Appendix

Data Cleaning:

```
# Check for missing values in bicuphi
> summary(bicuphi)
      X                  X.1                 X.2           
 Length:1325        Length:1325        Length:1325       
 Class :character   Class :character   Class :character  
 Mode  :character   Mode  :character   Mode  :character  
> # More detailed check
> sapply(bicuphi, function(x) sum(is.na(x)))
  X X.1 X.2 
  0   0   0 
```

```
~ Notes: There are no NA values in the data.  That does not mean that there could be other types of data errors.
```

```
# Convert X.2 to numeric, coercing any non-numeric strings to NA
> bicuphi$X.2 <- as.numeric(as.character(bicuphi$X.2))
Warning message:
NAs introduced by coercion
```

```
# Check for newly created NAs in X.2 (if any non-numeric values were present)
> sum(is.na(bicuphi$X.2))
[1] 2
```

```
# Identify which rows have NAs in X.2 introduced by coercion
> na_rows <- which(is.na(bicuphi$X.2))
> print(na_rows)
[1] 1 2
```

```
# Optional: View the rows with NAs in X.2 to understand what the non-numeric values were
> print(bicuphi[na_rows, ])
     X  X.1 X.2
1            NA
2 DATE TIME  NA
```

```
# Correctly count empty strings in each column
> empty_string_counts <- sapply(bicuphi, function(x) sum(x == ""))
> print(empty_string_counts)
  X X.1 X.2 
  1   1  NA 
```

```
    X  X.1 X.2
1            NA
2 DATE TIME  NA
> # Correcting the command to identify rows with empty strings
> empty_string_rows <- sapply(bicuphi, function(x) sum(x == ""))
> total_empty_strings <- sum(empty_string_rows)
> print(total_empty_strings)
[1] NA
```

```
>
> # Remove rows where X.2 is NA
> bicuphi_clean <- bicuphi[!is.na(bicuphi$X.2), ]
>
> # Check the dimensions to ensure rows are removed
> dim(bicuphi_clean)
[1] 1323    3
```

~ Notes: Two rows have been removed 1, 2.

```
# Renaming columns in the bicuphi_clean dataframe
> names(bicuphi_clean) <- c('date', 'time', 'demand')
>
> # Verify the changes
> head(bicuphi_clean)
      date time demand
3 1-Mar-05 6:30      1
4 1-Mar-05 6:45      2
5 1-Mar-05 7:00      4
6 1-Mar-05 7:15      0
7 1-Mar-05 7:30     10
8 1-Mar-05 7:45     13
```

~ Notes: Descriptive aspects of the columns have been resolved. Numeric type for demand is confirmed as numeric.

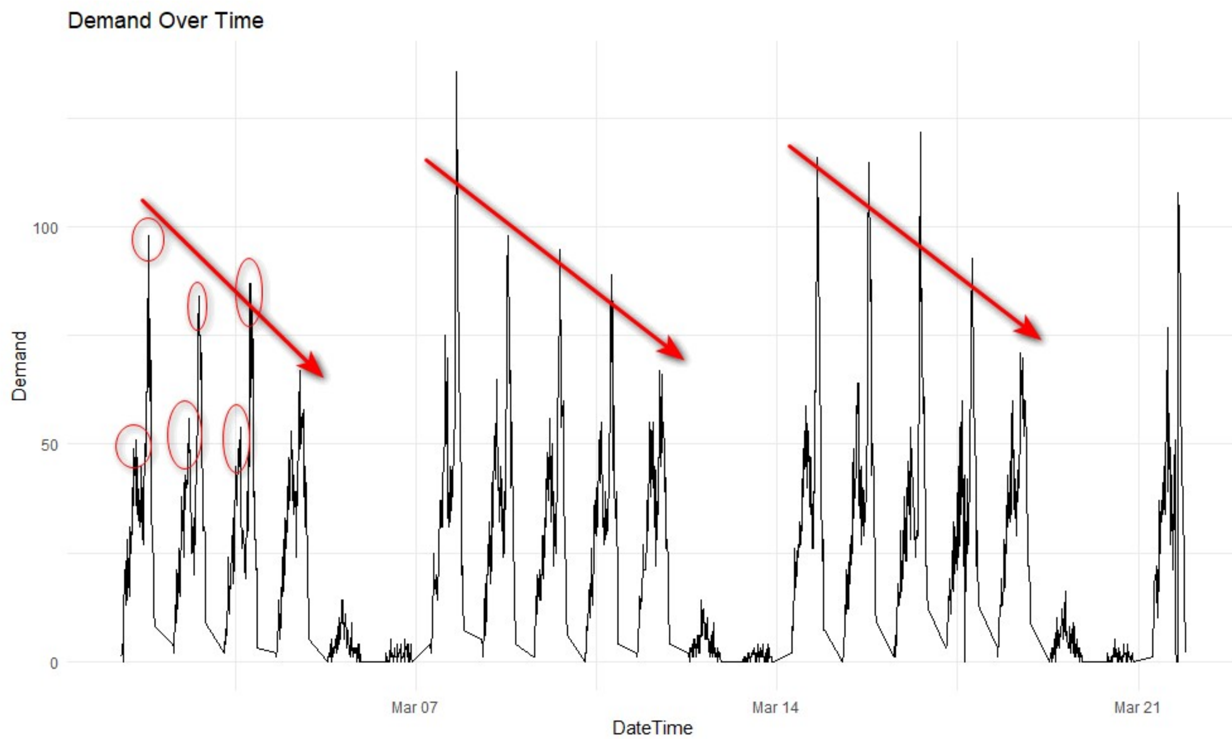
```
# Convert the 'date' column to Date format > bicuphi_clean$date <-
as.Date(bicuphi_clean$date, format="%d-%b-%y") > > # Assuming the 'time' column
is already in a suitable format, you might still want to combine 'date' and
'time' > # First, ensure 'time' is a character for concatenation >
bicuphi_clean$time <- as.character(bicuphi_clean$time) > > # Combine 'date' and
'time' into a single 'datetime' column > bicuphi_clean$datetime <-
as.POSIXct(paste(bicuphi_clean$date, bicuphi_clean$time), format="%Y-%m-%d
%H:%M") > > # Check if 'datetime' is correctly formatted and if time intervals
are consistent > summary(bicuphi_clean$datetime) Min. 1st Qu. Median Mean "2005-
03-01 06:30:00" "2005-03-06 10:22:30" "2005-03-11 14:15:00" "2005-03-11 14:15:00"
3rd Qu. Max. "2005-03-16 18:07:30" "2005-03-21 22:00:00"
```

