TSPM: 효과적인 건물 에너지 예측을 위한 건물 안내도 기반 2단계 시공간 예측 모듈

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TSPM: Two-stage Spatiotemporal Prediction Module with Floor Plan for Effective Building Energy Prediction

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요 약

Due to the increasing consumption in energy, accurate building energy prediction has become important, and recent studies achieve significant advancement with deep learning-based approaches. However, there are still some challenges. For accurate prediction, a complex structure that considers both temporal and spatial features must be applied, which makes it difficult to extend to other cases. Furthermore, some recent studies use simple time-series model as comparison, which may undermine the advantage of incorporating spatial features. In this paper, we propose novel Two-stage Spatiotemporal Prediction Module (TSPM) to overcome these limitations. Our TSPM can incorporate spatial features based on building floor plans images which can easily obtained. In addition, we conduct fair comparisons with promising time-series models to demonstrate effectiveness of our approach.

1. Introduction

As energy consumption and costs increase in recent years, the importance of efficient energy consumption has been emphasized. In response, governments are implementing new energy conservation policies. Consequently there is a growing need for effective management of building energy consumption, which accounts for approximately 40% of worldwide consumption [1]. Furthermore, with the recent advancement, many studies try to not only apply deep learning but also consider both temporal and spatial features for effective building energy prediction and management.

Although these tries have brought about significant advancement, there are still some challenges. Complex model structures or graph representations needed to effectively consider both temporal and spatial features, which make it difficult to extend to other cases. Furthermore, some recent studies use only relatively simple time-series prediction models as comparison, which may undermine the advantage of incorporating spatial features.

To overcome these limitations, we propose novel Two-stage Spatiotemporal Prediction Module (TSPM) with floor plan images. Our TSPM can be easily extended to other cases because it considers spatial features based on floor plan images which can easily obtained. In addition, we emphasize the importance of applying spatial features through conduct fair comparison experiments with some recent promising time-series prediction models.

2. Related Work

Sun et al [3] integrated spatial analysis into building energy assessment, emphasizing the

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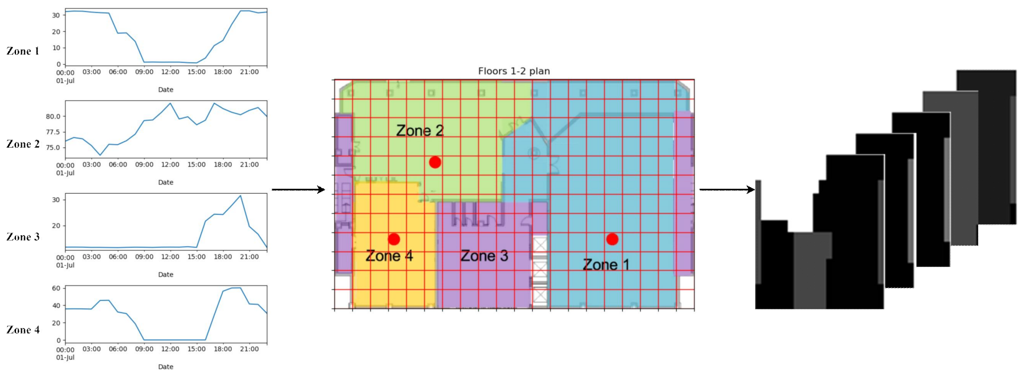


$x_T \in \mathbb{R}^{B \times T \times 4}$ $x_{ST} \in \mathbb{R}^{B \times T \times 12 \times 20}$

(Fig. 1) An illustration of data transform process.

advantage of incorporating spatial features through experiments. Jung et al [4] noted that predicting energy consumption in building level has limitations because it is difficult to consider the specificity of individual spaces with high energy consumption.

In response to this, with the recent advancement of deep learning and prediction techniques, attempts to incorporate spatial features to improve prediction accuracy are increasing. Wang et al [5] propose novel framework that integrates Graph Neural Network (GNN) and Long Short-Term Memory (LSTM) to learn spatiotemporal correlations and multivariate features. Jin et al [6] compared prediction methods that integrated spatiotemporal prediction models to emphasize the importance of incorporate spatial features. Although these studies have made significant advancement, they are difficult to extend to other cases due to complex structure or graph representations, or may undermine the advantages of incorporating spatial features by using only simple time-series models as comparison.

3. Two-stage Spatiotemporal Prediction Module

3.1. Preliminaries

First of all, we construct spatiotemporal data based on building floor plan image, as shown in Fig. 1, inspired by Jin et al [6]. Given temporal data $x_T \in \mathbb{R}^{B \times T \times 4}$, it is converted to spatiotemporal data $x_{ST} \in \mathbb{R}^{B \times T \times 12 \times 20}$ through a mapping process on a grid of size 12×20, where B and T denotes batch_size and number of time steps, respectively.

3.2. Overall Architectures

In this section, we introduce our novel TSPM as shown in Fig. 2. Specifically, TSPM consists of two spatiotemporal and temporal prediction modules and trained through a separate training processes. Through separate training processes, each module can effectively learn spatiotemporal and temporal features by focusing only on its purpose, respectively.

