Multivariate LSTM-Based Forecasting for Renewable Energy: Enhancing Climate Change Mitigation

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Motivation:

The increasing integration of renewable energy sources (RESs) into modern power systems presents significant opportunities but also notable challenges, primarily due to the inherent variability of RES generation.

Traditional approaches, such as deterministic methods and stochastic programming, frequently depend on representative scenarios generated through clustering techniques like K-means. These methods may fail to fully capture the complex temporal dependencies and non-linear patterns within RES data.

Holland et al. [1] examined why marginal carbon emissions in the U.S. electricity sector have not declined despite increasing renewable energy adoption. The study estimates marginal emissions across different regions and time periods, finding that shifts in the energy mix, particularly the reliance on natural gas rather than renewables for marginal generation, play a significant role. The authors discuss the implications of these findings for climate policy, suggesting that carbon pricing and more targeted policies are needed to ensure emissions reductions. Building on these findings, accurate forecasts of RESs generation are essential for addressing this challenge. Reliable generation forecasts enable better grid management, enhance the integration of renewables, and reduce reliance on carbon-intensive generation.

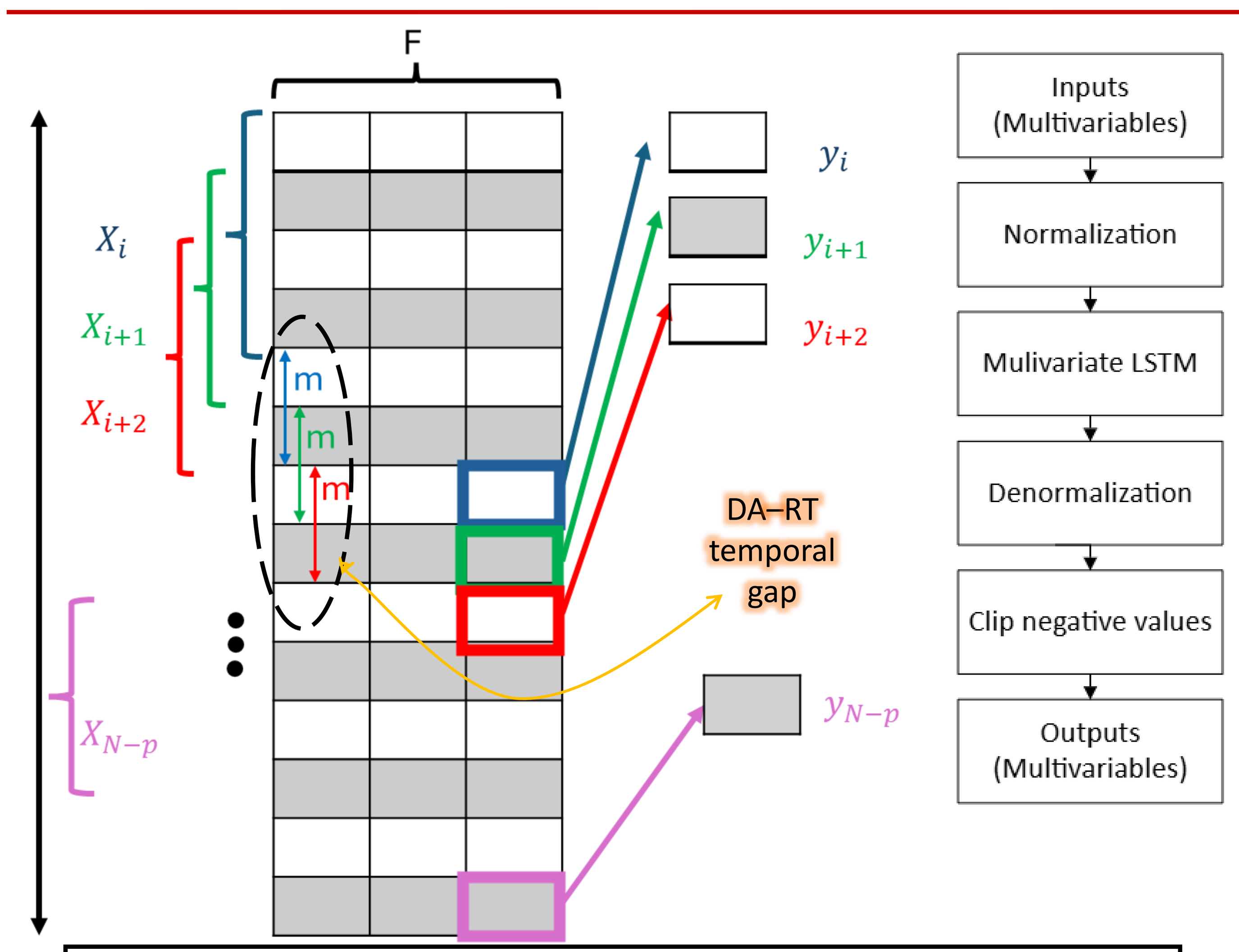
Novelty:

The primary contribution of this paper is the development of a Multivariate Long Short-Term Memory (M-LSTM)-based network for forecasting RESs generation. The proposed model leverages real-world data of RESs from various locations in Alberta province. Notably, the model predicts RES generation for a specific area by utilizing its historical data as well as data from neighboring areas. This contribution is pivotal for advancing RESs utilization and supporting climate change mitigation efforts. The model is tested in the day-ahead and real-time electricity markets to demonstrate the effectiveness of improved forecasting and its impact on CO_2 emissions. We consider the temporal gap between the day-ahead market closure and the start of the real-time market in the forecasting of RES.

Case study:

To quantify the impact of improved RES forecasting on reducing greenhouse gas emissions, we consider an Economic Dispatch (ED) problem. Three types of synchronous generators and one PV source are available to meet demand.
We compare three models for forecasting the PV generation in DA market:
(1) a K-means approach [2]
(2) a monthly average at each hour
(3) our M-LSTM model.

Methods:



Day Ahead Economic Dispatch

$$Obj^{da} = Min\Big(\sum_{v,t} C_v.p_{v,t} + \sum_{t} VOLL.ls_t\Big)$$

$$\sum_{v} p_{v,t} + p_t^{rnw} + ls_t = P_t \qquad \forall t$$
$$0 \le p_{v,t} \le \overline{P_v} \qquad \forall v,t$$
$$-R \le p_{v,t} - p_{v,t-1} \le R \qquad \forall v, t \neq 1$$
$$-R \le p_{v,t} - p_{v,T} \le R \qquad \forall v, t = 1$$
$$0 \le p_t^{rnw} \le \overline{P^{rnw}} \qquad \forall t$$
$$0 \le ls_t \le P_t \qquad \forall t$$

Real Time Economic Dispatch

$$Obj^{rt} = Min\Big(\sum_{v,t} C_v.p_{v,t}^{rt} + \sum_{t} VOLL.ls_t^{rt}\Big)$$

$$\sum_{v} p_{v,t}^{rt} + P_t^{rt,rnw} - p_t^{spill} - p_t^{rnw^*} + ls_t^{rt} = P_t \qquad \forall t$$
$$0 \le p_{v,t} + p_{v,t}^{rt} \le \overline{P_v} \qquad \forall v \in V_f, t$$
$$-R \le (p_{v,t}^* - p_{v,t-1}^*) + p_{v,t}^{rt} - p_{v,t-1}^{rt} \le R \qquad \forall v \in V_f, t \neq 1$$
$$-R \le (p_{v,t}^* - p_{v,t-T}^*) + p_{v^{rt},t} - p_{v^{rt},T} \le R \qquad \forall v \in V_f, t = 1$$
$$0 \le p_t^{spill} \le P_t^{rnw,rt} \qquad \forall t$$
$$0 \le ls_t + ls_t^{rt} \le P_t \qquad \forall t$$

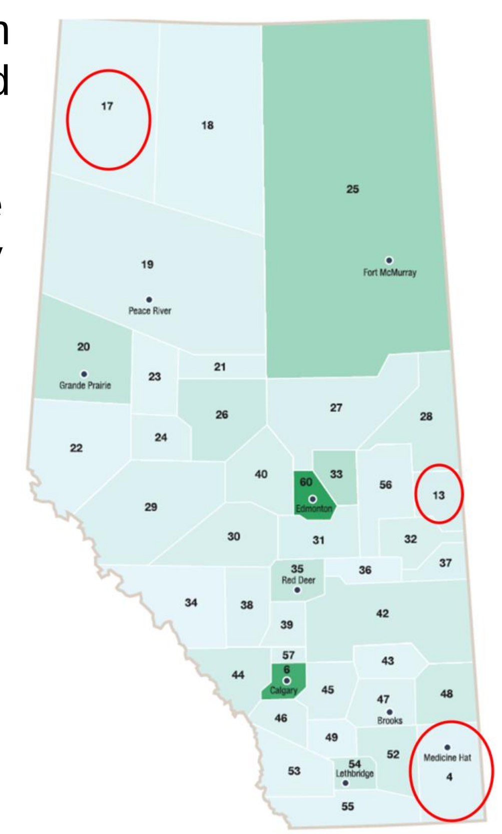
Main Results:

- Reduction in gas-fired unit usage:
  263.7 MW (Case 1) → 108.7 MW (M-LSTM)
- CO_2 emissions decrease:
  53,267 kg (Case 1) → 21,957 kg (M-LSTM), 58% reduction
- Load shedding eliminated:
  121.7 MW (Case 1), 5.79 MW (Case 2) → 0 MW (M-LSTM)
- Highest prediction accuracy:
  lowest NMAE using mean normalization (M-LSTM)

Research results:

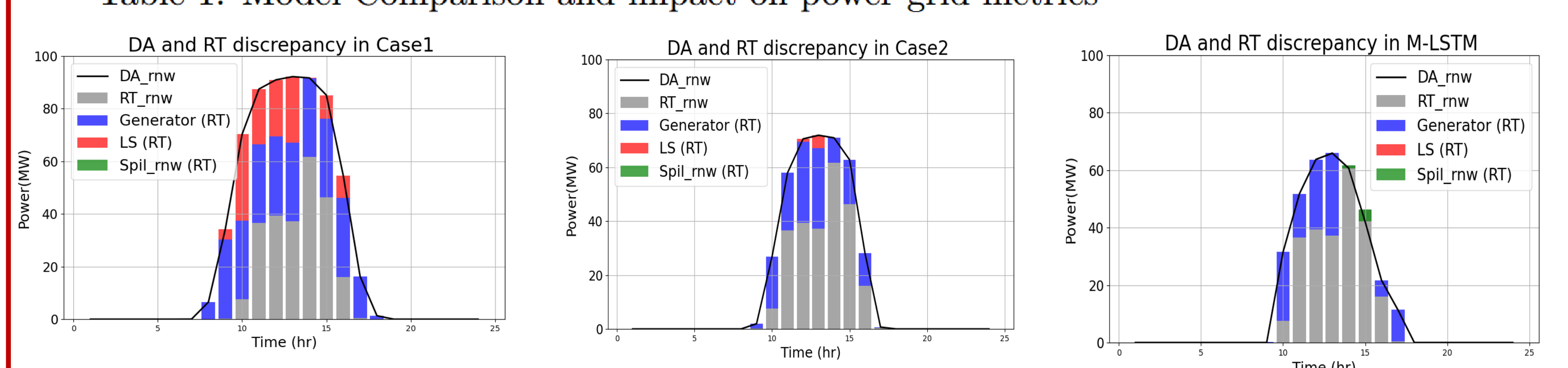
The forecasted RES generation is utilized in the day-ahead (DA) ED. However, in the real-time (RT) ED, the actual RES generation values become available and are used to adjust the system operation accordingly.

The discrepancy between the forecasted and actual RES values must be supplied by conventional generators in real-time. These generators are highly flexible, typically powered by natural gas, and contribute to CO_2 emissions.

