Forecasting Nuclear Outage Using Time Series Models

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I. Introduction

Based on the "Nuclear Power Plant Outage Optimisation Strategy" by International Atomic Energy Agency (IAEA), a nuclear outage refers to a scheduled shutdown period of a nuclear power plant during which essential activities, such as maintenance, inspections, testing, refueling, and equipment upgrades, are conducted. These outages occur between the disconnection and reconnection of the plant to the electrical grid. Although plant components are designed for long-term use, outages are crucial for ensuring continued safe and reliable operation. They are resource-intensive periods where significant planning and coordination are required to manage safety, regulatory compliance, cost, and duration. Efficient outage management directly influences plant availability, economic performance, and personnel safety.

But excessive and out of control outages can lead to some serious impact to society. Nuclear outages can be significantly influenced by environmental factors, especially those linked to climate change. High air and water temperatures, as well as reduced river flows during heatwaves and droughts, can force nuclear power plants to reduce their output or shut down entirely to comply with environmental regulations that protect aquatic ecosystems. These outages tend to peak during the summer months, when cooling water temperatures approach regulatory limits. In extreme years like 2003, this has resulted in measurable annual energy losses (up to 3.5% for some plants).

Just like the incident in Fukushima nuclear outage 2011, where about 100,000 residents were affected and forced to evacuate, including 84,000 people from within a 20-kilometer radius and an additional 15,000 from highly contaminated areas up to 40 kilometers away. Radiation levels at the site boundary peaked at 1,085 millirem/hour, vastly exceeding the public exposure limit of 100 millirem per year. Cesium deposition levels in some areas northwest of the plant reached values comparable to the most contaminated zones around Chernobyl, though the most severely affected land was estimated at only 8.5% the size of Chernobyl's comparable contamination zone. TEPCO estimated that nearly 100% of the fuel in Reactor Unit 1 had melted, with 57% in Unit 2 and 63% in Unit 3, resulting in significant radioactive emissions.

To prevent the incident of Fukushima or excessive nuclear outage, research in Indiana has been conducted using machine learning. The research presented in Forecasting of Nuclear Reactor Outages to improve the economic sustainability of nuclear energy by predicting reactor outages. The authors applied a Long Short-Term Memory (LSTM) neural network model, a type of recurrent neural network (RNN) capable of capturing long-term dependencies in time-series data. They used archival outage data from U.S. nuclear reactors (2008–2020) to train and test their model, focusing on reactors with power output above 880 MWe. Their results showed that the LSTM model successfully captured trends in outage behavior, with mean squared errors (MSEs) low enough to suggest that predictions were closely aligned with actual values, even in challenging cases like weeks with widespread shutdowns. These promising findings indicate the model's potential to forecast outages for SMRs in the absence of direct historical data.

This paper will conduct a study on predicting nuclear outages using the most recent nuclear outage data, building upon previous research in this field. Unlike prior studies that employed machine learning models, this research will utilize time series forecasting methods such as Naïve, Holt-Winters, ARIMA, SARIMA, and Neural Network-based models. These approaches are particularly well-suited for capturing patterns in the data, including trends and seasonality, which are often present in nuclear outage behavior. An advantage of using time series models is their ability to provide interpretable insights into the temporal structure of the data, making them effective for short- to medium-term forecasting where understanding past behavior is crucial for accurate future predictions.

A. Research Problem

Despite the critical role of nuclear energy in supplying stable electricity, nuclear power plants are vulnerable to planned and unplanned outages that can disrupt energy availability and pose various operational risks. However, there is still a limited understanding of the underlying patterns and causes of these outages. Moreover, proactive measures to prevent or mitigate their impacts are not yet fully optimized. Accurate forecasting of significant outages remains a challenge, particularly in capturing trends and seasonal variations that may influence outage behavior. Therefore, this study addresses the problem of how to effectively understand, anticipate, and minimize the effects of nuclear outages through predictive modeling and outage pattern analysis.

B. Research Objective

This study addresses the problem of limited understanding of nuclear outage patterns, the lack of effective preventive measures against their potential impacts, and the challenges in accurately predicting major outages. By analyzing outage dynamics and developing predictive models, the research aims to support more reliable and proactive management of nuclear power operations.

II. Method

A. Data Collection

The dataset that we are going to use is from API EIA (U.S. Energy Information Administration), a data that records nuclear outages in the US from 2007. Table 1 presents all the variables used in this study. The data is split into two parts, training data from 2007 to December 2024 (18 years) and testing data from January 1 to May 30, 2025 (5 months). This split provides a robust training period with sufficient historical data to capture long-term patterns, seasonal variations

Table 1. Research Variables

Variable	Description
Period	specific time during the outage is recorded or observed
Capacity	the total power generated
Outage	the power that is unavailable or non-functional

B. Naive Model

Naive forecasting is considered as a benchmark to compare other forecasting models, it is also one of the simplest forecasting model. The naive forecasting method uses the actual value from the same period in the previous seasonal cycle as the forecast. For example, the forecast for February is the observed value for February from the previous year. The forecast for March is the observed value for March from the previous year and so on. Formulas for the Naive method as follows:

$$Seasonal\ Naive\ Method\ = X_{t-s}$$

Where Xt = actual data in period t and s = seasonal period length. So, the forecast value for the following data is the same as the actual data from the corresponding period in the previous seasonal cycle.

C. Holt's Winter

The exponential smoothing model is one of the simplest time series forecasting methods. It works by assigning exponentially decreasing weights to past observations, which means recent data points are more influential in predicting future values. The basic form of this method assumes no trend or seasonality, making it suitable for time series that are relatively stable. The forecast $\hat{Y}_{t+h}$ at times $t + h$ is based on a level estimate $\widehat{a}_t$ which is recursively updated as:

$$\hat{a}_t = \alpha Y_t + (1 - \alpha)\hat{a}_{t-1}$$

Where $0 < \alpha < 1$ is the smoothing parameter. This method is simple and responsive to changes in the data but cannot handle trends or seasonal patterns, which limits its usefulness for more complex series.

