UNIVERSITY of LOUISIANA LAFAYETTE

Lecture 7
Machine Learning Modelets for Weather Forecasting

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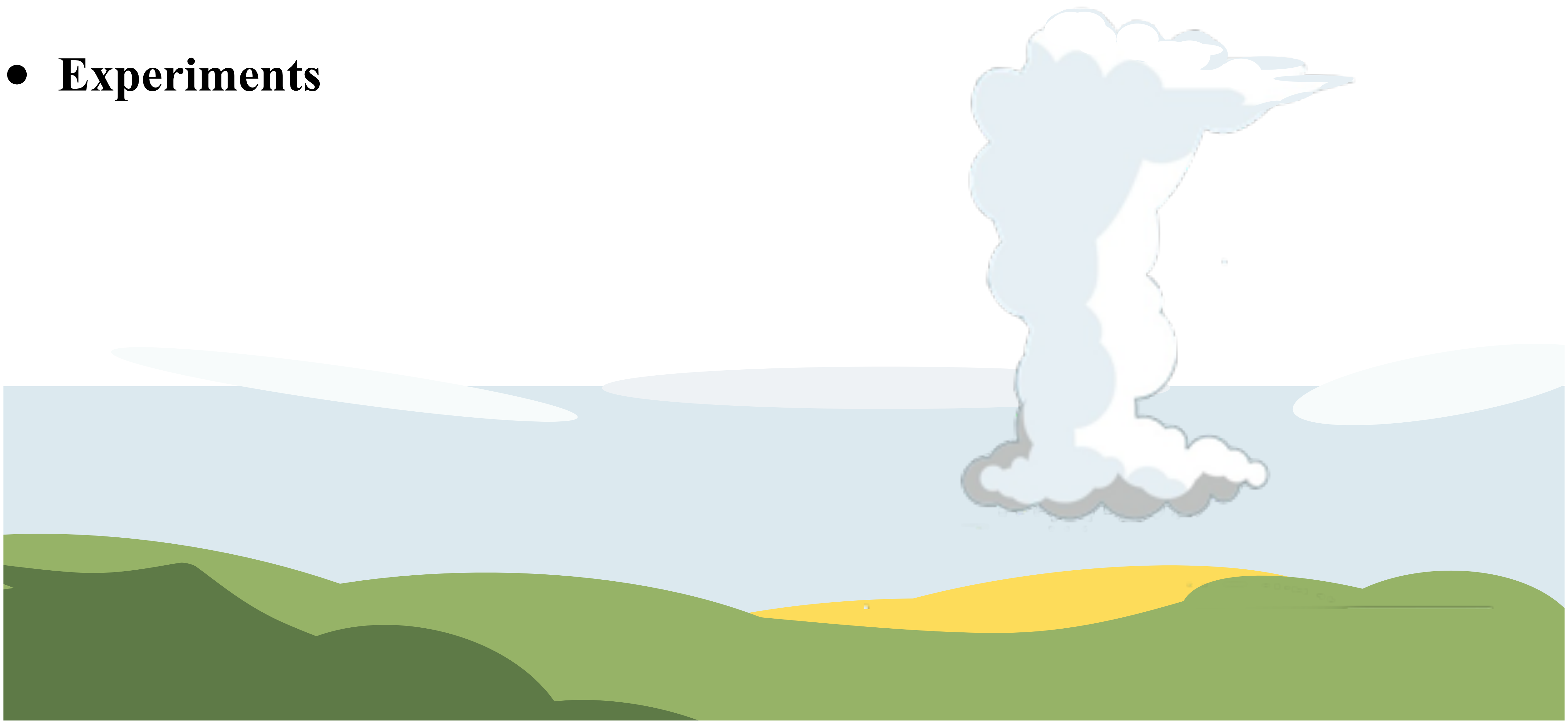
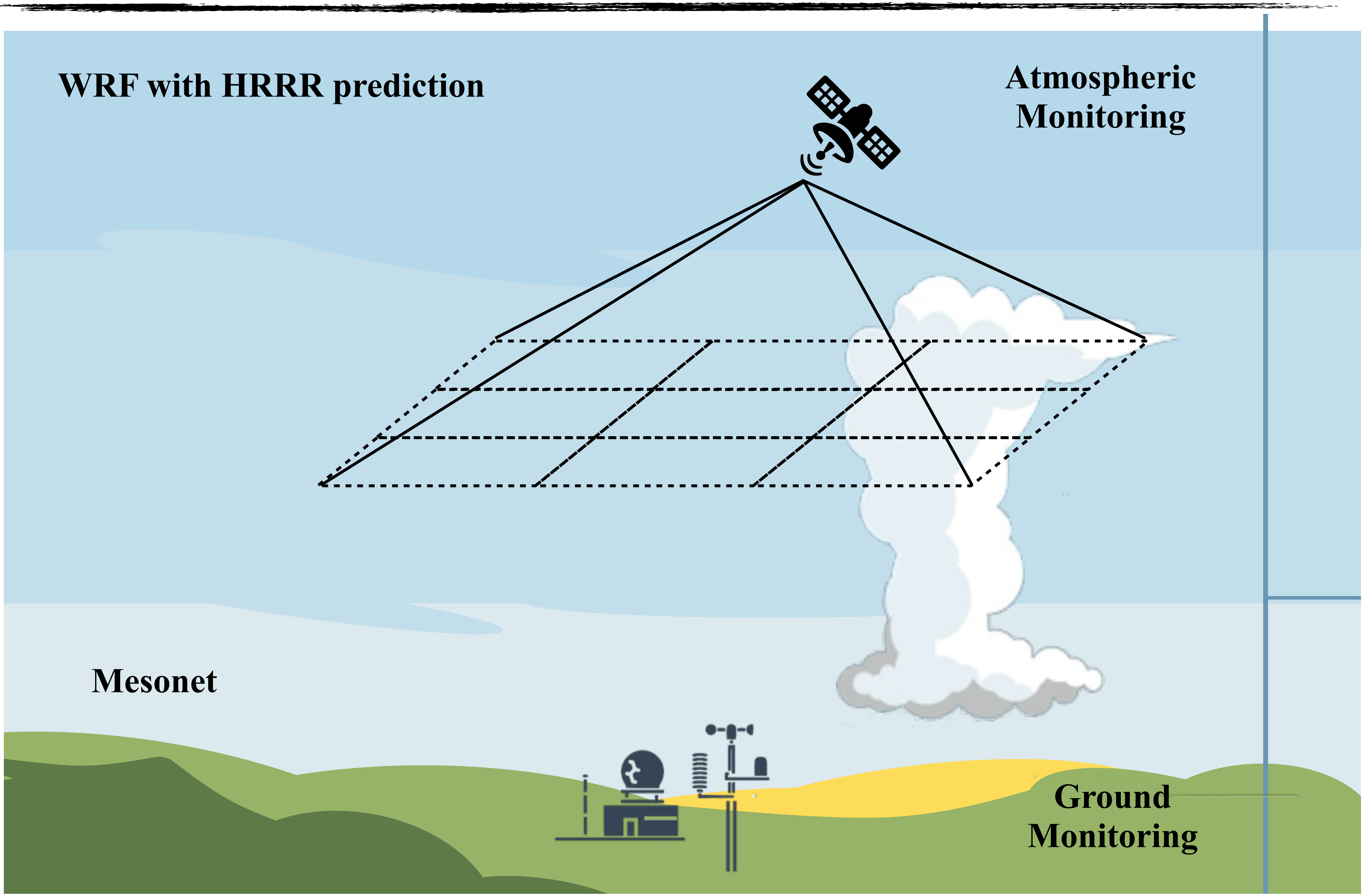
Outline

