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Window Incremental Forest for System Delay Prediction in Satellite Laser Ranging

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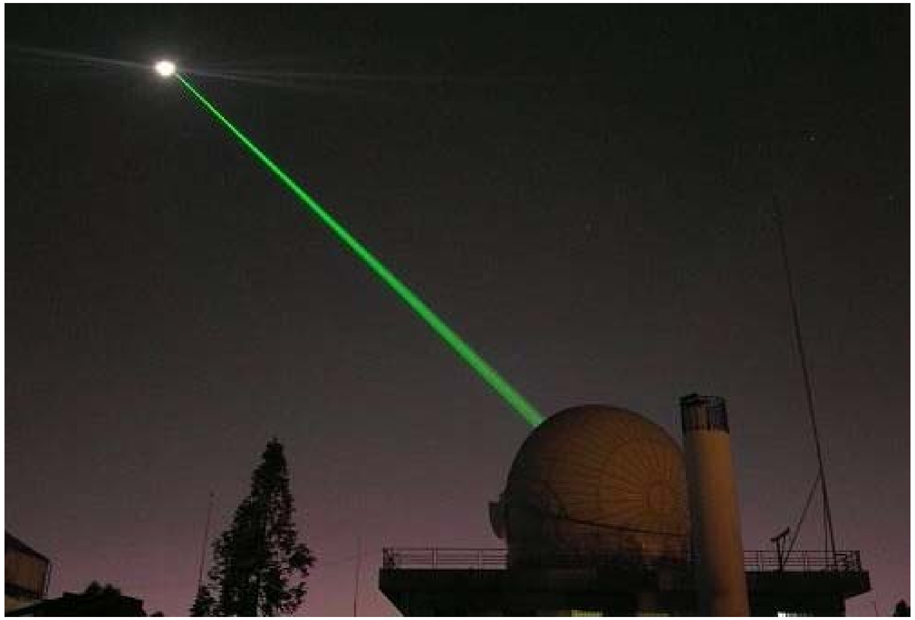
Content

1 Research Background

Satellite Laser Ranging (SLR)

The Satellite Laser Ranging (SLR) system precisely measures the round-trip time interval t of a laser pulse between the observation station and the satellite, enabling the calculation of the distance between them. $R = \frac{ct}{2}$

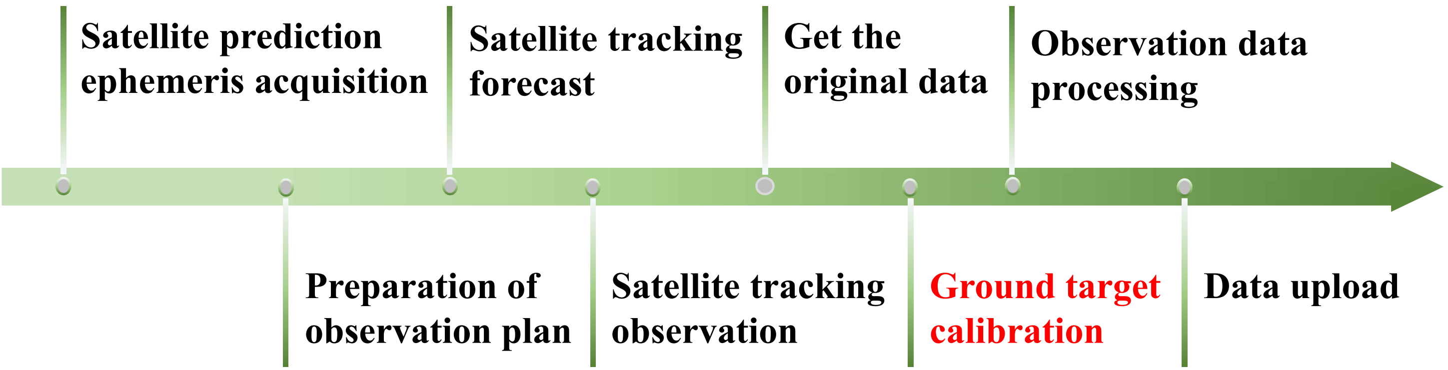


Satellite Laser Ranging

1 Research Background

System Delay

SLR data includes system delay, typically regarded as a whole, which is derived and subtracted through ground target measurements.



System Operation Flow

1 Research Background

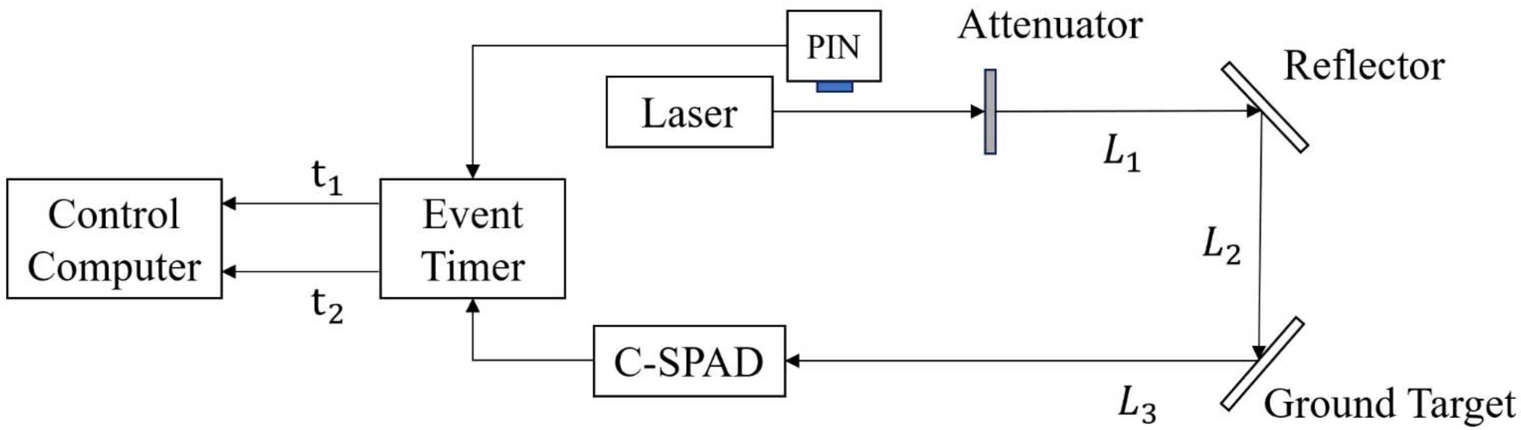
Steps for Target Calibration

① Control the telescope to point at a known ground target.

