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An LSTM-Based Online Prediction Method for Building Electric Load During COVID-19

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Motivation

- Accurate prediction of building electrics load is important to its efficient operation and necessary for some advanced functionalities
  - Frequency regulation
  - Virtual battery by exploiting the thermal capacity
- Challenges
  - Detailed building model and parameters are difficult to obtain
  - Load pattern can change during events like COVID-19
- Proposed method: LSTM-based online learning
  - Machine learning method only requires history load data
  - Online learning method can adapt to load pattern change automatically

Prediction Problem Statement

Given a variable of interest y and a feature vector $\boldsymbol{x}$, the single-step time series prediction problem is to learn a nonlinear mapping function F that uses the historical sequence $\{\boldsymbol{x}_k, \boldsymbol{x}_{k-1}, \dots, \boldsymbol{x}_{k-l+1}, \boldsymbol{x}_{k-l}\}$ are as input to make prediction for the next time step $\tilde{y}_{k+1}$,

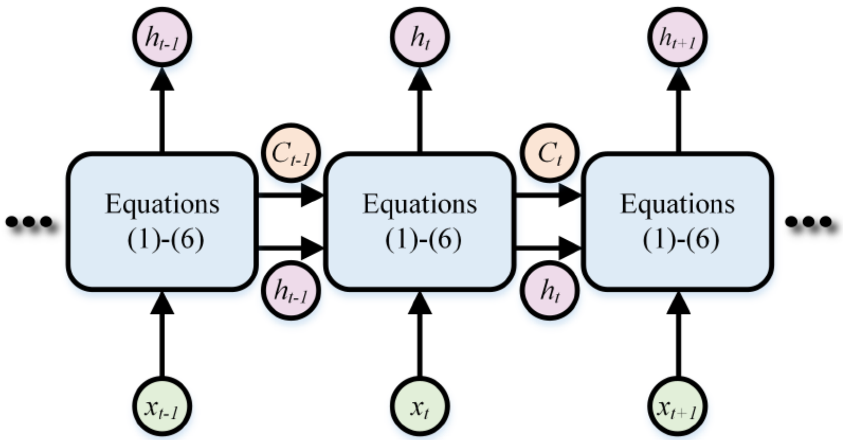
$$\tilde{y}_{k+1} = F(\boldsymbol{x}_k, \boldsymbol{x}_{k-1}, \dots, \boldsymbol{x}_{k-l+1}, \boldsymbol{x}_{k-l})$$

Where y_{k+1} is the variable of interest at time step $k+1$ and $\tilde{y}_{k+1}$ is its prediction. $\boldsymbol{x}_k$ is a vector that contains the input information at time step k. Note $\boldsymbol{x}_k$ commonly contains the true value of y_k and some other selected features.

LSTM Basics

Long short-term memory（LSTM) is a type of recurrent neural networks that is widely used for time series prediction. Its unique structure featuring input, forget, and output gates helps to pass information between steps.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{1}$$
$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{2}$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{3}$$
$$\tilde{C}_t = \tanh(W_C x_t + U_C h_{t-1} + b_C) \tag{4}$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$
$$h_t = o_t * \tanh(C_t) \tag{6}$$



Feature Selection for Building Electric Load Prediction

Identified features for LSTM model

- Historical electric load data y_k
- Outside air temperature T_{OAT}
- Hour of the day H
  - $H \in \{0,1\}^{24}$ is a 24-dimensional one-hot encoded vector
- Day of the week D
  - $D \in \{0,1\}^{7}$ is a 7-dimensional one-hot encoded vector
- Day type G
  - $G \in \{0,1\}^{1}$ is binary feature, $G = 1$ if it is a holiday and $G = 0$ otherwise