Holt's method extends exponential smoothing by adding a trend component to handle data that exhibits a consistent upward or downward movement. It forecasts future values based on both the level and the trend at time t. The forecast is given by:

$$\hat{Y}_{t+h} = \hat{a}_t + h\cdot\widehat{b}_t$$

Here, $\hat{a}_t$ is the level and $\widehat{b}_t$ is the trend estimate, updated with this formula:

$$\hat{a}_t = \alpha Y_t + (1 - \alpha)(\hat{a}_{t-1} + \widehat{b}_{t-1})$$

$$\widehat{b}_t = \beta(\hat{a}_t - \hat{a}_{t-1}) + (1 - \beta)bt - 1$$

where α and β are smoothing parameters for the level and trend, respectively. Compared to simple exponential smoothing, Holt's model adapts to linear trends by continuously adjusting both the level and slope based on recent changes. However, it still assumes no seasonality.

Winters' method, also known as the Holt-Winters method, further extends Holt's model by incorporating seasonal components, allowing it to model time series with both trend and seasonality. There are two versions: additive and multiplicative, depending on whether seasonal fluctuations are constant or proportional to the level.

a. Additive Version

$$\hat{y}_{\square+\square} = \hat{a}_{\square} + h \cdot \hat{b}_{\square} + \hat{s}_{\square}$$

$$\hat{a}_{\square} = \alpha(Y_{\square} - \hat{s}_{\square-\square}) + (1 - \alpha)(\hat{a}_{\square-1} + \hat{b}_{\square-1})$$

$$\hat{b}_{\square} = \beta(\hat{a}_{\square} - \hat{a}_{\square-1}) + (1 - \beta)\hat{b}_{\square-1}$$

$$\hat{s}_{\square} = \gamma(Y_{\square} - \hat{a}_{\square}) + (1 - \gamma)\hat{s}_{\square-\square}$$

b. Multiplicative Version

$$\hat{y}_{\square+\square} = (\hat{a}_{\square} + h \cdot \hat{b}_{\square}) \cdot \hat{s}_{\square}$$

$$\hat{a}_{\square} = \alpha(Y_{\square} / \hat{s}_{\square-\square}) + (1 - \alpha)(\hat{a}_{\square-1} + \hat{b}_{\square-1})$$

$$\hat{b}_{\square} = \beta(\hat{a}_{\square} - \hat{a}_{\square-1}) + (1 - \beta)\hat{b}_{\square-1}$$

$$\hat{s}_{\square} = \gamma(Y_{\square} / \hat{a}_{\square}) + (1 - \gamma)\hat{s}_{\square-\square}$$

Where $\hat{s}_{\square}$ is the seasonal component, p is the period (e.g., 12 for monthly data with yearly seasonality), and γ is the smoothing parameter for seasonality. This method captures both trends and repeating seasonal patterns in the data. The multiplicative version is especially suitable for series where seasonal Vers. grow over time.

D. Autoregressive Integrated Moving Average (ARIMA)

An ARIMA model is defined by three parameters: p, d, and q, where p is the order of Auto-Regressive (AR) term, d is the order of differencing required to make the time-series stationary, and q is the order of Moving Average (MA) term. AR (p) usually explains the present value Xt, unidirectionally it terms of its previous values $Xt-1$,$Xt-2$, $Xt-p$, and the current residuals εt. It can be expressed as this formula:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t$$

MA (q) refers to the current value of the time series Xt in terms of its current and previous residuals εt − 1, εt − 2,…, εt − q. It can be expressed as this formula:

$$X_t = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_p\varepsilon_{t-q}$$

The ARIMA model is the combination of AR model and MA model algorithms. I in the ARIMA (p,d,q) refers to Integrated. When time-series is stationary, the ARIMA (p,d,q) model is ARMA (p,q), as this formula:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t -$$

$$\theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_p\varepsilon_{t-q}$$

And then Transform it into

$$X_t - X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} =$$

$$\varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_p\varepsilon_{t-q}$$

The formula shown represents the ARIMA (AutoRegressive Integrated Moving Average) model, which combines three components: autoregression (AR), integration (I), and moving average (MA). The first equation is the ARMA(p, q) model, where the current value X_t is predicted based on its past values $X_t - X_{t-1} - \cdots - X_{t-p}$ weighted by coefficients $\phi_1, \phi_2, \cdots, \phi_p$ and past error terms $\varepsilon_{t-1}, \varepsilon_{t-2}, \cdots, \varepsilon_{t-p}$ weighted by coefficients $\theta_1, \theta_2, \cdots, \theta_p$ along with a new error ε_t The second equation applies differencing, shown as $X_t - X_{t-1}$, which is used to make a non-stationary series stationary by removing trends or seasonality, this is the "integration" part. The transformed equation represents an ARIMA (p,1,q) model, where the differenced series is modeled using ARMA, making it suitable for forecasting real-world time series data with trends.

E. Seasonal Autoregressive Integrated Moving Average (SARIMA)

SARIMA model is a classical statistical method used to forecast future values as a linear function of past observations. It is an extension of the ARIMA model proposed by Box and Jenkins, used to handle time series data with seasonal behavior, The SARIMA model is described mathematically as follows:

$$\phi_p(B)\Phi_p(B^s)\nabla^d\nabla_S^D y_t = \theta_p(B)\Theta_Q(B^s)\varepsilon_t$$

where ϕ is the regular AR polynomial of order p, Φ is the seasonal AR polynomial of order P, θ is the regular MA polynomial of order q, Θ is the seasonal MA polynomial of order Q, ∇^d is the differentiating operator, ∇_S^D is the seasonal differentiating operator yt is the wind speed at time t, εt is the residual error at time t, and B is the backshift operator as $B^k(y_t) = y_{t-1}$

F. Neural Network

Neural Network (NN) model is inspired by the human brain processes information. It has been largely used in different fields due to its high capability of generalization, such as image identification, recognizing diseases, energy price and demand forecasting, and market area.

$$V_k = \sum_{j=1}^{m} w_{kj} a_j + b_k$$

$$Z_k = \varphi(V_k)$$

where w_{kj} is the weight that goes from the input k to the hidden neuron j, b_k is the bias, a_j is the input of the neuron, φ is the activation function, and Z_k is the output of the neuron.