~ Notes: Create a single datetime column for clarity and simplicity.

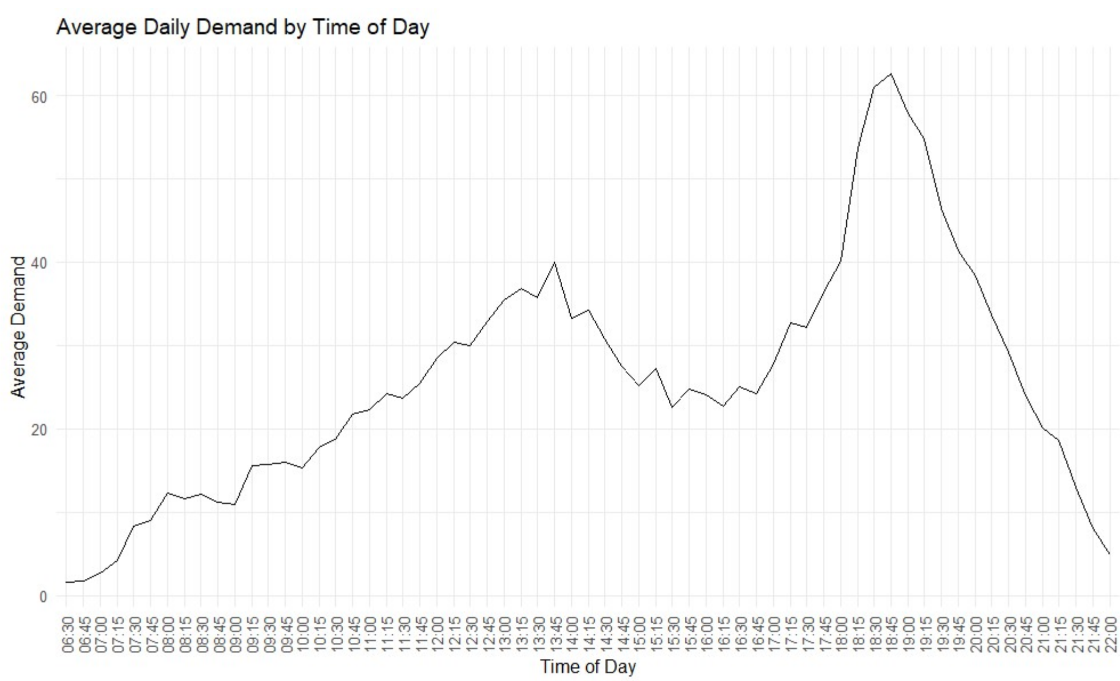
```
# Calculate differences between consecutive datetime entries
> time_diffs <- diff(bicuphi_clean$datetime)
>
> # Check if all differences are 15 minutes (900 seconds)
> all(time_diffs == 900) # Returns TRUE if all intervals are exactly 15 minutes
[1] FALSE
```

~ Notes: Not all intervals are 15 minutes

Data Visualization:



This is a time plot of the demand with a ‘datetime’ stamp on the x axis. Trend: Max usage is typically on Monday and decreases thru Sunday. Usage on weekdays builds steadily in the morning rush hour and peaks around the 5 pm rush hour.