The input feature is the concatenation of above features,

$$\boldsymbol{x}_k = concat(y_k, T_{OAT}, H, D, G)$$

Online Learning

Online learning steps

1. Make prediction

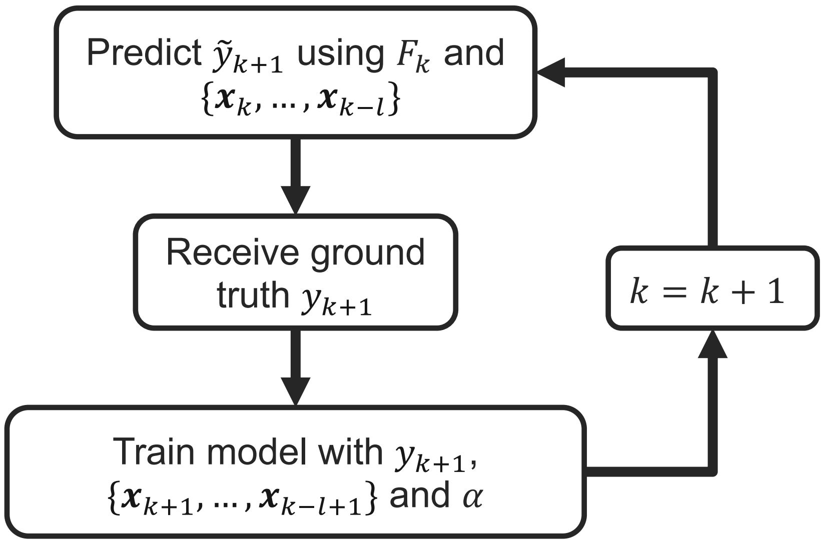
$$\tilde{y}_{k+1} = F_k(\boldsymbol{x}_k, \boldsymbol{x}_{k-1}, \dots, \boldsymbol{x}_{k-l+1}, \boldsymbol{x}_{k-l})$$