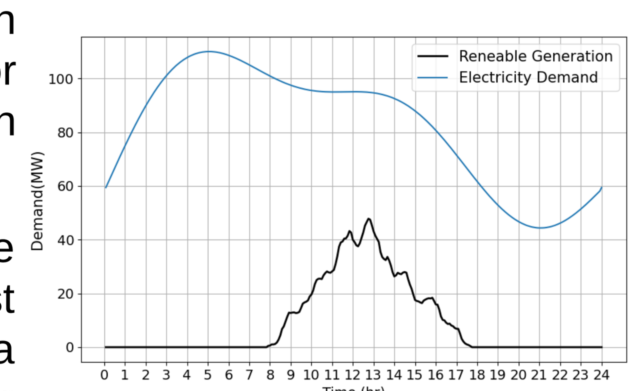


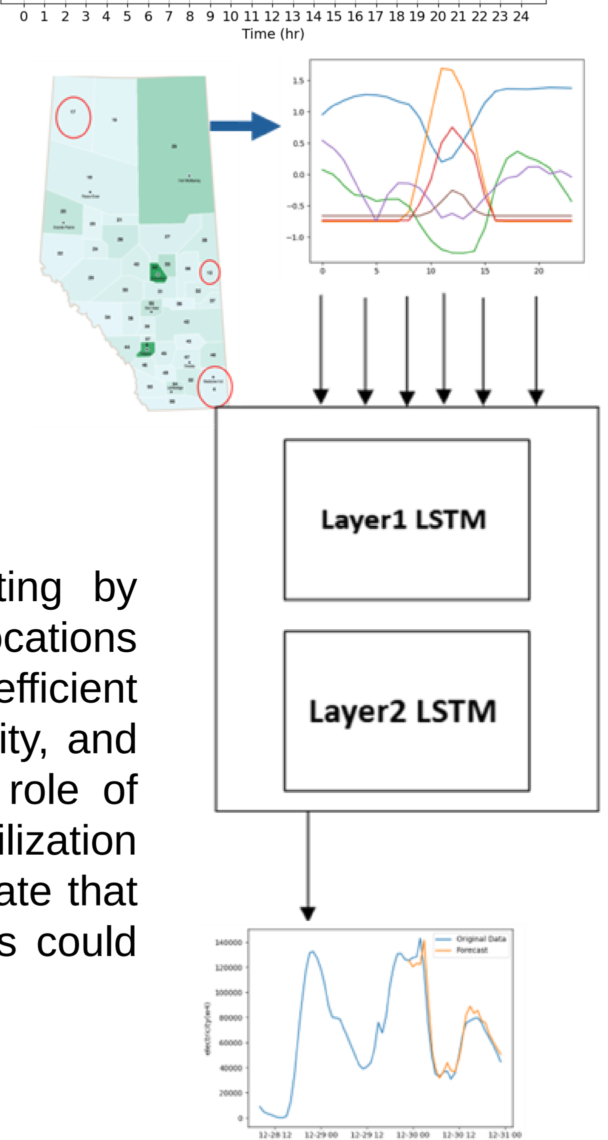
	Case1	Case2	M-LSTM
Gas fired unit (MW)	263.7	140.56	108.7
CO_2 emission (kg)	53,267	28,393	21,957
Load Shedding (MW)	121.7	5.79	0
RES Spillage (MW)	0	0	5
DA+RT Cost ($)	53,043	44,148	43,490
NMAE	1.57	0.59	0.46

Table 1: Model Comparison and impact on power grid metrics



- The dramatic reduction in gas-fired unit usage from 263.7 MW in Case 1 to 108.7 MW with M-LSTM highlights the potential for significant reduction in fossil fuel use in power systems through advanced AI-driven management techniques.
- This also substantially decreases CO_2 emissions across the different cases, with the M-LSTM approach achieving the lowest emissions at 21,957 kg, compared to 53,267 kg in Case 1 - a remarkable 58 % decrease. The M-LSTM method shows superior performance in load management, completely eliminating load shedding (0 MW) compared to 121.7 MW in Case 1 and 5.79 MW in Case 2, indicating its potential for enhancing grid stability and reliability.
- Based on the Normalized Mean Absolute Error (NMAE) using Mean Normalization, M-LSTM exhibits the lowest error, indicating the highest prediction accuracy compared to the ground truth.





Conclusion:

The proposed M-LSTM model enhances renewable energy forecasting by capturing complex temporal and spatial dependencies across multiple locations and RES types using historical data. Accurate forecasts lead to more efficient economic dispatch, reduced operational costs, enhanced system reliability, and reducing CO_2 emissions by 58%. This research highlights the critical role of advanced machine learning techniques in improving renewable energy utilization in modern power systems, to mitigate climate change. Results demonstrate that the scaled use of the M-LSTM model across power generation systems could significantly reduce CO_2 emissions.

References:

[1] Stephen P Holland, Matthew J Kotchen, Erin T Mansur, and Andrew J Yates. Why marginal CO_2 emissions are not decreasing for us electricity: estimates and implications for climate policy. Proceedings of the National Academy of Sciences, 119(8):e2116632119,2022.

[2] Farshid Kamrani, Sajjad Fattaheian-Dehkordi, Mohammad Gholami, Ali Abbaspour, Mahmud Fotuhi-Firuzabad, and Matti Lehtonen. A two-stage flexibility-oriented stochastic energy management strategy for multi-microgrids considering interaction with gas grid. IEEE Transactions on Engineering Management, 70(10):3330–3343, 2021.

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