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Research

A COMPREHENSIVE STUDY OF MODIFIED PROPHET MODEL FOR TIME SERIES COMPONENT IDENTIFICATION

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Abstract: Understanding time series components has been challenging in forecasting over a long time. Time series component identification plays a critical role in understanding underlying structures such as trend, seasonality, and irregular variations in temporal data. This study provides a comprehensive evaluation of the Modified Prophet Model (MPM) with a specific focus on its capability for automated component identification. The research examines the theoretical framework of Prophet as well as the Modified Prophet Model, its additive modeling structure, and its handling of trend changepoints and multiple seasonalities. Through a structured methodological approach, the study highlights the strengths and limitations of Prophet in accurately identifying time series components across different data contexts. The findings established an improved prophet in terms of performance through technical automation and enhanced models for robust forecasting and analysis.

Keywords: Modified, Comparative Analysis, Decomposition, Forecasting, Smoothing.

1. Introduction

Time series analysis remains a critical area of research within statistics, econometrics, engineering and data science due to its wide applicability in domains such as finance, energy demand forecasting, medical science, and environmental monitoring, as well as relevance in fields in which observations are recorded over time. It is any sequence of observations recorded at specified times and usually displayed as a time-series plot (P.J. Brockwell, 2010). Adam Hayes (2025) defines a time series as a sequence of data points that occur in successive order over some period of time. Thus, the set of times T at which

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observations are recorded according to P.J Brockwell (2010) may be a discrete set, as is the case when the observations are recorded at uniformly spaced or it may be a continuous interval, as when the data are recorded continuously.

Unlike cross-sectional data, time series observations exhibit temporal dependence, meaning that current values are often influenced by past behavior. This intrinsic structure necessitates specialized analytical techniques that account for time-based dependencies and evolving patterns.

A fundamental objective in time series analysis, most importantly, is the identification and separation of underlying structural components which typically comprises of trend, seasonality and random error.

The process of decomposing a time series into these components is commonly referred to as time series decomposition which is essential for both interpretability and forecasting.

Traditional methods for time series analysis, such as Autoregressive Integrated Moving Average, rely on statistical assumptions including linearity and stationarity. While these models have proven effective in many applications, they often require extensive manual intervention for parameter selection and preprocessing, such as differencing and transformation (Box, Jenkins, & Reinsel, 2015). Additionally, classical decomposition methods based on moving averages assume stable seasonal patterns and may struggle with complex real-world data characterized by multiple seasonalities, missing values, and structural breaks (Chatfield, 2004).

In response to these challenges, there has been a growing emphasis on developing models that combine automation, flexibility, and interpretability. One notable advancement in this direction is the Prophet model, introduced by Sean J. Taylor and Benjamin Letham. Prophet is an additive regression model specifically designed for time series forecasting and decomposition, with a focus on handling real-world business data that often exhibit irregularities and non-linear patterns (Taylor & Letham, 2018).

The Prophet model developed by Meta (formerly Facebook) in 2017 represents time series as a sum of interpretable components, including a trend function, seasonal effects, and optional holiday effects. Similar to the components of time series, the trend component however, is modelled using piecewise linear or logistic growth curves, with automatic detection of changepoints that allows the model to adapt to structural shifts in the data. Seasonal effects are captured using Fourier series, enabling the representation of multiple periodic patterns such as daily, weekly, and yearly seasonality. This flexible yet structured framework makes Prophet particularly well-suited for automated component identification.

A distinguishing factor of the Prophet model is its emphasis on usability and interpretability. Thus, the model is designed to require minimal manual tuning, allowing users with limited expertise in time series analysis to obtain meaningful results. At the same time, the model provides explicit decomposition outputs that make it possible to analyze individual components separately which balances automation and transparency thereby addressing key limitations of many modern machine learning approaches, which often achieve high predictive accuracy at the expense of interpretability.

