Review

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A Machine Learning Approach to Understand the Impact of Temperature and Rainfall Change on Concrete Pavement Performance Based on LTPP Data

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Abstract: Climate change is one of the most concerning global issues and has the potential to influence every aspect of human life. Like different components of society, it can impose significant adverse impacts on pavement infrastructure. Although several research efforts have focused on studying the effects of climate change on natural and built systems, its impact on pavement performance has not been studied extensively. Due to the weather effect the lifetime of pavement is getting lower on the other hand maintenance cost is getting higher and higher. The data has been collected from LTTP website and as a site The State of Texas has been considered. The primary objective of this project is to quantify the effect of temperature as well as precipitation changes on pavement response and performance prediction using the ARIMA model and develop a logistic regression model to analyze the forecast data.

Keywords: temperature; rainfall; concrete pavement; ARIMA; climate change

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Introduction

In LTPP website there are lots of parameters, among which the temperature and precipitation data has been considered for study. The main reason to choose temperature and precipitation is to identify the road damage due to temperature and precipitation. Due to global climate change, extreme weather conditions are now common in many parts of the world. Asphalt is very susceptible to these extreme weather effects. The maintenance cost, the durability of the road and pavement performance all are interconnected with global climate change. Analyzing data of the previous 50-70 years, for example rainfall and temperature, a thorough idea can be generated about the road performance. In the last decade the effect of this change has been significant. Asphalt physical and chemical property largely depend on the weather effects. Extremely low temperature causes asphalt to contract and shrink. This phenomenon causes tension on asphalt and ultimately cracks will develop on the pavement. On the other hand, extreme hot weather can also cause damage to pavement oxidation. Among all the frost heave causes the more damage compared to other. This creates potholes and cracks. The water is considered the biggest threat of the pavement. It deteriorates the pavement very slowly. Water also causes damage by stripping and rutting. Moreover, over precipitation can erode away asphalt seal coat slowly. But when precipitation and temperature change occur or in extreme cases the condition becomes more severe and ultimately causes more damage to the pavement structure.

By analyzing LTPP data, it is possible to estimate the maintenance of the pavement structure and how likely the change causes in pavement. In this study, multiple statistical distributions have been applied to see how data looks. A mathematical model ARIMA ("Autoregressive Integrated Moving Average) has been generated to forecast the precipitation and temperature data. A logistic regression model has been generated to analyze the projected data.

Synopsis:

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- Temperature and precipitation data has been considered as a part of climate change.
- Tried to find a connection between climate change and pavement damage.
- Forecasting the temperature and precipitation by ARIMA ("Autoregressive Integrated Moving Average) model.
- Early failure of pavement and greater distress has been considered.
- A logistic regression model has been generated and used to analyze the projected data.

Methodology

Literature review has been done to get a clear idea how temperature and precipitation affect the performance of pavement. Temperature and precipitation data for Texas has been collected from LTPP website. A data set of 65 years for precipitation and temperature has been studied. It was tried to develop prediction models month wise, but the output prediction data accuracy was very low. A different attempt was tried, and all the data set has been divided by 65 periods (twelve months per period). A mathematical model has been generated. Using ARIMA model, it was able to forecast 2 periods (period 66 & 67) and output data was good. Tried to forecast five periods but the output data was not that accurate since the data set was not organized. To train the logistic regression model, in the spreadsheet a yes/no condition has been developed. It is based on an optimum temperature and precipitation, beyond which it will affect the pavement performance. Among 46800 data, 37400 data have been used to train the model and 94 set of data has been tested to get an idea of the accuracy of the model. At last, the forecasting data has been tested on the logistic regression model to see whether it will affect pavement performance or not.Result and Discussion:

As the data set is huge, a statistical distribution study has been done. For this under 95% confidence interval, Normal distribution, Weibull distribution, Lognormal distribution and Exponential distribution has been tested for both temperature and precipitation data. In Figures 1–4, it has been shown. Mainly, mean value, standard deviation, P value has been considered for the temperature and precipitation value. Among all four distribution we found that Weibull distribution has provided the best result according to the P value.