- Background
- Micro Model
- Micro-Macro Model
- Experiments



Background



WRF with HRRR prediction
Atmospheric Monitoring
Mesonet
Ground Monitoring

Background

Only for hourly prediction and its prediction accuracy is far from satisfaction

	Parameters	Resolution	Frequency	Height	Accuracy	Future Prediction
WRF with HRRR	148	3 km * 3 km	1 hour	Upper air	Low	Yes
Mesonet	60	single point	1 minute	Near-surface	High	No

Gathering the current near-surface measurements, unable to predict future values

Weather Forecasting Problem

- *Suppose a Mesonet station monitors the weather conditions for the past several years, then based on this information, a computer program can learn and predict the weather conditions in next several days.*

Past several years'
observation

Weather Forecasting Problem

- *Suppose a Mesonet station monitors the weather conditions for the past several years, then based on this information, a computer program can learn and predict the weather conditions in next several days.*

Past several years' observation

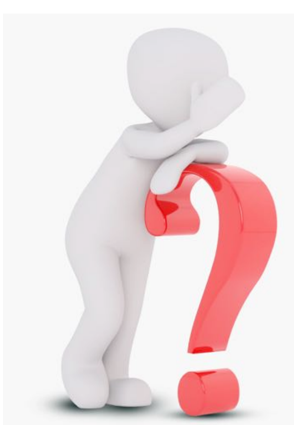
Last one week's observation

Tasks

Next week

Our Goal: Fine-grained Weather Predication

- **Flexible Fine-grained Temporal Domain Prediction**
  - Extracting the temporal variation features from the past measurements
  - Making precise prediction in the next few time horizons
  - Enabling flexible temporal resolution as desired, say 5 minutes, 10 minutes …