2. Receive new data ground truth y_{k+1}

3. Retrain model with gradient descent method,

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k - \alpha \nabla loss(W_k, y_{k+1}, \tilde{y}_{k+1})$$

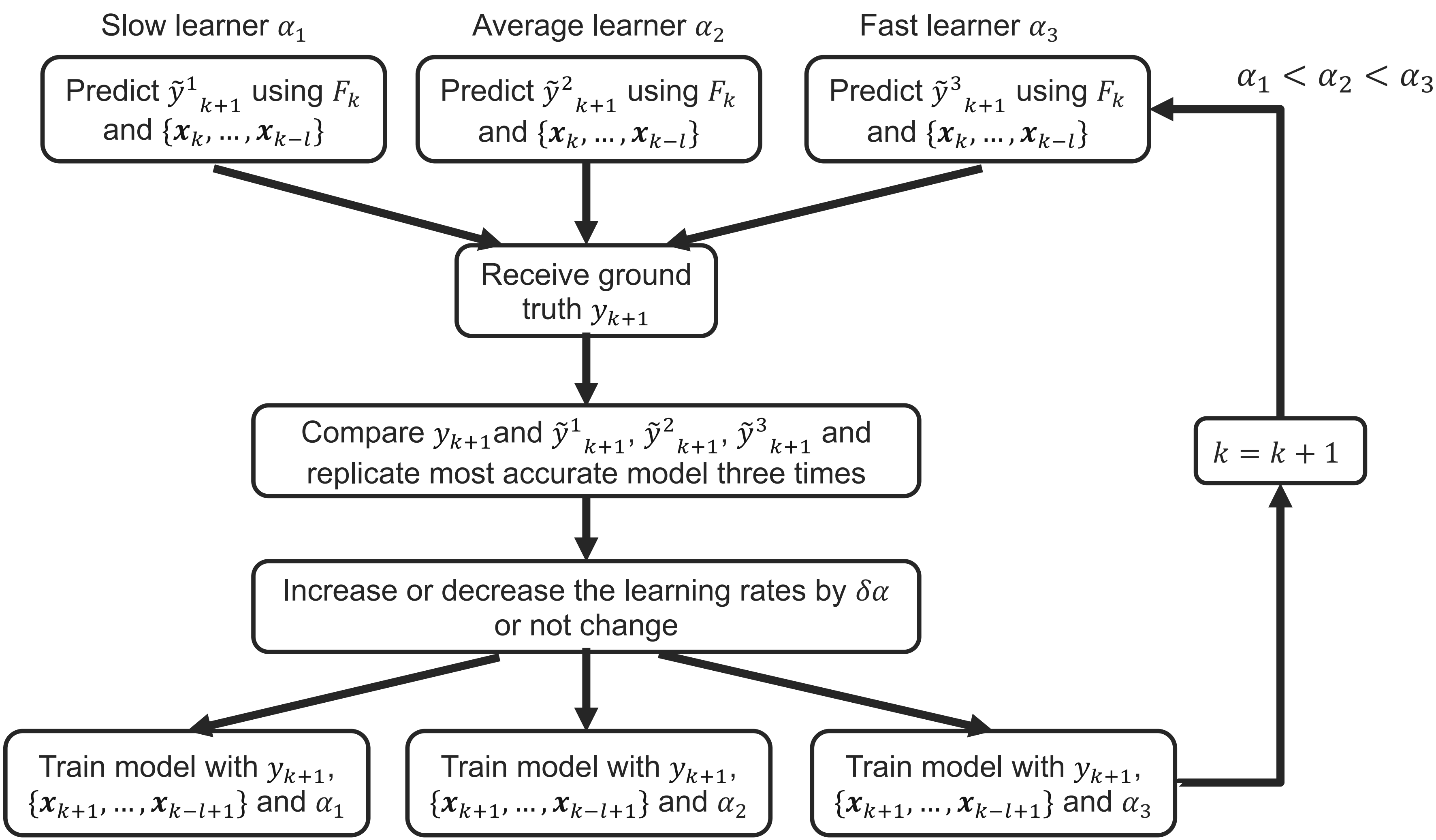
Where $\boldsymbol{W}_k$ is the set of all the parameters of model F_k at time step k.