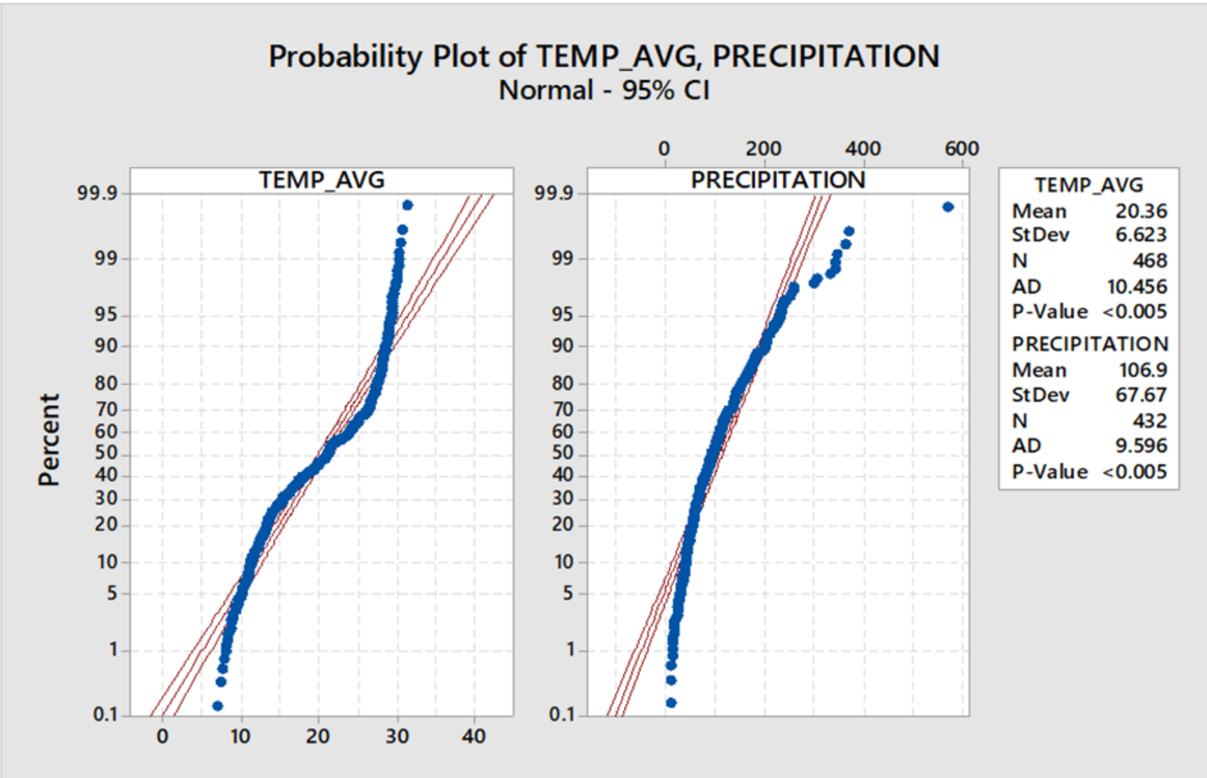

Figure 1. Normal distribution of temp avg and precipitation.

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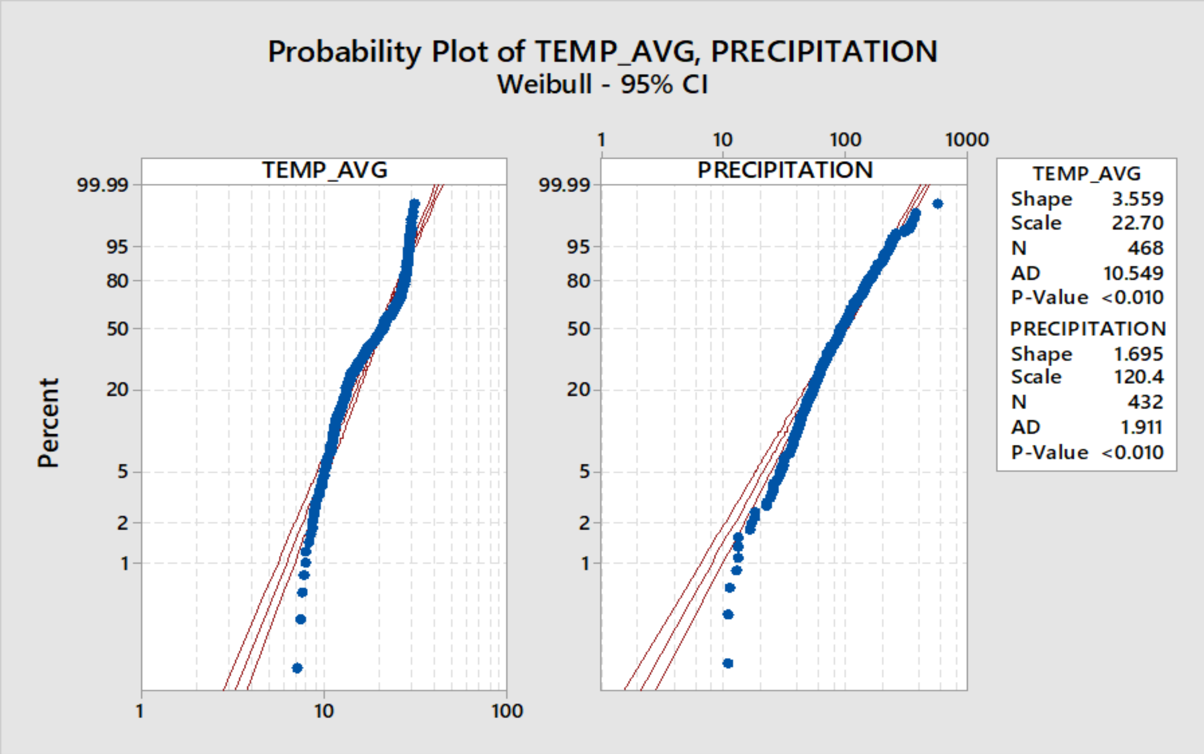

Figure 2. Weibull distribution for Temp avg and precipitation.

