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MULTI-STEP URBAN TRAFFIC CONGESTION PREDICTION FOR SMART-CITY MOBILITY MANAGEMENT: A DATA-DRIVEN STUDY USING SENSOR AND WEATHER INFORMATION IN TRONDHEIM

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Reliable short-term traffic forecasting is a core requirement for smart-city mobility management because congestion affects travel time reliability, signal control, routing, safety, and local air quality. This study develops a multi-location, multi-step forecasting framework for hourly urban traffic prediction in Trondheim, Norway, using data from six fixed traffic sensors combined with synchronized weather observations. The empirical design uses hourly passenger-car counts collected from December 2018 through January 2020, merged with meteorological variables and calendar-derived seasonality indicators. After data fusion, missing-value treatment, feature selection, and time-lag restructuring through a 24 h sliding window, a direct forecasting strategy is implemented for a 24-step horizon. The modeling framework compares a broad set of machine-learning and deep-learning regressors, beginning with 17 one-step-ahead candidates and then retaining the seven best-performing ensemble tree-based models for full multi-step forecasting, while recurrent neural networks are trained in parallel for comparison.

The results show that interpretable ensemble tree-based methods dominate across the Trondheim case study. For the first forecasting step, Extra Trees achieves the highest accuracy in all six locations, with R^2 values of 98.16%, 97.64%, 94.76%, 95.12%, 97.31%, and 96.22%, respectively. Across the full 24 h horizon, model accuracy declines gradually with increasing lead time, but ensemble tree-based models remain consistently stronger than the tested recurrent neural networks. Extra Trees and Random Forest perform especially well at longer horizons, whereas Histogram-Based Gradient Boosting Regressor and Light Gradient Boosting Machine emerge as the most reliable models overall across locations and forecast steps. The resulting framework is well aligned with the aims of urban development and smart-city research because it demonstrates how city-scale sensing infrastructure and interpretable predictive analytics can support proactive congestion management and operational transport planning under limited historical data.

Index Terms — smart cities; urban traffic forecasting; intelligent transportation systems; multi-step prediction; machine learning; ensemble tree-based models; weather-informed mobility analytics

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INTRODUCTION

Urban traffic congestion remains one of the most persistent operational challenges facing contemporary cities. Congestion increases travel time uncertainty, worsens fuel consumption, contributes to local emissions, and reduces the overall efficiency of urban transport networks. Within smart-city research, these pressures have elevated the importance of Intelligent Transportation Systems (ITS), especially systems that transform sensor-based data streams into actionable forecasts for routing, signal timing, and mobility planning. In this context, data-driven traffic prediction is not merely a computational exercise; it is a core urban-management function.

The Trondheim case provides a useful smart-city setting for this problem. The city has an established roadside sensing network capable of recording hourly traffic flow, allowing urban mobility patterns to be monitored continuously. In a sensor-rich but still data-constrained environment, the key methodological question is not only whether traffic can be forecast accurately, but which model families remain dependable when the historical record is modest and the prediction horizon extends beyond a single step.

This manuscript presents a polished and self-contained study of multi-step urban traffic congestion prediction using traffic sensor data and weather information for six Trondheim locations. The article is explicitly framed for a journal focused on urban development and smart cities because it addresses urban mobility governance through: (i) city-scale IoT sensing, (ii) interpretable predictive modeling, and (iii) operational decision support for traffic management. Rather than emphasizing algorithmic novelty alone, the study evaluates which forecasting structures provide the strongest practical performance under realistic municipal data conditions.

The contributions of the study are fourfold:

1. it formulates traffic prediction as a *multi-location, direct multi-step* forecasting problem over a 24 h horizon;
2. it integrates traffic counts, local weather descriptors, and engineered seasonality variables in a unified feature space;
3. it systematically compares machine-learning ensembles and recurrent neural networks under the same evaluation protocol; and
4. it shows that interpretable ensemble tree-based models provide the most robust overall performance for smart-city traffic forecasting in Trondheim.

The remainder of the article is organized as follows. Section summarizes the smart-city and forecasting context. Section describes the case study, data sources, preprocessing, feature engineering, and modeling design. Section presents the empirical results. Section interprets the findings for urban mobility management, and Section concludes.