② Measure the distance to the ground target.

③ Calculate the difference between the actual distance and the measured distance.

④ Rectify system delay.



SLR Target Calibration system

1 Research Background

Existing Target Delay Measurement Technologies

Distant Targets:

- Require atmospheric delay corrections,
- Present significant challenges in maintenance and management, as well as targeting.

Near Targets:

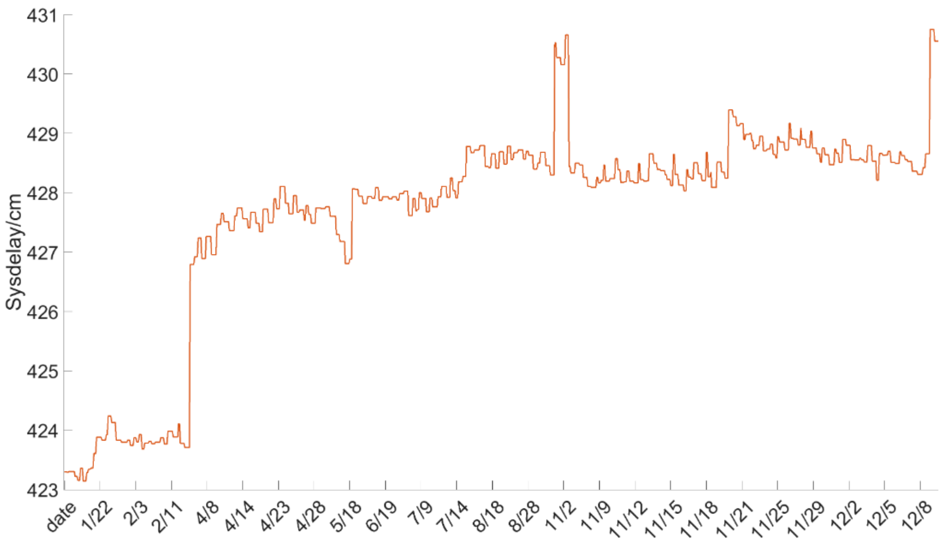
- Avoid the atmospheric effects;
- Calibration of ground targets and satellite observations cannot be performed simultaneously.
- A large amount of observational data corresponds to only one ground target value, failing to meet the real-time and effective calibration requirements for system delay.

1 Research Background

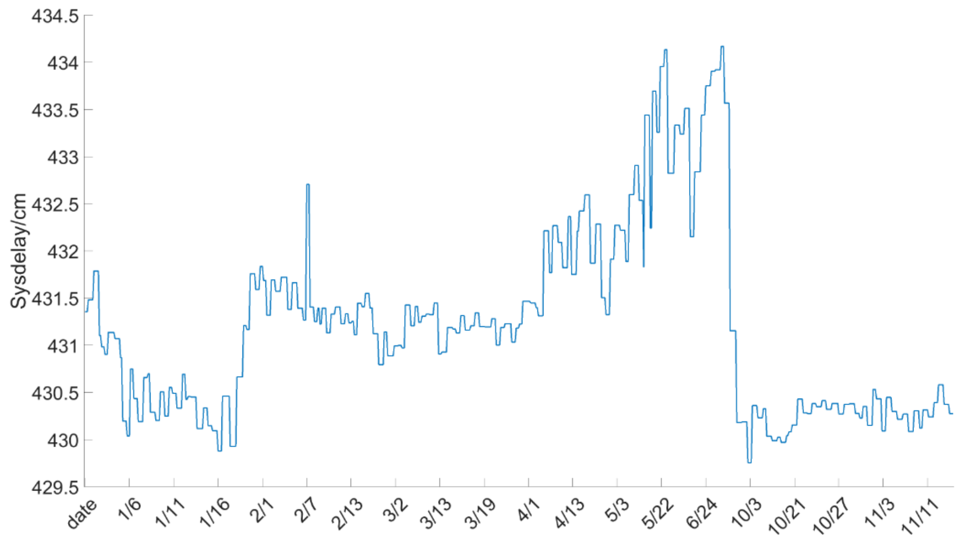
Target Calibration Stability

In 2022: relatively stable, some abnormal jumps.

In 2023: larger change range, more jumps and fluctuations.



2022 ground target measurement data



2023 ground target measurement data

The low accuracy and stability of ground target value lead to the instability of SLR data quality.

1 Research Background

Real-Time Correction Method for System Delay

In 2019, An Ning and and colleagues from the Changchun Satellite Observation Station designed a real-time calibration, but this solution necessitated modifications to the telescope's' barrel, making it difficult to extend to other ranging systems.

In the same year, He Zhengbin and colleagues proposed a system delay prediction method based on ARMA time series analysis. However, time series analysis relies on fixed time intervals, which complicates data collection and processing. Additionally, it can only predict delay values at fixed intervals, failing to accommodate predictions at arbitrary time.

Therefore, we propose a real-time prediction method based on Window Incremental Forest.

