LONG-TERM TRAFFIC FLOW FORECASTING

Using a hybrid CNN-BiLSTM model

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Main Objective

TRAFFIC CONGESTION IS ONE OF THE MAIN PROBLEMS OF MOST BIG CITIES. TRAFFIC FLOW FORECASTING IS AN ESSENTIAL TOOL FOR TRAFFIC MANAGEMENT, SPECIALLY, IN THE MOST CONGESTED AND FREQUENTED ROADWAYS.

THE HIGH PRESENCE OF SIGNALISATION IN CITIES MAKES URBAN TRAFFIC FLOW MORE UNPREDICTABLE AND RANDOM THAN TRAFFIC FLOW IN FREEWAYS.

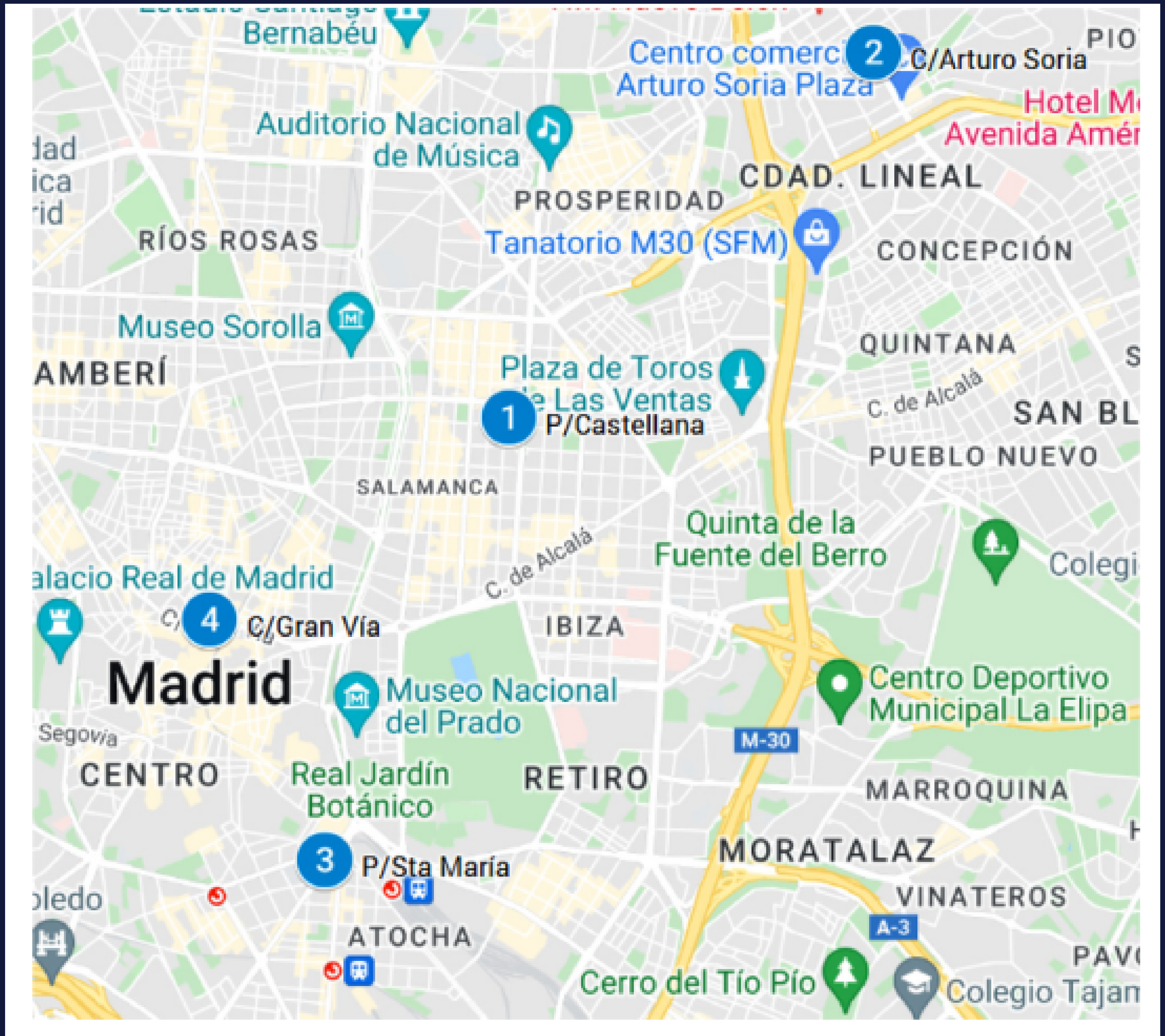
IN THIS PAPER WE PRESENT A HYBRID MODEL, COMBINING A CONVOLUTIONAL NEURAL NETWORK AND A BIDIRECTIONAL LONG-SHORT-TERM MEMORY NETWORK, AND APPLY IT TO LONG-TERM TRAFFIC FLOW PREDICTION IN URBAN ROUTES.