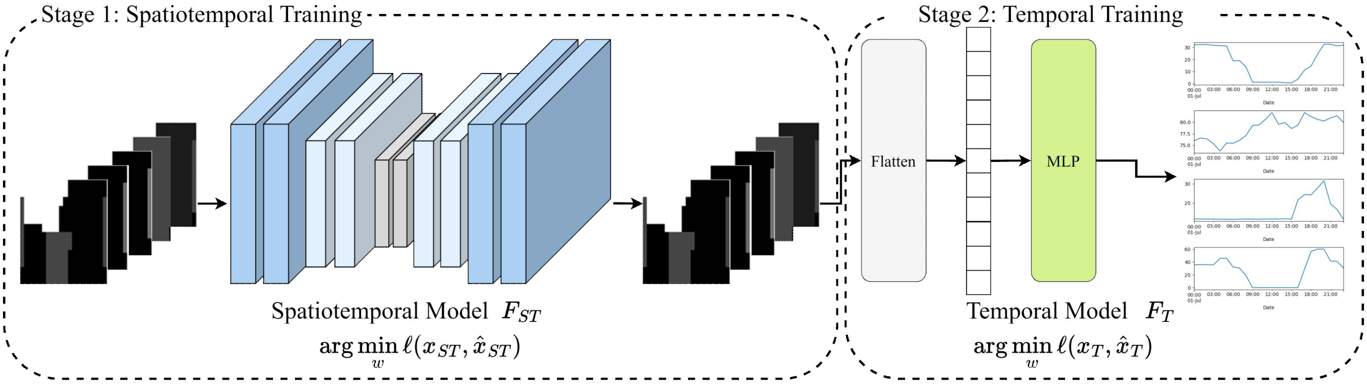
3.3. Spatiotemporal Training

First, we train spatiotemporal prediction model F_{ST} with mapped data. Although We used SimVPv2 [7], which can perform simple yet accurate prediction, for testing our TSPM, every spatiotemporal prediction models can be applied. During the first stage, F_{ST} trained with only spatiotemporal data, and spatiotemporal features are effectively learned. Prediction process of F_{ST} can be represented as (1):

$$\hat{x}_{ST} = F_{ST}(x_{ST}) \tag{1}$$

3.4. Temporal Training

After spatiotemporal training, we train temporal model F_T only. F_{ST} is fixed with pretrained weights. F_T receives flattened



(Fig. 2) Overall architecture of TSPM.

spatiotemporal output, stabilized the output based on Multi-Layer Perceptron (MLP), and focuses only on temporal features to enhance prediction accuracy. Finally, prediction process of our TSPM can be represented as (2):

$$\hat{x}_T = F_T(F_{ST}(x_{ST})) \tag{2}$$

Where MLP inside F_T consists of two Linear, LayerNormalization, Mish activation function, and additional Linear layer for final output.

4. Experiments

4.1. Experimental Environment

The experiments were conducted using Python 3.10.8 and pytorch 2.1.1 with NVIDIA RTX 3070 GPU, running on Windows 10 WSL. Training process was performed with Mean Squared Error (MSE) loss function and Adam optimizer during 30 epochs.

4.2. Metrics

To compare the performance of promising time-series models and building energy prediction, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are used as evaluation metrics in (3). RMSE takes the square of the error, so the larger the difference between prediction and actual values. On the other hand, MAE takes only the absolute value of the errors, providing a more intuitive interpretation.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

4.3. Dataset Preparation

To evaluate building energy prediction performance and incorporate spatial features. we use CU-BEMS dataset [8]. This dataset contains building energy consumption data collected from Bangkok from July 2018 to December 2019 per minutes. This paper also introduces with a building floor plan seperated by space. We use first and second floor data with four spaces.

Missing values are interpolated by linear method and resampled per hour. In addition, we divided the data per day using sliding window for experiment. Finally, out of a total 13,129 data samples, 10,503 samples were assigned to train and remaining 2,626 samples were assigned to test.

4.4. Experimental Results

To assessing the performance of our TSPM, we have selected some recent promising time-series prediction models [9-11] based on Recurrent Neural Network (RNN), MLP, and Transformer, etc. as well as LSTM.

We report quantitative comparison results in Table 1. Where TSPM with w/o. 2-stage means TSMP without 2-stage strategy.

Quantitative comparison results show that

<Table 1> Quantitative comparison results. (**bold**: best, underline: second)

Models	Floor 1		Floor 2	
	RMSE	MAE	RMSE	MAE
LSTM	0.2206	0.1781	0.2665	0.1729
SegRNN [9]	0.1548	0.1008	0.1594	0.0957
DLinear [10]	<u>0.1539</u>	0.1004	0.1595	**0.0870**
PatchTST [12]	0.1577	0.1068	0.1658	0.1068
TSPM (w/o. 2-stage)	0.1541	<u>0.1001</u>	<u>0.1531</u>	0.0904
TSPM (Ours)	**0.1445**	**0.0978**	**0.1495**	<u>0.0878</u>

TSPM achieves best results in most metrics, demonstrating the effectiveness of proposed approach while emphasizing the advantage of incorporating spatial features. In addition, prediction performance is reduced for TSPM without 2-stage, emphasizing the potential of proposed 2-stage training strategy.

5. Conclusion

In this paper, we propose a novel yet accurate TSPM to overcome the difficulties in extending to other cases, and its effectiveness is demonstrated by experimental results. Most of spatiotemporal prediction model can applied to TSPM, and floor plan image, which can easily obtained, based mapping can make ours easy to extend. Fair comparisons with recent promising time-series models strongly support experiments.

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