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Robust Decision-Making Framework for Sustainable Operations and Planning of MBTA Rapid Transit Vehicles

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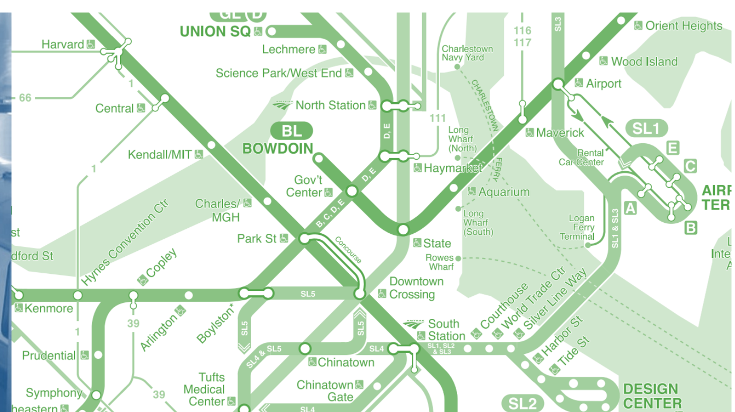

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16. Abstract
Urban Rail Transit (URT) systems play a critical role in modern cities but consume significant amounts of energy. Understanding and predicting energy consumption patterns in these systems is vital for sustainable urban planning, especially during disruptive events. This study presents a Long Short-Term Memory (LSTM) recurrent neural network, the model can accurately predict daily energy consumption and average daily temperature, with root mean squared errors (RMSE) of 50.6 MWh and 6.62°F. Additionally, a decision-making tool was developed to simulate various operational strategies and their impacts on energy consumption and temperature. These findings provide URT operators with a robust framework for making data-driven decisions and improving energy efficiency in URT systems.

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Robust decision-making framework for sustainable operations and planning of MBTA rapid transit vehicles
(RDMM)

Final Report

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Disclaimer

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Executive Summary

The urban rail transit (URT) system operated by the Massachusetts Bay Transportation Authority (MBTA) is the fourth busiest in the United States by passenger ridership. It comprises a light rail line (Green Line) and three heavy rail lines (Red, Orange, and Blue Lines). In 2019, the light and heavy rail systems of the MBTA area served 151 million rides and consumed 414 GWh of energy. In 2020, the system served 52 million rides yet consumed 385 GWh of energy. Given the medium to long-range planning required by the MBTA, there is an urgent need for decision support tools to facilitate effective and robust responses.

Given the medium to long-range planning required by the MBTA, particularly in light of imminent disruptive events (such as the recent pandemic) or natural disasters, there is an urgent need for decision support tools to facilitate effective and robust responses. Such a framework would allow planners at the MBTA's Energy and Environment division to reasonably predict the energy and cost impacts of a variety of strategies spanning schedule changes, train additions or removal, among others, in order to meet performance targets and budget constraints.

Data utilized in this study include energy consumption, train location data, tap-in ridership, and weather data from NOAA. This study used a Long Short-Term Memory (LSTM) recurrent neural network to predict daily energy consumption and average daily temperature. The modeling inputs included sequential historical energy data and temperature, with additional exogenous variables like ridership, number of trips, operating distance, and average speed. The results indicated that the model could reliably predict energy consumption with a root mean squared error (RMSE) of 50.6 MWh and temperature with an RMSE of 6.62°F. The high accuracy and reliability of this model underscore its effectiveness as an assistance of decision-making, providing urban planners and transportation authorities with valuable insights to improve energy efficiency and operational resilience in MBTA URT systems. A decision-making tool was developed to simulate various operational strategies and their impacts on energy consumption and temperature predictions. This tool allows for adjustments in operating distance, number of trips, and average speed, providing a valuable resource for MBTA officials in strategic planning.

The findings of this study offer a comprehensive framework for sustainable and energy-efficient planning of the MBTA URT system. The energy forecasting model and decision-support tool developed can aid in data-driven decision-making, enabling the MBTA to optimize operational strategies and enhance system resilience during disruptive events. The study underscores the importance of incorporating detailed operational data and scenario analysis in urban transit planning to achieve sustainability goals.

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List of Acronyms

Acronym	Expansion
DOT	Department of Transportation
EIA	Energy Information Administration
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration
MAPE	Mean Absolute Percentage Error
MassDOT	Massachusetts Department of Transportation
MBTA	Massachusetts Bay Transportation Authority
MAPE	Mean Absolute Percentage Errors
NOAA	National Oceanic and Atmospheric Administration
RMSE	Root Mean Squared Error
GTFS	General Transit Feed Specification
LSTM	Long short-term memory

1.0 Introduction

In today's rapidly urbanizing world, with the increasing threats of climate change impacts, pandemics and other extreme events, there is a growing need for transit systems to respond well to disruption. Particularly vulnerable to these disruptions are urban rail transit (URT) systems, which are often indispensable to the regions they serve and provide efficient transportation to millions of people daily [1]. However, the operations of these extensive transportation networks incur significant energy demands, accounting for a substantial portion of total energy consumption in many areas, and costing millions of dollars annually [2]. In 2019, operating rail transit systems in the United States consumed a substantial amount of energy, totaling 4953 GWh. At the same time, these systems facilitated a considerable volume of travel, with annual passenger miles reaching about 20 billion [3]. Moreover, the patterns of energy consumption significantly vary among different rail systems. For instance, electricity consumption in Beijing surged from 650 GWh in 2006 to 1400 GWh in 2017 [4]. An effective energy forecasting model thus serves not only as a tool for proactively managing demand in a sustainable and economical manner but also as a critical asset in planning and maintaining resilience under disruption.

Decision-making, forecasting, and assessment of the environmental impact played important roles in the URT systems. A tool based on fuzzy logic and algorithms has been developed to mitigate CO2 emissions from transportation, underlining the significance of stakeholder engagement and transparency in decision-making for sustainable transportation [5]. Sustainability indicators have been demonstrated to play a crucial role in guiding transportation planning and policy-making, particularly when there are well-established monitoring criteria [6]. The complexity of urban traffic systems and the multifaceted impacts of URT systems on traffic, economy, society, and environment can be practically analyzed using a system dynamics model [7]. Diverse forecasting models have been used to project the energy usage of URT systems in different contexts. For instance, in Queensland, Australia, the multivariate adaptive regression spline (MARS) and support vector regression (SVR) models were applied to short-term electricity demand forecasting. The MARS model was found to perform well for 0.5 and 1.0-hour predictions, whereas the SVR model excelled in daily forecasting, especially when considering various parameters such as weather data and economic factors [8]. Furthermore, binary nonlinear fitting regression (BNFR) and SVR models were also used to forecast energy consumption in URT. It was observed that the SVR model accurately predicted traction and total electricity consumption. However, both models faced challenges with HVAC system predictions due to complex influencing factors [9].

In spite of the various energy modeling efforts for urban rail transit systems, there remains a notable gap in their ability to effectively assist planners in evaluating how energy consumption could change in response to operational alterations. Current models do not specifically cater to the analysis of disruption-response strategies and their potential energy outcomes, highlighting a crucial need to address the current gap in research regarding energy planning for URT systems. In this paper, we estimate a system-energy forecasting model using planning variables as exogenous variables. The URT system in Boston served as the study area. Through scenario analyses, we demonstrate how such a model can be used to support decision-making in response to disruption for sustainable and energy-efficient outcomes.

In order to facilitate effective planning for current and future needs, the MBTA requires a framework that not only provides important consumption metrics but also explains the various contributors to energy consumption and their interactions. Furthermore, this framework should also be useful for predicting energy usage in order to evaluate the relevant impacts of proposed strategy decisions, particularly in response to disruptive events or financial constraints. Ultimately, there is a critical need to reduce costs while still meeting the mobility needs of the surrounding communities in the Boston area.

1.1 Aim and objectives

The overall aim of this project is to develop an energy planning tool that the MBTA can utilize to provide detailed energy forecasts for any given planning strategy defined by a set of planning metrics. Thus, the specific objectives are:

- Enumerate and analyze high-level operational planning metrics relevant the MBTA decision-making process
- Train a generative model that provides energy forecasts from the planning metrics
- Develop a decision-support tool with a user-friendly interface that the MBTA can use to specify planning strategies and compare energy outcomes of various plans.

Report Structure

The rest of the report is organized as follows. In Chapter 2, we describe the data structures and sources used in the project. In Chapter 3, we present the methods, followed by the results in Chapter 4. These consist of the performance of model prediction on energy and temperature. We conclude in Chapter 5 with a summary of our findings.