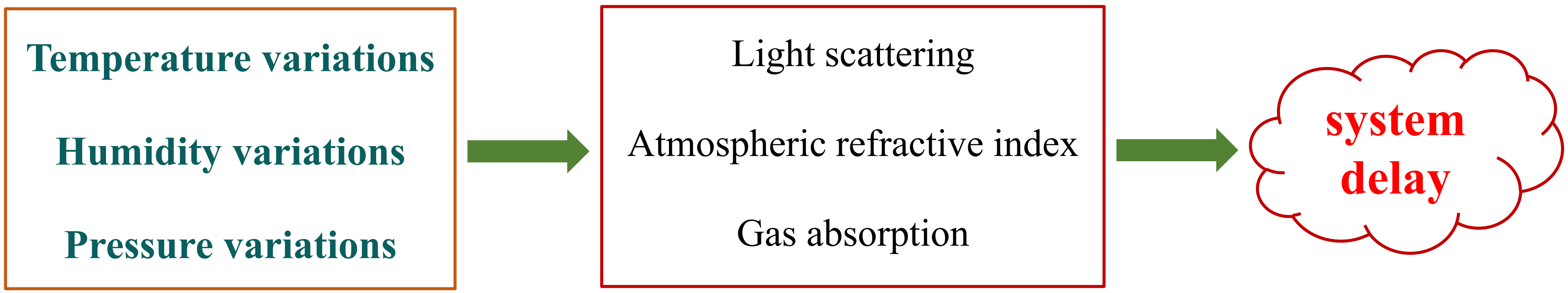
2 Analysis of Factors Affecting System Delay

Laser Ranging Equation

According to the laser ranging equation, various factors contribute to the system delay in laser ranging systems, including optical delays, electrical delays, and photoelectric conversion delays.

$$\eta_{pe} = \eta_q \left(E_T \frac{\lambda}{hc}\right) \eta_t G_t \sigma \left(\frac{1}{4\pi R^2}\right)^2 A_r \eta_r T_\alpha^2$$

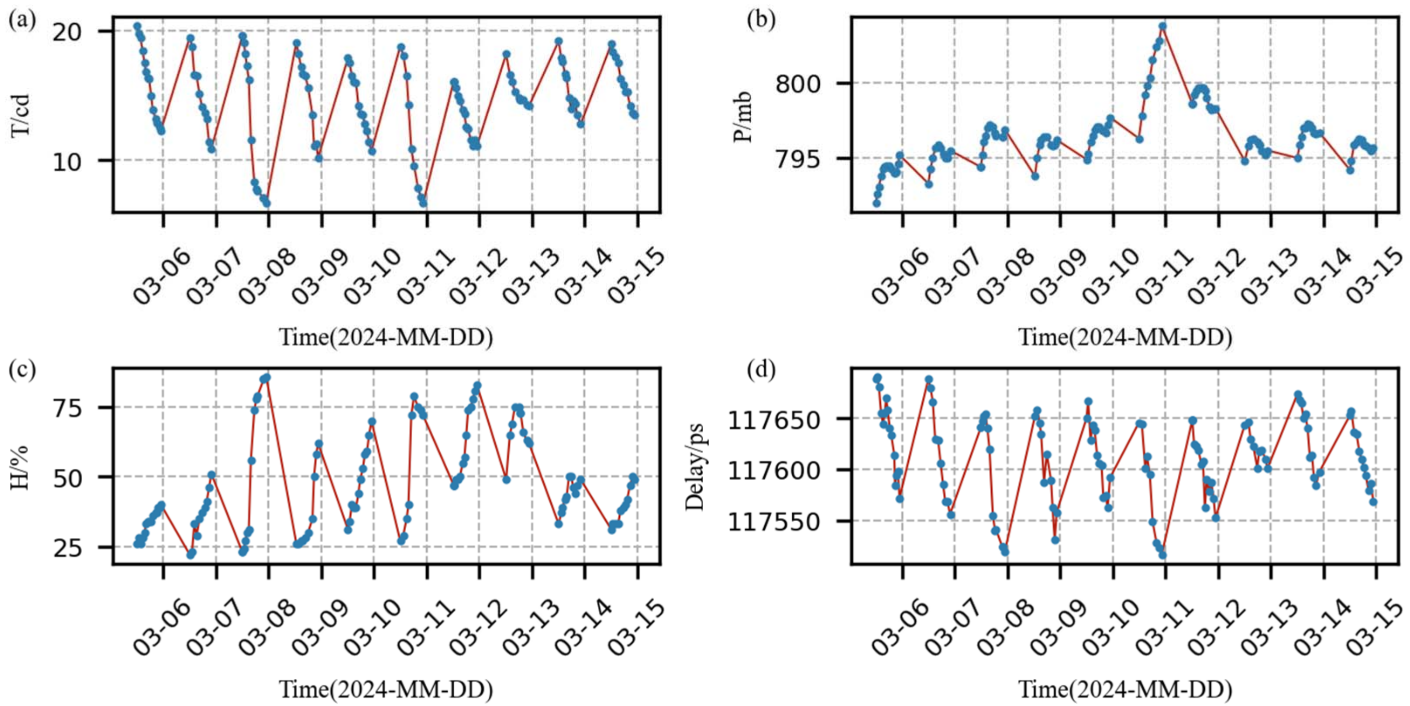
Impact of Meteorological Parameters on System Delay



2 Analysis of Factors Affecting System Delay

Impact of Meteorological Parameters on System Delay

By observing the variations in system delay and meteorological parameters, regular patterns in daily changes of temperature(T), humidity(H), pressure(P), and system delay (D)can be identified.