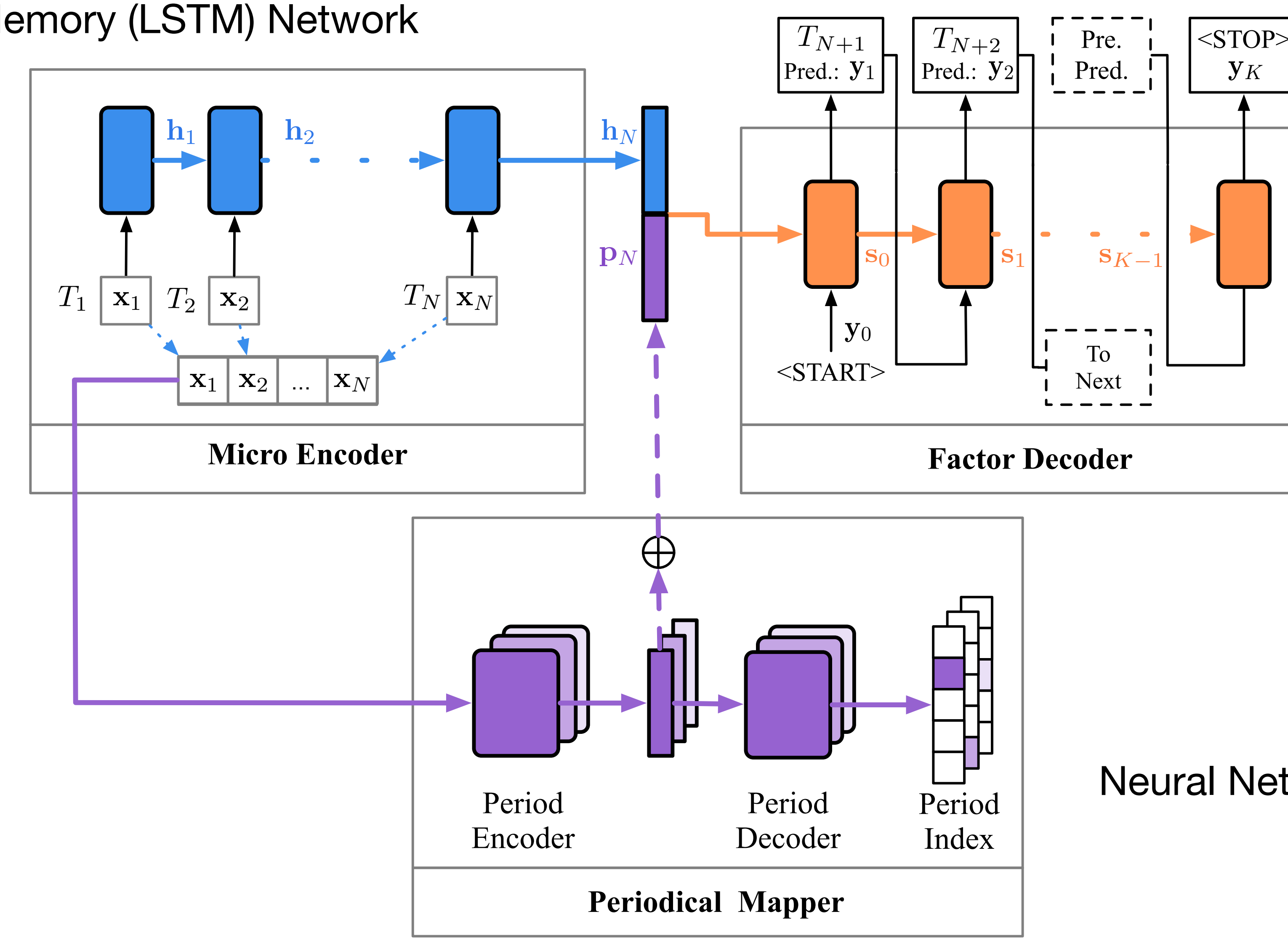
Weather Conditions

- **Continuous changes with time**
  - Having the time sequential patterns
  - Periodical patterns
- **Different from twitter data, whereas**
  - All tweets are independent
  - Less temporal domain relations

Micro Model

- **Micro Model**
  - Micro Encoder: capturing the sequential temporal patterns
  - Periodical Mapper: extracting the periodical patterns
  - Factor Decoder: Forecasting a set of weather parameters in the next few short time horizons

