# Summary of Discussion on ADPLL-Based Filtering for Prediction

## 1. Introduction

The discussion explored the effectiveness of using a Digital Phase-Locked Loop (DPLL)-based second-order filter for time-series prediction, as an alternative to Brown’s Double Exponential Smoothing (LES). The approach was inspired by the paper 'All Digital Phase-Locked Loop: Concepts, Design, and Application' by Y.R. Shayan and T. Le-Ngoc.

## 2. Key Findings

ADPLL-Based Filtering vs. Brown’s LES: Brown’s LES provides a simple linear trend estimation, but using two second-order DPLL filters allows for faster adaptation to changes and better noise rejection.

Similarity to Kalman Filters: ADPLL filtering dynamically adjusts weights to minimize phase error, much like a Kalman filter, but without the computational overhead of covariance matrix calculations.

Advantages of ADPLL-Based Prediction:

- Fast adaptation to trend changes

- Reduced lag compared to LES

- Stronger noise suppression

- Computational efficiency for real-time applications

Potential Limitations:

- Requires careful parameter tuning to avoid instability or oscillations

- Less commonly used in forecasting literature, making validation against traditional models necessary

## 3. Comparative Analysis of Prediction Techniques

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| --- | --- | --- | --- | --- |
| Method | Adaptability to Trend Changes | Lag Reduction | Handles Noise Well? | Complexity |
| Brown’s LES | Moderate | ❌ Lags behind shifts | ✅ Good for smooth trends | Low |
| ADPLL-Based Filtering | High | ✅ Minimal lag | ✅ Strong noise rejection | Moderate |
| Kalman Filter (KF) | High | ✅ Minimal lag | ✅ Excellent for noisy data | High |
| ARIMA | High for trends + seasonality | ❌ Moderate lag | ❌ Sensitive to noise | High |
| Neural Networks (LSTM, Transformer) | Extremely high | ✅ Minimal lag | ✅ Learns complex patterns | Very High |

## 4. Considerations for Future Work

- Tuning and Optimization: Fine-tuning loop gain parameters (Kp, Ki) for different datasets.

- Benchmarking: Comparing ADPLL filtering performance against Kalman Filters or ARIMA models.

- Hybrid Approaches: Exploring a combination of ADPLL and Kalman filters for robust adaptive filtering.

- Validation Metrics: Using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to quantify predictive accuracy.

## 5. Conclusion

The ADPLL-based filtering approach was confirmed to be a reasonable and effective method for short-term time-series prediction, with strong noise rejection and minimal lag. While alternative techniques exist, the computational efficiency and adaptability of ADPLL make it a strong candidate for real-time applications. The next steps involve further tuning and validation, but initial results show that this method is well-suited for the user’s objectives.

## 6. Next Steps

- Verification of coding implementation for efficiency.

- Comparing ADPLL filtering against Kalman filtering and ARIMA models.

- Exploring hybrid models for improved prediction accuracy.