BACKGROUND AND SMART-CITY CONTEXT

A smart city seeks to improve quality of life and resource efficiency through digitally enabled, data-informed services. Among the most visible of these services are transport systems that use interconnected sensors, communications infrastructure, and predictive analytics to improve traffic operations. In such environments, traffic forecasting supports congestion mitigation, route guidance, demand anticipation, and the optimization of transport infrastructure.

From a methodological standpoint, transforming traffic forecasting into a supervised learning problem typically requires the conversion of sequential data into lagged tabular features. A sliding-window representation is a standard approach, allowing historical observations to be used as predictors for future values. When the forecasting goal extends beyond one step, three broad strategies are common: direct forecasting, recursive forecasting, and sequence-to-sequence forecasting. This study adopts the direct strategy because it generates explicit forecasts for each future step and supports transparent, step-specific model comparison.

The literature shows strong recent interest in both machine-learning and deep-learning approaches for traffic prediction. Tree-based ensemble methods are widely valued for interpretability, robustness, and computational efficiency, while recurrent neural networks are often used to model temporal dependency. Yet model choice remains highly data-dependent. In urban case studies with limited historical depth, strong performance from deep models cannot be assumed. This practical issue is especially relevant in smart-city deployments, where reliability, traceability, and training cost matter alongside predictive accuracy.

MATERIALS AND METHODS

Case Study and Data Sources

The empirical setting is the city of Trondheim, Norway. Two raw data sources were used:

1. Traffic flow data: hourly sensor measurements from six traffic locations in Trondheim, reporting the count of vehicles shorter than 5.6 m (passenger cars).
2. Weather data: hourly meteorological observations for the same city and time period.

The traffic series span December 2018 through January 2020. The weather series cover the same interval and include variables such as relative humidity, temperature, wind speed, cloud coverage, snow depth, precipitation, and timestamp. The six traffic locations capture distinct functional roles in the urban network. Location 1 is the highest-volume site, with an average of roughly 1850 vehicles per hour and the greatest observed variability (standard deviation of approximately 1400), reflecting its role as an entry point to Trondheim before a highway bridge. Location 2 records a lower mean flow of roughly 830 vehicles per hour as a feeder route to the highway. Locations 3, 4, and 5 are not on the primary route toward the city center and exhibit comparatively lower traffic volumes, while Location 4 functions as a highway ramp. Daily profiles across all locations show a pronounced morning peak near 08:00 and an evening peak around 16:00, with lower regular commuting activity on weekends and holidays.

Data Preprocessing

Traffic and weather data were merged by hourly timestamp. Missing values were handled through forward/backward linear interpolation when the missing segment was shorter than four consecutive timestamps and the percentage of missing entries remained below 5%. After missing-data treatment, normalization was applied for the non-tree-based modeling pathways by scaling values to the range $[-1, 1]$ using min-max scaling. This choice is consistent with common practice in time-series regression and improves optimization stability for neural architectures.

Feature Selection and Engineering

An automated feature-selection procedure was applied to the weather variables by combining Recursive Feature Elimination with Cross Validation (RFECV) and Sequential Forward Selection (SFS), both implemented with Light Gradient Boosting Machine as the evaluation model. This dual procedure identified the weather variables that were consistently most informative for forecasting.

In parallel, the timestamp field was decomposed into seasonality indicators to better represent recurring urban mobility patterns. In addition to standard temporal descriptors such as hour, day, and month, engineered features were added to reflect commuting behavior, including working-hour indicators, off-hour indicators, weekend flags, and 3 h intra-day bins.

Table 1 summarizes the selected exogenous variables used in model training.

Table 1: Selected weather and seasonality features used in the forecasting framework.

Feature group	Variables	Count
Selected weather variables	temperature, feels-like temperature, relative humidity, precipitation, snow depth, wind speed, sea-level pressure, visibility, solar radiation	9
Seasonality variables	quarter, month, hour of day, day of week, weekend indicator, off-hours flag, working-hours flag, 3 h time-interval bin	8
Exogenous feature total	Weather and seasonality variables combined before lag generation	17
Lagged exogenous representation	Previous 24 h lagged values extracted through the sliding-window procedure	24 lag steps

The source study reports that after combining the weather-related and seasonality features, the final exogenous feature space used for training consisted of 24 parameters, and the previous 24 h lagged values were extracted through the sliding-window method.