THIS MODEL COMBINES THE CAPABILITY OF CNN TO EXTRACT HIDDEN VALUABLE FEATURES FROM THE INPUT MODEL AND THE CAPABILITY OF BILSTM TO UNDERSTAND THE TEMPORAL CONTEXT

TRAFFIC FLOW FORECASTING CAN BE CLASSIFIED IN SHORT-TERM AND LONG-TERM.

SHORT-TERM MODELS ARE ABLE TO PREDICT TRAFFIC FLOW FROM A FEW MINUTES TO ONE HOUR IN ADVANCE, THAT IS, IN A VERY CLOSE FUTURE.

LONG-TERM MODELS ARE ABLE TO PREDICT TRAFFIC FLOW FROM TWO HOURS TO SEVERAL DAYS IN ADVANCE.



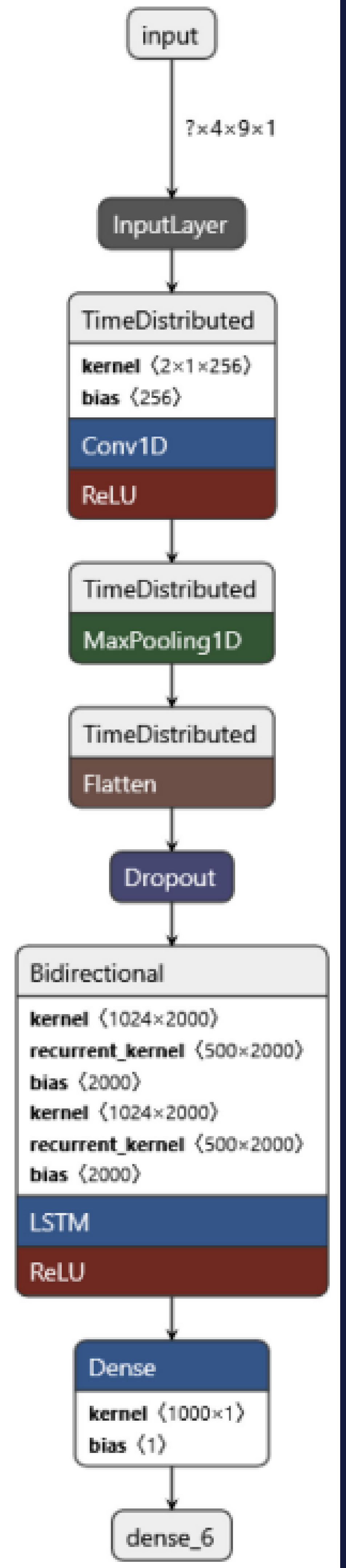
Approach

- In this paper they propose a novel hybrid CNN-BiLSTM architecture to forecast long-term traffic flow.
- The goal is to leverage the potential of a CNN block to extract complex characteristics from the input matrix and the capability of a BiLSTM block to find temporal dependencies between variables by understanding doubly (forward and backward) the context in each situation.

	aux1(t-12)	aux2(t-12)	original(t-12)	tmean(t-12)	rainfall(t-12)	tmin(t-12)	tmax(t-12)	typeday(t-12)	hour(t)	obj(t)
0	799	1442.0	658.0	76.0	0.0	36.0	116.0	festivo	13	468
1	894	903.0	458.0	76.0	0.0	36.0	116.0	festivo	14	201
2	760	397.0	190.0	76.0	0.0	36.0	116.0	festivo	15	243
3	669	312.0	147.0	76.0	0.0	36.0	116.0	festivo	16	349
4	665	299.0	124.0	76.0	0.0	36.0	116.0	festivo	17	430