G. Accuracy and Evaluation

Different popular metrics were adopted to evaluate the accuracy of the proposed forecasting approach: mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE). These performance indexes are computed as follows:

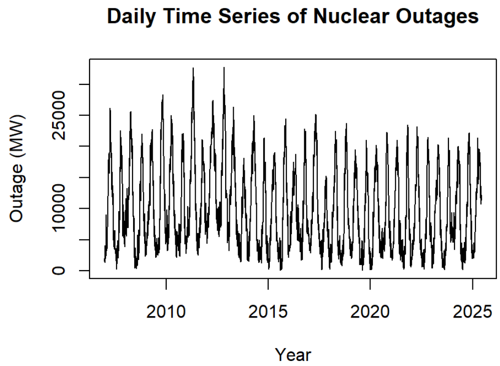
$$MAE = \frac{1}{N}\sum_{t=1}^{N} |\hat{Y}(t) - y(t)|$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\hat{Y}(t) - y(t)\right)^2}$$

$$MAPE = 100 \times \frac{1}{N}\sum_{t=1}^{N}\left|\frac{\hat{Y}(t)-y(t)}{y(t)}\right|$$

where N is the number of samples, $\hat{Y}(t)$ and $y(t)$ are wind speed forecasted and observed values at time t respectively.

III. Result



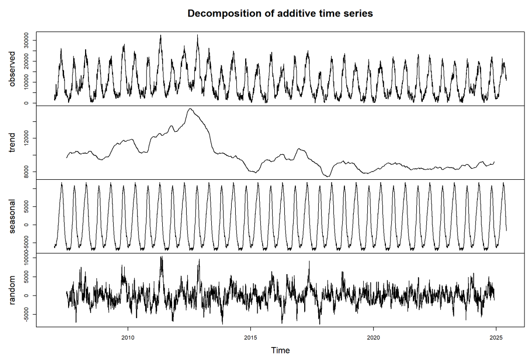


Figure 1, and Figure 2 represents the time series plot.

The time series plot in Figure 1 clearly shows a seasonal pattern, as the line follows a consistent shape with recurring highs and lows. This observation is further supported by the decomposition plot in Figure 2. While the trend component appears random and inconsistent, the residual and observed components also lack a clear structure. However, the seasonal component displays a distinct and repetitive pattern that is easy to interpret. Therefore, we can conclude that the data exhibits a seasonal pattern.

A. Naive Mode for Seasonal Data

a. Training Data

Model	MSE	RMSE	MAPE
Naive (Period Seasonal = 7)	6770054	2601.933	37.9347%
Naive (Period Seasonal = 12)	13589826	3686.438	50.2948%
Naive	14719638	3836.618	55.1271%

(Period Seasonal = 365)			
Naive (Period Seasonal = 30)	50377477	7097.709	95.2840%

RMSE values for each Naive model with different periods have a different value, the lesser the value the greater the model at predicting the Nuclear Outage. The best Naive model is the weekly period setting where it has 2601.933 RMSE value, meaning that the prediction is off by that number. The second best period is the monthly, where it has a 3686.438 RMSE value.

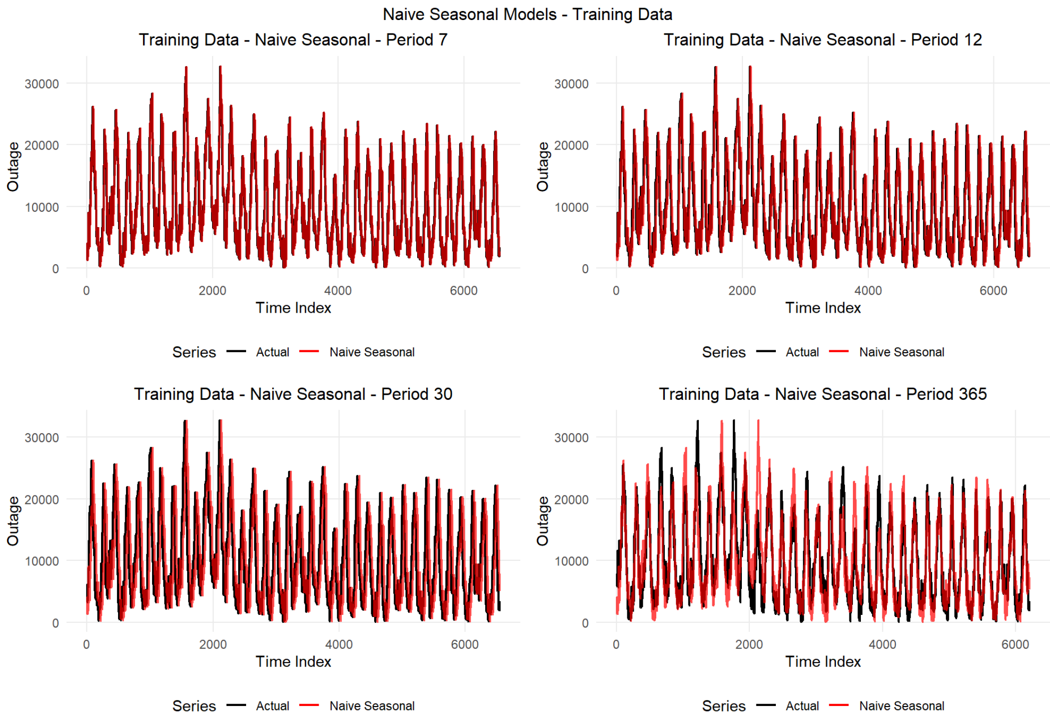


Figure 3. Prediction graph made with Naive Model

The black line represents the actual data from the dataset, while the red line represents the predictions made by the Naive model. The graph in Figure 3 shows that the most accurate red line comes from the Naive model with a weekly period, whereas the least accurate red line comes from the Naive model with a daily period. This indicates that the Naive model with a weekly period can more accurately predict the actual data and is therefore more reliable for forecasting future values.