Forecasting Strategy and Model Families

The forecasting task uses a direct multi-step strategy with a 24-step horizon (24 h ahead). The full dataset was split chronologically into 80% training and 20% testing, corresponding to nearly ten months of training data and two months of testing data.

The modeling design proceeded in two stages. First, 17 one-step-ahead regressors were evaluated. These included ensemble tree-based methods (RF, LGBM, XGB, HGBR, ET, BR, GBDT), classical regression baselines, and neural alternatives. Based on first-step performance, the top seven models were retained for the full multi-step study. All seven shortlisted models were ensemble tree-based methods: RF, LGBM, XGB, GBDT, HGBR, ET, and BR. Hyperparameters for these models were then tuned using Grid Search Cross Validation.

In parallel, three recurrent neural network architectures were trained for comparison: LSTM, biLSTM, and GRU. These models used a three-dimensional sliding-window representation, whereas the tree-based models operated on the standard two-dimensional tabular form.

Table 2 lists the recurrent-network configuration employed in the comparative analysis.

Table 2: Recurrent neural network configuration used in the comparative analysis.

Parameter	LSTM	biLSTM	GRU
Hidden layers	1	1	1
Units per hidden layer	24	24	24
Activation function	ReLU	ReLU	ReLU
Batch size	16	16	16
Epochs	35	35	35
Optimizer	Adam	Adam	Adam
Dropout	0.2	0.2	0.2
Sliding-window length	24	24	24
Loss function	MAE	MAE	MAE
Early stopping patience	10	10	10

Evaluation Metrics

Model performance was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2), and the coefficient of variation of RMSE (CVRMSE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|, \qquad \mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}, \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}, \qquad \mathrm{CVRMSE} = \frac{\mathrm{RMSE}}{\bar{y}}. \tag{2}$$

Algorithm 1 Workflow for multi-location, multi-step traffic forecasting

Require: Hourly traffic counts from six Trondheim sensors; hourly weather records for the same time span
Ensure: Location-specific forecasts for horizons $h = 1, \ldots, 24$

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Acquire traffic and weather datasets from the public sources
Merge both datasets by hourly timestamp
Fill short missing sequences using forward/backward linear interpolation
Apply min-max scaling to [−1,1] for the non-tree-based model pathways
Select informative weather features using RFECV and SFS with LGBM
Generate seasonality variables from the timestamp
Build a 24 h sliding-window representation of the data
Train 17 candidate one-step-ahead regression models
Rank models by MAE, RMSE, R², and CVRMSE
Retain the seven best-performing ensemble tree-based models
Tune the retained models with grid-search cross validation
Train LSTM, biLSTM, and GRU models under the same forecasting setup
for h = 1 to 24 do
    Fit direct-forecast models for each location and evaluate on the held-out test set
    Select the best-performing model by location and forecast step
end for
Report location-wise and horizon-wise comparative performance
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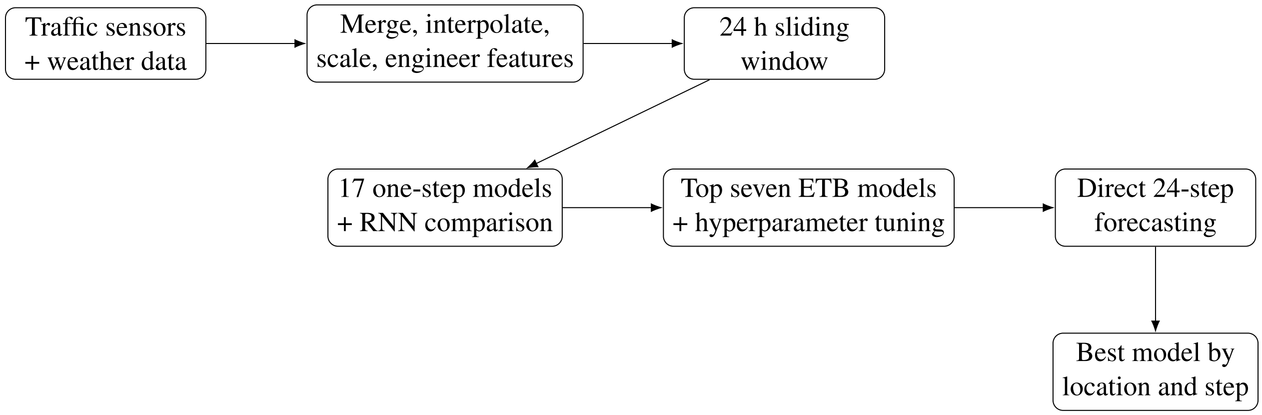