The first group of predictor variables are: type of day (public holiday, working day or weekend), daily average temperature, daily minimum temperature, daily maximum temperature and daily rain. In addition, we also consider as predictor variables the hourly amount of vehicles in the target station and in two auxiliary stations (two different for each target station).

$$y(h+k) = f\begin{pmatrix} x_1(h-3), \ldots, x_1(h), \\ x_2(h-3), \ldots, x_2(h), \\ \ldots \\ x_9(h-3), \ldots, x_9(h) \end{pmatrix} + \epsilon$$



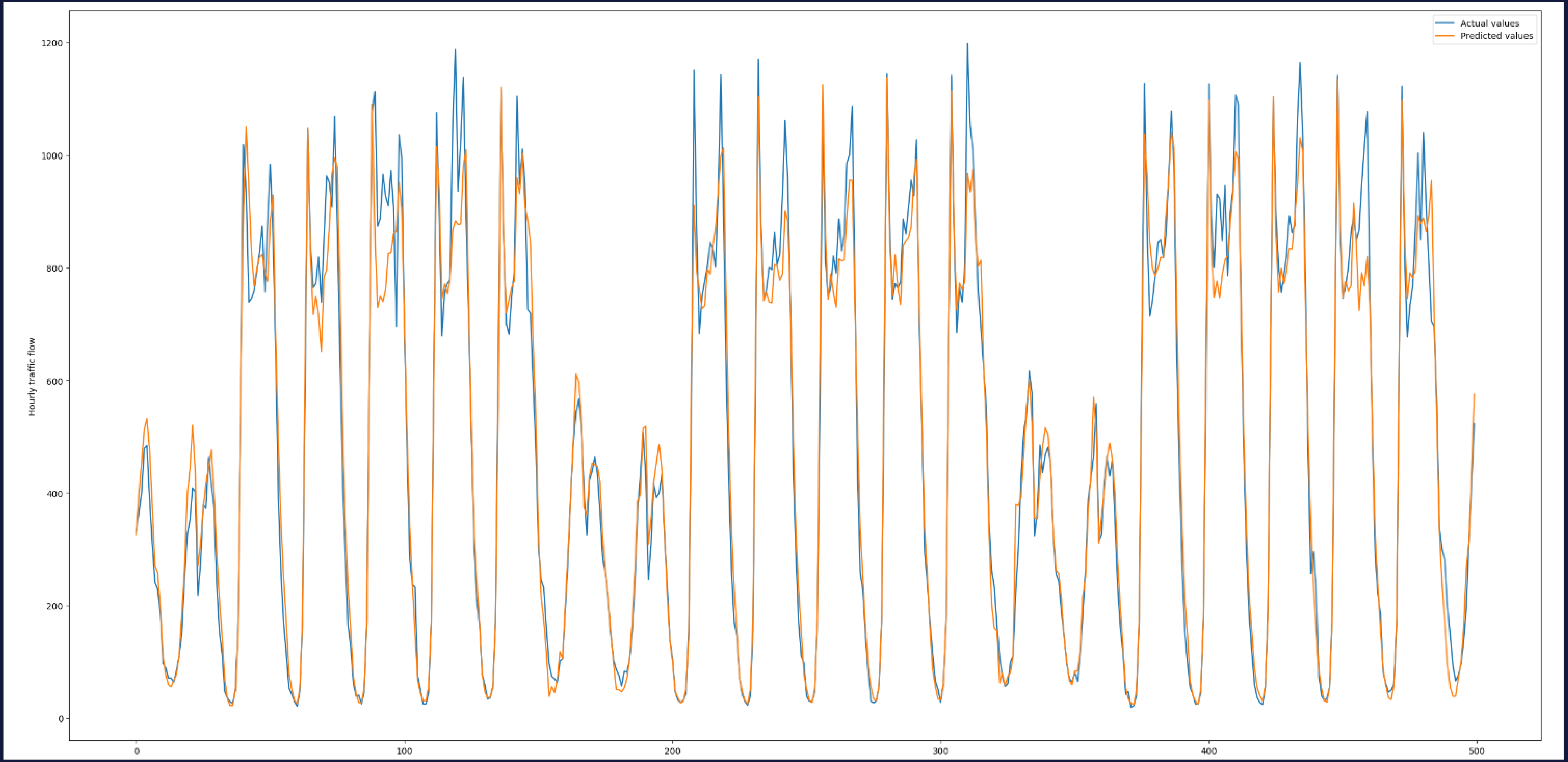
As kernel, we use a 2 × 2 matrix. Although this kernel dimension might look too small, we must take into account that the input matrix has also a relatively small dimension (9 × 4).