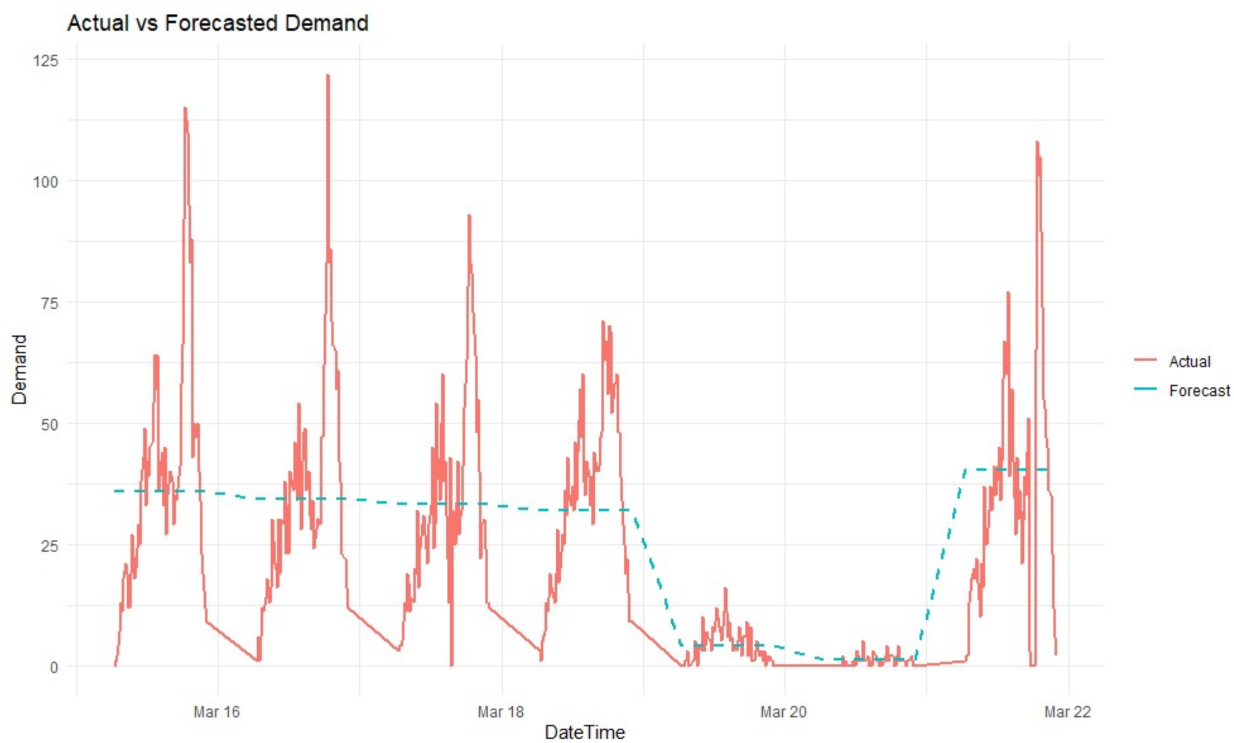


Average daily usage shows 2 peak periods that revolve around the workday hours. There is a spread our period in the morning and more concentrated usage period around evening rush hour.