Figure 1: Operational workflow for the Trondheim traffic forecasting framework.

RESULTS

First-Step Forecasting Performance

The first-step results show a clear advantage for the ensemble tree-based methods. Among all evaluated models, Extra Trees is the best performer in each of the six locations. Table 3 reports the exact first-step results for ET, LGBM, HGBR, and the strongest recurrent neural benchmark at each site.

These results establish three immediate points. First, the predictive performance is high across all locations, even in a heterogeneous urban network. Second, the strongest models are consistently tree-based. Third, although the recurrent neural networks remain competitive in some locations, they do not surpass the leading ensemble methods in the aggregate first-step comparison.

Multi-Step Behavior Across the 24 h Horizon

The multi-step results preserve the same ranking pattern while revealing the expected decline in performance with increasing forecast distance. As the lead time grows, all models experience reduced accuracy, which is consistent with the known difficulty of direct multi-step forecasting. Even so, the ensemble tree-based models continue to dominate the recurrent neural baselines at nearly all forecast steps.

A key substantive finding is that Extra Trees and Random Forest perform especially well at longer horizons. By contrast, Histogram-Based Gradient Boosting Regressor and Light Gradient Boosting Machine show the strongest *overall* reliability when all locations and all 24 forecast steps are considered jointly. This distinction matters operationally: ET and RF are especially attractive when longer lead times are prioritized, whereas HGBR and LGBM offer the most stable all-purpose performance across the full prediction cycle.

Table 4 reports the exact frequency with which each ensemble tree-based model appears among the top seven performers during the first four steps and across all 24 steps.

Table 3: First-step-ahead forecasting results by location using exact source values.

Location	Model	MAE	RMSE	R^2 (%)	CVRMSE
1	ET	107.89	190.68	98.16	0.105
	LGBM	115.54	208.42	97.80	0.114
	HGBR	117.76	211.43	97.74	0.116
	Best RNN (LSTM)	210.01	354.80	93.66	0.194
2	ET	64.74	115.00	97.64	0.130
	LGBM	71.24	124.20	97.25	0.140
	HGBR	70.18	122.59	97.32	0.138
	Best RNN (GRU)	172.40	296.89	93.41	0.200
3	ET	24.69	39.45	94.76	0.134
	LGBM	26.27	42.56	94.95	0.145
	HGBR	26.26	42.29	94.79	0.144
	Best RNN (biLSTM)	38.99	60.25	93.73	0.195
4	ET	11.89	19.92	95.12	0.191
	LGBM	12.39	20.24	94.96	0.194
	HGBR	12.45	20.72	94.72	0.198
	Best RNN (GRU)	16.50	28.61	94.17	0.190
5	ET	34.44	56.59	97.31	0.131
	LGBM	37.51	59.43	97.04	0.137
	HGBR	37.34	37.34	97.04	0.137
	Best RNN (biLSTM)	49.98	81.29	94.74	0.179
6	ET	68.71	101.57	96.22	0.138
	LGBM	66.75	102.95	96.12	0.140
	HGBR	66.11	100.59	96.30	0.137
	Best RNN (biLSTM)	69.75	108.54	95.26	0.165

For Location 3, LGBM attains a marginally higher R^2 than ET, but ET remains the strongest overall first-step model when the full metric profile and all six locations are considered jointly.

Table 4: Frequency counts for the top seven ensemble tree-based models across the first four steps and across all 24 steps.