b. Testing Data

	MSE	RMSE	MAPE
Naive(Period Seasonal = 7)	5275167	2296.773	16.3735%
Naive(Period Seasonal = 12)	9173995	3028.86	21.8808%
Naive(Period Seasonal = 30)	30782849	5548.229	39.3022%

RMSE values for each Naive model with different periods have a different value, the lesser the value the greater the model at predicting the Nuclear Outage. The best Naive model is the weekly period setting where it has 2296.773 RMSE value, meaning that the prediction is off by that number. The second best period is the monthly, where it has a 3028.86 RMSE value.

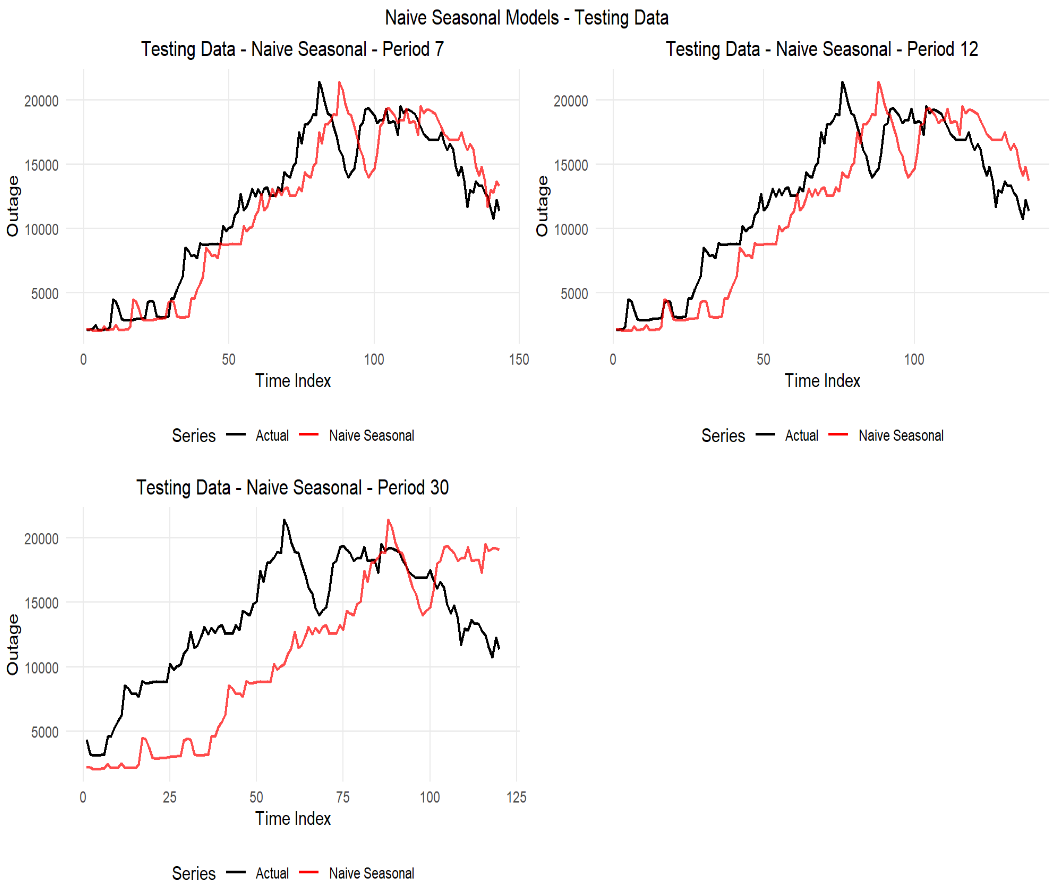


Figure 4. Prediction using Naive testing data

The black line represents the actual data from the dataset, while the red line represents the predictions made by the Naive model. The red lines that closely follow the shape of the actual data are from the Naive weekly and monthly periods. The weekly model accurately mirrors the pattern of the actual data but is slightly off in terms of timing. The monthly model also follows the general shape, but with a greater time lag and slight differences in the predicted values compared to the actual data. In contrast, the daily model shows a significant mismatch in both timing and shape, failing to resemble the actual data at all.

B. Holt Winters Model

a. Training Data

Model	MSE	RMSE	MAPE
Holt Winters (alpha = 0.9 , beta = 0, gamma = 0.3)	855825.8	925.1085	12.1980%
Holt Winters (alpha = 0.9 , beta = 0, gamma = 0.5)	862982.6	928.9685	12.21832%
Holt Winters (alpha = 0.9 , beta = 0.1, gamma = 0.3)	864209.4	929.6287	12.73421%
Holt Winters (alpha = 0.9 , beta = 0.1, gamma = 0.5)	875443.3	935.6513	12.67671%
Holt Winters (alpha = 0.9 , beta = 0, gamma = 0.7)	876901.9	936.4304	12.38805%

In Holt Winters, every parameter represents their own weight. Alpha controls how much weight is given to the most recent observation when estimating baseline value, Beta controls how much weight is given to the most recent changes in the trend, and

Gamma controls how much weight is given to the most recent seasonal changes.

The RMSE value is lowest when the beta parameter is set to 0, indicating that the data does not exhibit a significant trend component. Using a gamma value of 0.3 results in a lower RMSE 925.1085 compared to gamma 0.5 928.9685, suggesting that there is some seasonality in the data, but it is relatively moderate. When making predictions, it is best to use alpha = 0.9, beta = 0, and gamma = 0.3, as this combination yields the lowest RMSE value of 925.1085. This means the predicted values deviate from the actual data by approximately 925.1085 on average.