Naive Forecast

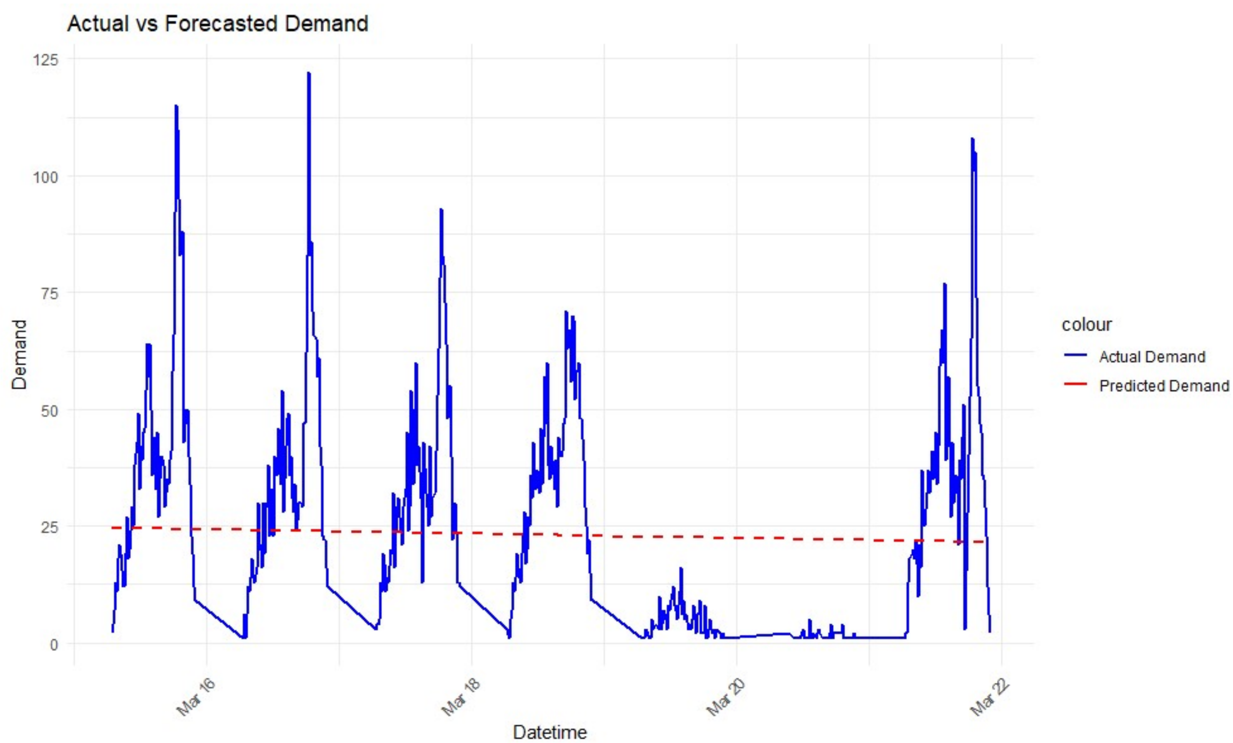
```
# Splitting the data
> training_set <- bicuphi_clean %>% filter(datetime < as.POSIXct("2005-03-15"))
> validation_set <- bicuphi_clean %>% filter(datetime >= as.POSIXct("2005-03-
15"))
>
> # Calculating weekly patterns from the training data
> weekly_pattern <- training_set %>%
+    mutate(day_of_week = wday(datetime, label = TRUE)) %>%
+    group_by(day_of_week) %>%
+    summarise(average_demand = mean(demand))
>
> # Viewing the weekly pattern
> print(weekly_pattern)
# A tibble: 7 × 2
  day_of_week average_demand
  <ord>                <dbl>
1 Sun                   1.12
2 Mon                  40.3
3 Tue                  35.9
4 Wed                  34.2
5 Thu                  33.2
6 Fri                  31.9
7 Sat                   4.11
>
> # Forecasting for the validation period
> validation_forecasts <- validation_set %>%
+    mutate(day_of_week = wday(datetime, label = TRUE)) %>%
+    left_join(weekly_pattern, by = "day_of_week") %>%
+    select(datetime, forecast_demand = average_demand)
>
> # Checking the forecasts
> head(validation_forecasts)
             datetime forecast_demand
1 2005-03-15 06:30:00         35.9127
2 2005-03-15 06:45:00         35.9127
3 2005-03-15 07:00:00         35.9127
4 2005-03-15 07:15:00         35.9127
5 2005-03-15 07:30:00         35.9127
6 2005-03-15 07:45:00         35.9127
>
> # Joining forecasts with actual demand
> validation_comparison <- validation_set %>%
+    select(datetime, actual_demand = demand) %>%
+    left_join(validation_forecasts, by = "datetime")
>
> # Calculating MAE
> mae <- mean(abs(validation_comparison$actual_demand -
validation_comparison$forecast_demand), na.rm = TRUE)
> print(paste("MAE:", mae))
[1] "MAE: 12.6568765072166"
>
> # Calculating RMSE
> rmse <- sqrt(mean((validation_comparison$actual_demand -
```

```
validation_comparison$forecast_demand)^2, na.rm = TRUE))
> print(paste("RMSE:", rmse))
[1] "RMSE: 18.9888449798315"
>
> # Ensure actual_demand and forecast_demand are numeric
> validation_comparison$actual_demand <-
as.numeric(validation_comparison$actual_demand)
> validation_comparison$forecast_demand <-
as.numeric(validation_comparison$forecast_demand)
>
> # Calculate MAPE
> mape <- mean(abs((validation_comparison$actual_demand -
validation_comparison$forecast_demand) / validation_comparison$actual_demand),
na.rm = TRUE) * 100
> print(paste("MAPE:", mape))
[1] "MAPE: Inf"

# Filtering out instances where actual_demand is zero to avoid division by zero
in MAPE calculation
> validation_comparison_filtered <- validation_comparison %>%
+    filter(actual_demand > 0)
>
> # Recalculating MAPE
> mape_filtered <- mean(abs((validation_comparison_filtered$actual_demand -
validation_comparison_filtered$forecast_demand) /
validation_comparison_filtered$actual_demand), na.rm = TRUE) * 100
> print(paste("Filtered MAPE:", mape_filtered))
[1] "Filtered MAPE: 127.594538853236"
>
```