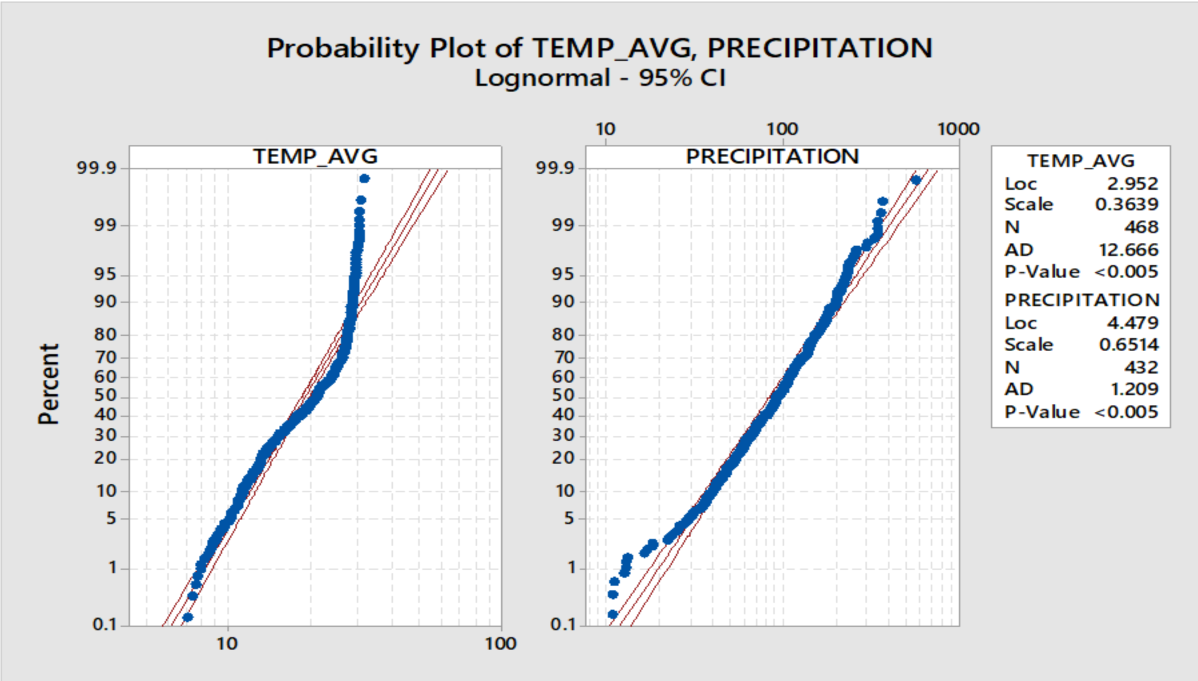

Figure 3. Lognormal distribution of temp avg and precipitation.

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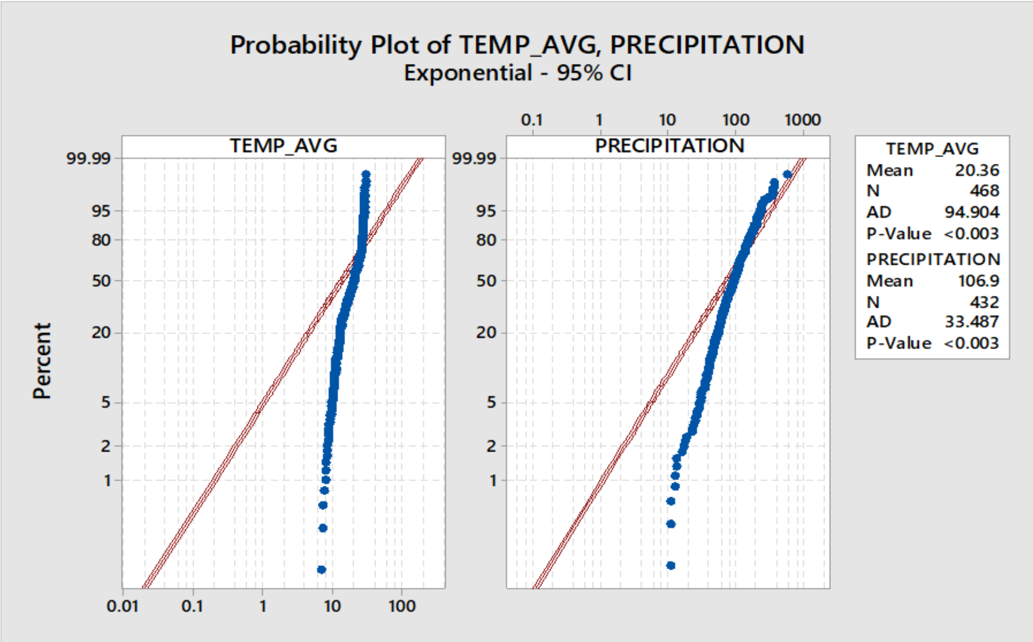

Figure 4. Exponential distribution of temperature avg vs precipitation.

A time series plot has been done to observe precipitation pattern over time in Figure 5.