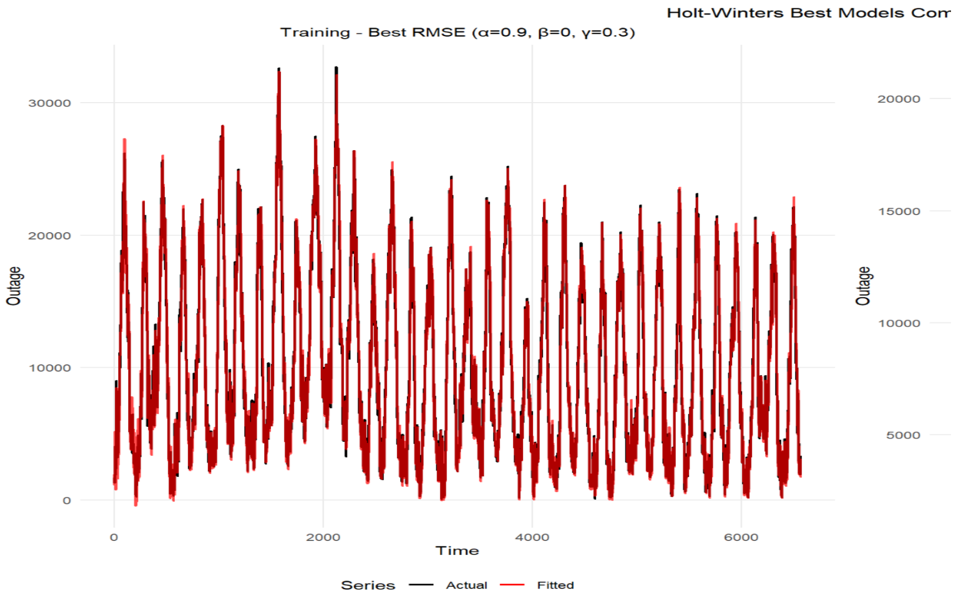


Figure 5. Predicting using Holt Winters training data using the best model

Because the Holt-Winters method produces a low RMSE value, the predicted values closely match the actual data. This indicates that the model is highly reliable for forecasting future values.

b. Testing Data

Model	MSE	RMSE	MAPE
Holt Winters(alpha = 0.9 , beta = 0, gamma = 0.5)	607545.8	779.4523	5.8145%
Holt Winters(alpha =	671253.9	819.3009	6.60%

0.9, beta = 0.3, gamma = 0.9)			
\Holt Winters(alpha = 0.5, beta = 0.5, gamma = 0.7)	1103176.09	1050.3219	8.85%
Holt Winters(alpha = 0.1, beta = 0.7, gamma = 0.7)	4323519.67	2079.3075	15.27%
Holt Winters(alpha = 0.7, beta = 0.1, gamma = 0.7)	715093.47	845.6320	6.76%

The RMSE value is lowest when the beta parameter is set to 0, indicating that the data does not exhibit a significant trend component. Using a gamma value of 0.5 results in a lower RMSE 779.4523 compared to other models with different parameters. When making predictions, it is best to use alpha = 0.9, beta = 0, and gamma = 0.5, as this combination yields the lowest RMSE value of 779.4523. This means the predicted values deviate from the actual data by approximately 779.4523 on average.

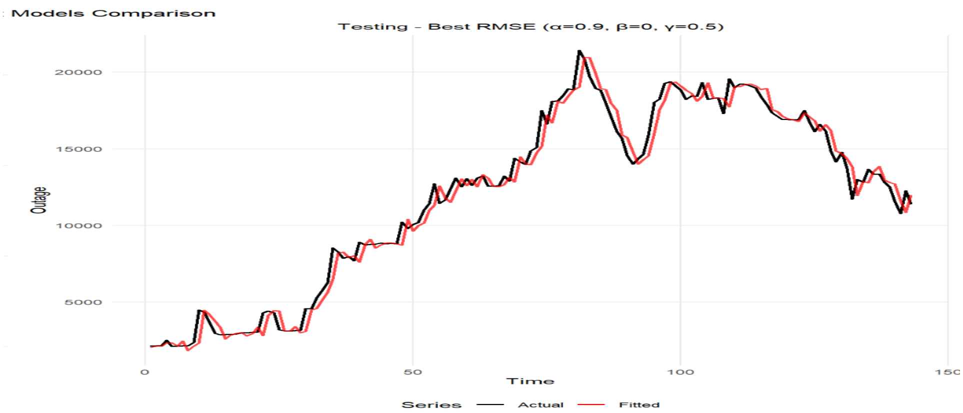


Figure 5. Predicting using Holt Winters training data using the best model

Because the Holt-Winters method produces a low RMSE value, the predicted values closely match the actual data. This indicates that the model is highly reliable for forecasting future values.

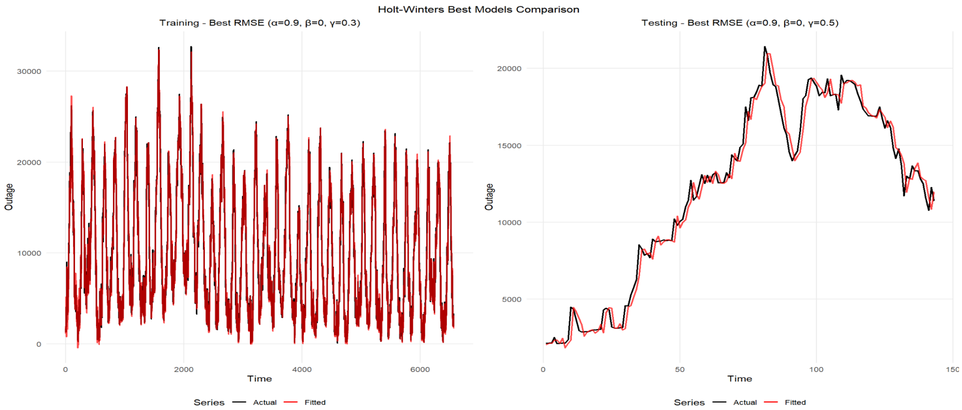


Figure 5. Predicting using Holt Winters training data using the best model

When comparing the prediction graphs for the training and testing data, the testing results appear to be better. This means that the model performs more accurately on the testing set, suggesting good generalization and indicating that the model is not overfitting the training data.