By using higher dimension kernel, a small number of hidden features would be extracted by the convolutional operation. In the max pooling layer, we use a 2 × 2 window with a stride of 2 to apply the max pooling operation.

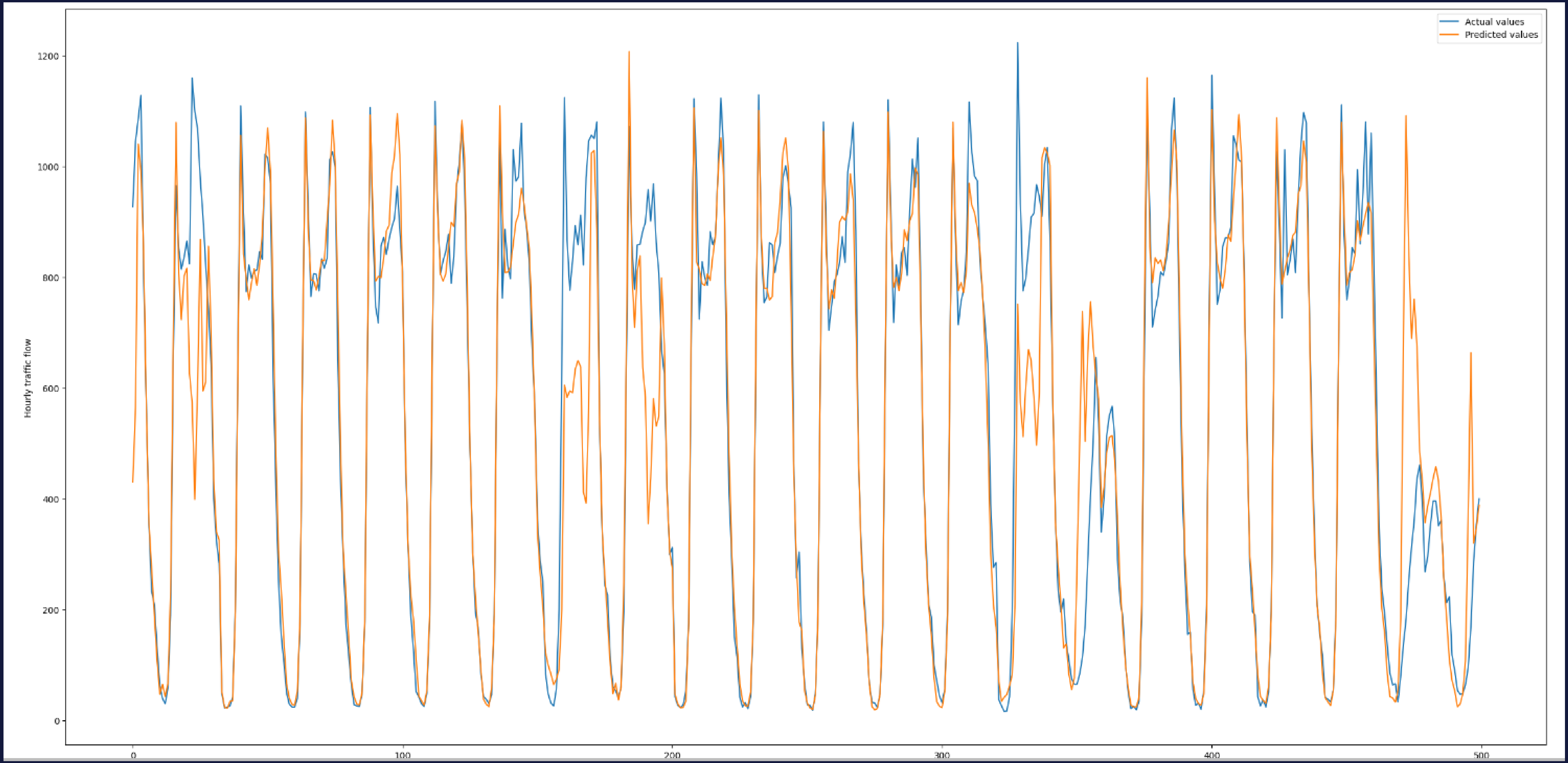
The convolutional layer contains 256 filters and BiLSTM layer contains 500 BiLSTM units (each of them is composed by a forward LSTM unit and a backward LSTM unit).