Online learning has the capability of adapting the model to new incoming data and discovering the underlying new pattern if a concept change has happened.

However, it is difficult to predetermine the optimal value for learning rate α.

Online Learning with Adaptive Learning Rate



Adaptive Online Learning Algorithm

Algorithm 1 Online LSTM with Adaptive Learning Rate

procedure PredictAndUpdate
  for $i = 1 \rightarrow 3$ **do**
    $\{\tilde{y}_{k+1}^{(i)}\} \leftarrow \text{PredictLearner}_i(x_k, ...x_{k-l}, \mathbf{W}_k^{(i)})$
  $\tilde{y}_{k+1} = (\tilde{y}_{k+1}^{(1)} + \tilde{y}_{k+1}^{(2)} + \tilde{y}_{k+1}^{(3)})/3$

  while (y_{k+1} is not available) **do**
    Wait

  for $i = 1 \rightarrow 3$ **do**
    $err^{(i)} = |\tilde{y}_{k+1}^{(i)} - y_{k+1}|$
  IdxBestLearner $\leftarrow$ index for lowest error $err^{(i)}$

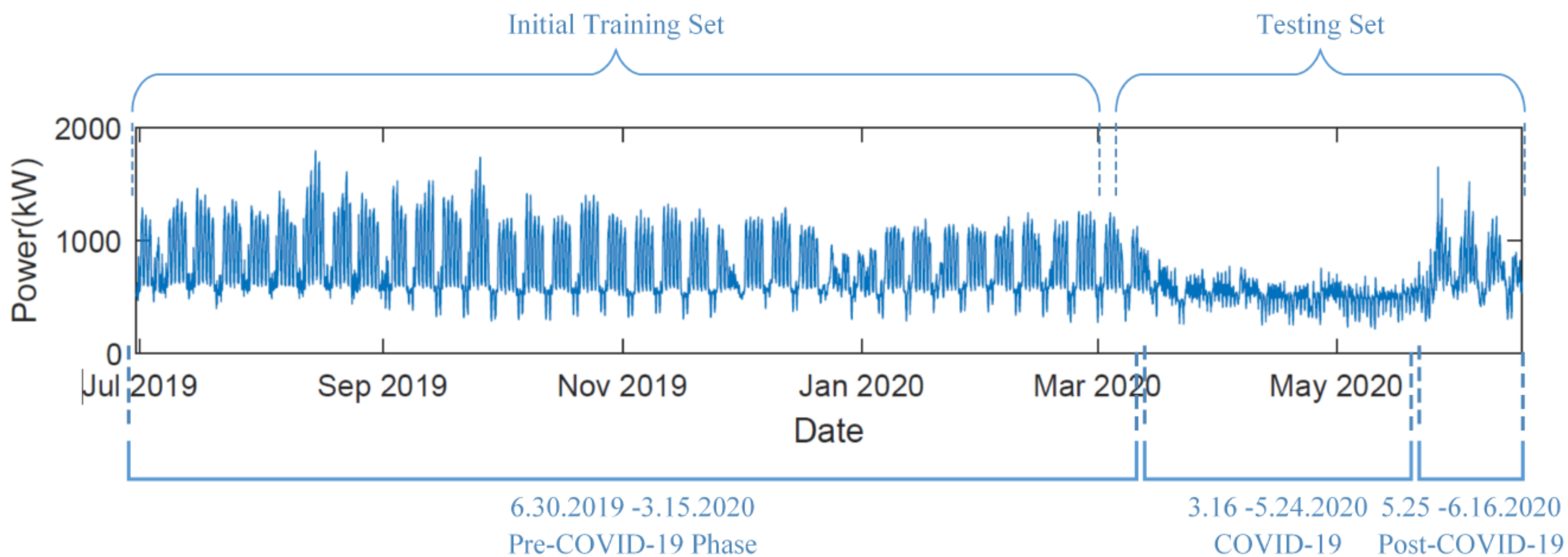
  if *IdxBestLearner* == 1 **then**
    $\{\alpha_1, \alpha_2, \alpha_3\} \leftarrow \{\alpha_1 - \delta\alpha, \alpha_2 - \delta\alpha, \alpha_3 - \delta\alpha\}$
    BestLearner $\leftarrow$ *SlowLearner*
  else if *IdxBestLearner* == 2 **then**
    $\{\alpha_1, \alpha_2, \alpha_3\} \leftarrow \{\alpha_1, \alpha_2, \alpha_3\}$
    BestLearner $\leftarrow$ *AverageLearner*
  else if *IdxBestLearner* == 3 **then**
    $\{\alpha_1, \alpha_2, \alpha_3\} \leftarrow \{\alpha_1 + \delta\alpha, \alpha_2 + \delta\alpha, \alpha_3 + \delta\alpha\}$
    BestLearner $\leftarrow$ *FastLearner*
  {*SlowLearner, AverageLearner, FastLearner*} $\leftarrow$ {*BestLearner, BestLearner, BestLearner*}

  for $i = 1 \rightarrow 3$ **do**
    TrainLearner$_i$ on $(x_k, ...x_{k-l}, y_{k+1})$ with α_i

Data Set Analysis

Electric load data for a building in California from July 2019 to July 2020

1. Pre-COVID-19 phase (6.30.2019-3.15.2020)
2. COVID-19 phase (3.16.2020-5.24.2020)
3. Post-COVID-19 phase (5.25.2020-6.16.2020)