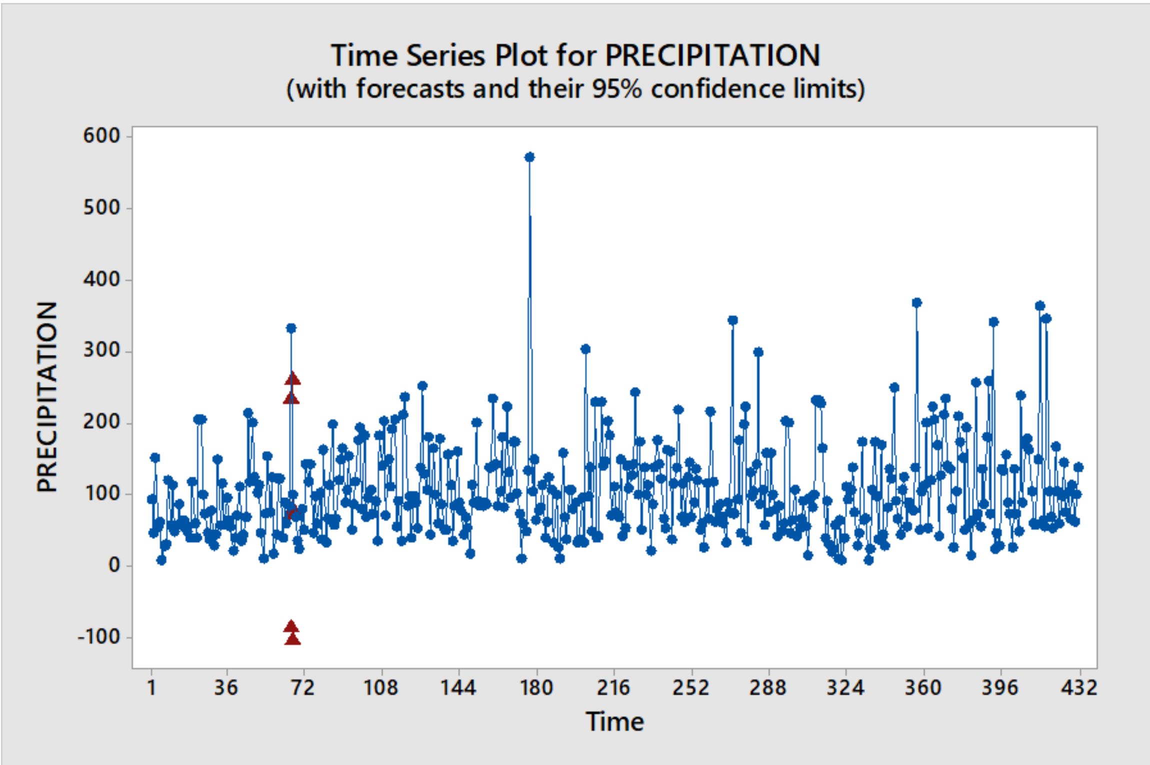

Figure 5. Precipitation vs Time (months).

In Figure 6, ACF (auto correction function) and PACF (partial auto correction function) residuals has been plotted for precipitation.

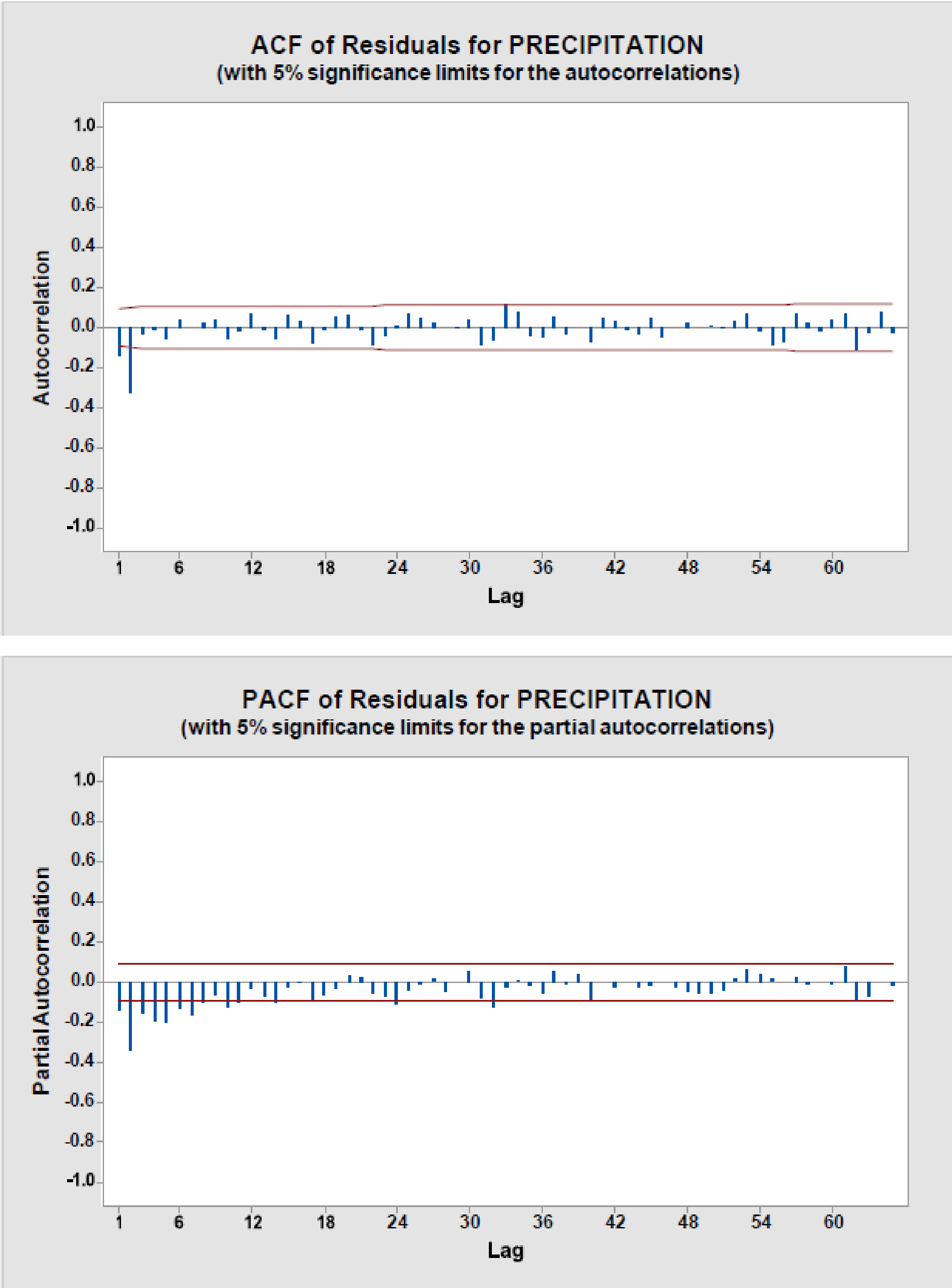

Figure 6. ACF and PACF residuals for Precipitation.