PREDECTION OF MODEL:

12 HOUR

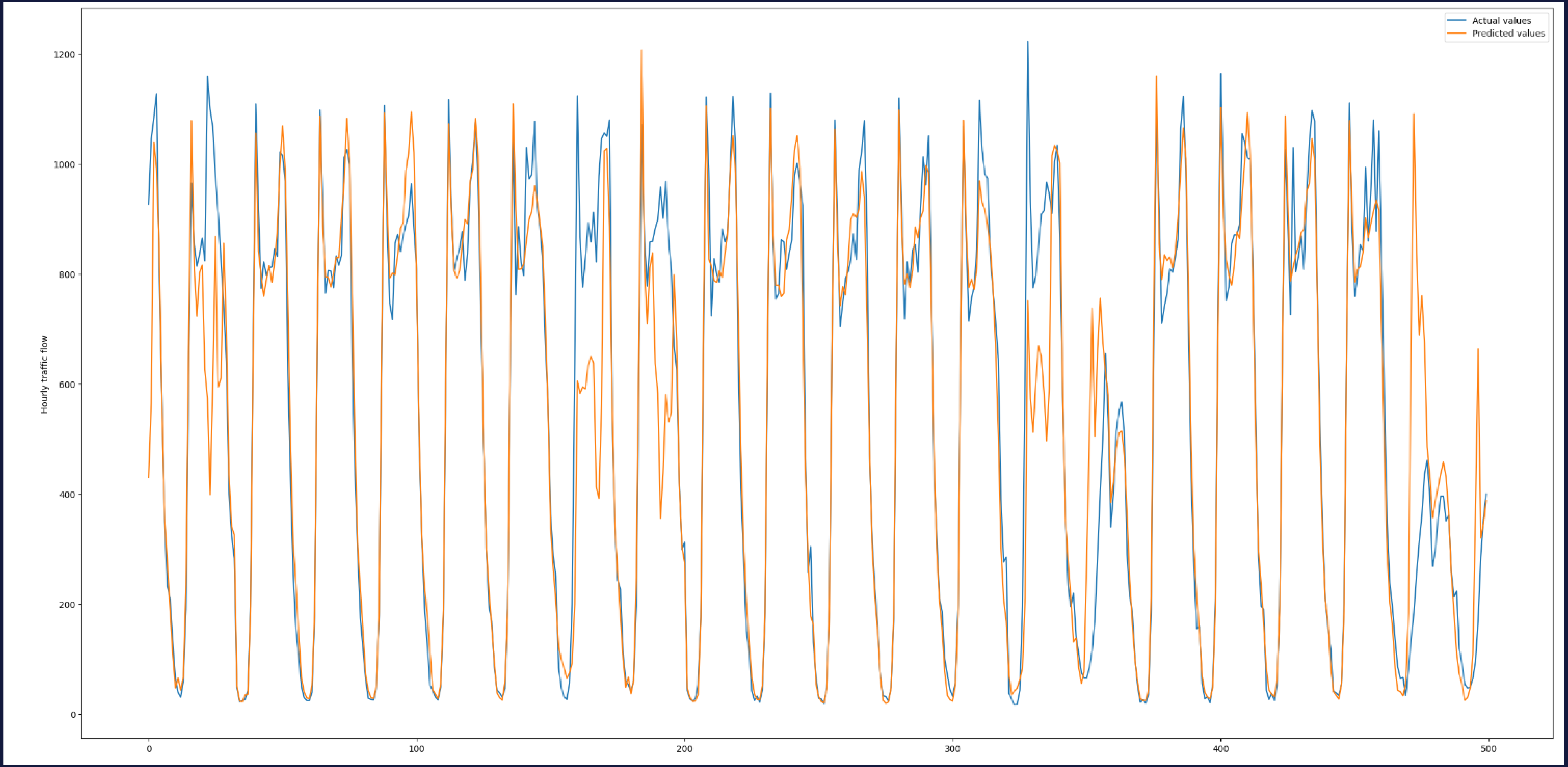


24 HOUR

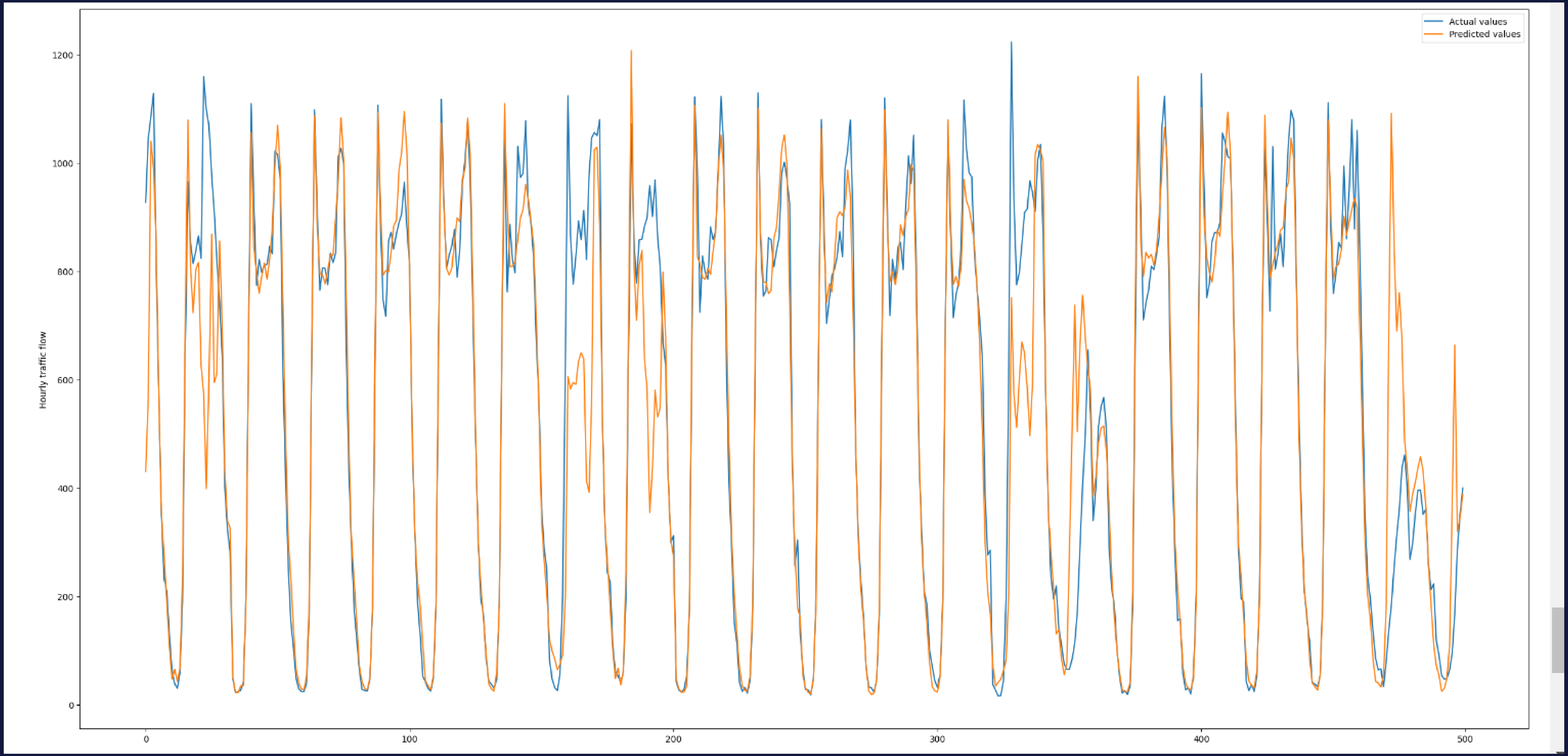


Actual values
Predicted values
Hourly traffic flow
1200
1000
800
600
400
200
0
100
200
300
400
500