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2.0 Data Summary

We utilized the following types of data and sources for this project:

1. Energy consumption data from 2019 through 2021 (provided by the MBTA as Excel spreadsheet)
2. Timestamped train location (latitude and longitude) data from the MBTA Research Database (for light and heavy rail vehicles)
   a. Tables obtained from 2019 and 2021
3. Timestamped tap-in ridership, also from the MBTA Research Database
   a. Tables obtained from 2019 to 2021
4. Daily average temperature for Boston from 2019 and 2021 (obtained from National Oceanic and Atmospheric Administration (NOAA) historical records)
5. General Transit Feed Specification (GTFS) for MBTA from 2019 to 2021

2.1 Study area

The case study area for the forecasting model was the Massachusetts Bay Transportation Authority's (MBTA) urban rail transit (URT) system (Figure 1). The fourth largest transit agency in the U.S., the MBTA URT served 1.7 billion passenger miles in the area in [10]. Comprising a light rail line (Green Line) and three heavy rail lines (Red, Orange, and Blue Lines), this network accounted for an annual average electricity consumption of 422 GWh at a cost of approximately $38 million between 2009 and 2020 [11].

In addition to system energy aggregated at the daily level, we obtained five planning variables—ridership, operating speed, distance, and operating time and average speed---at the same temporal resolution to serve as predictive variables for energy consumption. The planning variables were selected as possible instruments for modifying service in order to plan for sustainability as well as respond to disruptive events. We sourced energy data directly from the MBTA, while the planning variables were derived from the MIT-MBTA research database [10,11].

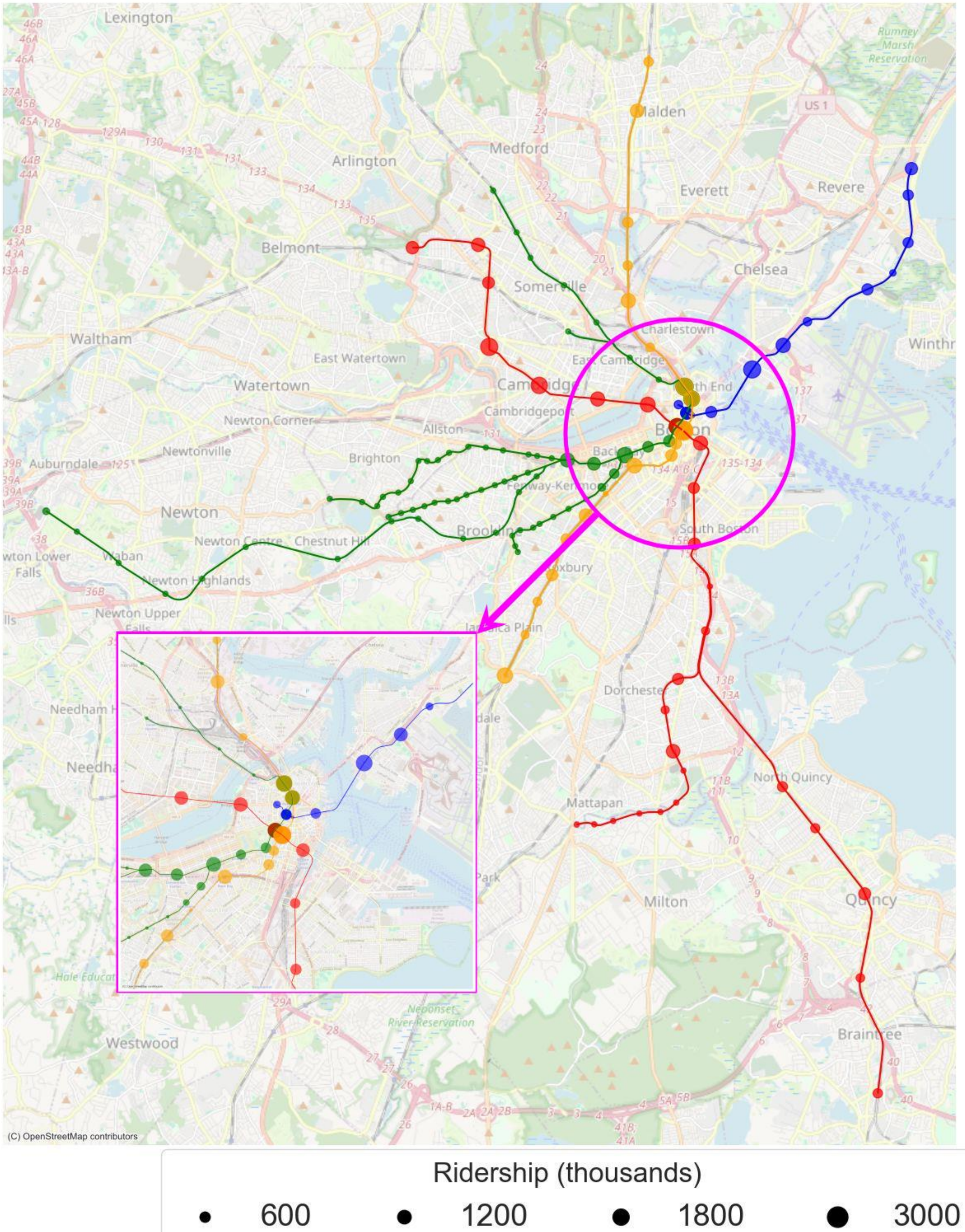

Figure 1 The map of MBTA urban rail transit system with the marker size indicating the annual ridership in 2021 across stations

2.2 Energy consumption

We collected and analyzed system energy data from the MBTA urban rail transit rail network over the period 2019 to 2021. The data were obtained from energy meters installed throughout the system and captured at an hourly resolution. For the purpose of our analysis, however, we aggregated this data into daily totals as shown in Figure 2.

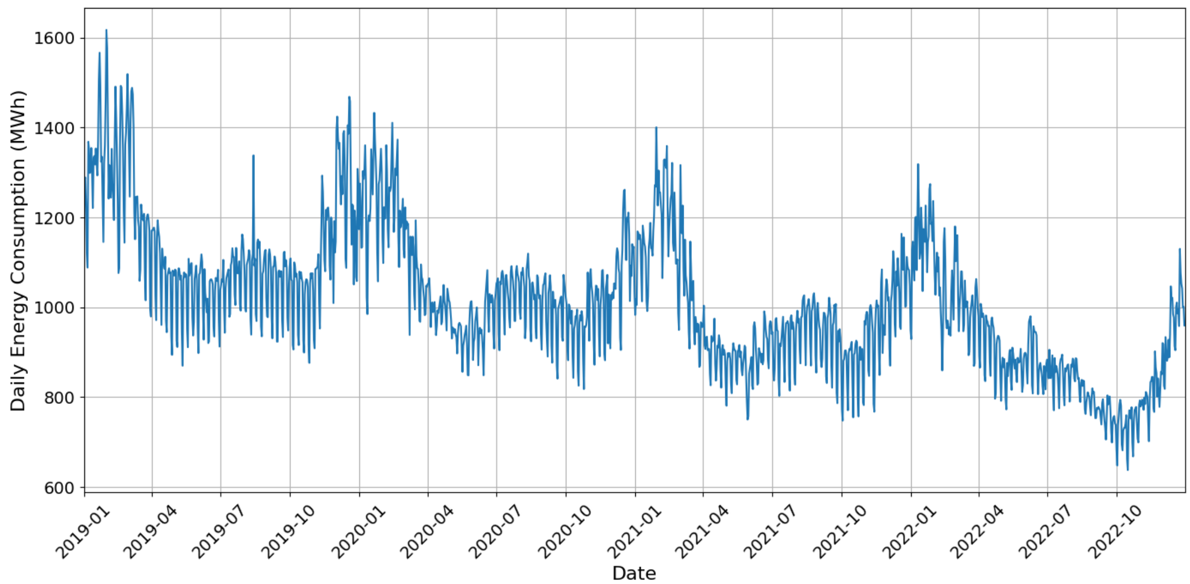

Figure 2 The daily energy consumption time series from 2019 to March in 2023

Figure 3 provides a visual representation of the distribution of energy consumption over the years. This graphical illustration offers insights into temporal trends and patterns in energy usage, facilitating a better understanding of how consumption has evolved over time. In 2019, the mean daily system energy was 1135 MWh, with a median of 1093 MWh. The maximum system energy reached roughly 1617 MWh, while the minimum was around 870 MWh. In 2020, both the mean and median system energy decreased, reflecting a lower overall energy consumption compared to the previous year. The mean system energy was around 1049 MWh and the median was 1029 MWh. The maximum system energy also decreased to around 1433 MWh, while the minimum slightly decreased to 18 MWh. This trend continued into 2021, with further reductions in both the mean and median system energy, which were approximately 976 and 958 MWh respectively. The maximum system energy also decreased to around 1401 MWh. Interestingly, the minimum system energy decreased considerably to 748 MWh, suggesting a reduction in the lowest level of energy consumption in the system.