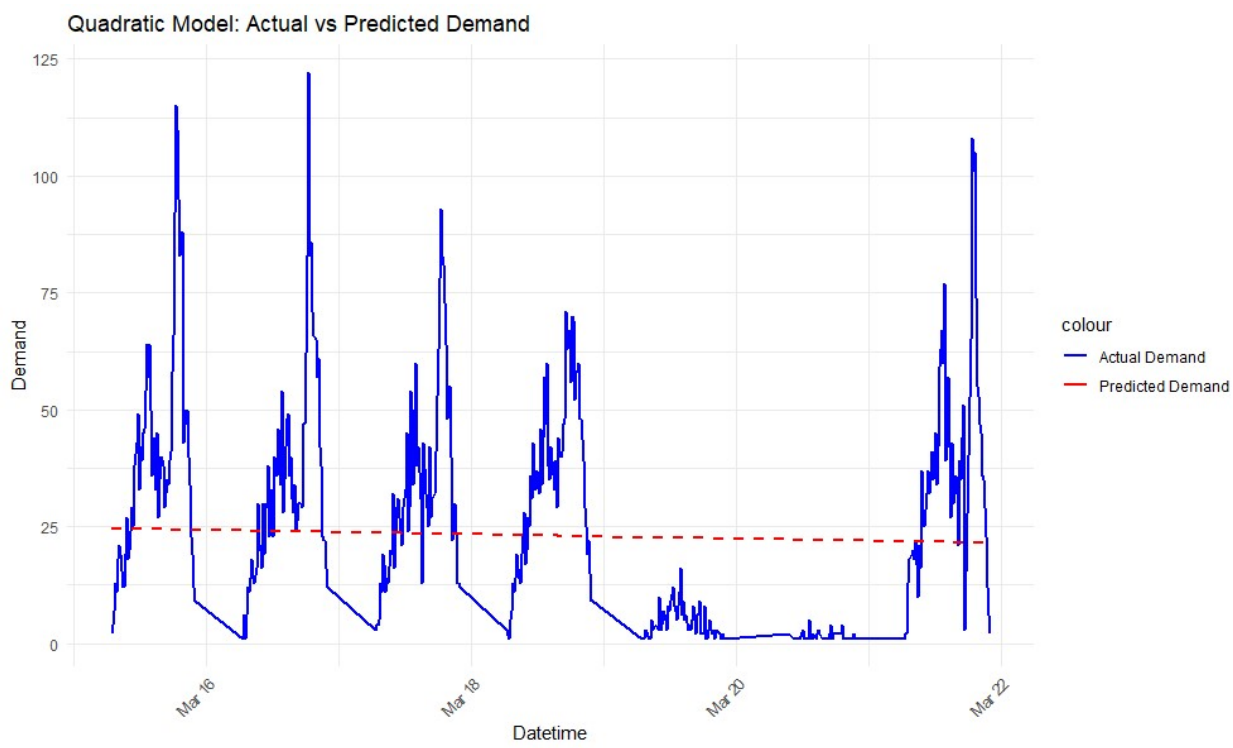
Linear Regression Model:

```
# Summary of the model
> summary(lm_model)

Call:
lm(formula = demand ~ datetime, data = training_set)

Residuals:
 Min 1Q Median 3Q Max
-29.989 -20.950 -1.847 13.339 107.994

Coefficients:
 Estimate Std. Error t value Pr(>|t|)
(Intercept) 5.917e+03 2.548e+03 2.323 0.0204 *
datetime -5.305e-06 2.295e-06 -2.312 0.0210 *
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 22.9 on 814 degrees of freedom
Multiple R-squared: 0.006523,   Adjusted R-squared: 0.005302
F-statistic: 5.345 on 1 and 814 DF, p-value: 0.02104


# Print the error metrics
> print(paste("MAE:", mae))
[1] "MAE: 18.6840522177133"
> print(paste("MAPE:", mape))
[1] "MAPE: 314.343608815863"
> print(paste("RMSE:", rmse))
[1] "RMSE: 24.1018505149405"
```