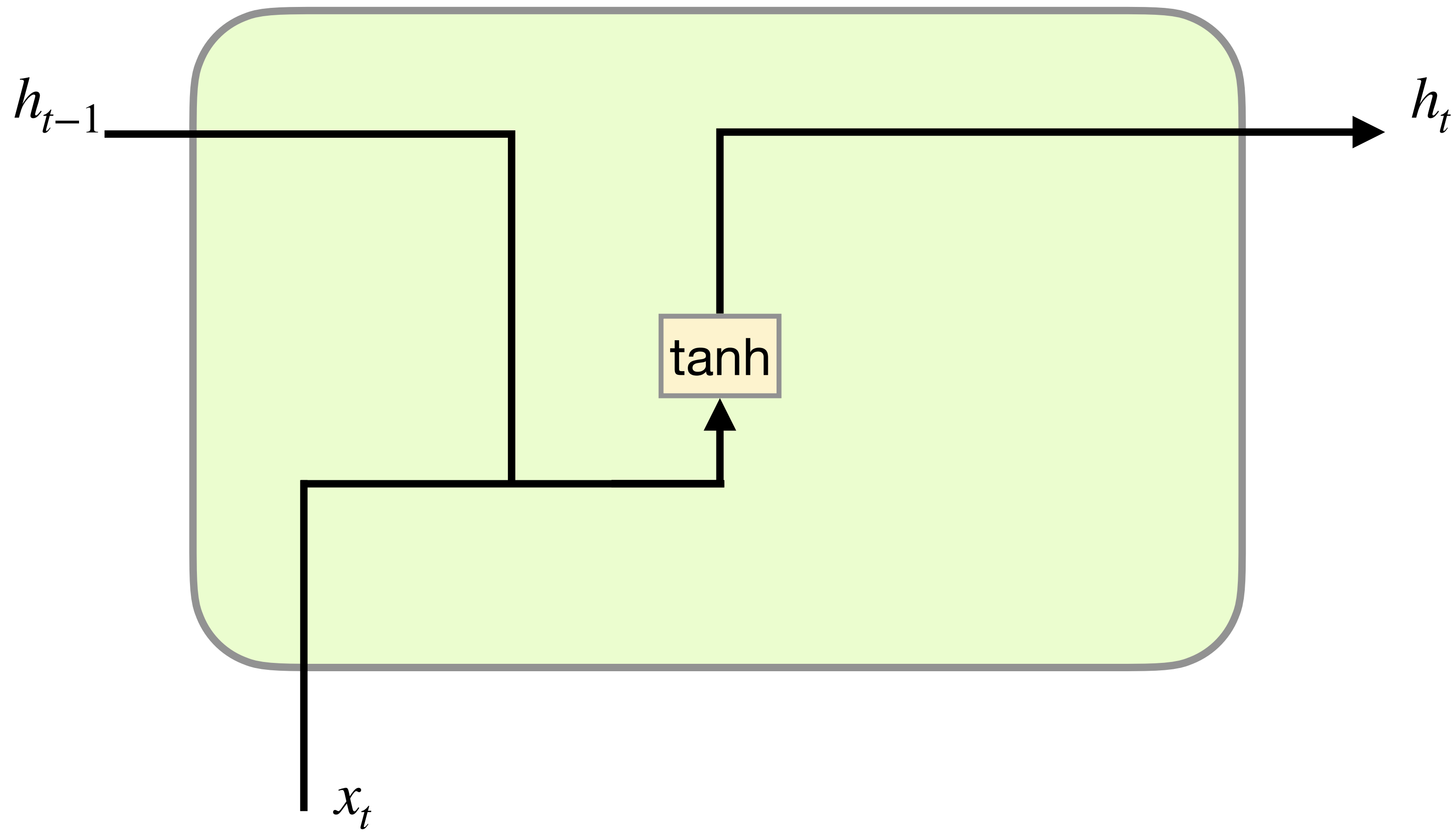
Long Short-term Memory (LSTM) Network



Neural Networks

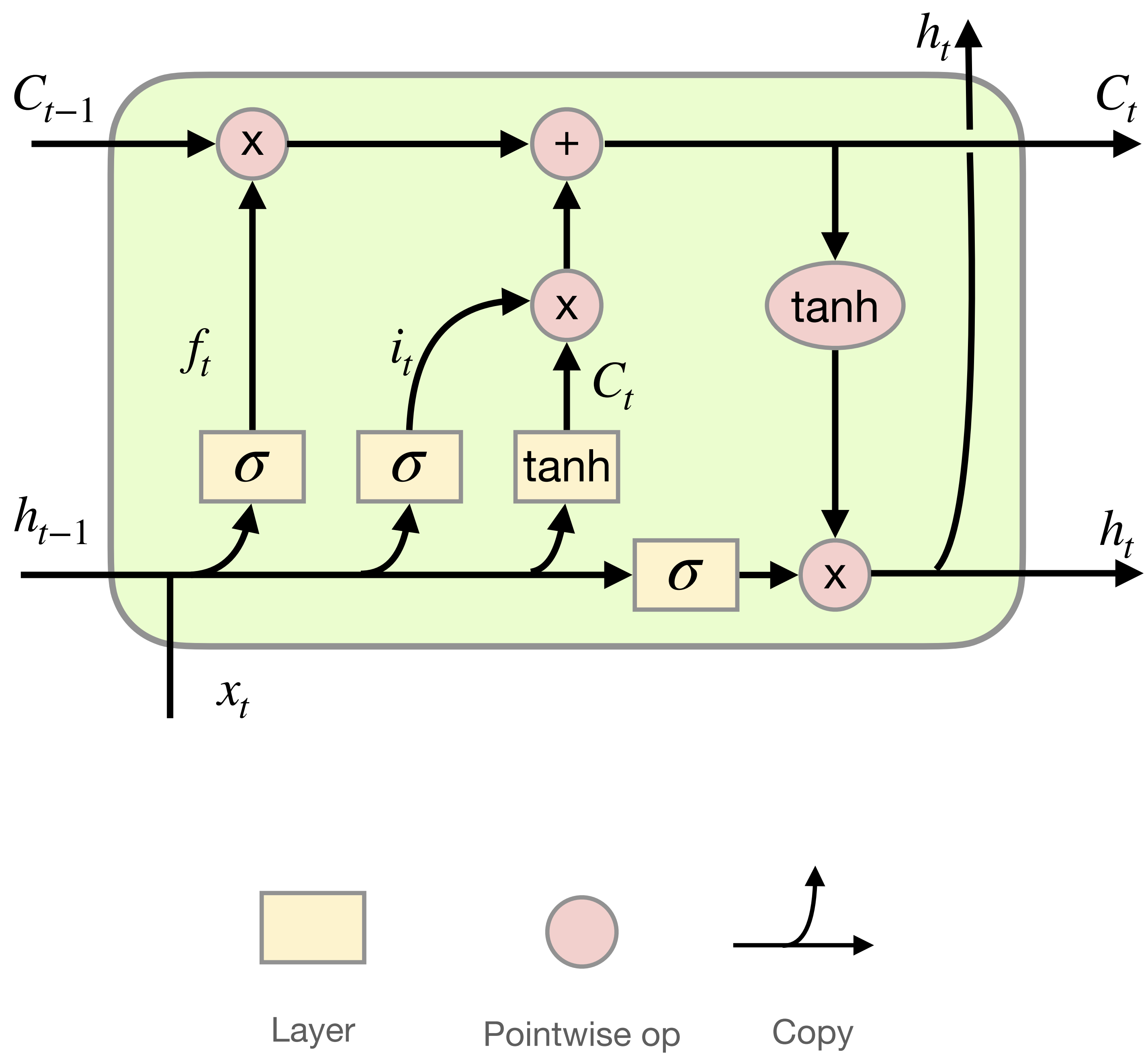