Meteorological Parameters and System Delay

2 Analysis of Factors Affecting System Delay

Sample Correlation Matrix Analysis

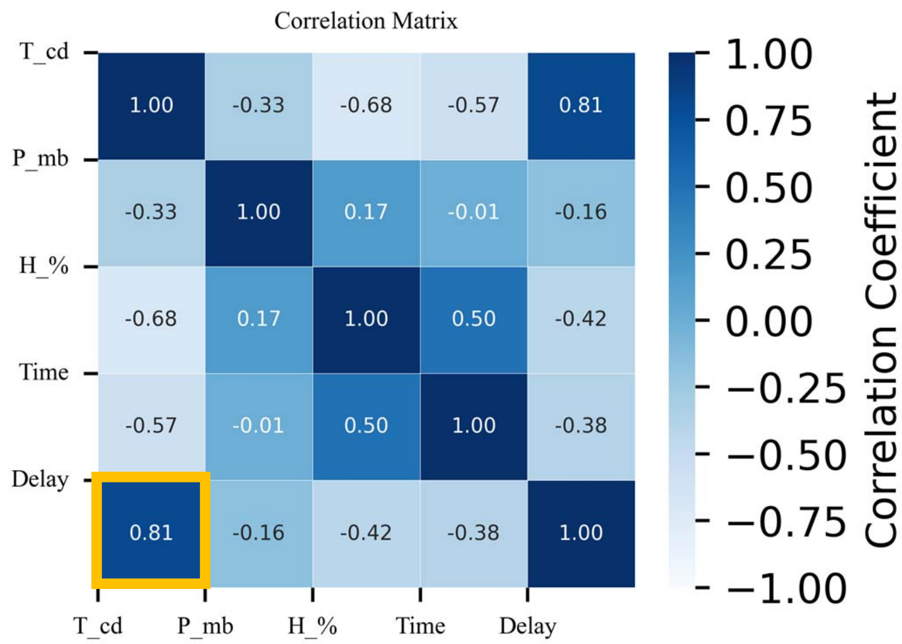
T and D: strong linear relationship ($r_{ij} = 0.81$)

H, P and D: weaker linear relationship,

T, H, P: interdependencies

$$r_{ij} = \frac{Cov(X_i, X_j)}{\sigma_{X_i}\sigma_{X_j}}$$

The sample correlation coefficient r_{ij} measures the linear relationship between two variables, ranging from$[-1,1]$:



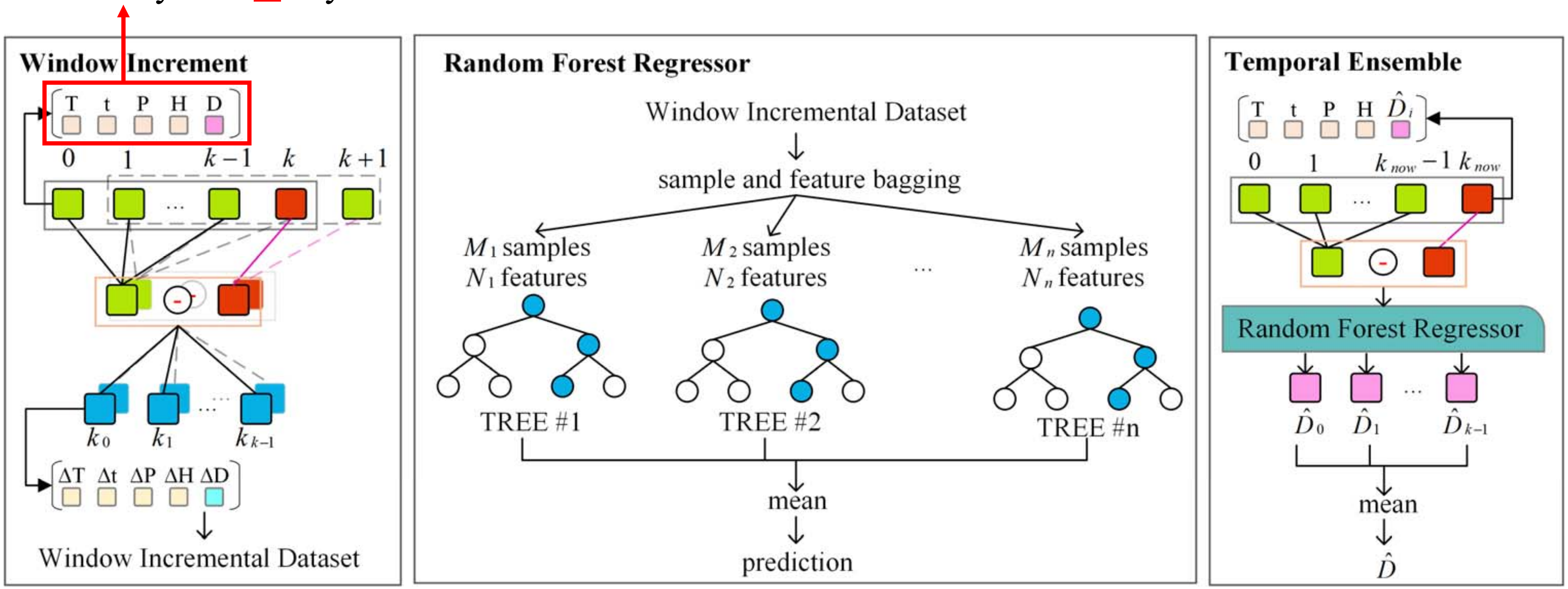
Sample Correlation Matrix Analysis

3 Methods

Window Incremental Forest(WIF)

