

DECEMBER 2023



CityTFT: Temporal Fusion Transformer For Urban Building Energy Modeling

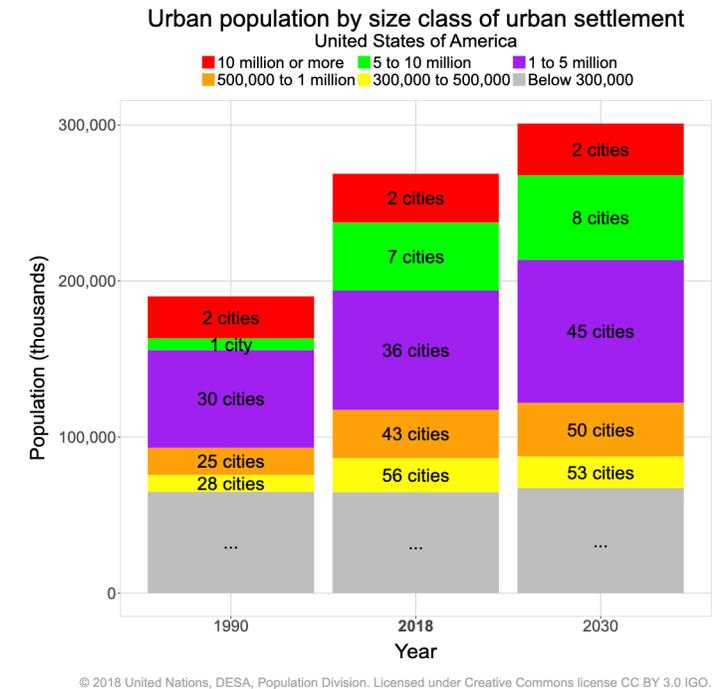
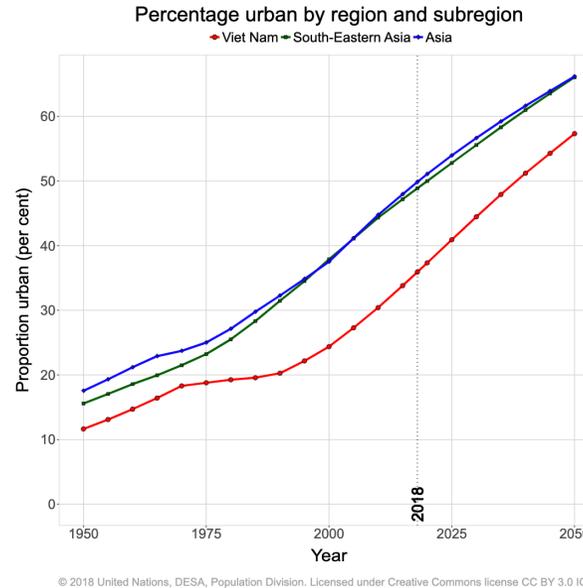
Ting-Yu Dai¹, Dev Niyogi^{1,2}, Zoltan Nagy¹

¹ Civil, Architectural and Environmental Engineering, The University Of Texas At Austin