In Figure 7: Residuals for precipitation has been shown where're normal probability plot, residual vs fitted value, histogram and versus order have been shown for precipitation.

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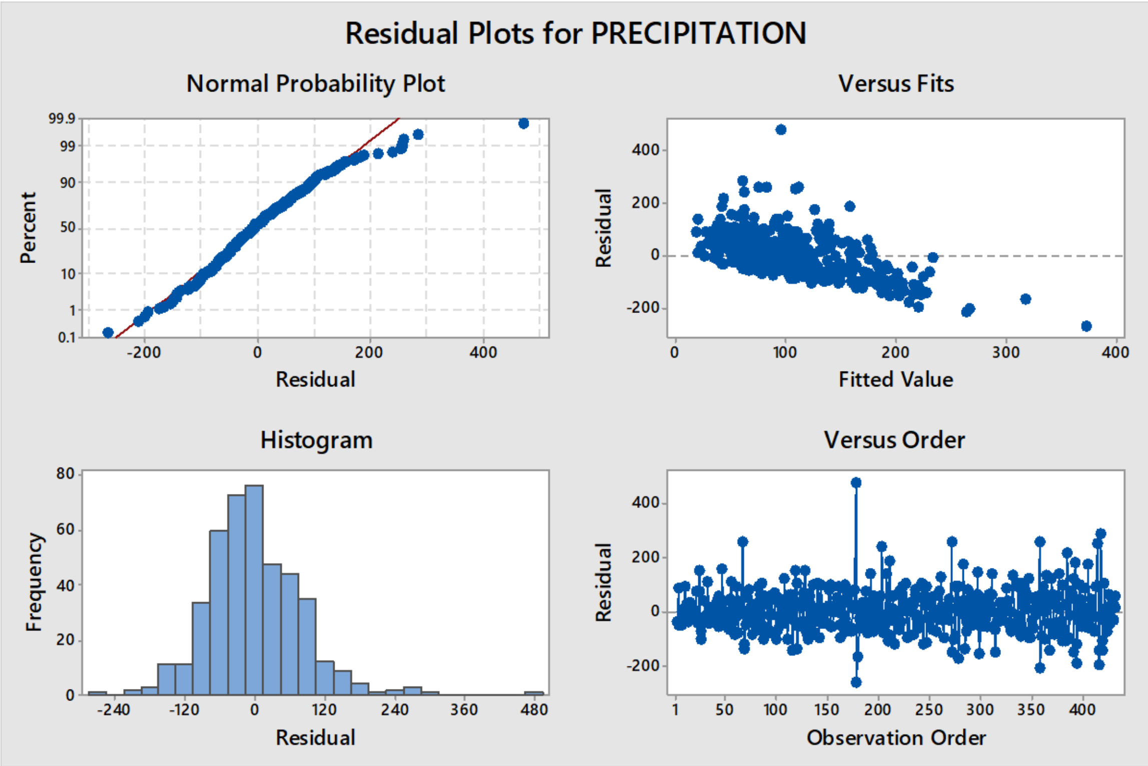


Figure 7. Residual Plots for Precipitation.

In Figure 8, time series plot for average temperature has been plotted to get an idea of temperature change over a certain time period.