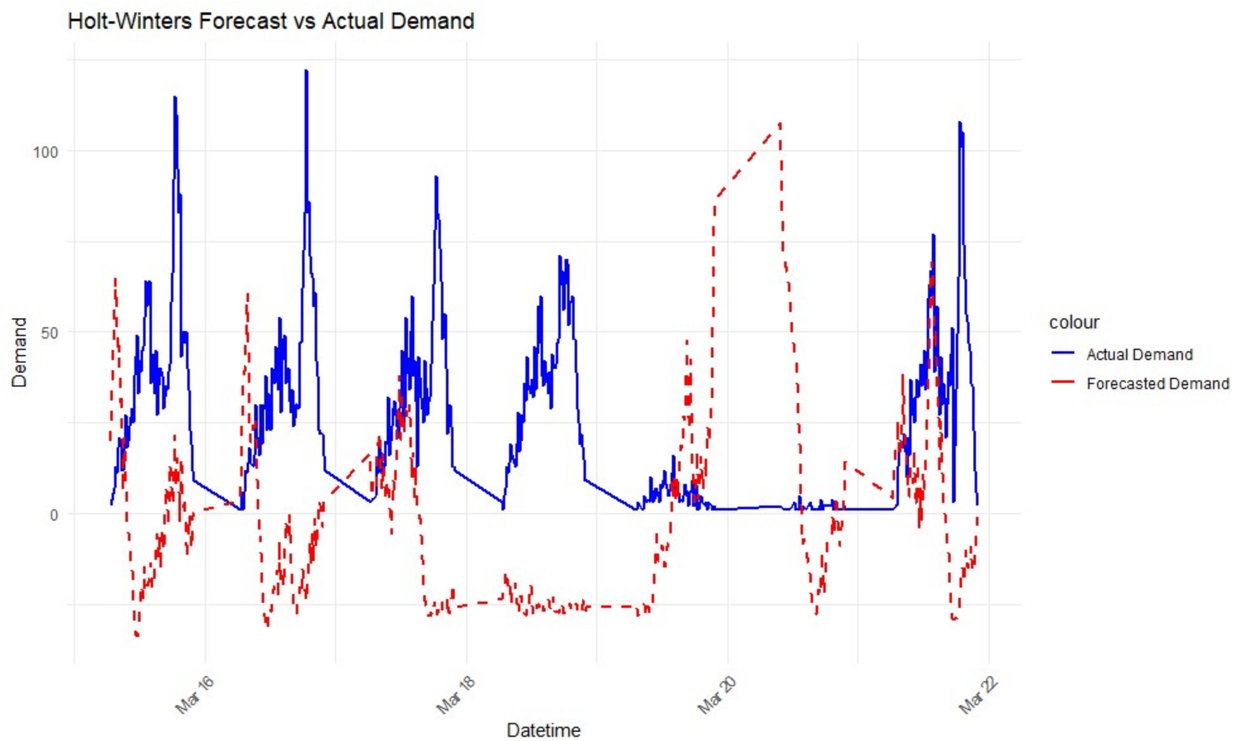
Quadratic Model:

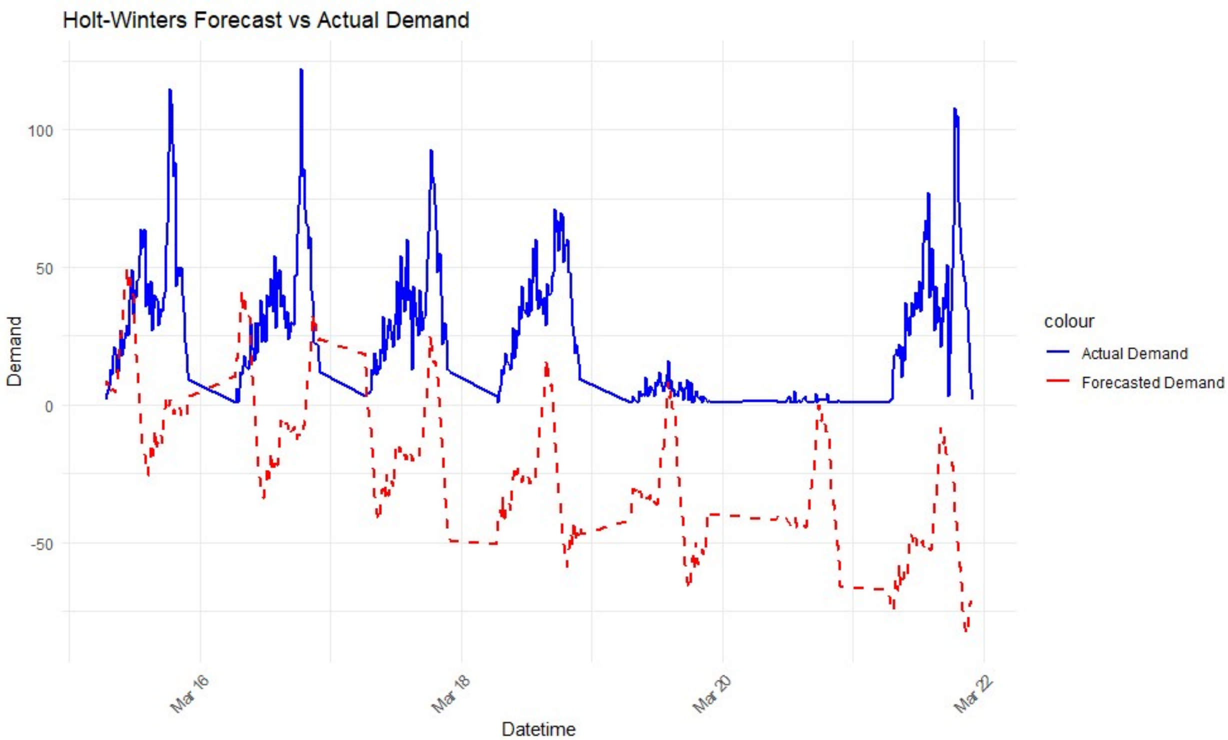
```
# Summary of the quadratic model
> summary(lm_quadratic_model)

Call:
lm(formula = demand ~ datetime_numeric + I(datetime_numeric^2),
    data = training_set_filtered)

Residuals:
    Min      1Q  Median      3Q     Max 
-29.989 -20.950  -1.847  13.339 107.994 

Coefficients: (1 not defined because of singularities)
                        Estimate Std. Error t value Pr(>|t|)  
(Intercept)            5.917e+03  2.548e+03   2.323   0.0204 *
datetime_numeric      -5.305e-06  2.295e-06  -2.312   0.0210 *
I(datetime_numeric^2)         NA         NA      NA       NA  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 22.9 on 814 degrees of freedom
Multiple R-squared:  0.006523,	Adjusted R-squared:  0.005302 
F-statistic: 5.345 on 1 and 814 DF,  p-value: 0.02104
```