Micro Model

- **Recurrent neural network (RNN)**



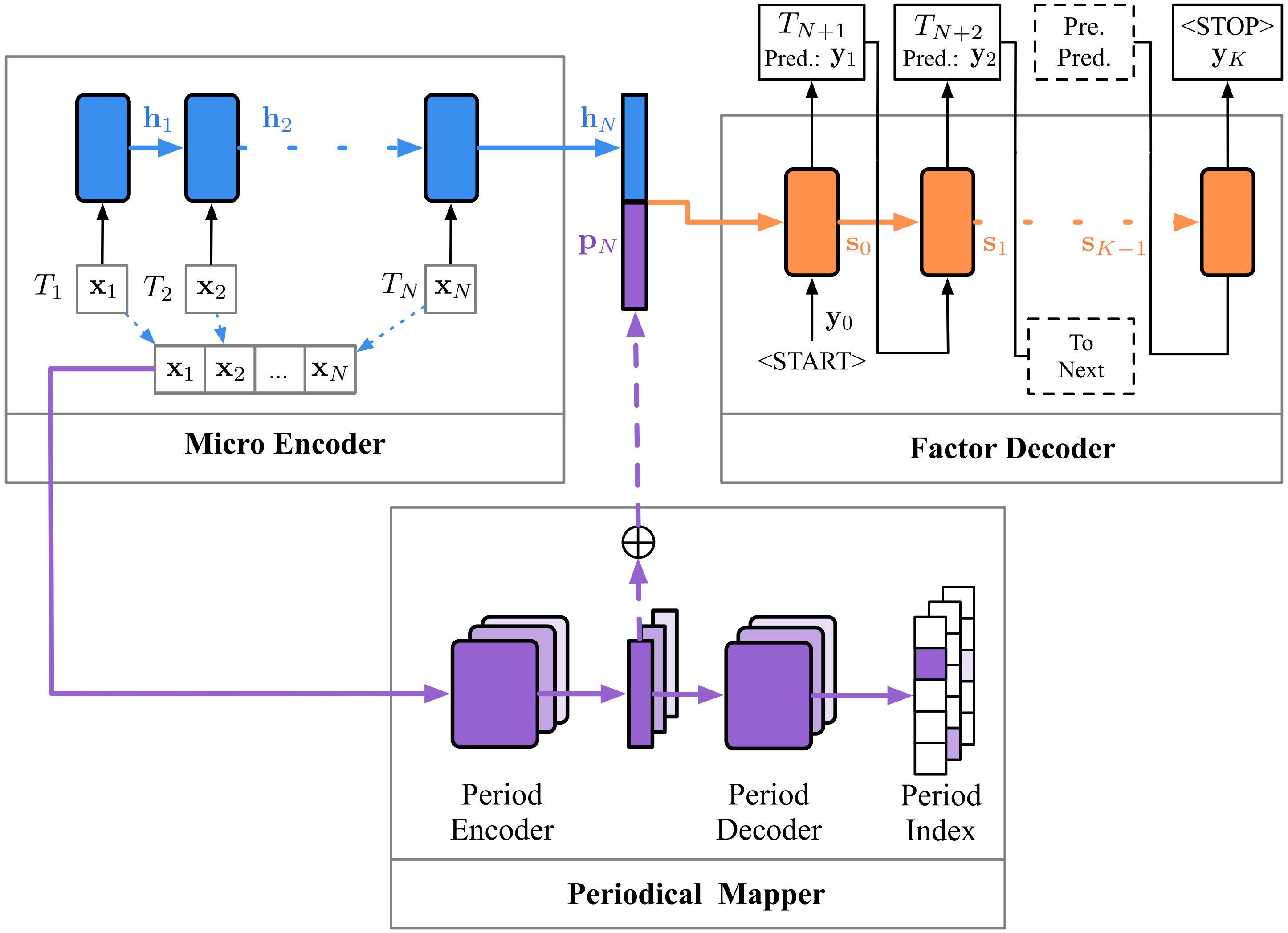
Micro Model

- **Long Short-Term Memory (LSTM)**