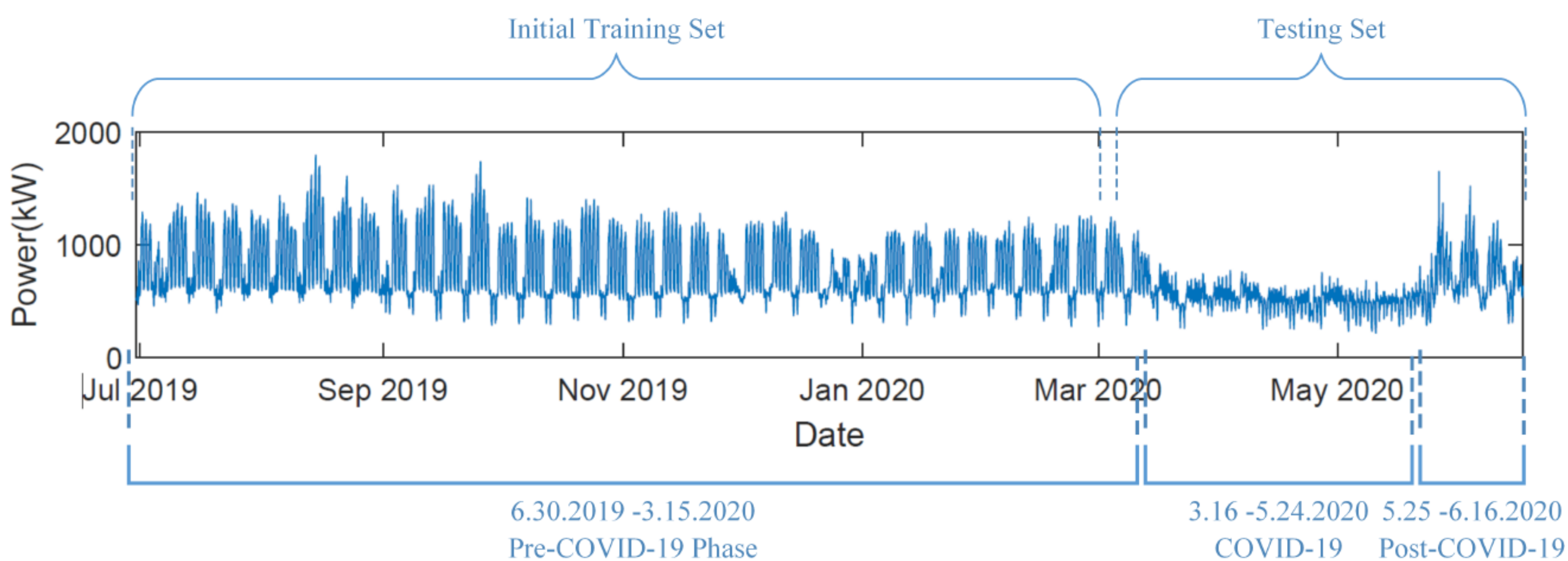


Baselines

Two basslines:

1. Off-line LSTM (Off-LSTM): this is LSTM model without online training. In this case, the data from 6.30.2019 to 3.5.2020 are used for training.
2. Online LSTM with fixed learning rate (On-LSTM-FLR): takes the trained off-line LSTM model and update the model on new samples every time step with a fixed learning rate $\alpha = 0.02$.

Proposed method: takes the trained off-line LSTM model and update the model as described.



Results

Experiment results:

Phase Week	Pre-COVID-19 3.9-3.15	COVID-19 3.16-3.22	3.23-3.29	5.4-5.10	5.11-5.17	5.18-5.24	Post-COVID-19 5.25-5.31	6.1 - 6.7	6.8-6.14
Off-LSTM	31.5	34.3	35.9	43.0	41.3	54.8	76.2	62.0	59.1
On-LSTM-FLR	35.0	35.5	31.3	33.4	34.9	51.3	69.1	59.7	53.0
Proposed	31.7	30.9	30.5	31.4	32.4	44.4	67.5	55.9	51.5

Performance metric: mean absolute error(MAE):

$$\mathrm{MAE} = \frac{1}{N} \sum_{k=N_0+1}^{N_0+N} |\tilde{y}_k - y_k|$$

Where N is the number of predictions and is selected to be 168, which corresponds to one-week long hourly data

Results

Experiment results:

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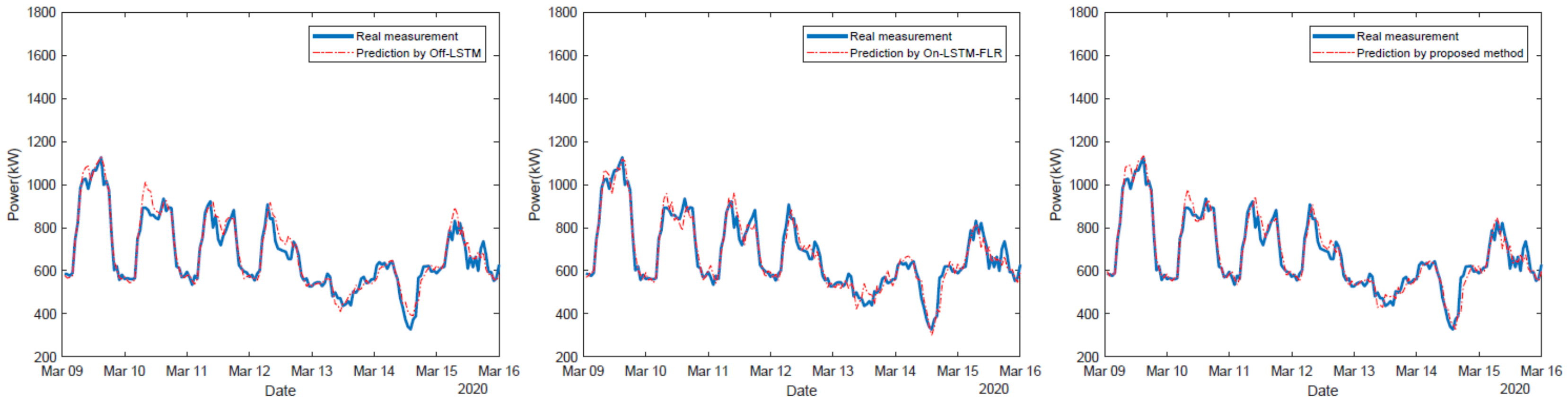

(a) Off-LSTM, MAE = 31.5 kW (b) On-LSTM-FLR, MAE = 35.0 kW (c) Proposed method, MAE = 31.7 kW

Results for pre-COVID-19 phase, week from Mar 9 2020 to Mar 15 2020

Results

Experiment results:

Phase	Pre-COVID-19	COVID-19					Post-COVID-19		
Week	3.9-3.15	3.16-3.22	3.23-3.29	5.4-5.10	5.11-5.17	5.18-5.24	5.25-5.31	6.1 - 6.7	6.8-6.14
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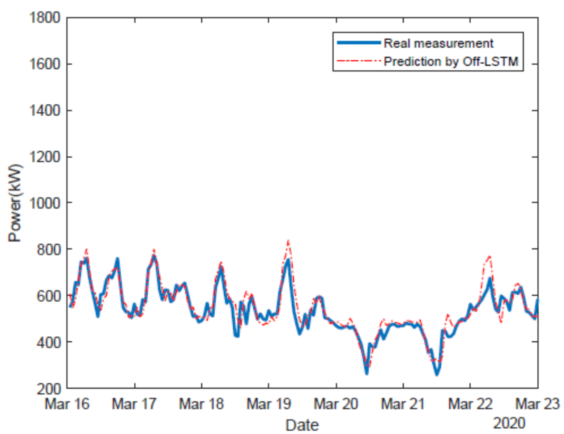
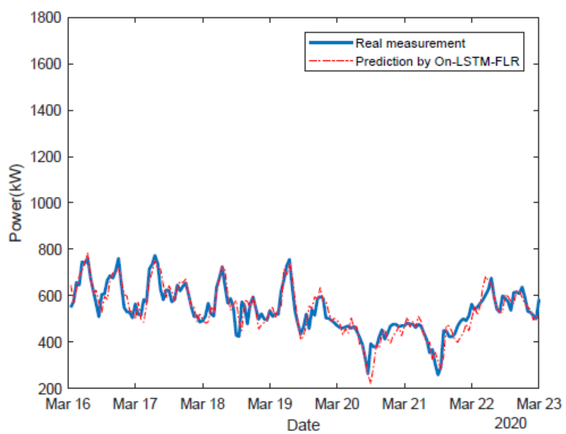
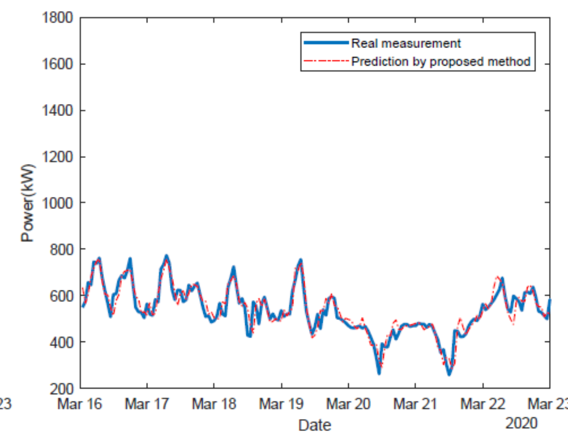