Despite its widespread adoption, the application of Prophet has been largely focused on forecasting performance rather than the accuracy and reliability of its component identification capabilities. While the model inherently produces decomposed components, there is limited research evaluating how well these components reflect the true underlying structure of the data.

This study seeks to provide a comprehensive examination of the Prophet model with a specific focus on its role in time series component identification. By analyzing both its theoretical foundations and practical behavior, the research aims to assess its effectiveness in automatically extracting meaningful components from time series data. The findings are expected to highlight key strengths and limitations of the model, thereby establishing a foundation for subsequent improvements and the development of enhanced methodologies for automated time series analysis.

2. Literature Review

Time series analysis has long emphasized the importance of decomposing temporal data into interpretable components such as trend, seasonality, and irregular variations. Various studies on time series modelling have so far established decomposition as a key preprocessing step for understanding the non-stationary behavior and the need to improve the accuracy of time series forecasting. Classical approaches assume that a time series either be an additive or multiplicative combination of components, typically estimated using smoothing techniques such as moving averages (Chatfield, 2004; Hyndman & Athanasopoulos, 2018).

Furthermore, decomposition techniques have gone beyond simple smoothing with methods such as Fourier transforms, wavelet transforms, principal component analysis, and empirical mode decomposition (EMD) being widely applied to extract latent structures from time series data (Rios & de Mello, 2012; Zeng et al., 2023).

Decomposition-based forecasting has therefore become a major research direction, where the original series is separated into components that are modeled independently and later recombined. Reviews of decomposition methods highlight their ability to improve interpretability and predictive performance across various applications, including power systems and demand forecasting.

On the other hand, Traditional statistical models, particularly Autoregressive Integrated Moving Average (ARIMA), have played a central role in time series forecasting. ARIMA models capture temporal dependencies using autoregressive and moving average components, combined with differencing to ensure stationarity. These models have been widely applied due to their strong theoretical grounding and interpretability (Box et al., 2015). ARIMA-based approaches have several limitations which; require manual identification of parameters (p, d, q), are sensitive to non-stationarity, and often struggle with multiple seasonal patterns and non-linear relationships. Extensions such as Seasonal Autoregressive Integrated Moving Average (SARIMA) and state-space models attempt to address these issues, but they still demand significant expertise and computational effort (Hyndman & Athanasopoulos, 2018; Harvey, 1990).

Furthermore, decomposition within these models is often implicit rather than explicit, making it difficult to directly interpret individual components.

2.1 Machine Learning and Hybrid Approaches

The increasing availability of large-scale temporal data has led to the adoption of machine learning methods for time series forecasting. Neural networks, including recurrent neural networks (RNNs), long short-term memory (LSTM) models, and transformer-based architectures, have demonstrated strong performance in capturing complex non-linear dependencies and long-range temporal patterns.

Hybrid models that combine decomposition techniques with machine learning algorithms for example have integrated seasonal-trend decomposition (STL) with LSTM networks to improve forecasting accuracy by isolating structured components before modeling residual patterns Serdar Arslan (2022). Similarly, hybrid approaches combining decomposition with ensemble learning or convolutional networks have shown improved performance in energy forecasting and related applications (Mo, J., Wang, R., Cao, M. et al. 2023)

2.2 The Prophet Model and Its Decomposition Framework

The Prophet model as earlier discussed represents a significant advancement in automated time series analysis by explicitly integrating decomposition into its modeling framework. Developed by Sean J. Taylor and Benjamin Letham, Prophet models a time series as an additive combination of trend, seasonality, and holiday effects (Taylor & Letham, 2018).

The trend component in Prophet is modeled using piecewise linear or logistic growth functions, with automatic detection of changepoints that allows the model to adapt to structural changes in the data. Seasonal components are represented using Fourier series, enabling the capture of multiple periodic patterns such as daily, weekly, and yearly cycles. This explicit decomposition framework aligns closely with classical time series theory while incorporating modern computational techniques.