² Department of Earth and Planetary Sciences, The University Of Texas At Austin

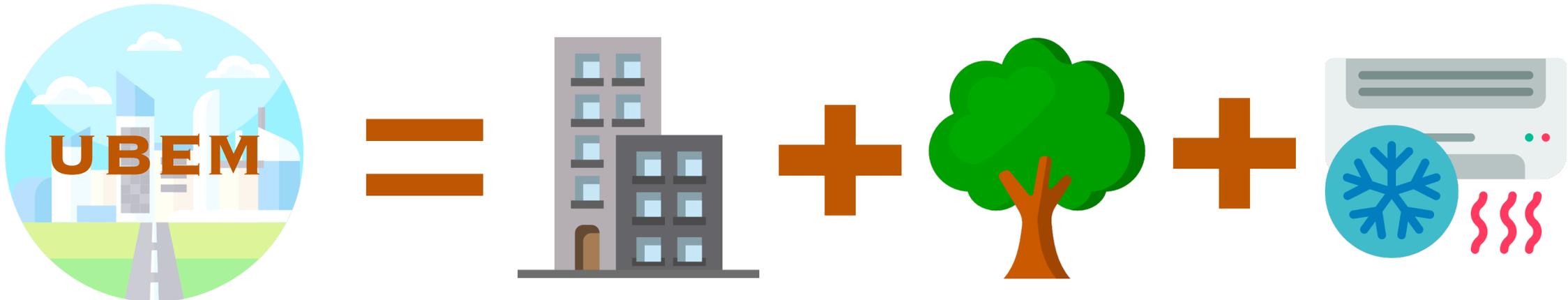
The Demand

- **Urbanization** is one of the greatest challenges of modern society.
- **33%** of global greenhouse gas emissions come from buildings and **70%** of energy is consumed by urban.



Urban Building Energy Modeling (UBEM)

- **Aims to** simulate and analyze the intricate dynamics of energy consumption within urban environments.
- **Compared to building energy modeling**, UBEM simulates while considering building height, surface coverage, and spatial arrangement, probing their interactions and discerning their collective influence on energy dynamics at the urban scale.



The barrier

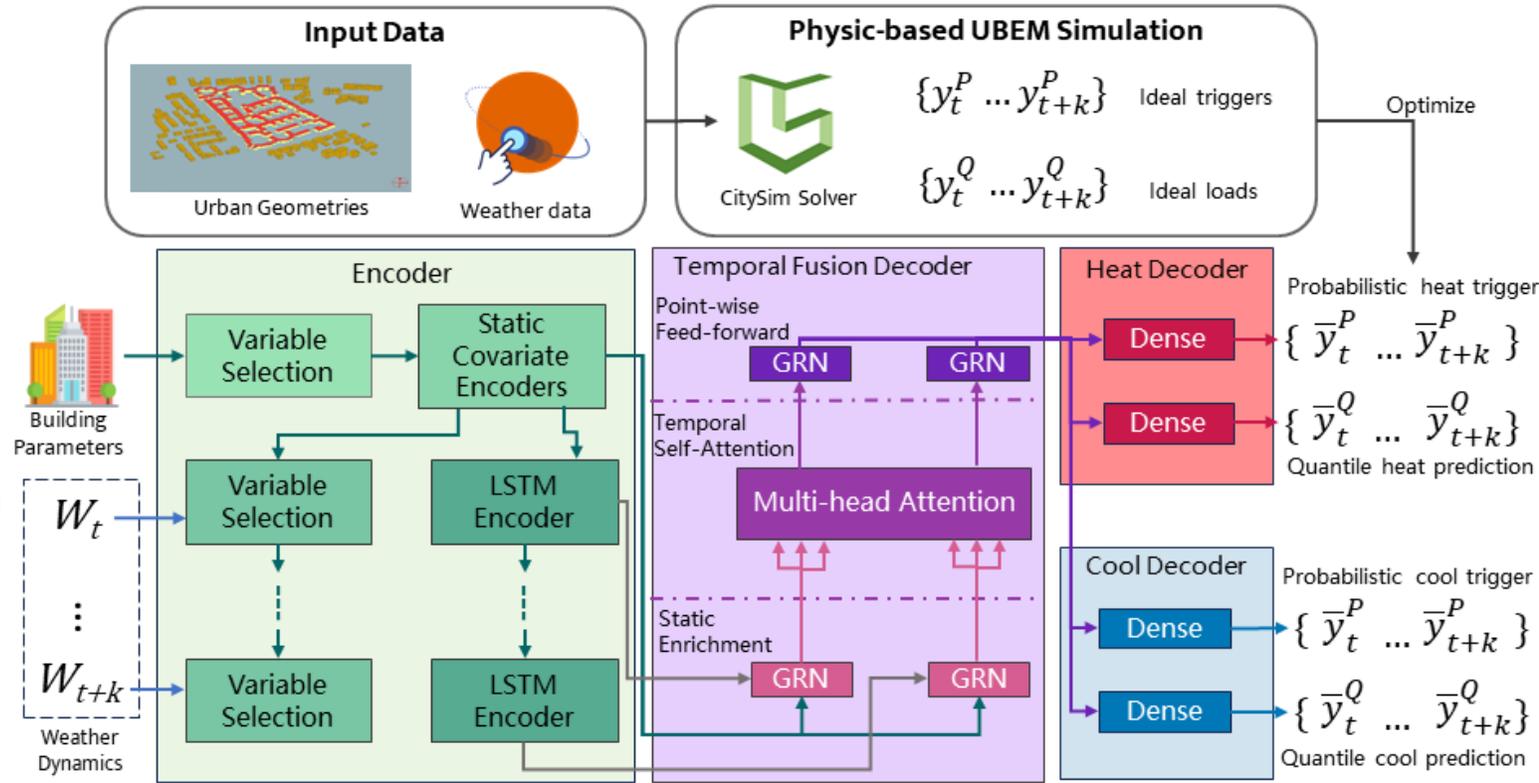
- Physic-based models are computationally demanding.
 - Simulate 226 buildings with one weather file \cong 50 minutes
- The previous work “CityDNN” does not consider temporal relation.