C. Autoregressive Integrated Moving Average (ARIMA)

a. Box-Cox Power Transform

Training

	Lambda	P-Value
Before Transform	0.3624	2.22e-16
After Transform	1.0067	0.86177

H_0: $\lambda = 1$ and H_1: $\lambda \neq 1$

Since the p-value from before we transform the data is 2.22e-16, which is less than 0.05, we reject the null hypothesis (H_0). This indicates that lambda is not equal to 1, meaning the data is not stationary in variance. Because the data is not stationary in variance and the rounded lambda value is 0.36, the data is transformed using the formula: data^0.36. A variance stationarity test is then performed on the transformed data. The resulting p-value in the After Transform is 0.86177, which is greater than 0.05, indicating that the transformed data is stationary in variance.

Testing

	Lambda	P-Value
Without Transform	0.9162	0.56366

H_0: $\lambda = 1$ and H_1: $\lambda \neq 1$

Since the p-value from before we transform the data is 0.56366, which is more than 0.05, we fail reject the null hypothesis (H_0). This indicates that lambda is equal to 1, meaning the data is stationary in variance. In this case, we don't have to transform it because the data is already stationary in variance.

b. Augmented Dicky-Fuller Test

H_0: Data is not stationary in mean
H_1: Data stationary in mean

Training

P-Value	0.01

Since the p-value is 0.01, which is less than 0.05, we reject the null hypothesis (H_0). Means that the data is already stationary in mean.

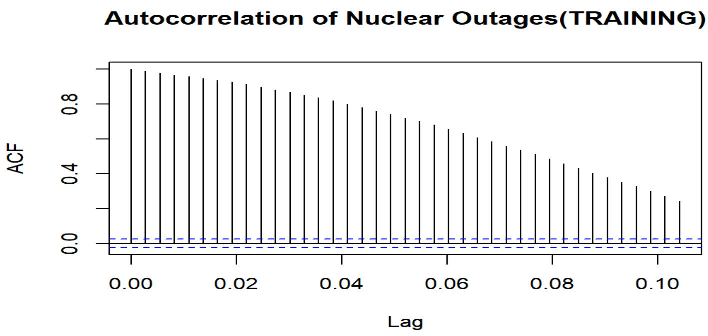
Testing

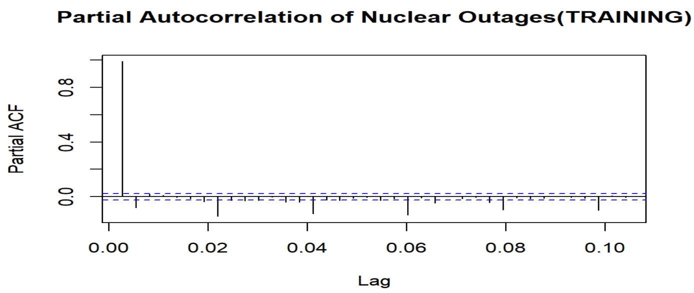
	P-Value
Before Differencing	0.9768
First Differencing	0.01

Since the p-value is 0.9768, which is greater than 0.05, we fail to reject the null hypothesis (H_0). This means that the data is not stationary in mean. Therefore, differencing must be applied to make the data stationary. After differencing, the p-value becomes 0.01, which is less than 0.05. Thus, we reject the null hypothesis, indicating that the differenced data is now stationary in mean.

c. ACF and PACF

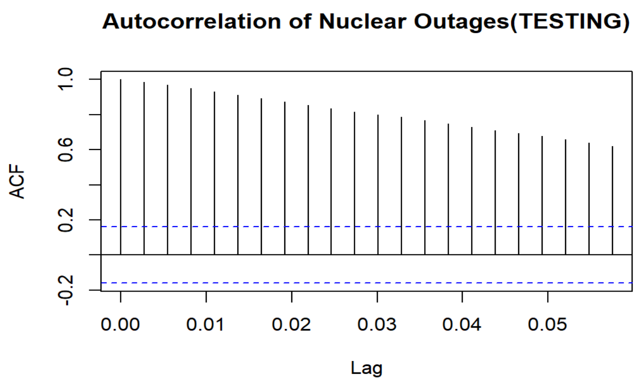
Training

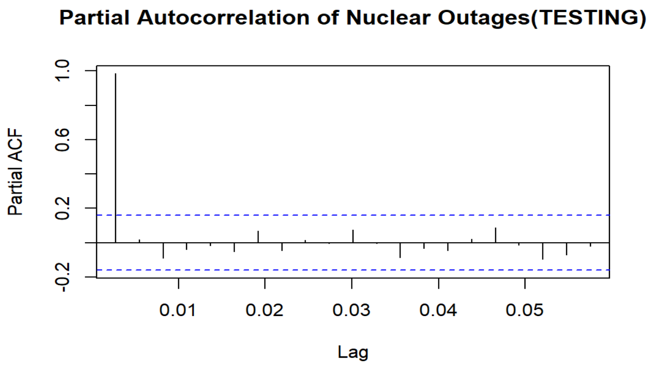




The ACF plot shows a gradual decline, resembling a dying-down or tailing-off pattern, while the PACF plot displays a sharp cut-off after the first lag. This pattern is a typical indication of an autoregressive process of order 1, or AR(1). The slow decay in the ACF suggests that the current values of the series are influenced by past values over several periods, while the significant spike at lag 1 in the PACF followed by non-significant lags indicates that the primary influence comes from the immediate previous value. Therefore, an AR(1) model would be appropriate for capturing the time series structure.