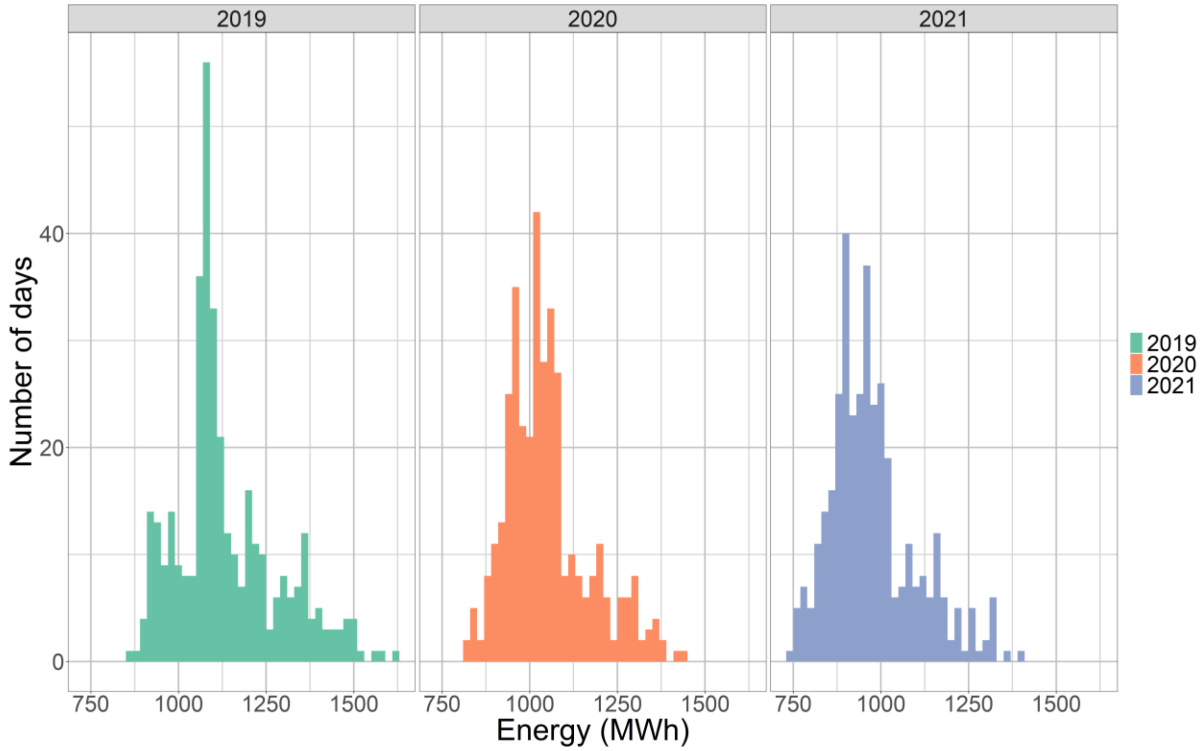

Figure 3 The daily energy distributions in each year from 2019 to 2021

The URT system witnessed a consistent decrease in energy consumption from 2019 to 2021 because of COVID-19. This analysis provides crucial insights for understanding the system's energy performance, which could inform energy-saving strategies and sustainability measures for the URT system.

2.3 Ridership

Figure 4 reveals variations in total ridership from January 2019 to December 2021, with an initial period of high and relatively stable ridership levels until early 2020. The onset of the COVID-19 pandemic in March 2020 led to a dramatic and immediate drop in ridership, reflecting the impact of lockdowns and travel restrictions. This sharp decline marked a significant disruption in train operations, with ridership remaining low through much of 2020. As restrictions gradually eased and vaccines were rolled out, a slow recovery began around mid-2020.

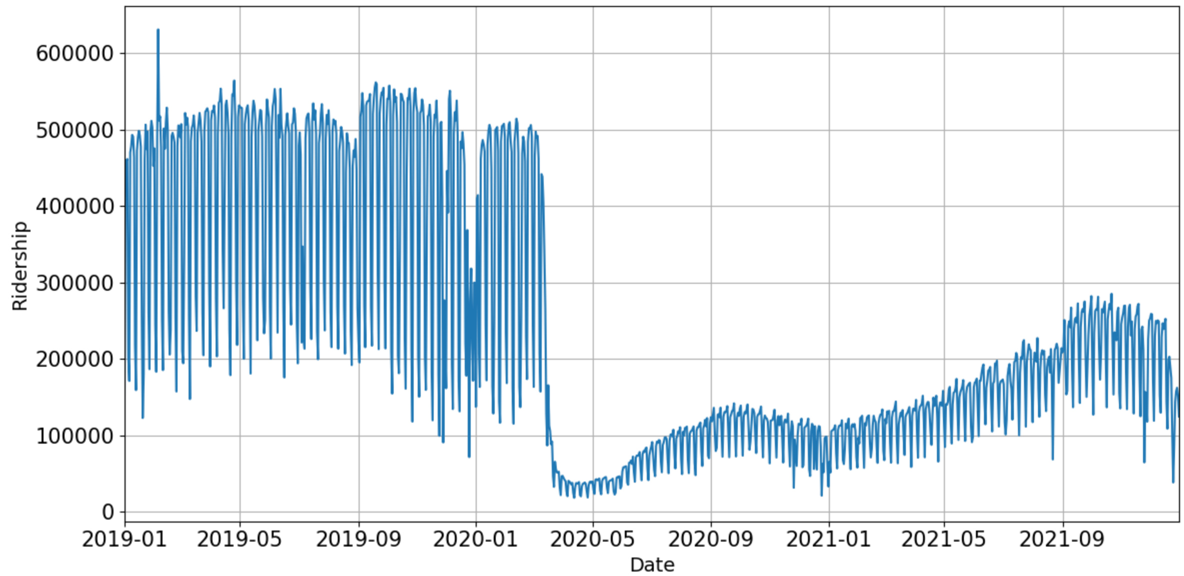

Figure 4 The daily ridership distribution across months from 2019 to 2021

2.4 Weather

We obtained average daily temperatures in Boston from the National Oceanic and Atmospheric Administration (NOAA) database for the years 2008 through 2020. Figure 5 shows the time series of the temperatures from 2019 to 2021. As expected, we observe a seasonal pattern in the data.

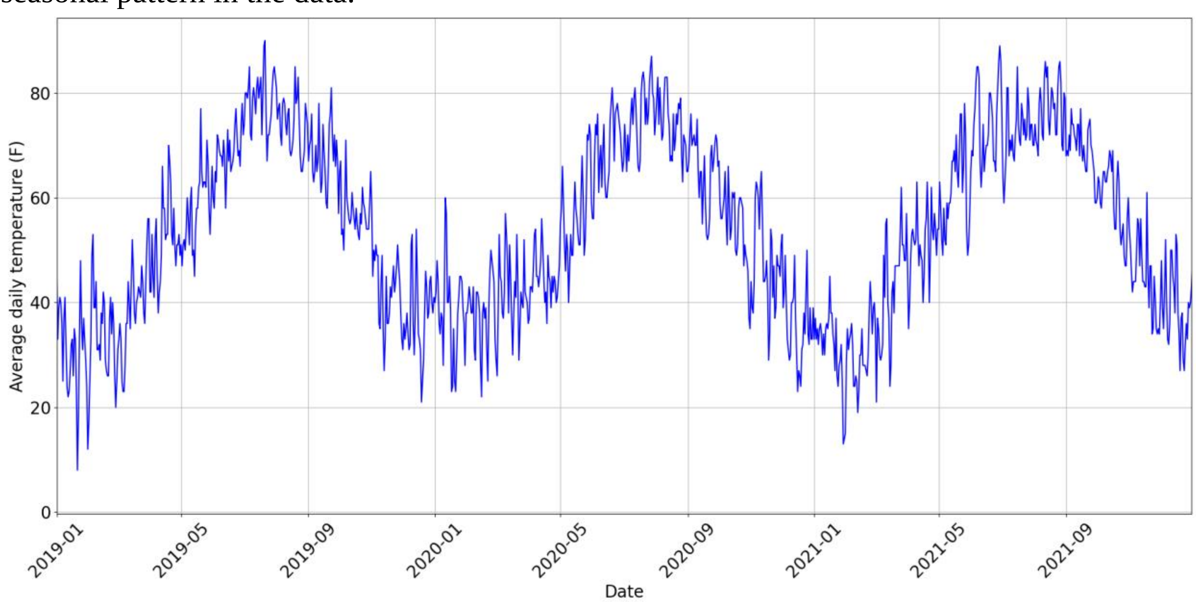

Figure 5 Average daily temperature in Boston from January 2019 through December 2023 (Source: NOAA)

2.5 Operating distance

We compiled line-specific daily operating distances from the high-resolution train location data obtained from the MBTA database shown in Figure 6. The Mattapan is a branch of the Red Line that is a light rail, and thus, we compute metrics for this branch separately. To begin with, the Green Line, which is a light rail, exhibits the highest daily operating distance across the years 2019 to 2021. However, there has been a decrease in both the mean and median operating distance over the years. The mean distance dropped from approximately 18,797 miles in 2019 to about 15,779 miles in 2021, indicating a decrease of 16% on the Green Line. The minimum operating distance also decreased by 29% over the same period.

