ADAPTIVE AND COGNITIVE SYSTEMS LABS

CAIR

STGNN FOR SHARE TREND LINE PREDICTION & CHANGE POINT DETECTION ON JSE

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ABSTRACT

This research explores Spatial-Temporal Graph Neural Networks (STGNNs) for predicting trend lines and detecting change points on the Johannesburg Stock Exchange (JSE). We present baseline DNN experiments of our LSTM, TCN & Graph wavenet baselines models and, then show how hyperparameter optimization affects RMSE and sMAPE. The key finding is that TCN with trend-aware features preserves slope variation better and attains the lowest RMSE overall, while sMAPE is a reliable diagnostic metric for slope reconstruction quality.

OBJECTIVES

- Compare the capabilities of STGNNs with DNN baselines for trend line prediction.
- Compare STGNNs with DNN baselines for change point detection.
- Evaluate trend line prediction for short and long-term investment decisions.
- Visualize the dynamics of the Johannesburg Stock Exchange Market.

BASELINE SAMPLE RESULTS - POINTDATA

RMSE	SLOPE	DURATION	AVERAGE
LSTM (before)	**90.37**	0.86	45.62
LSTM (after)	94.38	0.88	47.63
TCN (before)	88.57	**0.84**	**44.71**
TCN (after)	99.08	1.21	50.15
GWN	109.79	**0.48**	59.34

sMAPE	SLOPE	DURATION	AVERAGE
LSTM (before)	162.19	45.63	103.91
LSTM (after)	149.32	46.06	97.69
TCN (before)	199.76	40.39	120.08
TCN (after)	**143.09**	**55.26**	**99.18**
GWN	**137.65**	**13.80**	**75.73**

BASELINE SAMPLE RESULTS - POINTREND

RMSE	SLOPE	DURATION	AVERAGE
LSTM	95.57	0.84	48.21
TCN	**84.82**	0.84	**42.83**

sMAPE	SLOPE	DURATION	AVERAGE
LSTM	126.90	43.97	85.44
TCN	**57.48**	**41.19**	**49.34**

BASELINE SAMPLE RESULTS - TREND

RMSE	SLOPE	DURATION	AVERAGE
LSTM	107.14	0.83	54.00
TCN	**82.91**	0.83	**41.87**

sMAPE	SLOPE	DURATION	AVERAGE
LSTM	111.33	42.75	77.04
TCN	**60.70**	**39.65**	**50.18**

ANALYSIS We performed a grid search over learning rate, dropout, weight decay, and other model parameters. Results showed that learning rate, dropout, and weight decay were the most influential hyperparameters. Specifically, higher learning rates combined with lower dropout and weight decay values (< 0.2) led to lower sMAPE values that yeilded more sensible slope predictions, though often at the expense of higher RMSE Figures 1 & 2 show single-step predictions of the next-day trend slope and duration, while Figures 3 & 4 plot continuous reconstructions over 100 days. These visualizations illustrate how optimization altered slope prediction behavior. The continuous plots reveal that when sMAPE exceeds 150, models tend to collapse to near-zero slope predictions Figure 3. After optimization, sMAPE values dropped below 150 more frequently, leading to more realistic slope predictions Figures 4. This demonstrates that sMAPE is a key indicator of slope prediction quality.

MATHEMATICAL FORMULATION

The input to the models, where X is the input matrix is:

$$X \in \mathbb{R}^{N \times T \times F}$$

The trend sequence is approximated using piecewise linear segmentation:

$$X = \{\langle L1, S1\rangle, \ldots, \langle Lk, Sk\rangle\}$$

where:

Lk = Length (duration) of the k-th trend segment

Sk = Slope of the k-th trend segment

Hence, the aim is to predict the next trend segment (as depicted in Fig: [1,2] based on a 21 day input window(blue), the next day true (green) vs predicted trend (orange)):

$$\langle Sk+1, Lk+1\rangle$$

STGNN Formulation. The goal is to learn a function:

$$f : \{X\} \rightarrow \{\langle Sk+1, Lk+1\rangle\}$$

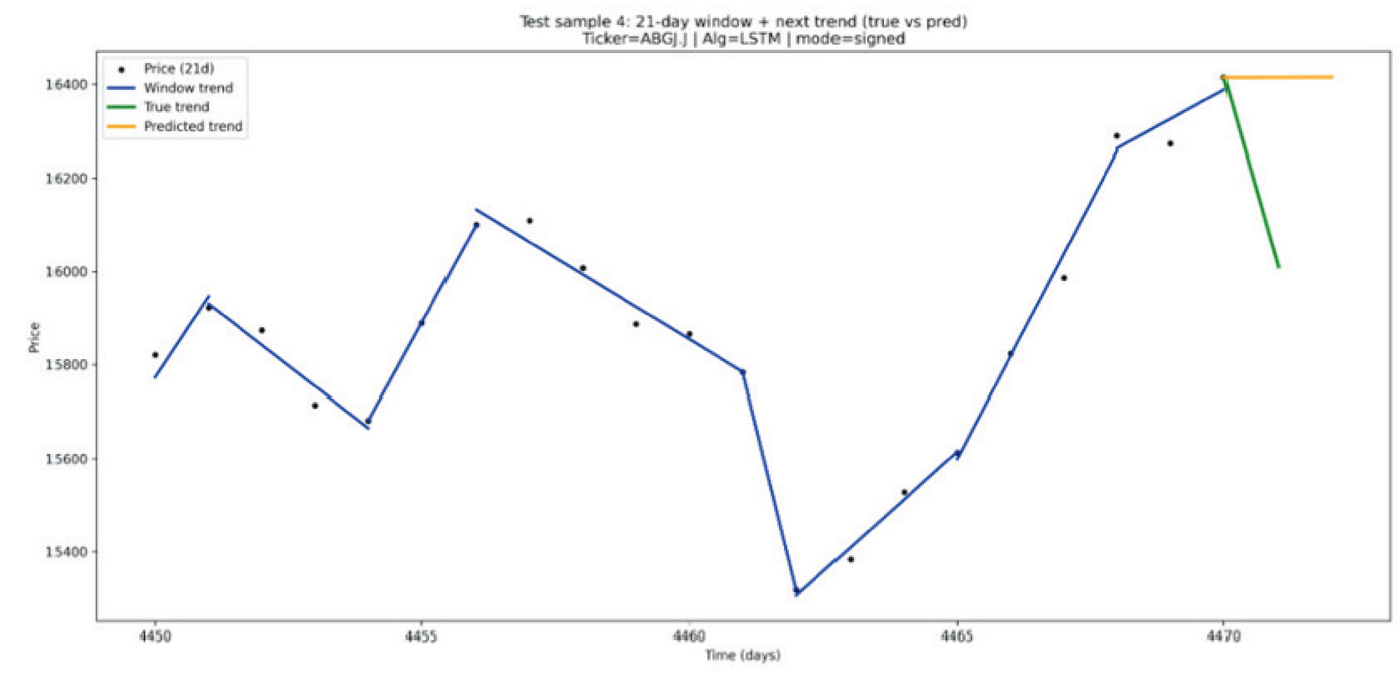
that captures both temporal dynamics and spatial relationships from the input and maps to an output:

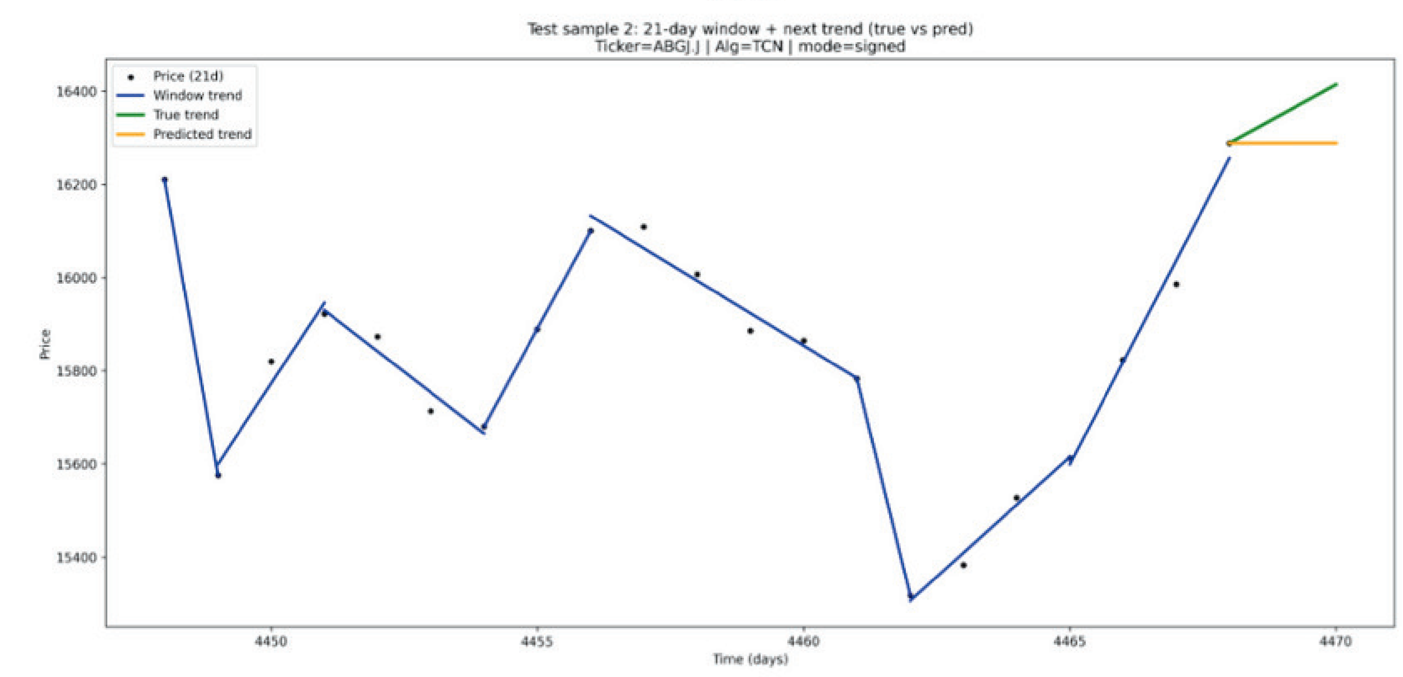
Next trend line:

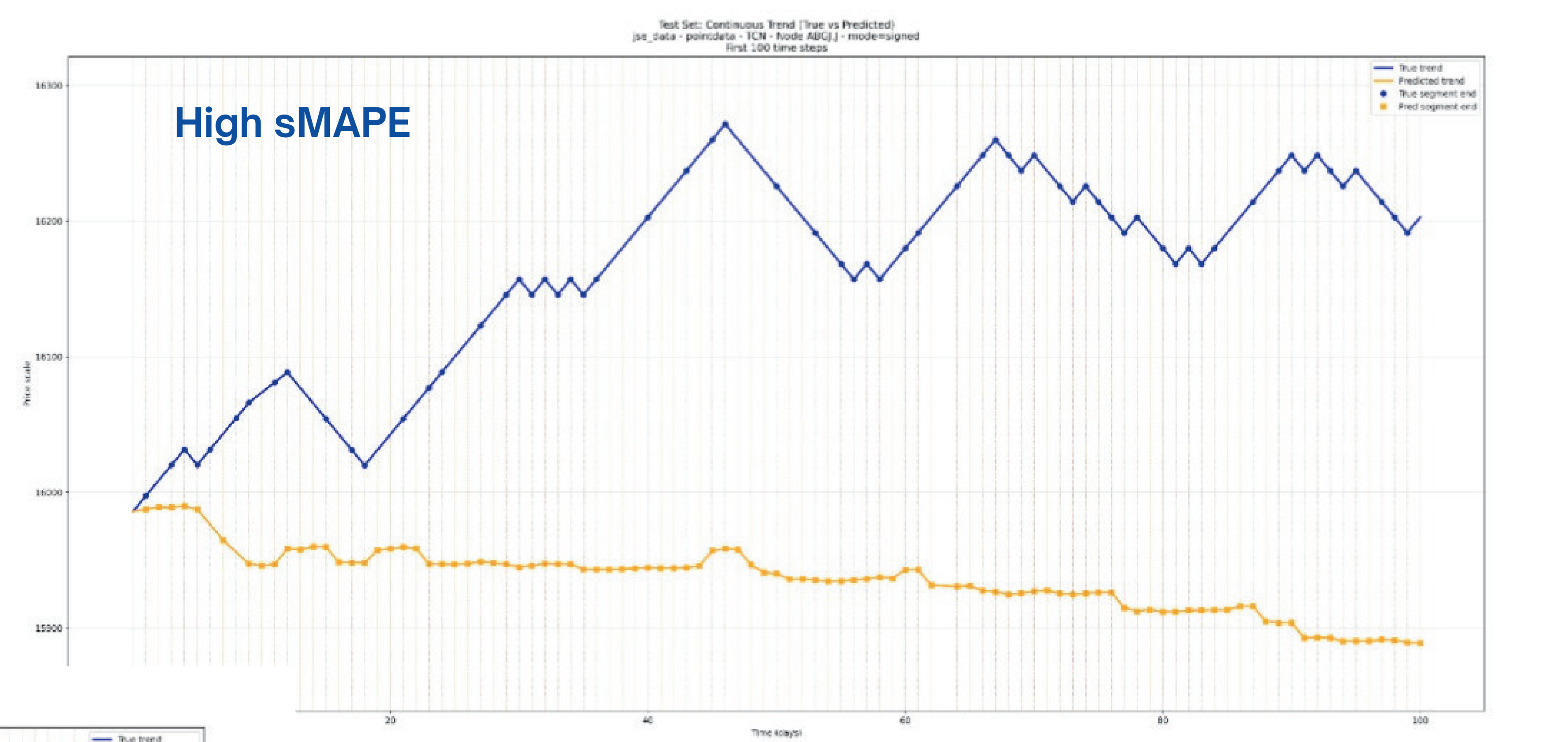
$$\langle Sk+1, Lk+1\rangle$$

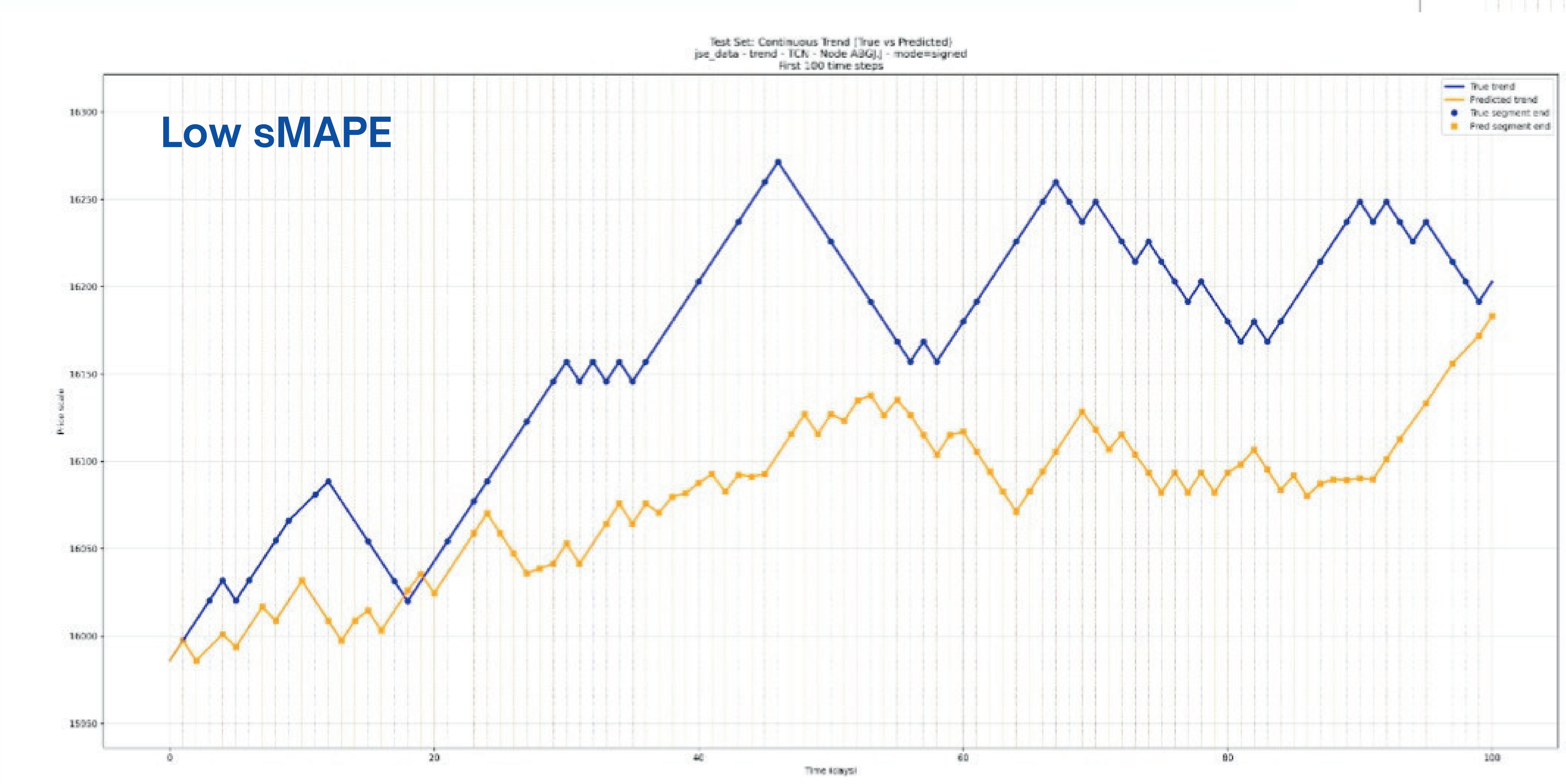
predicted slope and duration of the next trend segment.

SAMPLE PLOTS









In summary, the results across feature types confirm that sMAPE is the most reliable diagnostic for slope prediction quality. Lower sMAPE values are consistently associated with more meaningful and realistic slope predictions. Among the feature types, trend features yield the strongest results, followed by pointrend, with pointdata trailing. Across all cases, TCN emerges as the more effective architecture for both slope and duration forecasting.