Features: Temperature, time, Pressure, Humidity

Labels: System Delay



Window Incremental Forest model

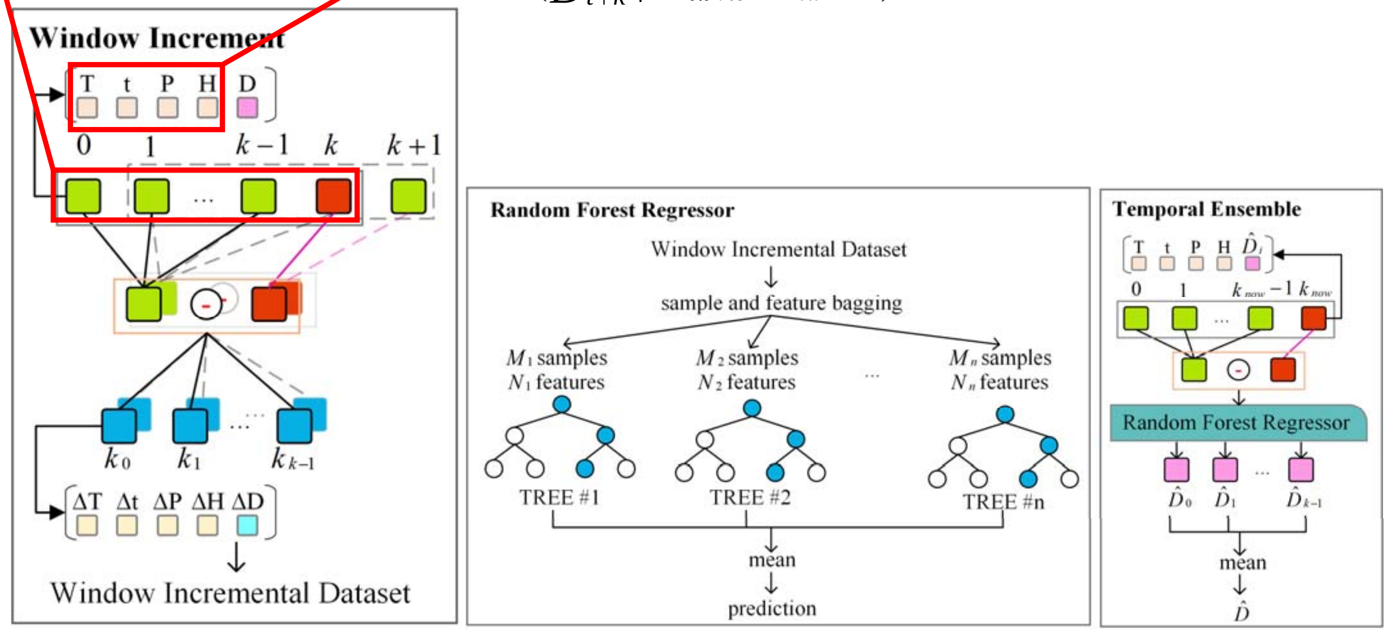
3 Methods

Window Increment(WI)

Within window k: Using observation results $o_{t:t+k}$ and measurement results $D_{t:t+k-1}$ to predict the ground target value $\widehat{D}_{t+k}$ at time $t+k$.

Model Strategy:

$$\pi(\hat{D}_{t+k} \mid O_{t:t+k}, D_{t:t+k-1})$$



Window Incremental Forest model

3 Methods

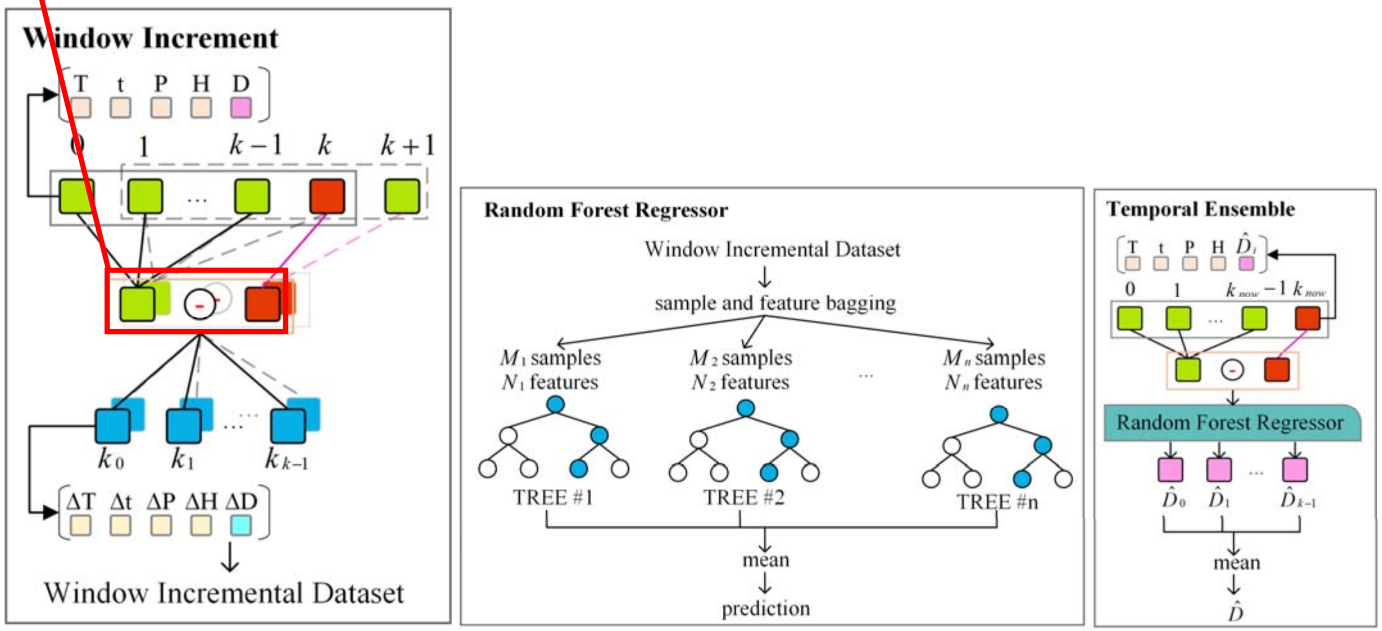
Window Increment

Window Increment: Within window k , perform difference operations on O_{t+k} and $\widehat{D}_{t+k}$ compared to $O_{t:t+k-1}$ and $D_{t:t+k-1}$.