Research Aim

- A surrogate data-driven approach to accelerate the simulation process
- Improve the model structure and change the I/O structure to consider temporal effects.

Overview and Experimental Setup

- A campus model with **226** buildings
 - Varied building parameters.
 - Different building heights to create shading.
- **22** TMY files from different climate zones
- Using CitySim to create ideal heating/cooling loads → over **39 millions** samples to train on

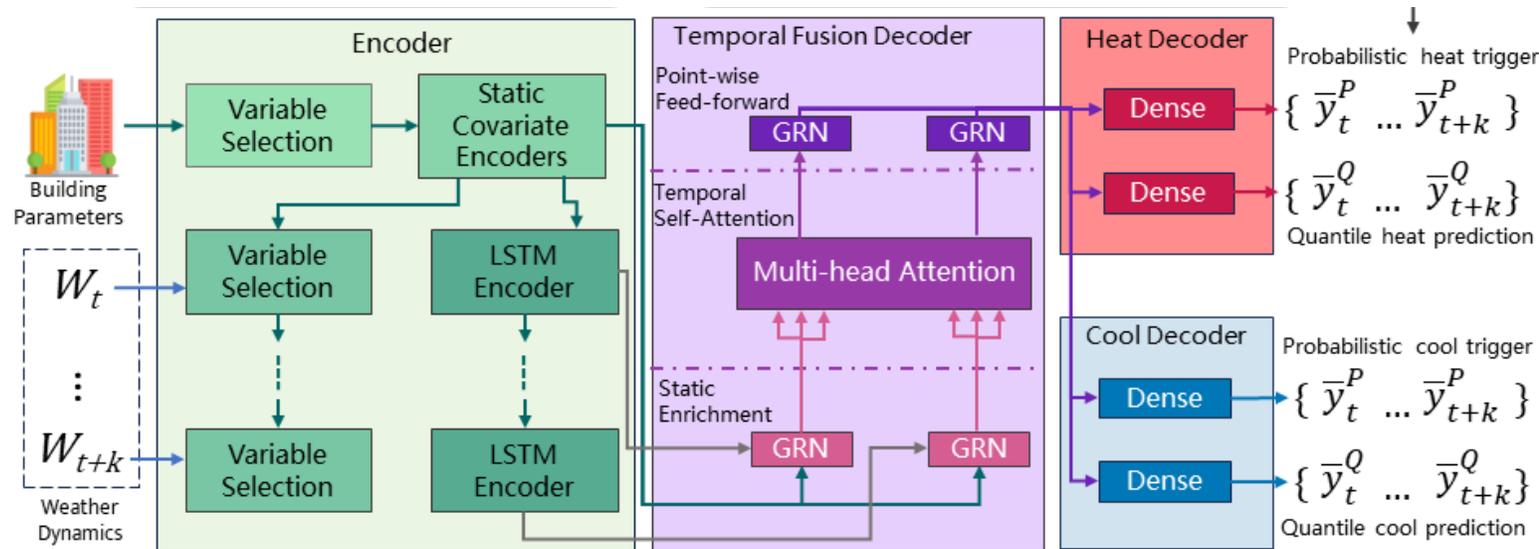


Model structure - Temporal Fusion Transformer

- Variable selection network and static covariate encoders are applied for interpreting building parameters
- Variable selection network and LSTM are used to capture weather dynamics.
- Gated Residual Network are use for combining both processed latent and fee-forward with the attention layers.