Research has shown that Prophet performs particularly well in applications involving strong seasonal patterns and business-related time series data. Comparative studies indicate that Prophet achieves competitive accuracy relative to traditional models such as ARIMA and advanced models such as LSTM, particularly in scenarios with well-defined seasonal structures.

In addition, Prophet's ability to handle missing data, outliers, and irregular sampling makes it suitable for real-world applications. Its implementation in platforms such as R and Python further enhances its accessibility and widespread adoption.

2.3 Limitations of the Prophet Model

Despite its advantages and robustness, the Prophet model has several limitations that affect its effectiveness in time series component identification and forecasting accuracy.

One of which arises from Prophet's reliance on an additive decomposition structure, where the observed time series is expressed as the sum of trend, seasonal, and holiday components. While this formulation enhances interpretability, it assumes that these components act independently and combine linearly. In real-world scenarios, interactions between components may be non-linear or multiplicative in nature, leading to potential misrepresentation of underlying dynamics (Hyndman & Athanasopoulos, 2018; Chatfield, 2004).

Another limitation is that Prophet's default assumptions such as piecewise linear trends and normally distributed errors may not hold in all applications, potentially affecting the models performance (Taylor & Letham, 2018).

The representation of seasonality using Fourier series causes additional constraints. While Fourier terms are effective for modeling smooth and regular periodic patterns, they may not adequately capture irregular, time-varying, or asymmetric seasonal effects commonly observed in real-world data. For example, seasonal patterns in domains such as energy consumption or financial markets may evolve over time, violating the assumption of fixed periodicity (Hyndman & Athanasopoulos, 2018).

Furthermore, the Prophet model assumes that residual components are independently and identically distributed, typically following a normal distribution. In real-world scenarios, this assumption may not hold particularly for time series with heteroscedasticity and autocorrelated errors. However, the residual component may still contain structured information, indicating incomplete separation of underlying patterns (Box et al., 2015).

Taylor & Letham, (2018), Hyndman & Athanasopoulos (2018), have also shown that Prophet's performance is sensitive to the characteristics of the data. Their studies have shown that the model tends to perform well in time series with strong and stable seasonal patterns, such as business or web traffic data, but may perform less effectively in datasets characterized by high noise, weak seasonality, or complex non-linear dependencies.

3. Methodology

The Prophet model, proposed by Taylor and Letham (2018), has gained widespread adoption due to its flexibility, interpretability, and ability to model trend and seasonality using additive components. However, despite its strengths, several limitations motivate the need for modification:

1. **Implicit Component Identification:** The model internally estimates trend and seasonal components but does not explicitly automate the statistical identification and classification of time series components, particularly the distinction between seasonal, cyclical, and irregular effects.
2. **Sensitivity to Volatility:** Prophet assumes relatively smooth structural changes and may underperform when applied to highly volatile empirical data characterized by abrupt shocks, regime switches, or heteroskedastic disturbances.

3. **Limited Statistical Decomposition Transparency:** The default Prophet implementation abstracts mathematical estimation within predefined functions, limiting fine-grained statistical control required for academic inference and component-level diagnostics.
4. **Comparative Performance Gaps**: In volatile environments, traditional statistical models (e.g., ARIMA) or data-driven models (e.g., LSTM) may outperform Prophet due to explicit stochastic modeling or nonlinear learning capabilities.

These limitations however, necessitate the development of a Modified Prophet Method (MPM) that enhances automated component identification, improves volatility handling, and maintains interpretability.

3.1 Baseline Prophet Formulation

The classical Prophet model is expressed as:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

where:

$$g(t) = the\ trend\ component s(t) = seasonality h(t) = holiday\ effects \varepsilon_t = random\ error\ term$$

3.2 Modified Prophet Method (MPM) Formulation

Thus, the proposed MPM is defined as:

$$y(t) = g(t) + s(t) + c(t) + r(t)$$

where:

$$g(t) = the\ trend\ component s(t) = seasonality c(t) = cyclical\ component r(t) = irregular\ component$$

3.3 Trend Component Modeling

The trend component captures long-term systematic movement in the time series.