48 HOUR

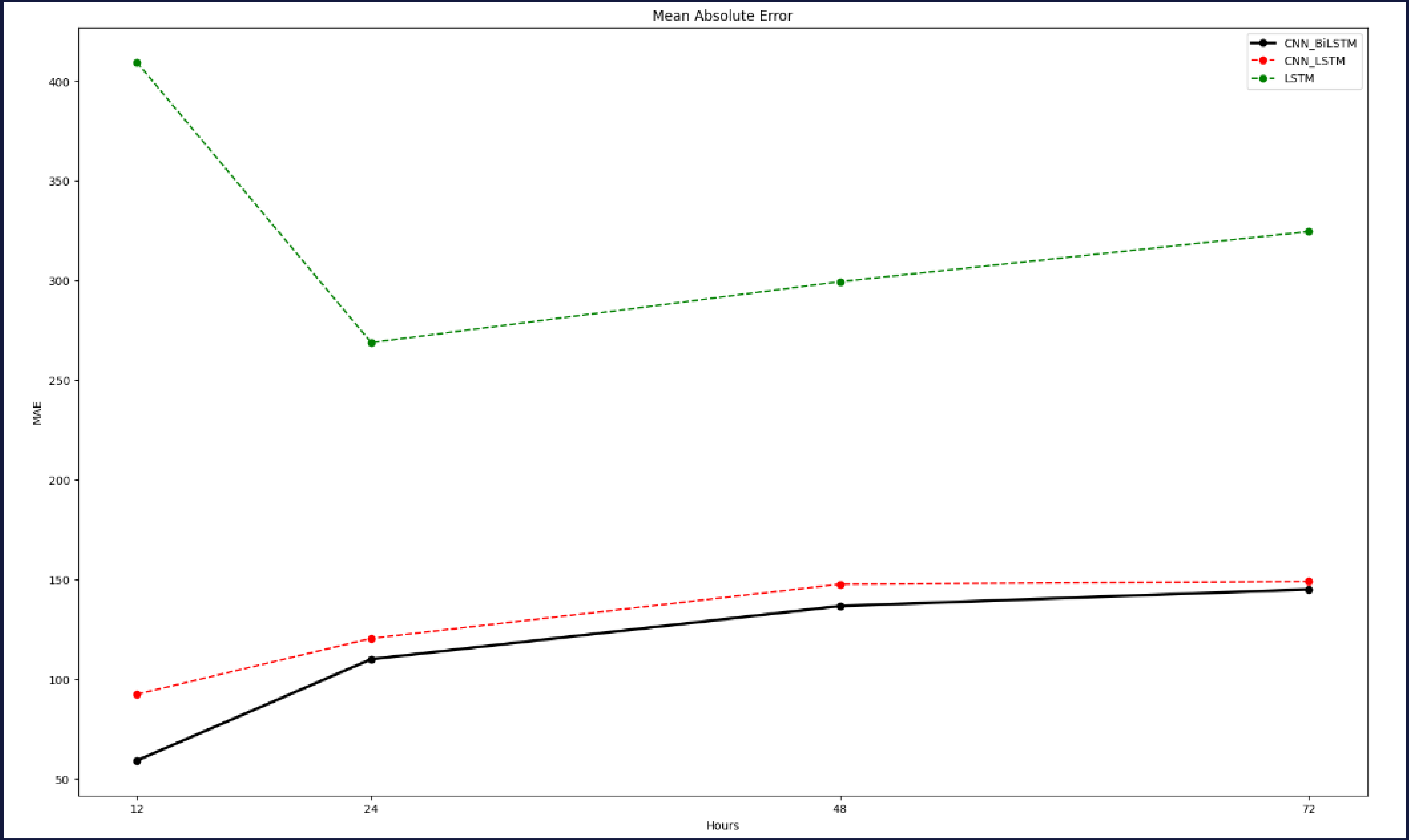

Actual values
Predicted values
Hourly traffic flow
0
200
400
600
800
1000
1200
0
100
200
300
400
500