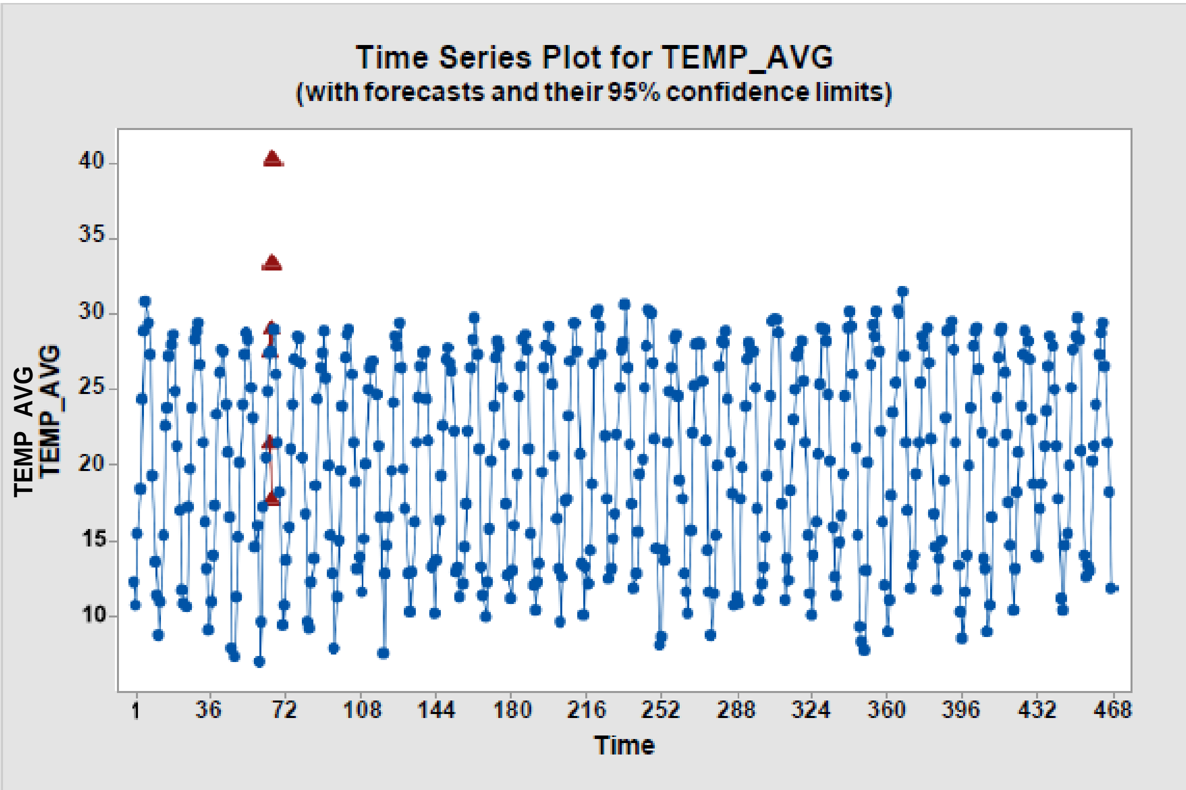
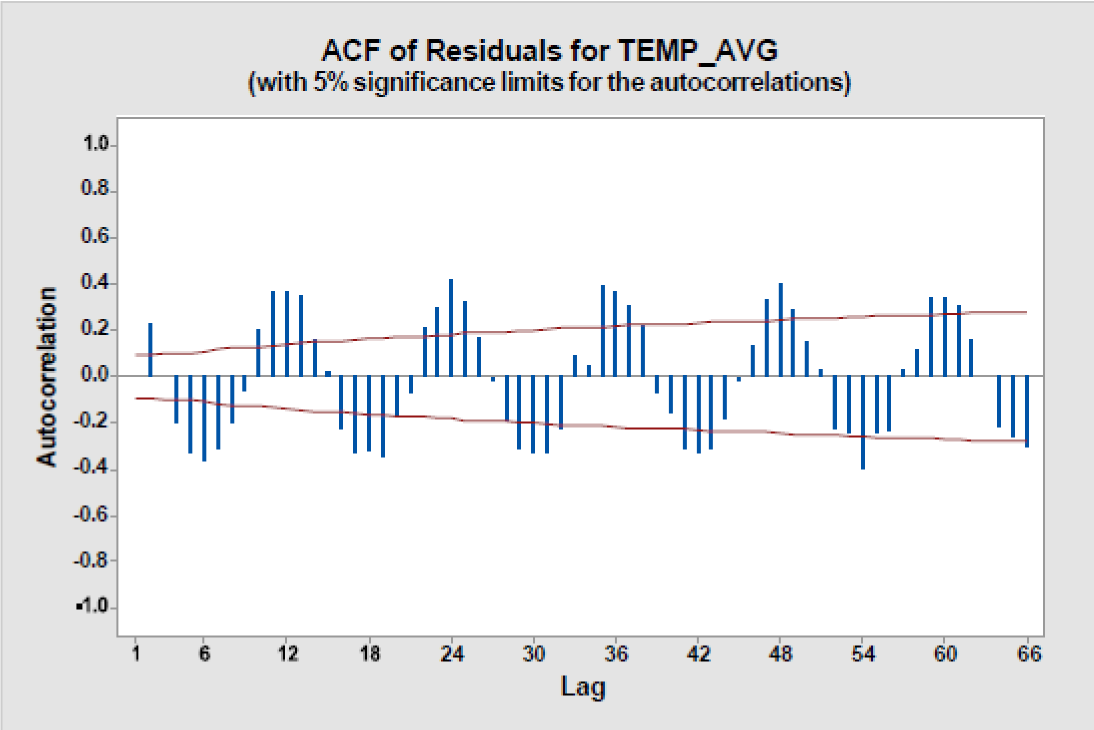


Figure 8. Temperature avg vs Time (months) plot.

In Figure 9: ACF and PACR of residuals has been plot for average temperature.