Testing





For both the ACF and PACF plots, the testing data exhibits the same pattern as the training data. ACF suggests that the current values of the series are influenced by past values over several periods, while the significant spike at lag 1 in the PACF followed by non-significant lags indicates that the primary influence comes from the immediate previous value. Therefore, an AR(1) model would be appropriate for capturing the time series structure.

d. Normality and White Noise test

Training Model	P-Value	
	Normality Test(Lillie.test)	White Noise (Box-Ljung test)
ARIMA(1,0,0) Normality Test: FAIL White Noise Test: FAIL	2.2e-16	2.2e-16
ARIMA(2,0,0) Normality Test: FAIL White Noise Test: FAIL	2.2e-16	2.2e-16
ARIMA(1,0,1) Normality Test: FAIL White Noise Test: FAIL	2.2e-16	2.2e-16

Testing Model	P-Value	
	Normality Test(Lillie.test)	White Noise (Box-Ljung test)
ARIMA(1,1,0)	2.782e-09	0.5288

Normality Test: FAIL White Noise Test: PASS		
ARIMA(2,1,0) Normality Test: FAIL White Noise Test: PASS	9.214e-08	0.7943
ARIMA(0,1,1) Normality Test: FAIL White Noise Test: PASS	1.817e-09	0.5178

Since the Lilliefors test and the white noise (Ljung-Box) test reject the null hypothesis in the ARIMA model evaluation, this indicates that some residuals are not normally distributed and some exhibit significant autocorrelation. As a result, the ARIMA model is not suitable for this dataset and should not be used for forecasting.

D. Seasonal Autoregressive Integrated Moving Average (SARIMA)

a. Normality and White Noise test

Training Model	P-Value	
	Normality Test(Lillie.test)	White Noise (Box-Ljung test)
SARIMA(1,0,0)(1,0,0) Normality Test: FAIL White Noise Test: FAIL	2.2e-16	2.2e-16
SARIMA(1,0,1)(1,0,1) Normality Test: FAIL White Noise Test: FAIL	2.2e-16	4.93e-12
SARIMA(2,0,1)(1,0,1) Normality Test: FAIL White Noise Test: FAIL	2.2e-16	2.661e-10

Testing Model	P-Value	
	Normality	White Noise

	Test(Lillie.test)	(Box-Ljung test)
SARIMA(1,1,0)(1,0,0)[7] Normality Test: FAIL White Noise Test: PASS	3.037e-09	0.5612
SARIMA(1,1,1)(1,0,1)[7] Normality Test: FAIL White Noise Test: PASS	5.164e-08	0.7186
SARIMA(2,1,1)(1,0,1)[7] Normality Test: FAIL White Noise Test: PASS	1.944e-08	0.8363

Since the Lilliefors test and the white noise (Ljung-Box) test reject the null hypothesis in the ARIMA model evaluation, this indicates that some residuals are not normally distributed and some exhibit significant autocorrelation. As a result, the ARIMA model is not suitable for this dataset and should not be used for forecasting.

E. Neural Network Autoregression (NNAR)

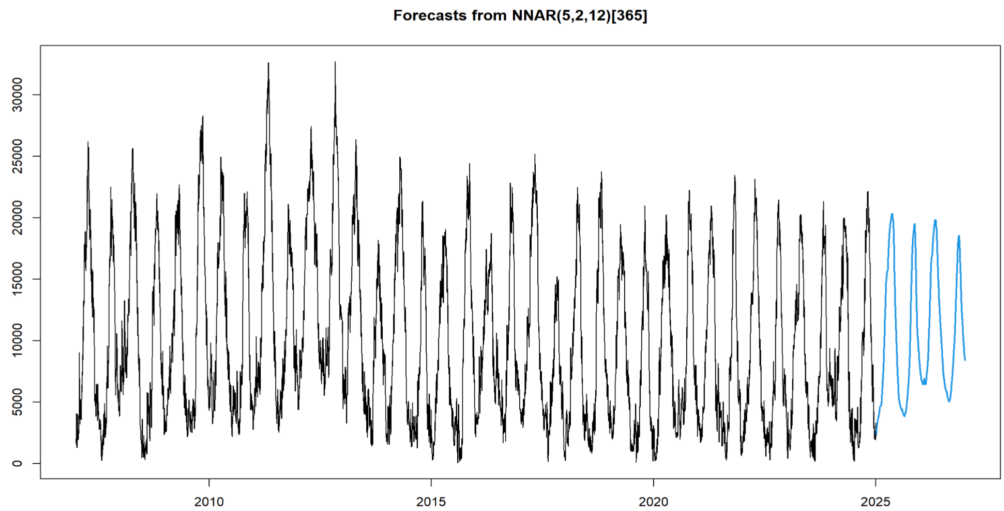
Training

Model	MSE	RMSE	MAPE
NN(5, 2, 12)	773355.44047	879.4063	12.2832%
NN(3, 2, 15)	784278.14978	885.5948	12.3966%
NN(5, 1, 12)	793694.97009	890.8956	12.4326%
NN(4, 2, 8)	799409.26658	894.0969	12.4475%
NN(2, 2, 10)	805862.41736	897.6984	12.4207%
NN(3, 1, 15)	807372.15481	898.5389	12.4234%
NN(4, 1, 8)	813406.65436	901.8906	12.3481%
NN(3, 2, 5)	813841.96499	902.1319	12.4944%

NN(2, 2, 5)	819601.40537	905.3184	12.4608%
NN(1, 2, 10)	823927.09623	907.7043	12.5851%

The best-performing neural network model in the table is NN(5, 2, 12), where the notation represents a network with 5 input neurons, 2 hidden layers, and 12 neurons in the output layer. This model achieves the lowest Mean Squared Error (MSE) of 773,355.44, the lowest Root Mean Squared Error (RMSE) of 879.41, and the lowest Mean Absolute Percentage Error (MAPE) of 12.28% among all tested configurations. A lower MSE and RMSE indicate that the predicted values are very close to the actual values on average, and a lower MAPE means that the percentage error relative to actual values is smaller, which is crucial in applications where relative accuracy matters. Therefore, NN(5, 2, 12) is considered the most accurate and reliable model in this experiment due to its minimal prediction error across all three evaluation metrics.