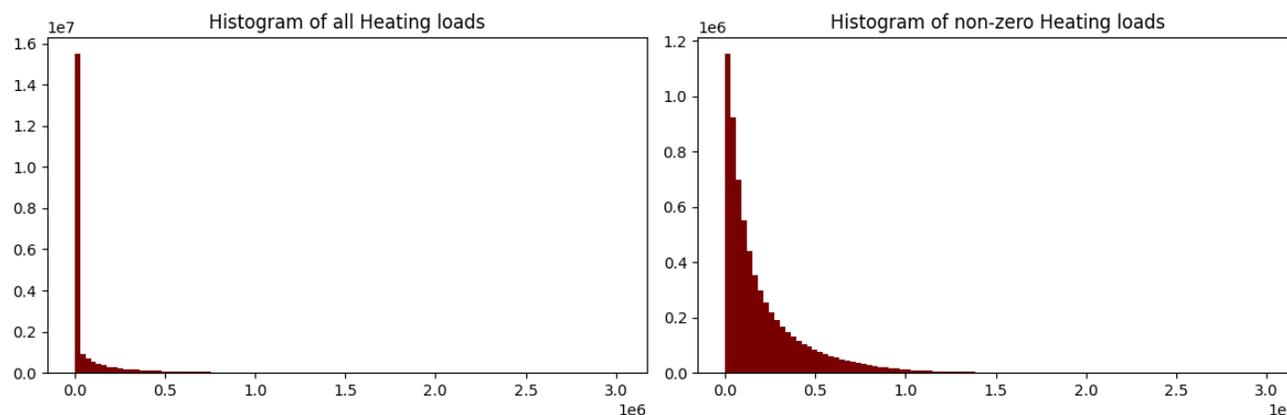
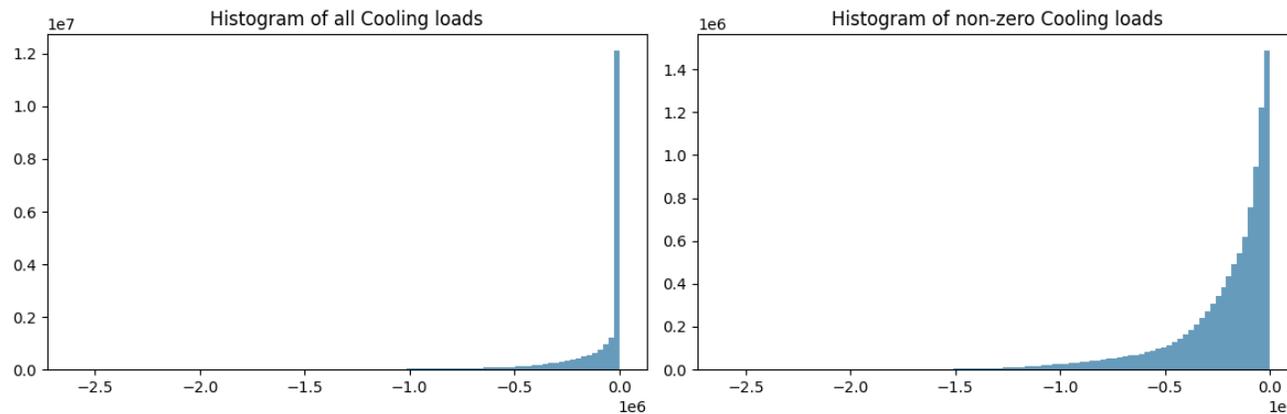
- Separate decoders are used to predict:

- Separate Heating/Cooling demands
- Whether the AC system triggers
- How much the energy consumption is.



Probabilistic Loss: Will it trigger and how much it will cost

Due to the large proportion of zero load, divide the loss function into probabilistic part and quantile regression part.



$$l = l_{prob}(t, y^P) + l_{quantile}(a, y^Q)$$

BCELoss for optimizing the trigger probabilities.

$$l_{prob}(t, y^P) = \frac{1}{N} \sum_{n=1}^N \{-w_n (y_n^P \log(t_n)) + (1 - y_n^P) \log(1 - t_n)\}$$

Quantile Loss for optimizing the energy consumption.