3.3.1 Linear Trend Specification

$$g(t) = \beta_0 + \beta_1 t$$

where:

$$\beta_0 = the\ intercept$$

$$\beta_1 = the\ rate\ of\ change\ over\ time$$

3.3.2 Piecewise Linear Trend with Structural Breaks

To capture regime shifts, MPM incorporates changepoints for automation of structural changes:

$$g(t) = \beta_0 + \beta_1 + \sum_{j=1}^{J} \delta_j (t - \tau_j)^+$$

Where:

$\tau_j = changepoint\ locations \delta_j = slope\ adjustments (x)^+ = max(0, x)$

3.3.3 Seasonal Component Specification

Seasonality reflects periodic and recurring patterns at fixed frequencies and are selected based on statistical significance, ensuring automated identification.

3.3.4 Fourier Series Representation

$$s(t) = \sum_{k=1}^{K} \left[a_k \sin sin \left(\frac{2\pi kt}{P}\right) + b_k cos(\frac{2\pi kt}{P}) \right]$$

Where:

$P\ denotes\ the\ seasonal\ period K = the\ number\ of\ harmonics$

3.3.5 Cyclical Component Modeling

The cyclical component captures medium-to-long-term oscillations that are not fixed in frequency or strictly periodic.

$$c(t) = \gamma_1 \sin sin \left(\frac{2\pi t}{C}\right) + \gamma_2 \cos cos \left(\frac{2\pi t}{C}\right)$$

Where

$C\ is\ the\ estimated\ cycle\ length \gamma_1\ and\ \gamma_2\ are\ cycle\ amplitudes$

Unlike seasonality, cyclical effects may vary in amplitude and duration, making their explicit modeling critical for volatile datasets.

3**.3.6 Irregular Component Estimation**

The irregular component represents unexplained stochastic variation:

$$r(t) = y(t) - [g(t) + s(t) + c(t)]$$

The error is assumed to follow:

$$r(t) \sim \mathrm{N}(0, \sigma_t^2)$$

allowing for time-varying volatility.

4 Data Analysis and Interpretation

```
print(t)
```

```
##   [1]   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17  18
##  [19]  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35  36
##  [37]  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53  54
##  [55]  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71  72
##  [73]  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89  90
##  [91]  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107 108
## [109] 109 110 111 112 113 114 115 116 117 118 119 120
```

```
summary(t)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##    1.00   30.75   60.50   60.50   90.25  120.00
```

From the results above, the **print(t)** output shows that the time index runs sequentially from 1 to 120, confirming 120 evenly spaced observations in the series.

The **summary(t)** output indicates a minimum of 1 and a maximum of 120, with a mean and median of 60.5, showing that the time variable is symmetrically and uniformly distributed across the sample period, making it suitable for time series decomposition.

```
# ---------- Prophet-style model Plot ----------
p1 <- ggplot(data, aes(t, trend_p)) +
  geom_line(color = "red") +
  labs(title = "Prophet: Trend")
```

```
p2 <- ggplot(data, aes(t, season_p)) +
  geom_line(color = "green") +
  labs(title = "Prophet: Seasonality")

p3 <- ggplot(data, aes(t, random_p)) +
  geom_line(color = "grey") +
  labs(title = "Prophet: Random")

p1 / p2 / p3
```