In contrast, the heavy rail lines have considerably lower operating distance than the Green Line. Among the heavy rail lines, the Red Line reports the highest mean and median distance, followed by the Orange Line, with the Blue Line trailing behind. The Red Line showed a slight increase in mean operating distance from 2019 to 2020, but then a decrease in 2021. Despite these fluctuations, the Red Line's operating distance remains noticeably higher than the Blue and Orange Lines. The Blue Line exhibited a slight decrease in mean and median operating distance from 2019 to 2021. The maximum operating distance for the Blue Line also decreased during this period, but interestingly, the minimum operating distance increased. This suggests a possible narrowing of the range of operating distance over these years. The Orange Line, however, saw an increase in the mean operating distance from 2019 to 2020, followed by a decrease in 2021. Its maximum operating distance followed a similar trend, whereas the minimum distance increased significantly from 2019 to 2020 and then slightly decreased in 2021.

While the light rail component (Green Line) still has the highest operating distance, there is a noticeable downward trend over the years. Among the heavy rail systems, there are some fluctuations in the operating distance, with the Red Line consistently outperforming the others.

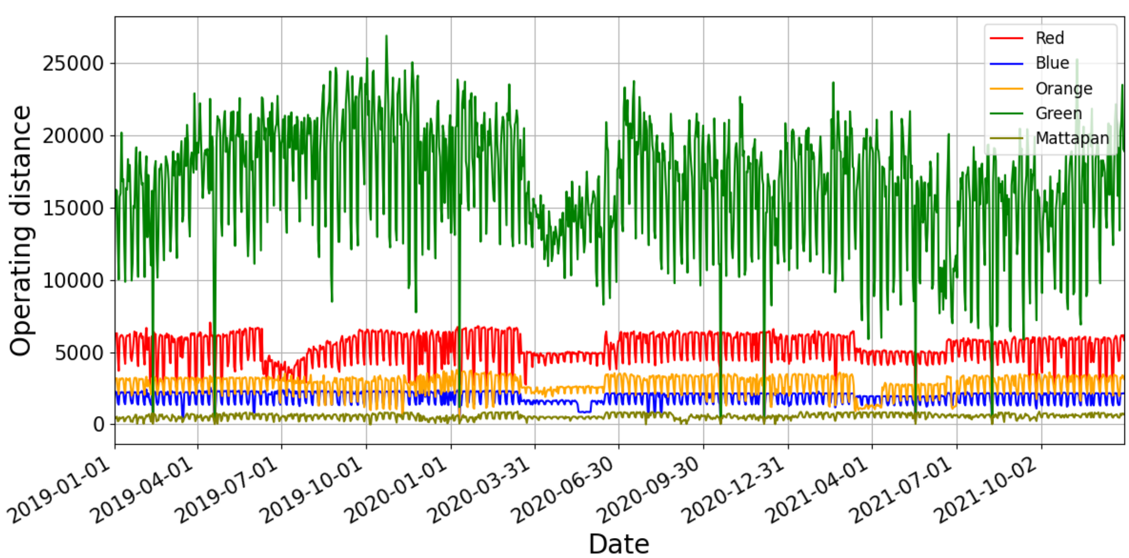

Figure 6 Time series of the daily operating distance from 2019 to 2021

2.6 Operating time

The operating time refers to the total duration for which all the trains across each line are in operation. It was calculated from trajectory data and aggregated to the daily level. The line-specific time series of the daily operating time from 2019 through 2021 are shown in Figure 7.

We observe that the Green Line (light rail) has the highest operating time among all lines, as shown in Figure 7. However, a decreasing trend is observed in the mean and median operating hours from 2019 to 2021. This aligns with the observed trend in operating distance, indicating a potential reduction in service hours or frequency. The maximum operating hours also decreased during this period, but the minimum hours increased slightly, hinting at a possible reduction in the variability of operating hours. For the heavy rail lines, the Red Line exhibits the longest operating hours, followed by the Orange Line, with the Blue Line operating for the shortest hours. The Red Line experienced a decrease in its mean and median operating hours from 2019 to 2021, but the minimum operating hours increased, which might suggest a greater consistency in service hours. The Orange Line also showed a decrease in the mean and median operating hours from 2019 to 2021. Interestingly, while the maximum operating hours decreased over this period, the minimum operating hours in 2020 increased compared to 2019, followed by a significant decrease in 2021. The Blue Line, similar to the other lines, showed a decrease in mean and median operating hours from 2019 to 2021. Both the maximum and minimum operating hours saw minor fluctuations during this period.

The operating hours mirror the patterns observed in the operating distance. The Green Line, despite its decreasing trend, still operates for the longest hours. Among the heavy rail lines, the Red Line consistently leads in operating hours.

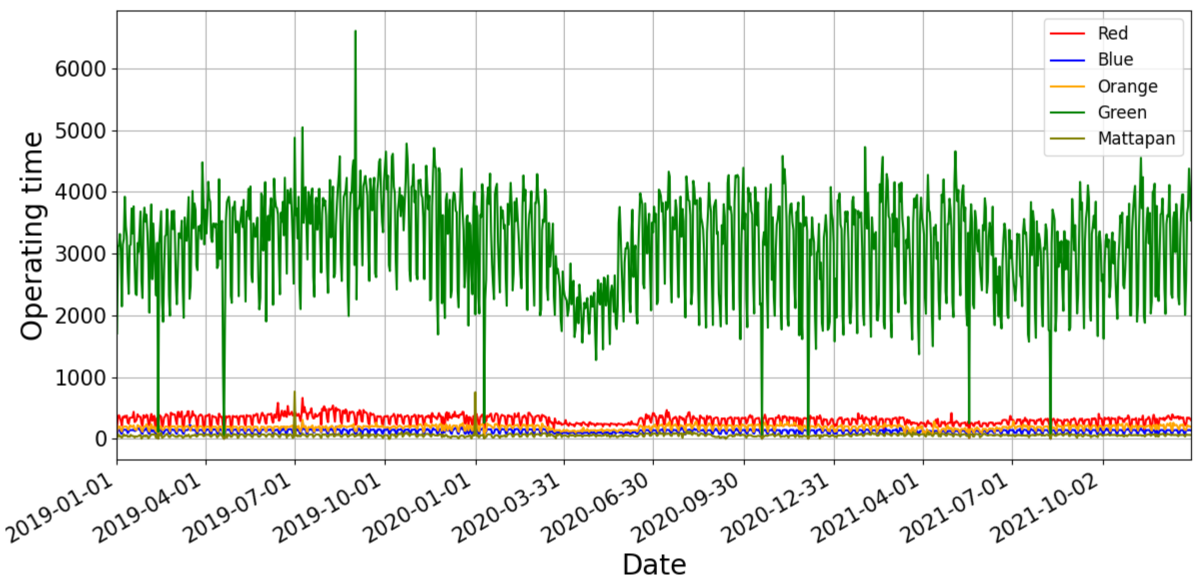

Figure 7 Time series of the daily operating time from 2019 to 2021.

2.7 Planning metrics

We collected the train schedules from the GTFS data. Based on our discussions with the MBTA planning team, we identified daily trips, daily operating distance, and average speed by Line as the planning metrics to extract from the schedules.

2.7.1 Daily trips

Figure 8 depicts the daily trips for each Line from January 2019 to January 2022. The Green Line consistently shows the highest number of daily trips, peaking around 1400 trips per day. This indicates that the Green Line is the most frequently used line in the system. In contrast, the other lines show significantly lower daily trips, with the Red Line averaging around 400 trips per day, and the Blue, Orange, and Mattapan Lines showing even fewer trips.

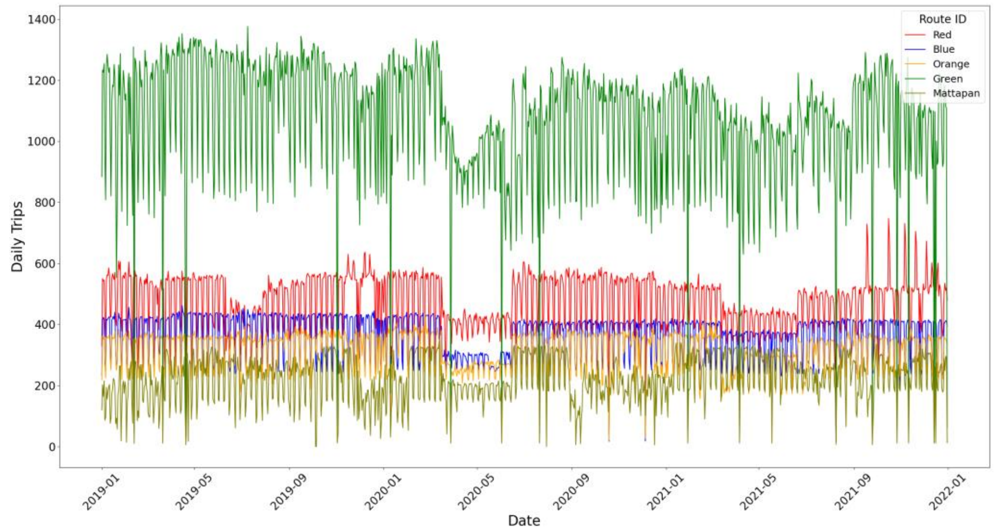

Figure 8 Time series of the scheduled daily trips across different Lines

2.7.2 Average daily speed

Figure 9 illustrates the average daily speeds by Line of a transit system from January 2019 to December 2021. The Red, Blue, Mattapan, and Orange Lines generally maintain higher average speeds, ranging between 16 to 20 mph. These lines exhibit relatively consistent speeds over the observed period, with some minor fluctuations. The Green Line, however, shows significantly lower average speeds, mostly ranging between 8 to 12 mph. This discrepancy could be attributed to the Green Line is the only light rail in the system.