(a) Off-LSTM, MAE = 34.3 kW



(b) On-LSTM-FLR, MAE = 35.5 kW



(c) Proposed method, MAE = 30.9 kW

Results for COVID-19 phase, week from Mar 16 2020 to Mar 22 2020

Results

Experiment results:

Phase	Pre-COVID-19	COVID-19					Post-COVID-19		
Week	3.9-3.15	3.16-3.22	3.23-3.29	5.4-5.10	5.11-5.17	5.18-5.24	5.25-5.31	6.1 - 6.7	6.8-6.14
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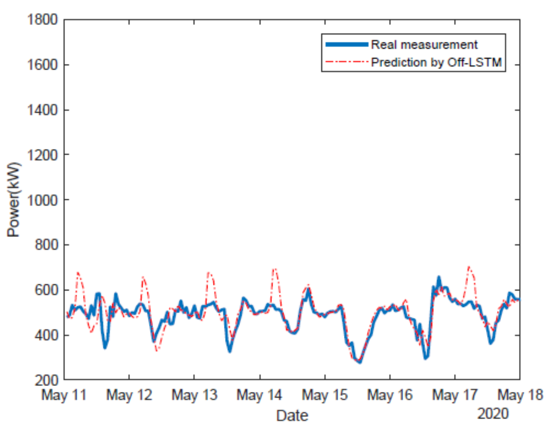
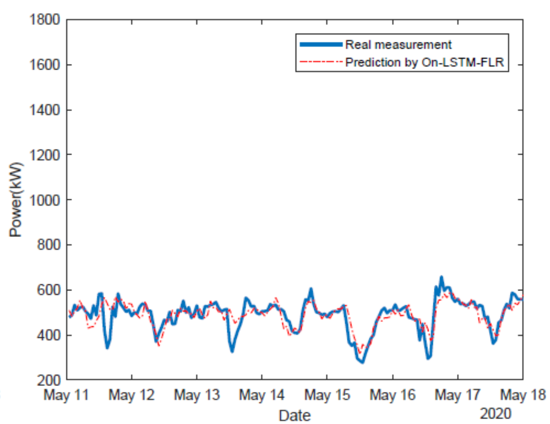
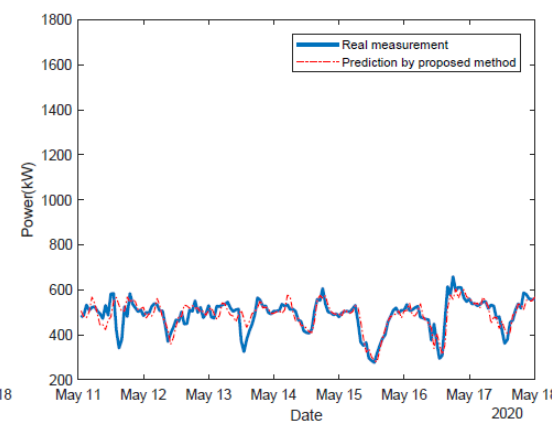