Prediction Using NN(5, 2, 12)



Date	Day	Forecast Value	Actual Value
2025-01-06	6	2389.409	2076.261
2025-01-07	7	2580.077	2409.751
2025-01-08	8	2757.661	2126.641

2025-01-09	9	2861.441	2142.351
2025-01-10	10	2934.433	2134.911
…	…	…	…
2025-02-01	31	4171.138	3183.267
2025-02-02	32	4267.854	3111.427
2025-02-03	33	4343.465	3097.995
2025-02-04	34	4434.135	3141.245
2025-02-05	35	4503.085	3162.563

Testing

Model	MSE	RMSE	MAPE
NN(5, 1, 12)	133763.62631	365.7371	3.17%
NN(5, 2, 12)	139487.83327	373.4807	3.12%
NN(3, 2, 15)	201871.74804	449.3014	3.80%
NN(3, 1, 15)	206954.57199	454.9226	3.77%
NN(4, 1, 8)	254463.44646	504.4437	4.18%
NN(4, 2, 8)	255125.40388	505.0994	4.17%
NN(2, 2, 10)	360827.99554	600.6896	4.89%
NN(3, 2, 5)	414508.055	643.8230	5.15%
NN(2, 1, 5)	453928.68680	673.7423	5.35%
NN(1, 2, 10)	493519.73809	702.5096	5.34%

The best-performing neural network model in the table is NN(5, 1, 12), which consists of 5 input neurons, 1 hidden layer, and 12 output neurons. This model achieved the lowest Mean Squared Error (MSE) of

133,763.63, the lowest Root Mean Squared Error (RMSE) of 365.74, and a very low Mean Absolute Percentage Error (MAPE) of 3.17%, making it the most accurate among all tested configurations. Although one model has a slightly lower MAPE (3.12%), NN(5, 1, 12) significantly outperforms the others in terms of MSE and RMSE, which are critical indicators of prediction accuracy. These results show that NN(5, 1, 12) produces predictions that are closest to the actual values, both in scale and in relative percentage, making it the most reliable model overall.

F. Model Comparison

This comparison evaluates all models, Naive, Holt Winters, and Neural Network, to identify the one with the best performance.

Model	MSE	RMSE	MAPE
Naive (Period Seasonal = 7) Weekly Period	5275167	2296.773	16.3735%
Holt Winters (alpha = 0.9 , beta = 0, gamma = 0.5)	607545.8	779.4523	5.8145%
NN(5, 1, 12)	133763.62631	365.7371	3.17%

The model comparison table presents the performance of three forecasting methods—Naive, Holt-Winters, and a Neural Network (NN), evaluated using three metrics, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The Naive model with a weekly period (seasonal period = 7), performs the poorest among the three, showing the highest MSE (5,275,167), RMSE (2,296.773), and MAPE (16.3735%), indicating large prediction errors and low forecasting accuracy. The Holt-Winters model, incorporating level smoothing (alpha = 0.9), but no trend (beta = 0), and moderate seasonality smoothing (gamma = 0.5), significantly improves upon the Naive approach with much lower MSE (607,545.8), RMSE (779.4523), and MAPE (5.8145%), demonstrating better handling of the data's seasonal patterns. However, the best performing model is the Neural Network (with input lags of (5, 1, and 12), which achieves the lowest MSE (133,763.62631), RMSE (365.7371), and MAPE (3.17%), indicating superior prediction accuracy. This suggests that the NN model effectively captures both short- and long-term dependencies in the data, outperforming both the simplistic Naive model and the traditional statistical Holt-Winters method.

IV. Conclusion

This study addresses the critical issue of limited understanding regarding the patterns and behaviors of nuclear outages, the absence of effective preventive strategies to mitigate their potential impacts, and the ongoing challenges in accurately predicting major outage events. Despite the availability of extensive historical data, there remains a gap in leveraging this information to identify trends and seasonal behaviors that could inform timely interventions. As such, the research aims to comprehensively analyze the dynamics of nuclear outages over time and to develop predictive models capable of capturing both short-term fluctuations and long-term seasonal patterns. By applying various time series forecasting techniques—including Naive, Holt-Winters, ARIMA, SARIMA, and Neural Network Autoregression (NNAR)—the study seeks to enhance understanding of outage movement, prevent future risks by anticipating potential disruptions, and improve the accuracy of forecasts for significant outages.

This study successfully evaluates these forecasting methods using data from the U.S. Energy Information Administration (EIA). The analysis results indicate that the data exhibits a significant seasonal component, although the trend and residuals are not consistently stable. Therefore, approaches that can effectively capture seasonal patterns are crucial in forecasting these outages. From the model evaluation results, the Naive method with a weekly period performed best among the Naive variants, but overall, it still had relatively high prediction errors. The Holt-Winters method showed significant improvement with lower RMSE and MAPE values, demonstrating its ability to capture moderate seasonal patterns. However, the Neural Network Autoregression (NNAR) model, particularly NN(5,1,12), achieved the best results with an RMSE of 365.74 and a MAPE of only 3.17%, proving its effectiveness in capturing both short-term and long-term dependencies in outage data.

Based on these results, this study concludes that neural network-based models outperform conventional statistical approaches such as Holt-Winters and ARIMA in the context of nuclear outage forecasting. The NNAR model not only provides more accurate predictions but also demonstrates good generalization on test data without overfitting. This research highlights the potential of applying machine learning in the proactive management of nuclear power plant operations, especially in risk mitigation and efficient maintenance scheduling.

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