Incremental Model:

$$D_{t+k,t+i} = \Delta D_{t+k,t+i} + D_{t+i}$$

$$O_{t+k,t+i} = \Delta O_{t+k,t+i} + O_{t+i}$$



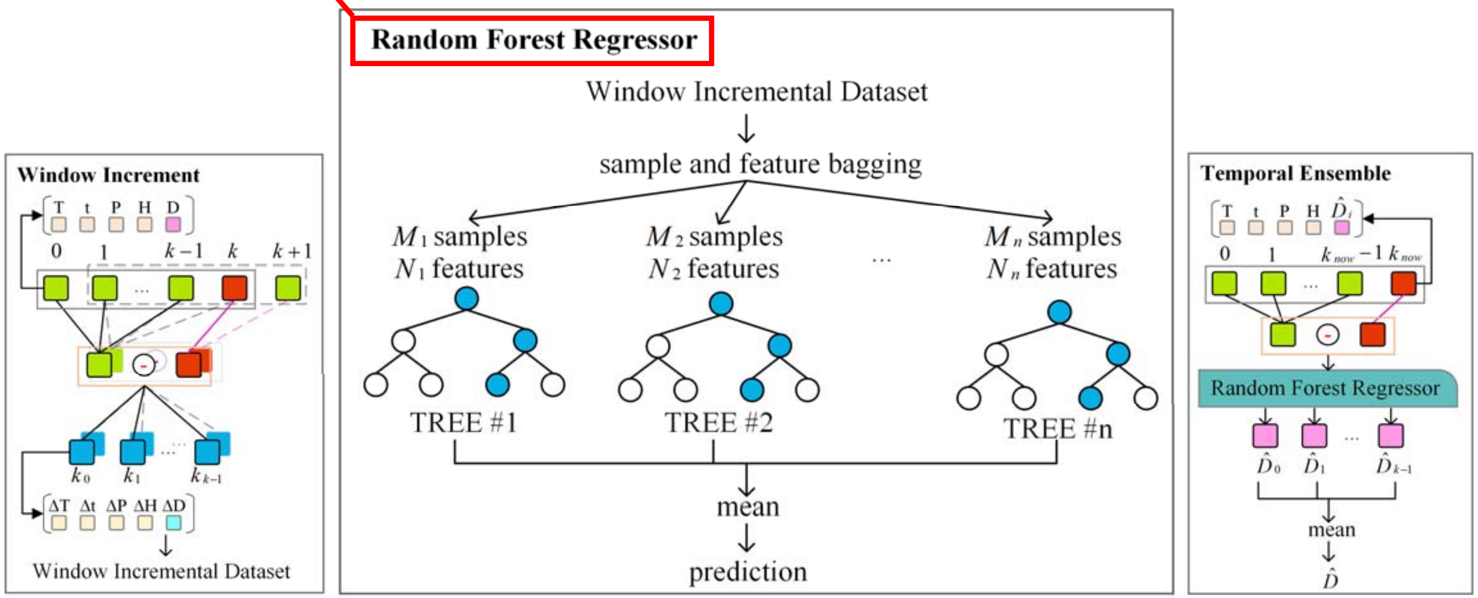
Window Incremental Forest model

3 Methods

Window Incremental Forest

Random Forest Regression Learning Incremental Part:

$$\begin{aligned}\hat{D}_{t+k,t+i} &= \boxed{\Delta D_{t+k,t+i}} + D_{t+i} \\ &= RFR(\Delta T_{t+k,t+i}, \Delta t_{t+k,t+i}, \Delta P_{t+k,t+i}, \Delta H_{t+k,t+i}) + D_{t+i} \\ &= \boxed{RFR(\Delta O_{t+k,t+i})} + D_{t+i}\end{aligned}$$