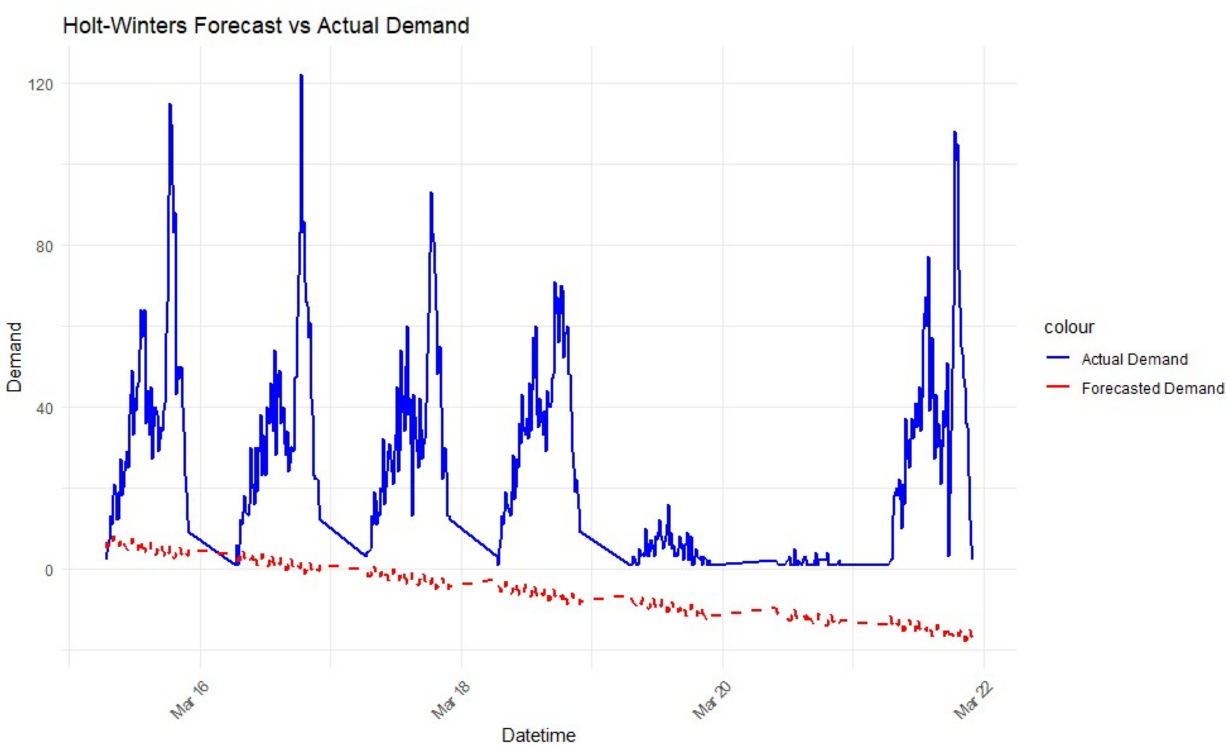


Holt Winters Method:

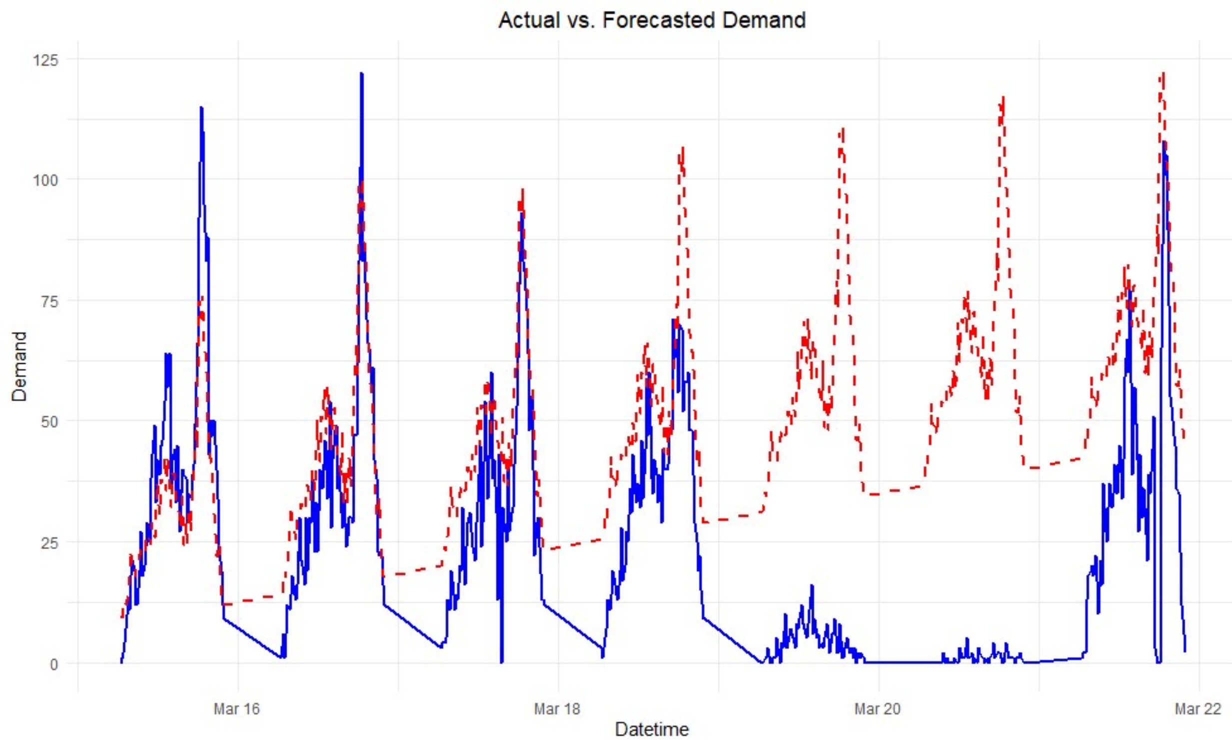
```
> # Print the error metrics
> print(paste("MAE:", mae))
[1] "MAE: 39.7316740676646"
> print(paste("MAPE:", mape))
[1] "MAPE: 394.020267682534"
> print(paste("RMSE:", rmse))
[1] "RMSE: 49.0510276675861"
>
```




Holt-Winters Forecast vs Actual Demand
100
50
0
-50
Demand
Mar 16
Mar 18
Mar 20
Mar 22
Datetime
colour
Actual Demand
Forecasted Demand


Holt-Winters Forecast vs Actual Demand
120
80
40
0
Demand
Mar 16
Mar 18
Mar 20
Mar 22
Datetime
colour
Actual Demand
Forecasted Demand

Arima


Actual vs. Forecasted Demand
125
100
75
50
25
0
Demand
Mar 16
Mar 18
Mar 20
Mar 22
Datetime