12, 0, 4) is calculated as Table 4

[1] "For 4-Combined-Flights data; Aircraft 3th in ASN. p=12 & q=4 in arima(p,0,q) model."

[1]	3.71987e-04	-2.02777e-04	-2.36069e-05	-2.78047e-04	1.43877e-05
[6]	3.66777e-05	5.50166e-05	5.02489e-05	5.39051e-05	6.57346e-05
[11]	3.56272e-05	5.36436e-05	-3.38005e-04	3.33822e-04	-1.38888e-05
[16]	3.17574e-04				

Table 4: Variances of coefficient of *arima*(12, 0, 4) for a 4-Combined-Flights data.

(0.0003720, -0.0002028, -0.00002361, -0.0002780, 0.00001439, 0.00003668, 0.00005502, 0.00005025, 0.00005391, 0.00006573, 0.00003563, 0.00005364, -0.0003380, 0.0003338, -0.00001389, 0.0003176)

Thus, the ratio of coefficient to variance of coefficient $\frac{x.fit\$coef[k]}{x.fit\$var.coef[k]}$ can be calculated as Table 5.

[1] "For 4-Combined-Flights data; Aircraft 3th in ASN. p=12 & q=4 in arima(p,0,q) model."

ar1	ar2	ar3	ar4	ar5	ar6	ar7
487.84053	1.17735	635.56092	116.77848	2053.07132	61.09184	1046.78616
ar8	ar9	ar10	ar11	ar12	ma1	ma2
805.91445	119.59551	171.66453	349.29842	401.21157	148.69178	139.28730
ma3	ma4					
1508.97825	41.56904					

Table 5: The absolute ratio of \$coef to \$var.coef of *arima*(12, 0, 4) for a 4-Combined-Flights data.

(487.84, 1.18, 635.56, 116.78, 2053.07, 61.09, 1046.79, 805.91, 119.60, 171.66, 349.30, 401.21, 148.69, 139.29, 1508.98, 41.57)

The second AR coefficient (AR2) is not significant because its ratio of coefficient to variance of coefficient valued as of 1.18. The rest of the coefficients of *arima*(12,0,4) model are significant. Therefore the PSC can be calculated as

$$PSC = \frac{\text{Sum of the Number of Significant } x.fit\$coef[k]}{(p + q)} = \frac{15}{16} = 0.9375 = 93.75\%$$

Lower than 100% indicating some coefficients are not significant. It is estimated that compounding factors and non-flight-state-separated data play roles to make some of the *arima* model coefficients non-significant.

(plots here)

The following plots demonstrate the scan study results for various *arima*(p,0,q) model applied to 1-flight-data, 4-combined-flights-data and 7-combined-flights-data.

(plots here)

7 Linear Regression Model Adequacy

List of Figures

1	Locations illustrated for three interested sensors (T2C, NG and IGV)	2
2	The ts(VG(t)), diff(ts), acf(diff(ts) and pacf(diff(ts))).	4
3	The ts(VG(t)), diff(ts), acf(diff(ts) and pacf(diff(ts))).	5
4	First order differenced values of ts transformed VG data for a 4-Combined-Flights.	14

List of Tables

1	Type of compressor stalls	2
2	Defination code for data used for this report.	3
3	Coefficients of <i>arima</i> (12, 0, 4) for a 4-Combined-Flights data.	10
4	Variances of coefficient of <i>arima</i> (12, 0, 4) for a 4-Combined-Flights data.	10
5	The absolute ratio of \$coef to \$var.coef of <i>arima</i> (12, 0, 4) for a 4-Combined-Flights data.	11

References

- [1] S. Ganguli, S. Deo, and D. Gorinevsky. “Parametric Fault Modeling and Diagnostics of a Turbofan Engine”. In: *IEEE CCA/ISIC/CACSD*. Taipei, Taiwan, 2004.
- [2] Luca Marinai, Rita Singh , Barry Curnock, and Douglas Probert. “Detection and Prediction of the Performance Deterioration of a Turbofan Engine”. In: *Proceedings of the International Gas Turbine Congress*. Tokyo, Japan, 2003.
- [3] Field Engineering Unit/H564 Northrop Electronics Division. *Field Engineering A-10 TEMS Software Handbook, A-10 Turbine Engine Monitor System, for Version 54.1 and 56.1 software, section 3.1.4 VG Schedule*. 2010.

```
> seekData <- function ( workDir = "/home/albert/simplifiedthesis/data",
+                          Num = 4,    ## number of flights combined
+                          K = 3       ## the Kth data ie. the Kth Aircraft Series Number
+ ) {
+   pattern <- paste("comb_", Num, sep = "")
+   filez <- list.files(path = workDir, pattern = pattern, full.names = TRUE)
+   faultStatus <- substr(filez[K], 44, 51)
+   Dat <- read.csv(filez[K])
+   Dat <- Dat[which(Dat[,2] < 9.999 & Dat[,2] > -9.999), ]
+   Dat <- ts(Dat[,2])
+   return(Dat)
+ }
> Dat <- seekData(, Num=4, K=3)
> par(mfrow=c(1,1))
> plot(diff(Dat), main="diff(ts(VG(t)))")
```

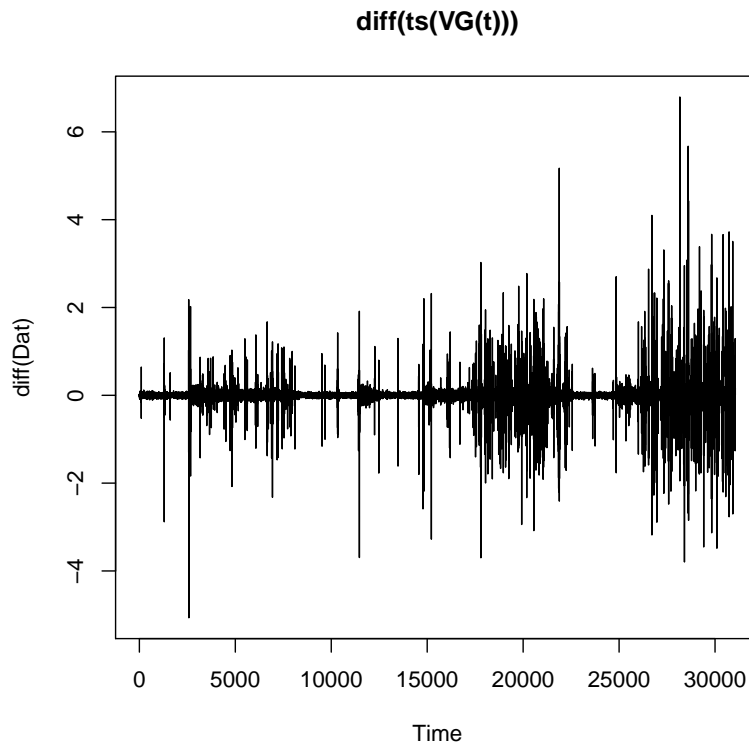


Figure 4: First order differenced values of ts transformed VG data for a 4-Combined-Flights.