72 HOUR

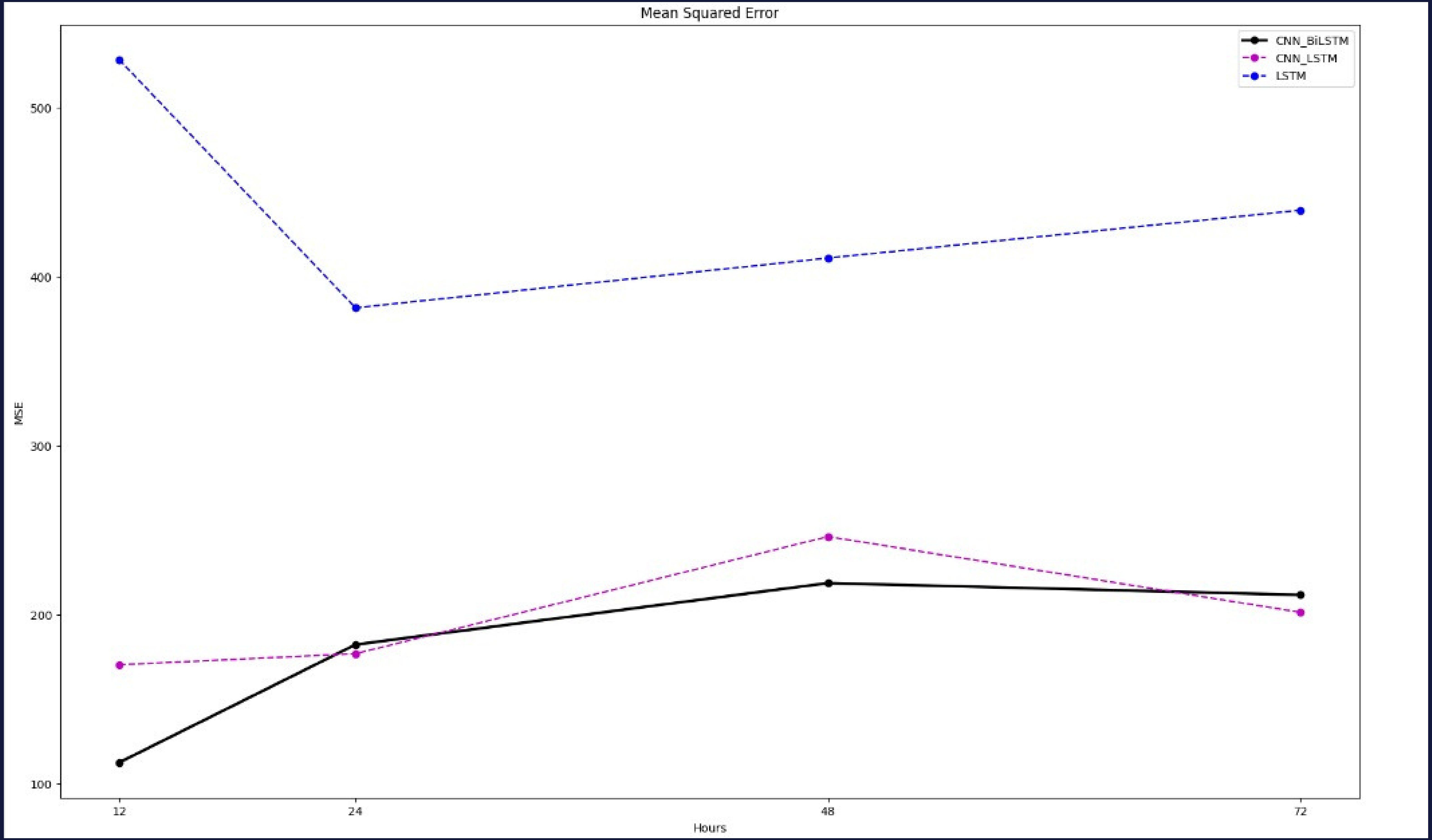


Actual values
Predicted values
Hourly traffic flow
1200
1000
800
600
400
200
0
0
100
200
300
400
500

MEAN ABSOLUTE ERROR:



MEAN SQUARED ERROR



REFERENCE PAPER BY:

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THANK YOU !!!

BY TEAM MAVERICKS