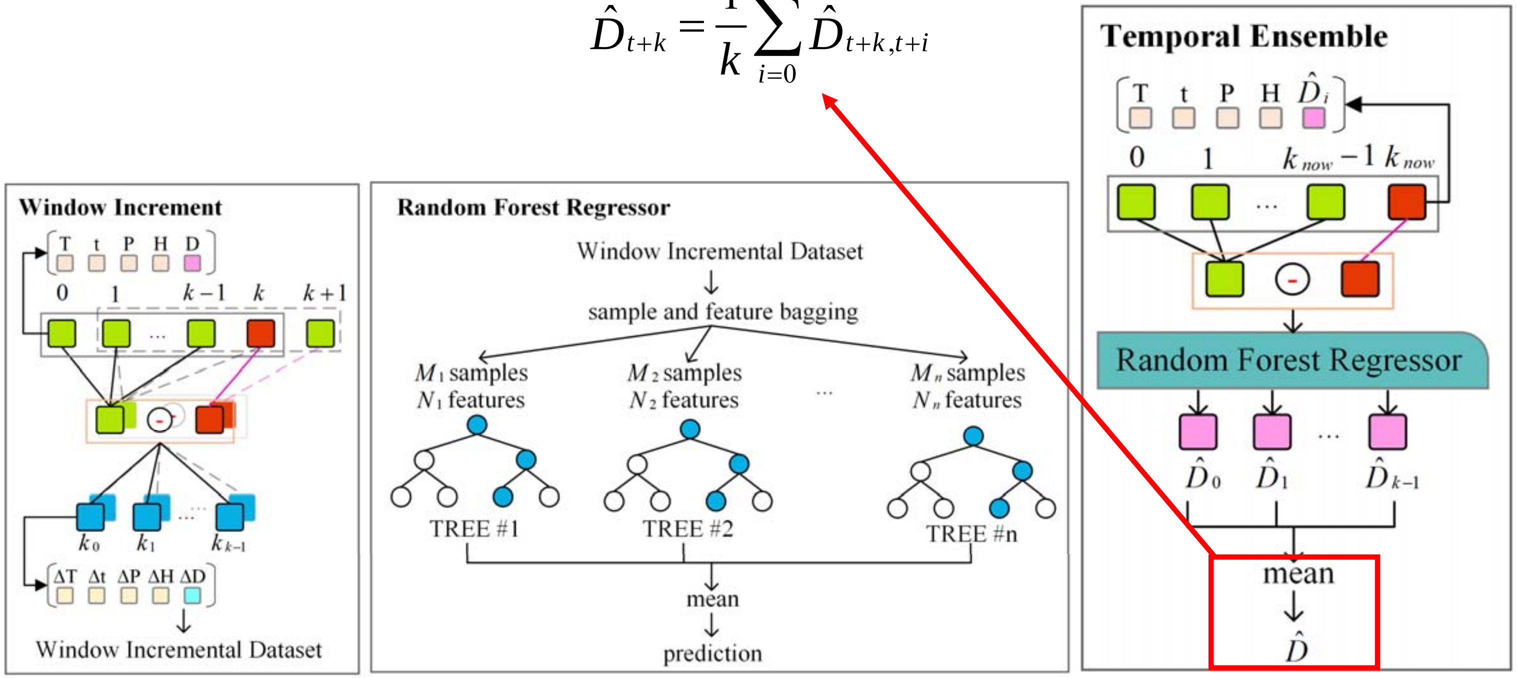
Window Incremental Forest model

3 Methods

Window Incremental Forest

Temporal Integration: Take the mean of the k predicted values $\hat{D}_{t+k,t+i}$ from $\Delta O_{t+k,t+i}$ and D_{t+i} to obtain the predicted value at time $t+k$.

$$\hat{D}_{t+k} = \frac{1}{k}\sum_{i=0}^{k}\hat{D}_{t+k,t+i}$$



Window Incremental Forest model

4 Experiments

Data Collection

System Delay: ground target measurements of the Kunming SLR system.

Meteorological Parameters: Weather forecasts from meteorological parameter measuring instruments.

Details: Ground target measurements are conducted approximately every hour, while weather forecasts are updated every minute. The most recent weather forecast is used as the meteorological parameter affecting the ground target measurement results.

4 Experiments

Experimental Setup and Evaluation Criteria

Dataset Division: Training: Validation: Testing = 6.4 : 1.6 : 2

Comparison Experiments: LR, SVR, DT, MLP, GBRF.

Evaluation Criteria: MSE, RMSE, MAE, R^2, Adjusted R^2.

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 ; RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} ; MAE = \frac{1}{m}\sum_{i=1}^{m}|(y_i - \hat{y}_i)|$$

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (\bar{y}_i - y_i)^2} ; R^2\_adjusted = 1 - \frac{(1-R^2)(n-1)}{n-p-1}$$

Linear Regression(LR), Support Vector Regression(SVR), Decision Trees(DT), Multi-layer Perceptrons(MLP), Gradient Boosted Regression Forests(GBRF).

Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), Adjusted Coefficient of Determination (Adjusted R^2).