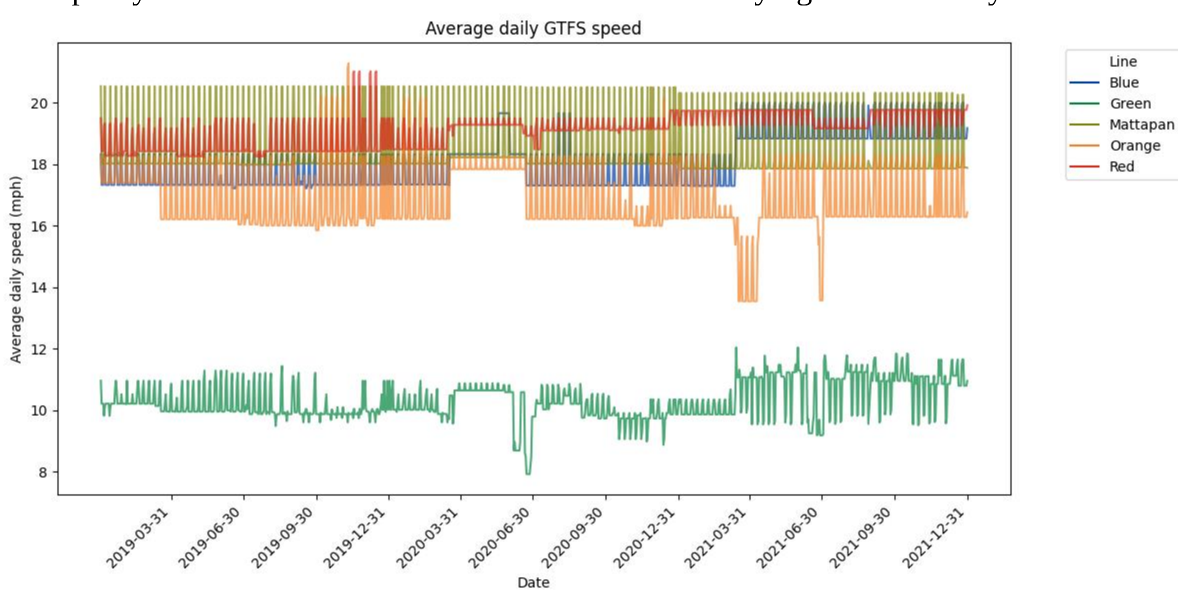

Figure 9 Time series of the scheduled average daily speeds across different Lines

2.7.3 Operating distance

Figure 10 shows the scheduled operating distances of different Lines from early 2019 to the end of 2021. The Green line exhibits the highest and most variable operating distances, frequently fluctuating between approximately 6000 and 9000 miles. Both the Red and Orange lines maintain relatively stable distances, with the Red line covering between 6000 and 8000 miles and the Orange line between 4000 and 6000 miles. These lines show some periodic adjustments, suggesting a consistent service pattern with occasional operational changes. All lines experienced a significant reduction in operating distance around mid-2020, likely due to the COVID-19 pandemic, followed by a gradual recovery.

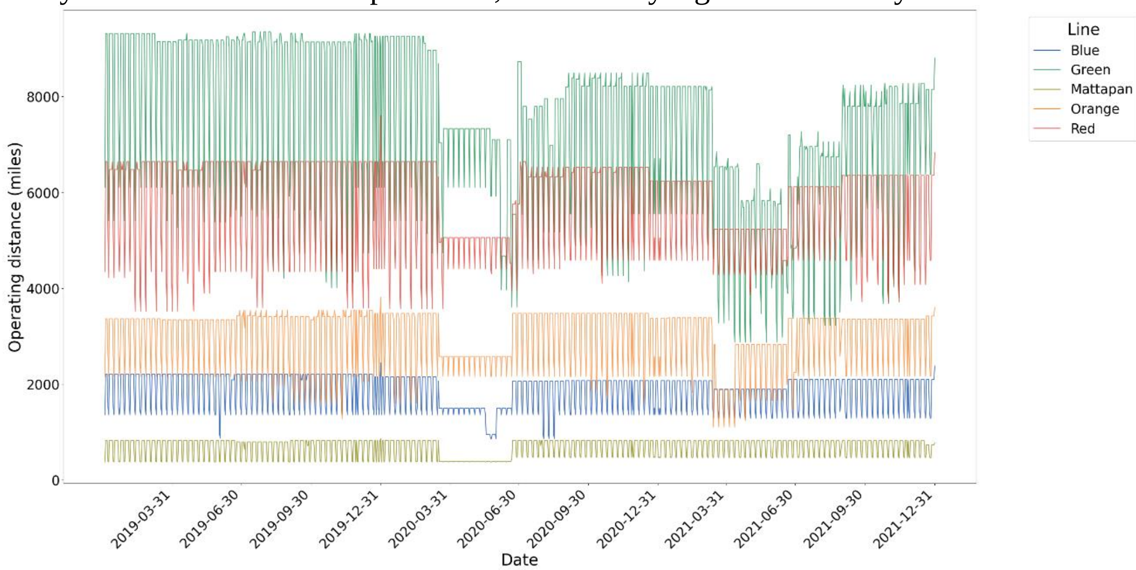

Figure 10 Time series of the scheduled operating distance across different Lines

2.8 Correlation between running time and operating distance

Figure 11 reveals the relationship between operating distance (in miles) and running time (in hours) for different transit lines. Across all lines, there is a clear positive correlation between operating distance and running time. Given the strong linear relationships observed, it is feasible to express the relationship between operating distance and running time using linear equations. In this way, we can efficiently compute the running time given the operating distance and vice versa. Understanding these patterns allows for the development of predictive models that can enhance planning efficiency.

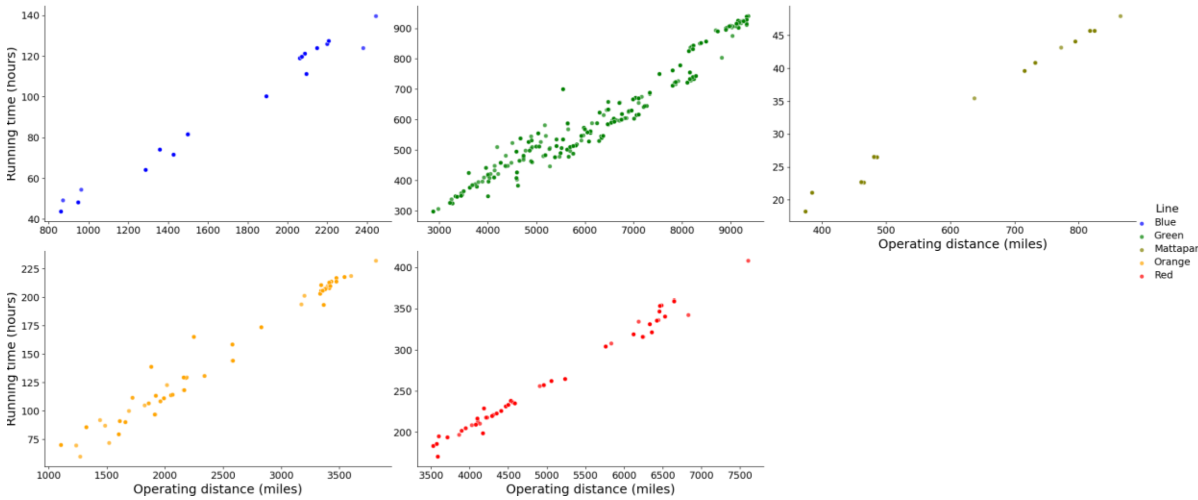

Figure 11 Correlation between running time and operating distance by Line

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3.0 Research methodology

3.1 Noise estimation and generation

Based on our analysis of actual train trajectories and schedule data, we identified a discrepancy between actual operations and scheduled times. To address this, we estimated the distributions of these discrepancies using a systematic approach. First, we computed the discrepancies and tested multiple predefined distributions (such as normal, exponential, gamma, etc.). For each distribution, we estimated the parameters that maximize the likelihood of observing the given data under that distribution. We then computed goodness-of-fit statistics (such as AIC, BIC, and others) to assess how well each distribution fit the data as shown in Figure 12. The distribution with the best goodness-of-fit statistics was selected as the best-fitting distribution as shown in Table 1.