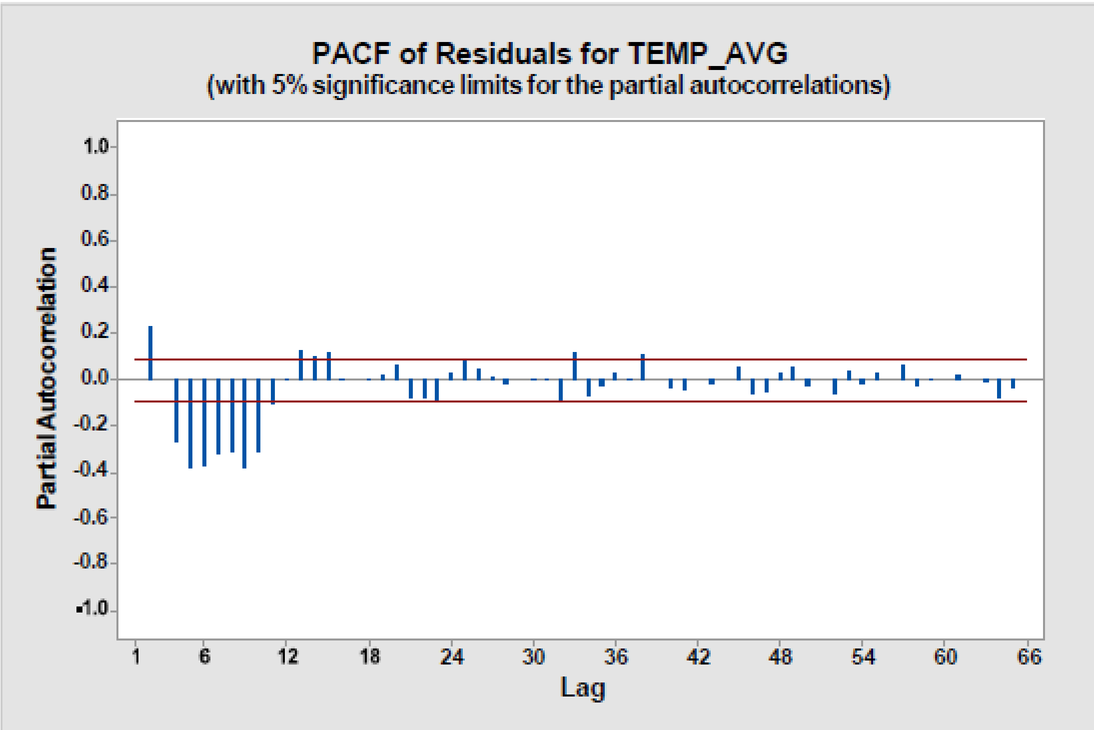


Figure 9. ACF and PACF residuals for Temp avg.

In Figure 10: residual plots have been generated for average temperature where percent vs residual plot, versus fits, versus order and histogram have been plot.

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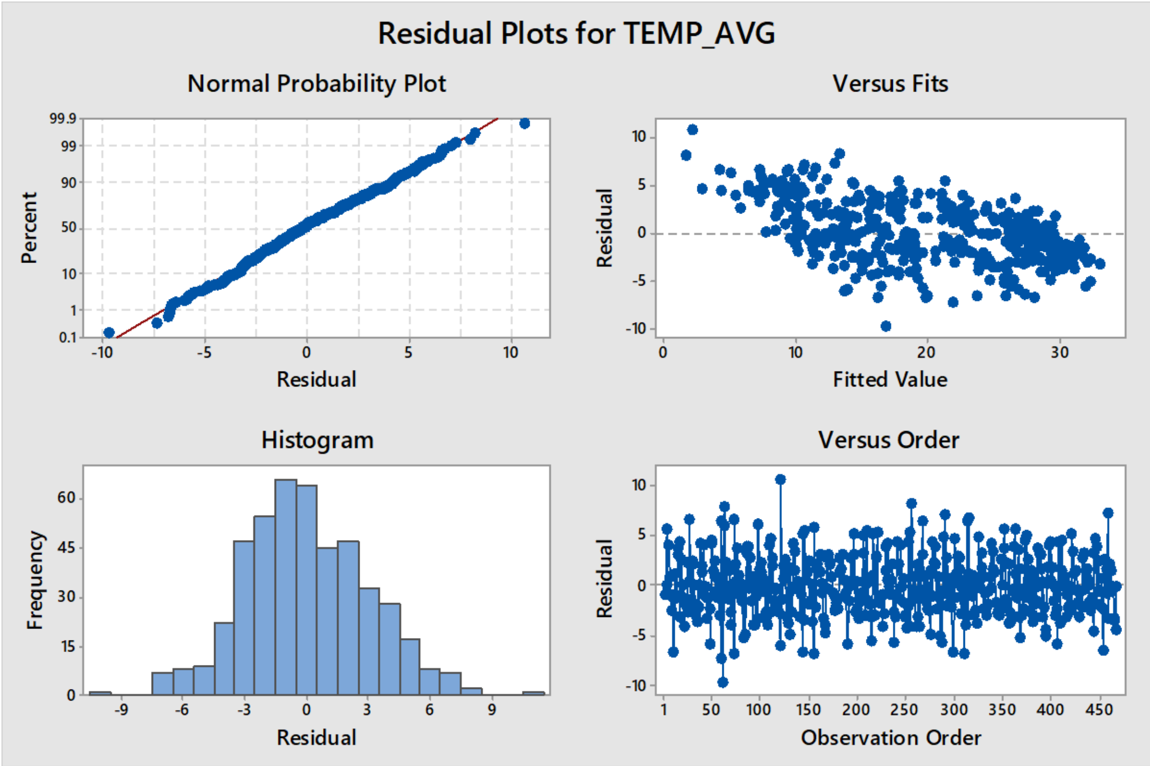

Figure 10. Residual Plots for Temp avg **Result from ARIMA model for average temperature:** Estimates at each iteration.