(a) Off-LSTM, MAE = 41.3 kW



(b) On-LSTM-FLR, MAE = 34.9 kW



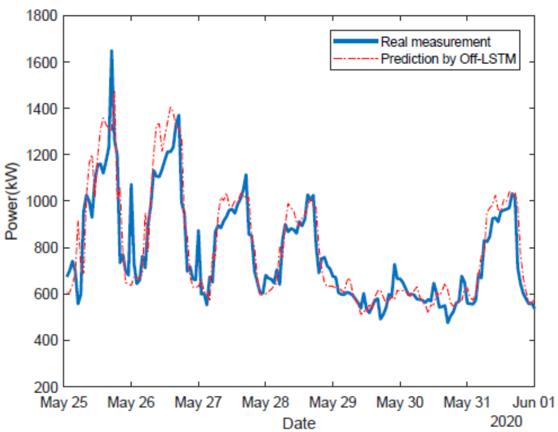
(c) Proposed method, MAE = 32.4 kW

Results for COVID-19 phase, week from May 11 2020 to May 17 2020

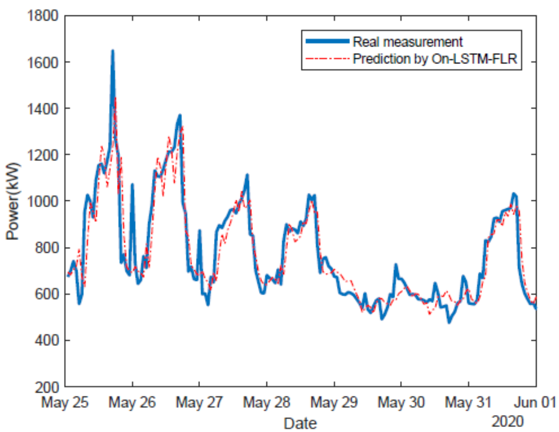
Results

Experiment results:

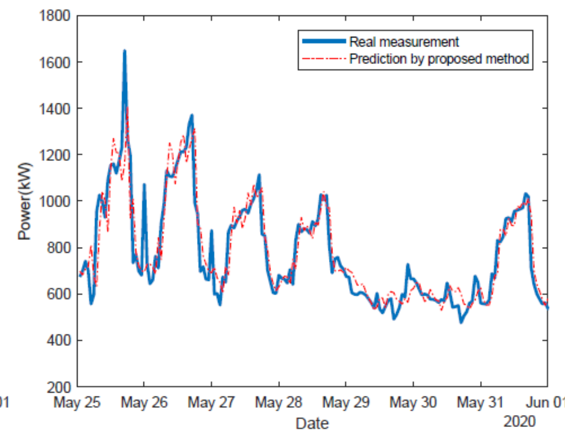
Phase Week	Pre-COVID-19 3.9-3.15	COVID-19 3.16-3.22	3.23-3.29	5.4-5.10	5.11-5.17	5.18-5.24	Post-COVID-19 5.25-5.31	6.1 - 6.7	6.8-6.14
Off-LSTM	31.5	34.3	35.9	43.0	41.3	54.8	76.2	62.0	59.1
On-LSTM-FLR	35.0	35.5	31.3	33.4	34.9	51.3	69.1	59.7	53.0
Proposed	31.7	30.9	30.5	31.4	32.4	44.4	67.5	55.9	51.5



(a) Off-LSTM, MAE = 76.2 kW



(b) On-LSTM-FLR, MAE = 69.1 kW



(c) Proposed method, MAE = 67.5 kW

Results for post-COVID-19 phase, week from May 25 2020 to May 31 2020

Conclusion

Experiment results:

Phase	Pre-COVID-19	COVID-19					Post-COVID-19		
Week	3.9-3.15	3.16-3.22	3.23-3.29	5.4-5.10	5.11-5.17	5.18-5.24	5.25-5.31	6.1 - 6.7	6.8-6.14
Off-LSTM	31.5	34.3	35.9	43.0	41.3	54.8	76.2	62.0	59.1
On-LSTM-FLR	35.0	35.5	31.3	33.4	34.9	51.3	69.1	59.7	53.0
Proposed	31.7	30.9	30.5	31.4	32.4	44.4	67.5	55.9	51.5

Conclusion:

The proposed method can quickly adapt the model to the concept changes during COVID-19 and reduce the prediction errors.

Thank you for your time.