Table 1 The summary of the estimated distributions of discrepancies for each planning metric by Line

Planning metrics	Line	Estimated distributions	Estimated Parameters
Average daily speed (mph)	Red	Exponential power	(0.88, -2.21, 7.79)
	Orange	Exponential power	(0.58, -1.40, 2.07)
	Blue	Exponential power	(0.87, 1.43, 3.59)
	Green	Cauchy	(4.73, 0.38)
	Mattapan	Exponential power	(0.29, 5.3, 1.28)
Operating distance (miles)	Red	Rayleigh	(-6350.27, 4209.57)
	Orange	Power law	(3.38, -3502.01, 4396.01)
	Blue	Power law	(4.11, -2240.23, 2885.58)
	Green	Cauchy	(10455.29, 1515.99)
	Mattapan	Power law	(1.50, -826.48, 1280.53)
Number of trips	Red	Cauchy	(-97.51, 14.38)
	Orange	Power law	(3.38, -3502.01, 4396.01)
	Blue	Power law	(0.51, -74, 308)
	Green	Power law	(0.56, -218, 149)
	Mattapan	Power law	(1.24, -179.23, 505.23)

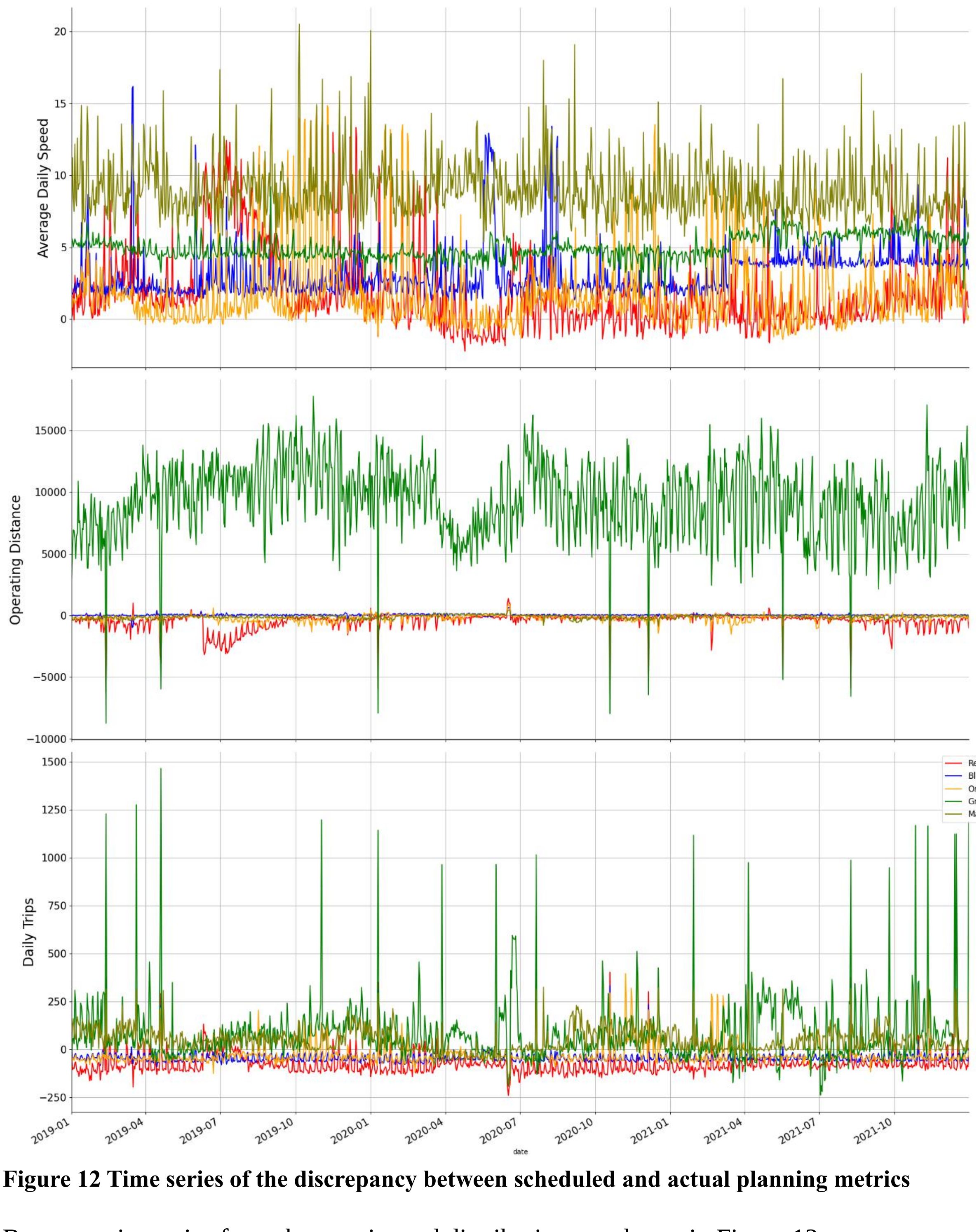

Figure 12 Time series of the discrepancy between scheduled and actual planning metrics

By generating noise from these estimated distributions as shown in Figure 13, we can simulate new variations as new data is obtained. This generated noise can then be added to the schedule, resulting in predictions that more closely align with real operations. This method allows us to measure the differences more accurately and improve schedule precision.

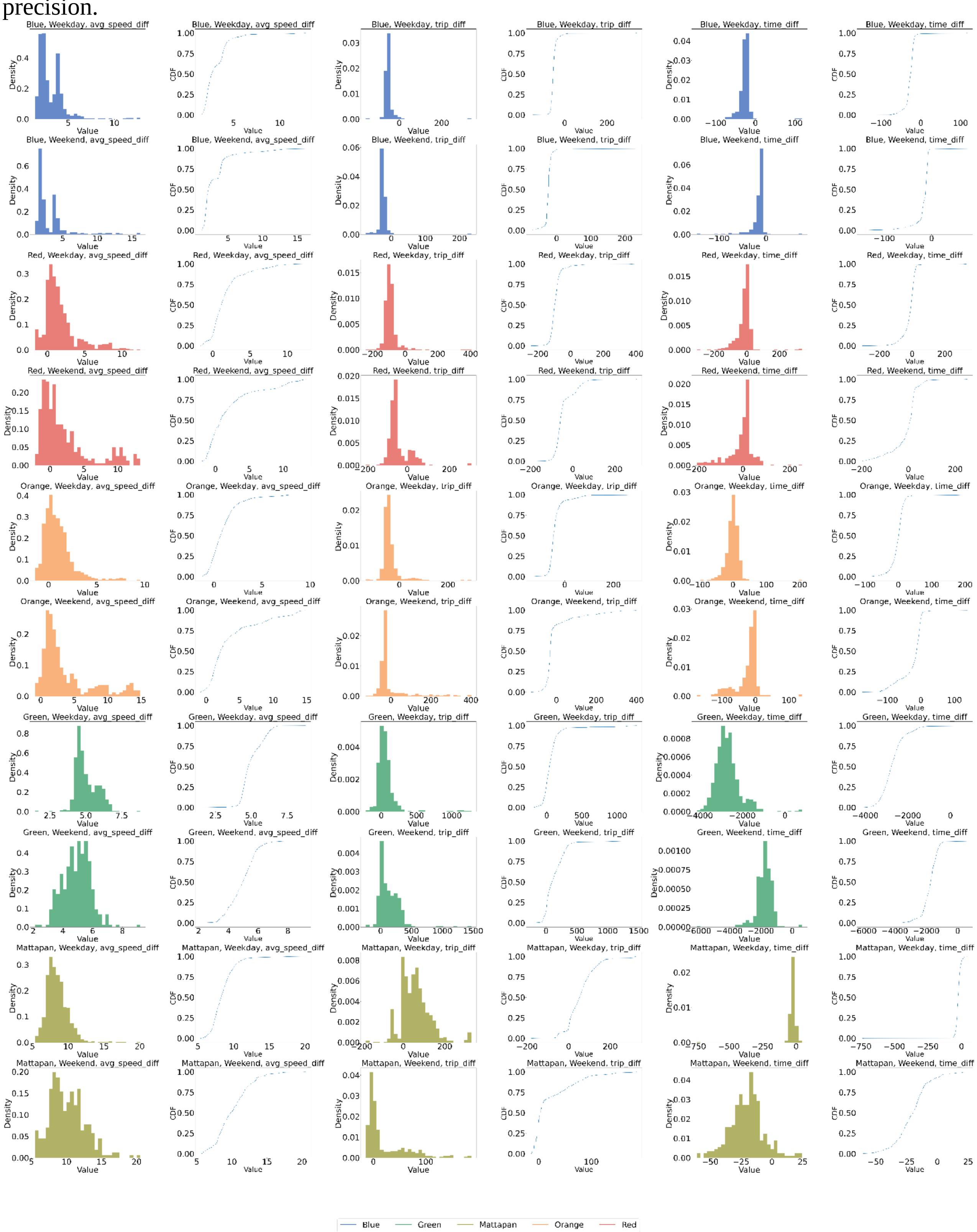

Figure 13 Estimated distributions and CDF of the discrepancy between schedule and train trajectories for each Line

3.2 Long short-term memory network

Recurrent Neural Networks (RNNs) are a type of neural networks designed to recognize patterns in sequences of data, such as time series, speech, or text. They perform well in tasks where understanding the context and order of inputs is crucial, as they can maintain a memory of previous inputs through hidden states. However, traditional RNNs struggle with long-term dependencies due to issues like vanishing gradients, which is where Long Short-Term Memory (LSTM) networks excel.