Location	RF	ET	HGBR	LGBM	XGB	GBDT	BR
First four forecast steps							
1	4	4	4	3	3	2	0
2	4	4	4	4	3	1	0
3	4	4	4	4	3	1	0
4	3	4	4	4	3	0	2
5	4	4	4	4	2	0	2
6	4	4	4	4	4	0	0
All 24 forecast steps							
1	24	23	22	21	17	8	5

The frequency pattern reinforces the model-ranking narrative. HGBR and LGBM appear with high regularity across locations and steps, while RF and ET display particularly strong dominance in specific locations and later horizons. GBDT and BR trail the leading ensemble models more consistently.

Interpretation for Smart-City Operations

From an urban-management perspective, the results are important for three reasons. First, they show that accurate traffic prediction is achievable from standard city sensing infrastructure without requiring extremely large datasets. Second, the strongest-performing models are interpretable ensemble methods that are easier to train, validate, and operationalize than more complex deep architectures. Third, the use of a 24 h horizon provides actionable lead time for practical ITS functions such as route advisories, congestion alerts, signal optimization, and daily mobility planning.

DISCUSSION

The Trondheim results indicate that model performance in smart-city traffic forecasting depends strongly on the interaction between data volume, forecast horizon, and model class. A central finding is that recurrent neural networks do not automatically outperform ensemble tree-based models in a relatively compact hourly dataset. This outcome is consistent with the broader practical observation that deep temporal models often require larger and more diverse training corpora to realize their theoretical advantages.

The strongest operational message is therefore methodological rather than purely algorithmic: for municipal traffic prediction tasks with moderate data availability, *interpretable tree ensembles are not merely competitive—they are preferable*. They provide high accuracy, low execution time, and strong stability across locations, all of which are desirable in urban decision-support environments.

The study is also well aligned with the substantive aims of urban development and smart-city scholarship. Urban transport is a central component of sustainable urban systems, and the integration of sensor infrastructure with applied predictive analytics directly supports smarter urban operations. By showing that robust forecasts can be generated from public traffic and weather data, the manuscript contributes to practical discussions of scalable, data-driven city management.

LIMITATIONS AND FUTURE RESEARCH

The study has several limitations. First, the empirical findings are conditioned by the statistical characteristics of the Trondheim dataset. Different cities, road hierarchies, or time granularities may yield different model rankings. Second, the training record covers roughly one year at hourly resolution; while this is sufficient for the current comparison, larger datasets would likely improve model generalization and may change the relative performance of deep-learning architectures.

Third, although the framework captures temporal and exogenous influences through weather and seasonality variables, it does not incorporate additional urban mobility signals such as public transit arrivals, incident data, ride-hailing demand, or lane-level operational changes. These features may encode spatial spillovers and hidden interactions across urban sub-areas more directly. Future work should therefore investigate more diverse traffic locations and sensors, incorporate closely related spatial variables, and reassess deep-learning performance under larger and more complex training datasets. The integration of traffic forecasting into broader smart-city frameworks, such as local electric-vehicle charging demand prediction or network-level mobility coordination, is also a promising direction.

CONCLUSION

This study presents a data-driven framework for multi-location, multi-step urban traffic congestion prediction using hourly traffic sensor data and weather information from Trondheim. The empirical design combines public traffic and weather records, automated feature selection, engineered seasonality variables, a 24 h sliding window, and a direct 24-step forecasting strategy. Across the full comparative analysis, ensemble tree-based methods consistently outperform the tested recurrent neural networks.

Extra Trees is the strongest model in the first-step forecasting comparison across the six monitored locations, while Extra Trees and Random Forest remain particularly effective at longer horizons. When the entire 24 h forecasting cycle is considered, Histogram-Based Gradient Boosting Regressor and Light Gradient Boosting Machine emerge as the most reliable overall models. These findings are operationally relevant because they show that smart-city traffic forecasting can achieve strong accuracy, interpretability, and computational efficiency without relying on data-intensive deep-learning approaches.

Taken together, the results support the use of interpretable ensemble methods as a dependable foundation for urban mobility analytics and intelligent transportation decision support in cities with moderate but realistic sensing capacity.

DATA AVAILABILITY

The study uses the same public traffic and weather sources described in the source case study. Traffic data were retrieved from the Norwegian Public Roads Administration traffic portal, and the weather observations were retrieved from the Visual Crossing weather service.

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