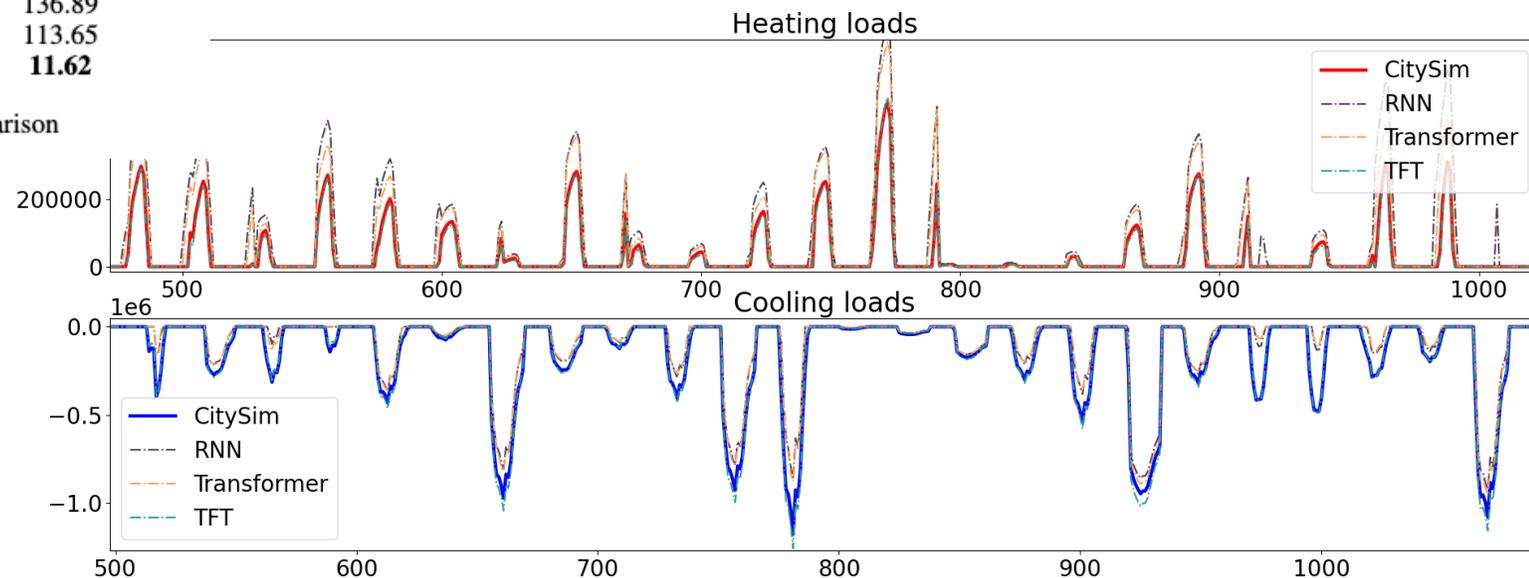
$$l_{quantile}(a, y^Q) = \frac{1}{N} \sum_{n=1}^N \begin{cases} q \cdot (a_n - y_n^Q) & , y_n^Q \leq a_n \\ (1 - q) \cdot (y_n^Q - a_n) & , y_n^Q > a_n \end{cases}$$

Result & Discussion

- **Ability to simulate unseen climate dynamics.**
 - Testing on unseen TMY files and still capture weather dynamics.
- **Ability to anticipate the trigger of heating and cooling.**
 - Compare the F1 score to evaluate the probabilistic prediction.

	F1 score (%)	Non-zero RMSE (kWh)	Total RMSE (kWh)	Non-zero MAPE (%)
RNN	91.91	114.06	75.91	136.89
Transformer	91.33	118.43	79.74	113.65
TFT	99.98	21.34	13.57	11.62

Table 1: F1 score, RMSE with total loads and non-zero loads Comparison



Conclusion & Future work

Conclusion:

- Components like static variate encoder or variable selection network from TFT helps to improve the energy modeling task.
- The custom probabilistic loss is critical to model the demand distribution.
- CityTFT has the generalization ability to predict heating and cooling demand in a unseen weather scenario.

Future work:

- Modeling the interaction between buildings
- Investigate on the generalization ability on different urban forms.

THANKS!