We used an LSTM recurrent neural network [12] modeling approach to predict daily energy consumption using various planning metrics. The modeling pipeline is shown in Figure 15. The input layer was configured to accept energy data and average daily temperature as sequential inputs to the LSTM hidden layer. Within each LSTM neuron as shown in Figure 15, the current input data and the hidden and cell states from the previous time step are processed through three gates: the input gate, forget gate, and output gate. The input gate filters the incoming data, the forget gate determines which information to retain or discard from the previous cell state, and the output gate regulates the influence of the updated cell state on the hidden state. This mechanism allows the LSTM to maintain and use long-term dependencies for forecasting future observations.

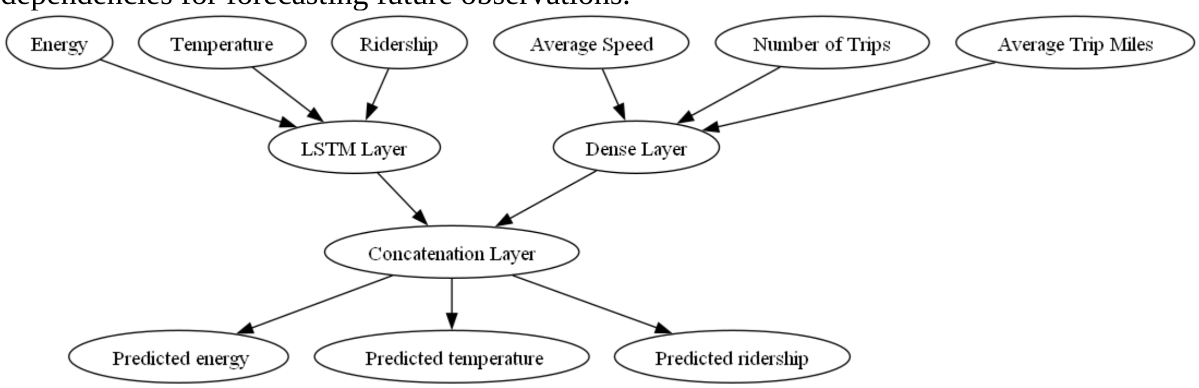

Figure 14 The modeling pipeline of co-predicting energy and temperature

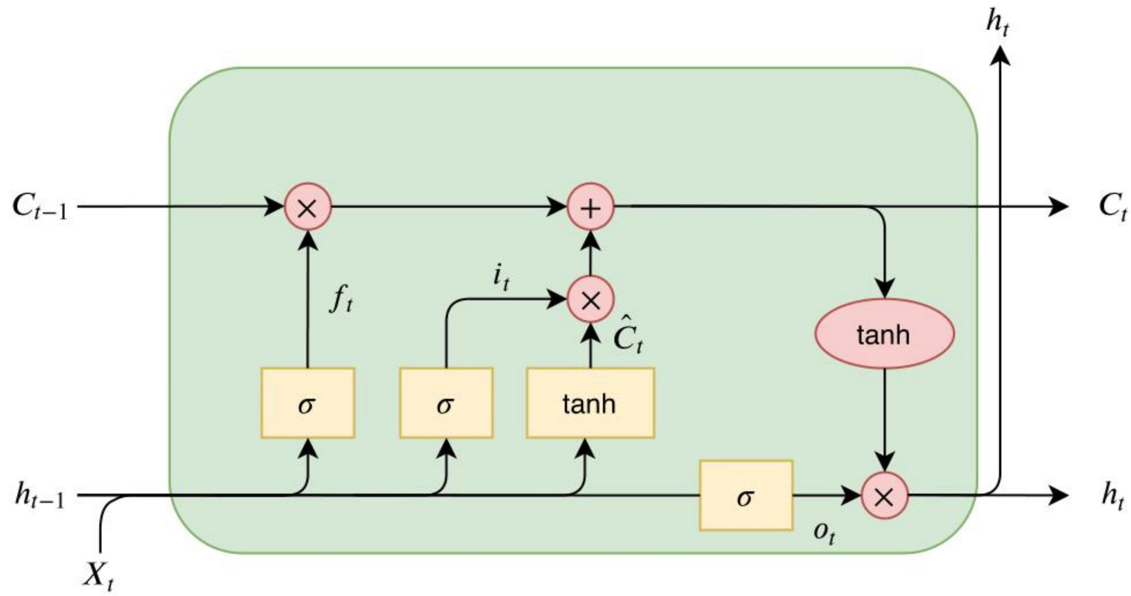

Figure 15 The architecture of the LSTM cell[1]

3.3 Model specification and training

Additionally, ridership and line-specific planning metrics, including the number of trips, operating distance, and average speeds, were incorporated as exogenous variables fed into the dense layer. To reduce the risk of overfitting, we added dropout layers between the layer transitions. For optimizing the model, we conducted a grid search to select the hyperparameters, including the dropout rate, number of layers, types of activation functions, and number of epochs used to train the model. A concatenation layer was then used to combine the intermediate outputs from the LSTM layer and the dense layer.

Figure 16 illustrates the training and validation loss of the model over 50 epochs, with the loss being measured as the mean squared error (MSE). Initially, both the training and validation losses are relatively high, indicating that the model is just beginning to learn from the data. During the first few epochs, there is a sharp decline in both losses, showing rapid learning as the model adjusts its weights to better fit the training data. As training progresses, the rate of decrease in the training loss slows down, reflecting that the model is refining its learning by making smaller adjustments.
In the middle epochs, both the training and validation losses continue to decrease but at a more gradual rate, with the validation loss showing signs of stabilization. This suggests that the model is improving its performance on unobserved data. Towards the later epochs, both losses converge and fluctuate around a low value, which signifies that the model has reached a point where further significant improvements are minimal. The close alignment of the training and validation losses in these later stages indicates that the model performs consistently well on both training and validation datasets.

[1] Source: https://thorirmar.com/post/insight_into_lstm/

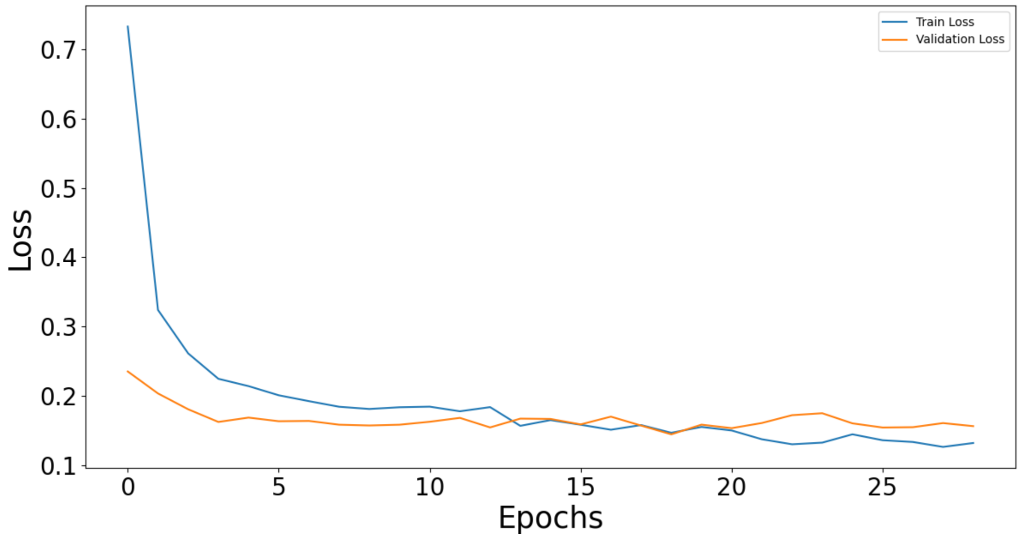

Figure 16 The loss curve presents how the model converges to the optimal point

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4.0 Results

4.1 Model performance

Figure 17 shows the energy prediction performance over time, demonstrating the model's reliability with a root mean square error (RMSE) of 50.6 MWh and a MAPE of 4.44%, as indicated in Table 2. Similarly, Figure 18 illustrates the average daily temperature prediction performance, with an RMSE of 6.62°F and a mean absolute percentage error (MAPE) of 9.01%, also detailed in Table 2. These metrics highlight the model's ability to co-predict both energy and temperature fairly accurately.