4 Experiments

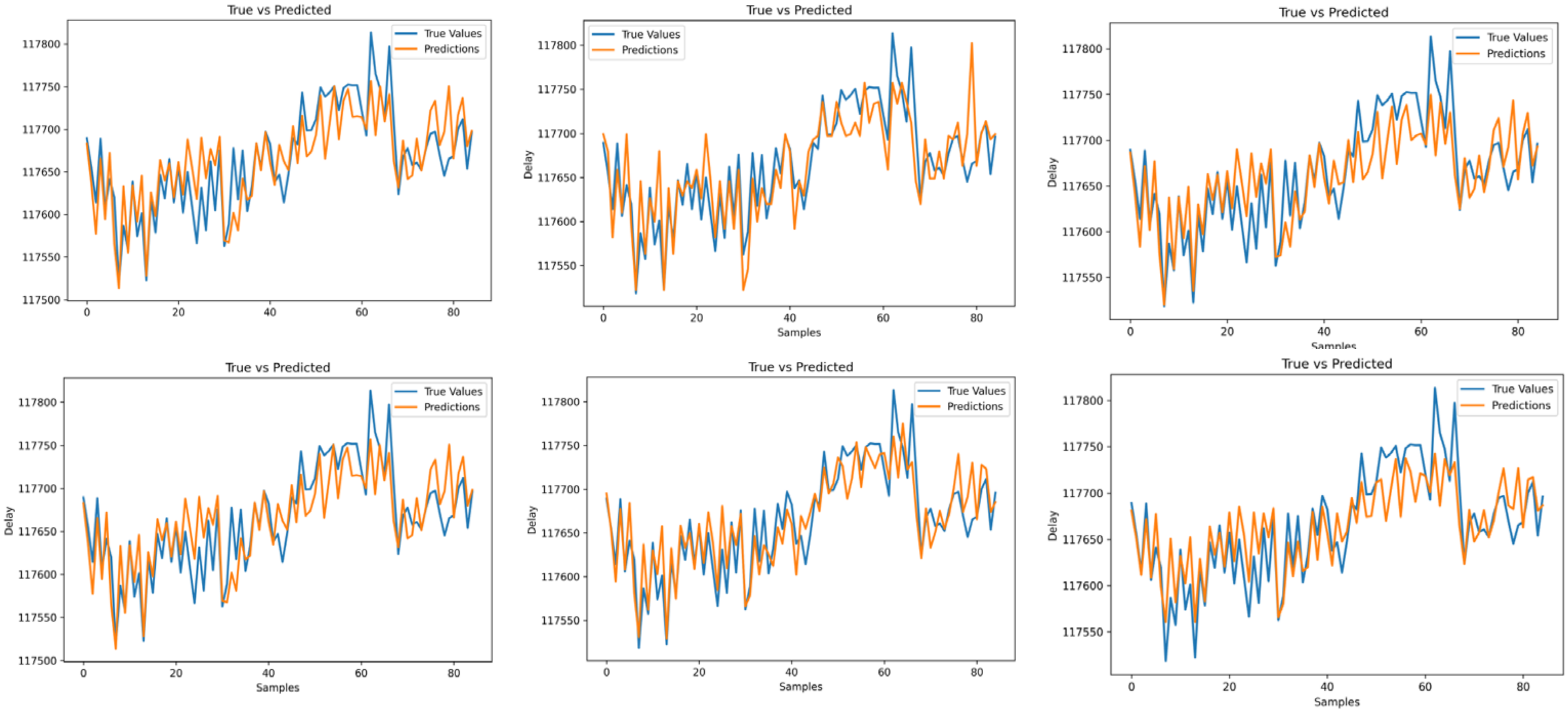
Experimental Results

Table 1: Comparison of System Delay Prediction Results

	MSE / ps	RMAE / ps	MAE / ps	R^2	$R^2\_adjusted$
LR	1016.6070	31.8843	24.5429	0.7108	0.6964
DTR	1044.6589	32.3212	23.6877	0.7028	0.6880
SVR	1061.5688	32.5817	25.2712	0.6980	0.6829
MLP	1016.6050	31.8842	24.5428	0.7108	0.7108
GBRF	920.3529	30.3373	23.6628	0.7382	0.7251
RFR	697.5677	26.4115	20.8563	0.8015	0.7916
WIF	**382.6508**	**19.5614**	**15.5185**	**0.8791**	**0.8725**

4 Experiments

Experimental Results

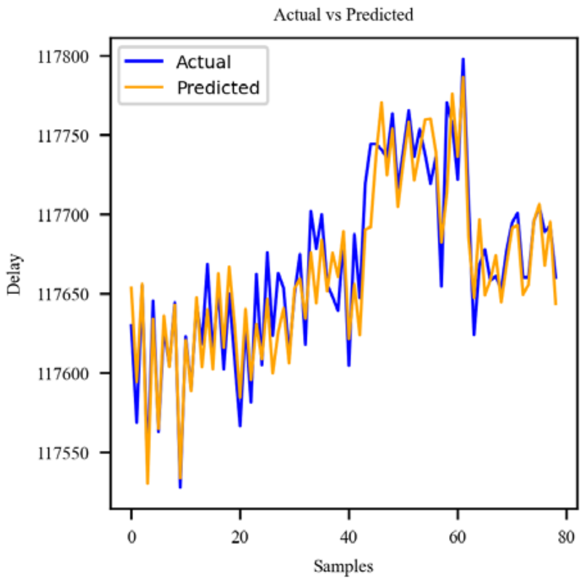


4 Experiments

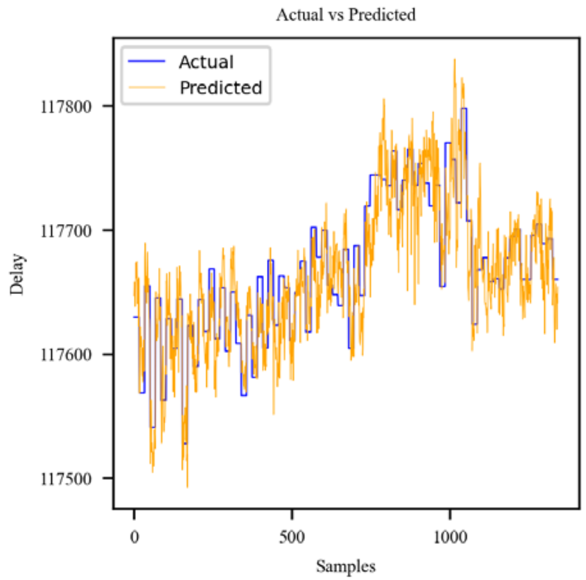
Result Analysis

Table 2: Analysis of Performance Improvement Reasons for WIF

	MSE / ps	RMAE / ps	MAE / ps	R^2	$R^2\_adjusted$
RFR	697.5677	26.4115	20.8563	0.8015	0.7916
WI+RFR	**755.8726**	**27.4931**	**21.4041**	**0.7612**	**0.7605**
WIF	382.6508	19.5614	15.5185	0.8791	0.8725



WIF prediction result



WI+RFR prediction result

4 Experiments

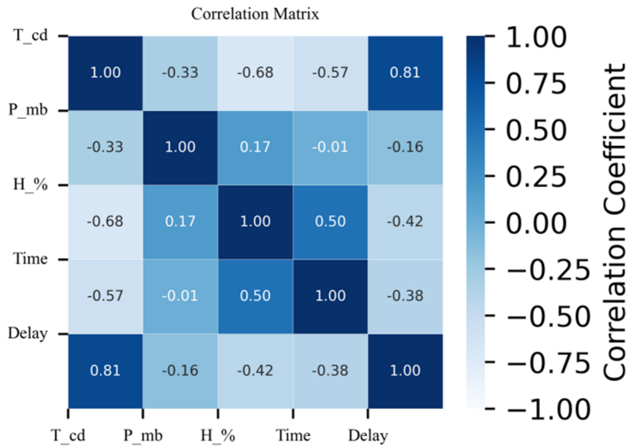
Feature Contributions

T_cd_deta: 0.7805126913582128

P_mb_deta: 0.08454859724880665

Time_deta: 0.08273485778259129

H_%_deta: 0.05220385361038928



Sample Correlation Matrix Analysis

Parameter Tuning Process and The contribution of temperature increment

- **Suitable:** around 0.78
- **Over-fitting:** more than 0.93
- **Under-fitting:** less than 0.73
- This provides a reference for the real contributions of each feature on system delay.

5 Conclusion

Conclusion

The experimental results show that the methodology has good prediction performance. Consequently, the Window Incremental Forest can effectively predict system delays, offering a robust solution for monitoring the accuracy and stability of ground target measurements and thereby enhancing the overall quality of SLR data.

Thank you for your attention.

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