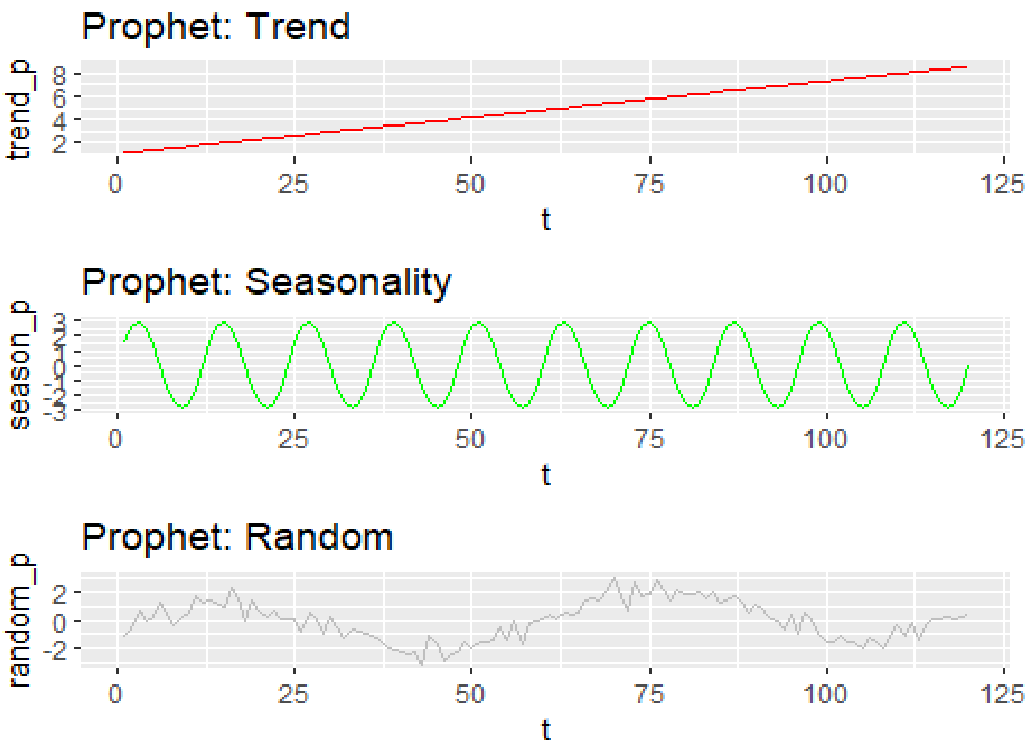

Figure 4.1.1: Prophet-style model Plot

Figure 4.1.1 above shows a clear separation of the series into trend, seasonal, and random components. The trend component displays a steady and approximately linear upward movement over time, indicating a consistent increase in the underlying level of the series throughout the 120 periods which suggests the model successfully captures the long-run growth pattern embedded in the data.

The seasonal component exhibits a regular and repeating sinusoidal pattern with constant amplitude, reflecting stable periodic fluctuations. The cycles occur at consistent intervals, indicating strong and systematic seasonality that the model identifies effectively while the random component fluctuates irregularly around zero without a clear pattern or structure. Although there are short-term deviations, no systematic trend or seasonality remains in this residual series, implying that most of the structured variation has been captured by the trend and seasonal components.

```
# ---------- Modified Prophet Method Plot ----------
p4 <- ggplot(data, aes(t, trend_m)) +
  geom_line(color = "red") +
  labs(title = "MPM: Trend")

p5 <- ggplot(data, aes(t, season_m)) +
  geom_line(color = "green") +
  labs(title = "MPM: Seasonality")

p6 <- ggplot(data, aes(t, cycle_m)) +
  geom_line(color = "purple") +
  labs(title = "MPM: Cyclical")

p7 <- ggplot(data, aes(t, irregular_m)) +
  geom_line(color = "grey") +
  labs(title = "MPM: Irregular")

p4 / p5 / p6 / p7
```