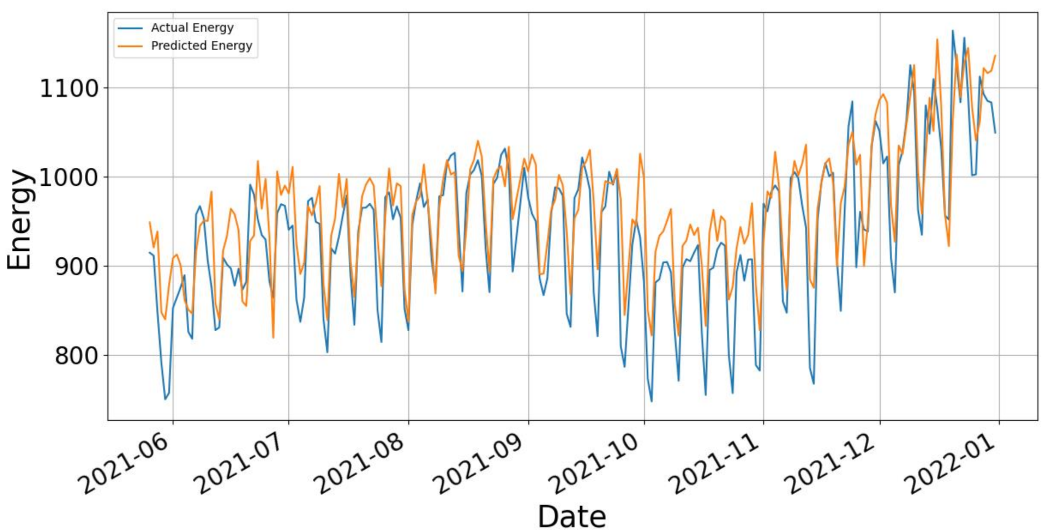

Figure 17 Energy predictions from 2021-06 to 2022-01

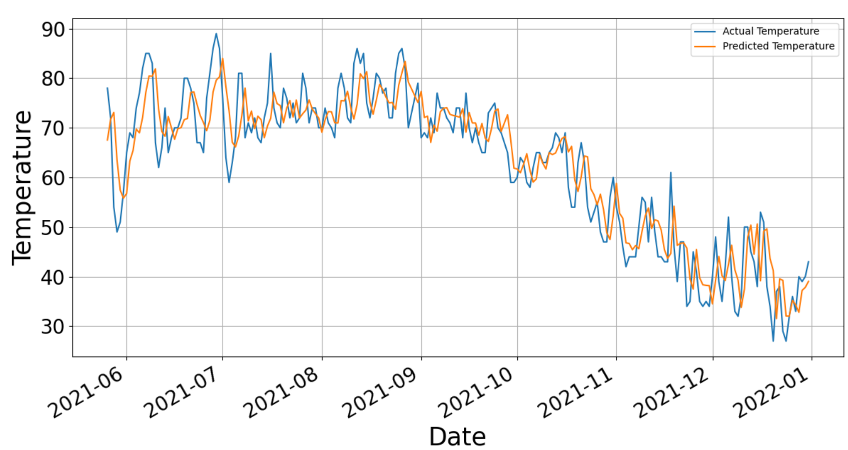

Figure 18 Average temperature predictions from 2021-06 to 2022-01

Table 2 Summary of the model performance in predicting the energy and temperature

Variables	Performance metrics	
	RMSE	MAPE (%)
Energy consumption (MWh)	50.6	4.44
Average daily temperature (F)	6.62	9.01

4.2 Scenario analysis

To demonstrate the capability of our framework in assessing energy forecasts for various decision-making scenarios, we implement two hypothetical operation plans for a 6-month test period (06-2021 to 12-2021). Plan A addresses speed reduction, which can be required in order to reduce track degradation. Plan B addresses distance reduction, which could be necessitated under disruption (either due to construction or a pandemic). The base plan is the historical plan that was followed during the test period. The plans are summarized in Table 3.

Table 3 Hypothesis of the operational changes to the MBTA URT system

Scenario	Percentage change (%)				
	Green	Orange	Red	Blue	Mattapan
Base Plan	0	0	0	0	0
Plan A: Speed reduction	-5	-10	-10	-10	-5
Plan B: Distance reduction	-5	-15	-15	-15	-5

The forecast energy and temperature of the base and hypothetical plans are shown in Figure 19. We observe that the base plan generally shows higher energy consumption as shown in Table 4. while both reduction strategies tend to lower energy usage. Notably, the distance reduction scenario appears to have a more pronounced impact on reducing energy consumption, as evidenced by the lower and more variable energy levels compared to the base plan and speed reduction scenario. The temperature predictions are relatively consistent across the different plans with minor variations. This suggests that while the speed and distance reduction strategies significantly affect energy consumption, their impact on temperature predictions is less substantial.

Figure 19 Time series of model predictions on various plans

Table 4 The summary of energy statistics for all cases

Scenario	Mean	Variance	Max	Min
Base Plan	965.21	4964.72	1153.94	819.32
Plan A	959.07	4560.58	1151.89	821.24
Plan B	961.68	3890.28	1131.74	827.31

4.3 Decision-making tool

The decision-making tool for the MBTA URT system is designed to evaluate the effects of various strategies on energy consumption. Users can simulate various operational scenarios and analyze their impact on energy and temperature predictions by adjusting sliders for different input features such as operating distance, number of trips, and average speed. This functionality is particularly valuable for strategic planning, enabling MBTA officials to anticipate the effects of different operational strategies and assist with decision-making. A preliminary version of the tool is shown in Figure 20.

Figure 20 An example of the first version of a decision-making tool for the MBTA URT system

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5.0 Conclusion

In this project, we developed a comprehensive pipeline for predicting energy consumption and temperature based on planning metrics, ridership data, and historical sequences. The model demonstrated high accuracy, with a MAPE of 4.44% for energy predictions and 9.01% for temperature predictions, underscoring its reliability and effectiveness.

Additionally, we implemented two hypothetical plans in order to showcase the practicality of our framework in forecasting the energy outcome for a given operational plan. By analyzing plans involving speed reduction and distance reduction, we demonstrated the model's capability to provide insightful forecasts that inform decision-making processes.

Finally, for user interaction and technology transfer, we developed a decision-making tool that allows operators to specify planning metrics for a given plan over a specified horizon (month, quarter, etc). Under the hood, the model computes the energy forecasts. Ultimately, this tool will enable MBTA to forecast energy requirements for various planning strategies, and potentially save costs and improve service outcomes.

6.0 References

[1] "APTA." Accessed: Jul. 31, 2023. [Online]. Available: https://www.apta.com/research-technical-resources/transit-statistics/ridership-report/

[2] B. Shang and X. Zhang, "Study of Urban Rail Transit Operation Costs," *Procedia - Soc. Behav. Sci.*, vol. 96, pp. 565–573, Nov. 2013, doi: 10.1016/j.sbspro.2013.08.066.

[3] S. C. Davis and R. G. Boundy, "Transportation Energy Data Book Edition 40," Transportation Energy Data Book. Accessed: Jul. 05, 2023. [Online]. Available: https://tedb.ornl.gov/

[4] Z. Chenchen, L. Dongyin, X. Xuemei, and W. Yanhui, "Modeling and analysis of global energy consumption process of urban rail transit system based on Petri net," *J. Rail Transp. Plan. Manag.*, vol. 21, p. 100293, Mar. 2022, doi: 10.1016/j.jrtpm.2021.100293.

[5] L. Barcellos de Paula and F. A. S. Marins, "Algorithms applied in decision-making for sustainable transport," *J. Clean. Prod.*, vol. 176, pp. 1133–1143, Mar. 2018, doi: 10.1016/j.jclepro.2017.11.216.

[6] A. S. Santos and S. K. Ribeiro, "The use of sustainability indicators in urban passenger transport during the decision-making process: the case of Rio de Janeiro, Brazil," *Curr. Opin. Environ. Sustain.*, vol. 5, no. 2, pp. 251–260, Jun. 2013, doi: 10.1016/j.cosust.2013.04.010.

[7] Y. Yang, P. Zhang, and S. Ni, "Assessment of the Impacts of Urban Rail Transit on Metropolitan Regions Using System Dynamics Model," *Transp. Res. Procedia*, vol. 4, pp. 521–534, Jan. 2014, doi: 10.1016/j.trpro.2014.11.040.

[8] M. S. Al-Musaylh, R. C. Deo, J. F. Adamowski, and Y. Li, "Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia," *Adv. Eng. Inform.*, vol. 35, pp. 1–16, Jan. 2018, doi: 10.1016/j.aei.2017.11.002.

[9] Z. Tang, H. Yin, C. Yang, J. Yu, and H. Guo, "Predicting the electricity consumption of urban rail transit based on binary nonlinear fitting regression and support vector regression," *Sustain. Cities Soc.*, vol. 66, p. 102690, Mar. 2021, doi: 10.1016/j.scs.2020.102690.

[10] Z. Han, E. Gonzales, E. Christofa, and J. Oke, "Modeling System-Wide Urban Rail Transit Energy Consumption: A Case Study of Boston," *Transp. Res. Rec.*, vol. 2676, no. 12, pp. 627–640, Dec. 2022, doi: 10.1177/03611981221096442.

[11] Z. Han, E. Gonzales, E. Christofa, and J. Oke, "Line-Specific Energy Modeling Framework for Urban Rail Transit Systems: A Case Study of Boston," *Transp. Res. Rec.*, p. 03611981231170181, May 2023, doi: 10.1177/03611981231170181.

[12] R. C. Staudemeyer and E. R. Morris, "Understanding LSTM -- a tutorial into Long Short-Term Memory Recurrent Neural Networks." arXiv, Sep. 12, 2019. doi: 10.48550/arXiv.1909.09586.

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