Iteration SSE Parameters
0 5948.330.100 0.089
1 5088.330.250 0.063
2 4527.710.400 0.036
3 4266.460.550 0.009
4 4245.690.603-0.007
5 4245.630.606-0.010
6 4245.630.606-0.010
7 4245.630.606-0.010
Relative change in each estimate less than 0.0010 Final Estimates of Parameters
Type Coef SE Coef T P AR 1 0.6058 0.0371 16.34 0.000
Constant -0.0104 0.1398 -0.07 0.941
Differencing: 1 regular difference
Number of observations: Original series 468, after differencing 467 Residuals: SS = 4245.13 (backforecasts excluded)
MS = 9.13 DF = 465
Modified Box-Pierce (Ljung-Box) Chi-Square statistic Lag 12 24 36 48
Chi-Square 370.0 788.8 1201.9 1609.0
DF 10 22 34 46
Forecasts from period 65
95% Limits
Period Forecast Lower Upper Actual 66 27.3945 21.4712 33.3178 27.3000
67 28.9558 17.7507 40.1609 27.4000
Result from ARIMA model for Precipitation:
Iteration SSE Parameters
0 5948.330.100 0.089
1 5088.33 0.250 0.063

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2 4527.71 0.400 0.036
3 4266.46 0.550 0.009
4 4245.69 0.603-0.007
5 4245.63 0.606-0.010
6 4245.63 0.606-0.010
7 4245.63 0.606-0.010
Relative change in each estimate less than 0.0010 Final Estimates of Parameters
Type Coef SE Coef T P AR 1 0.6058 0.0371 16.34 0.000
Constant -0.0104 0.1398 -0.07 0.941
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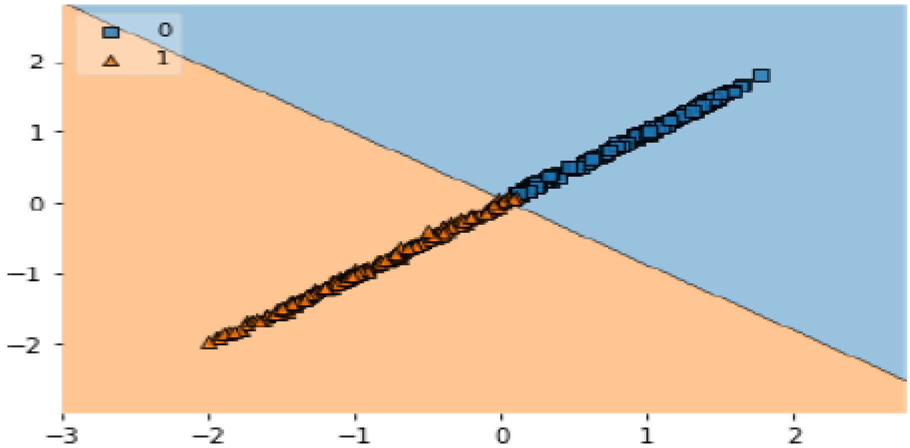
DF 10 22 34 46
Forecasts from period 468
95% Limits
Period Forecast Lower Upper Actual 469 75.386 64.048 87.821 76.310
470 80.542 70.953 96.037 77.500

Figure 11: A logistic regression model has been generated. Among 468 data set, 374 data have been used to train the model and 94 set of data was used to test the model. The test value chart has been shown in Figure 11.



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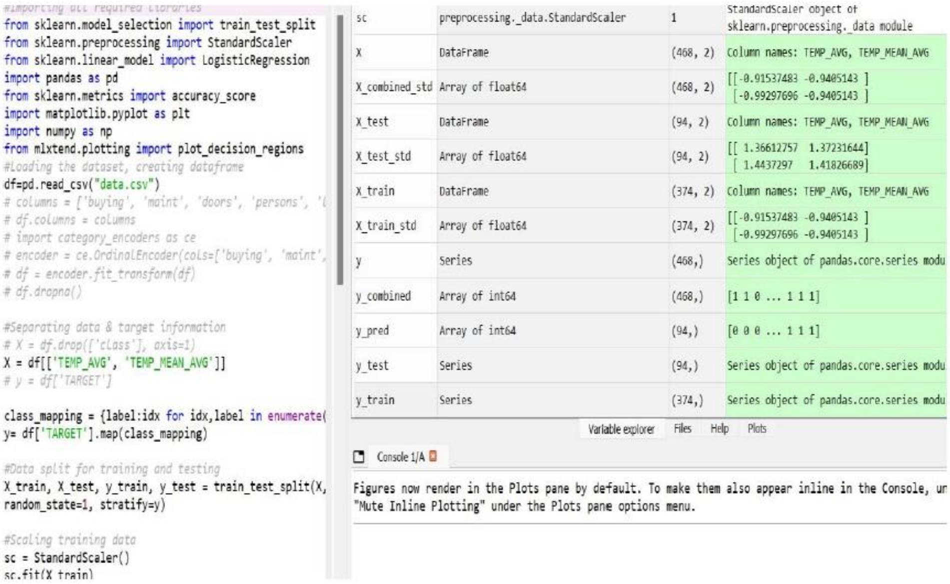

Figure 11. A visual representation of logistic regression model.

Conclusion

From ARIMA model, 2 periods of data (per period 12 months) both for temperature and precipitation has been generated. After analyzing this data, from our developed Logistic Regression Model, it has found that both will have a negative effect on pavement performance. From the training, it has found that the regression model gives an idea if a value of temperature and precipitation has been given to the model. Since the model has been developed over a small scale of data, the output result accuracy will not be the desired one.

Recommendation from this study:

- In the prediction model, there is substantial variation in terms of the magnitude.
- No specific pavement damage has been mentioned
- Only Yes or No condition is not enough for the data projection.
- A clear matrix should be generated with pavement distress which will give us a high accuracy projection.
- Long series of data set is recommended to train the mathematical model to get a better projection.

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