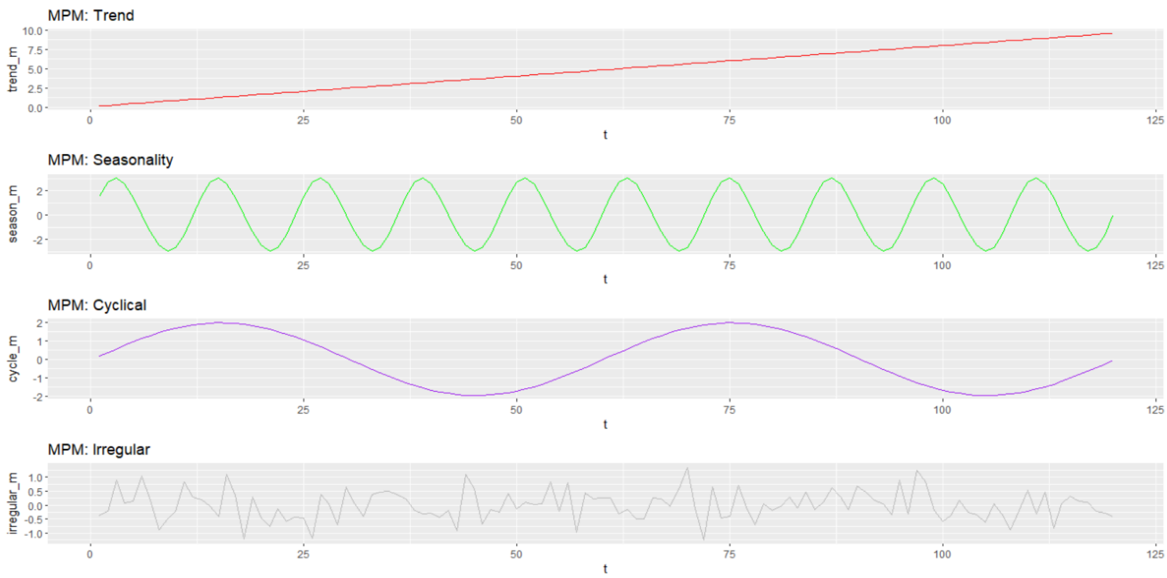

Figure 4.1.2: Modified Prophet Method Plot

Figure 4.1.2 above shows the trend component exhibits a steady and approximately linear upward movement over time, indicating persistent long-run growth in the series. This confirms that the model effectively captures the underlying structural increase embedded in the data. The seasonal component displays a regular and repeating sinusoidal pattern with stable amplitude, reflecting consistent short-term periodic fluctuations. The repetition across the time horizon suggests that the model successfully isolates systematic seasonality.

Similarly, the cyclical component reveals a slower-moving, long-wave oscillation compared to the seasonal pattern. Unlike seasonality, which repeats frequently, the cyclical movement spans longer intervals, capturing medium- to long-term fluctuations that are distinct from both the linear trend and short-term seasonal effects. The irregular component also fluctuates randomly without a clear systematic pattern. Its relatively small and unsystematic variations indicate that most of the structured information in the series has been successfully explained by the trend, seasonal, and cyclical components, leaving only random noise in the residual.

5. Conclusion

This study provides a comprehensive examination of the Modified Prophet Model (MPM) with particular emphasis on its capability for time series component identification. The findings from the literature and empirical analysis reaffirm that decomposition remains a fundamental aspect of time series modeling, enabling both interpretability and improved forecasting performance. While traditional approaches such as ARIMA and classical decomposition techniques offer strong theoretical foundations, they often require substantial manual intervention and may struggle with complex, non-linear, or multi-component structures.

The Modified Prophet model (MPM) addresses many of these limitations by offering an automated, flexible, and interpretable framework that explicitly decomposes time series into trend and seasonal components.

Thus, this study establishes that while the Prophet model represents a major advancement in automated time series analysis, its effectiveness in component identification can be further enhanced through methodological extensions such as MPM.

6. WEAKNESS AND FUTURE RESEARCH

This study investigates and improved prophet algorithm for better performance and specification of usage. Increasing the scope and frame to extend to other techniques of forecasting can be a full study.

7. AUTHORS CONTRIBUTIONS

All authors contributed immensely to the aspect of technical writing.

8. Acknowledgment

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9. Ethics

This is the original manuscript; there will be no expectation of any ethical problems.

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