Micro Model

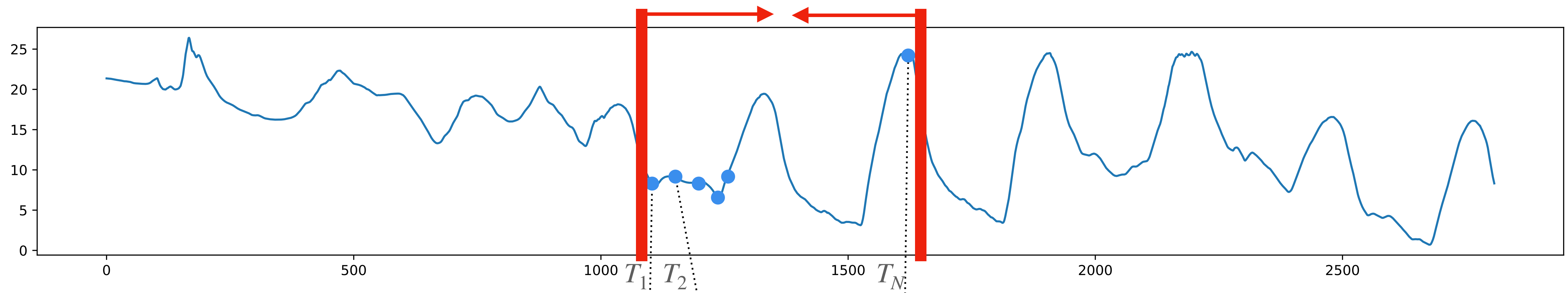
- **Micro Model**
  - Micro Encoder
  - Periodical Mapper
  - Factor Decoder

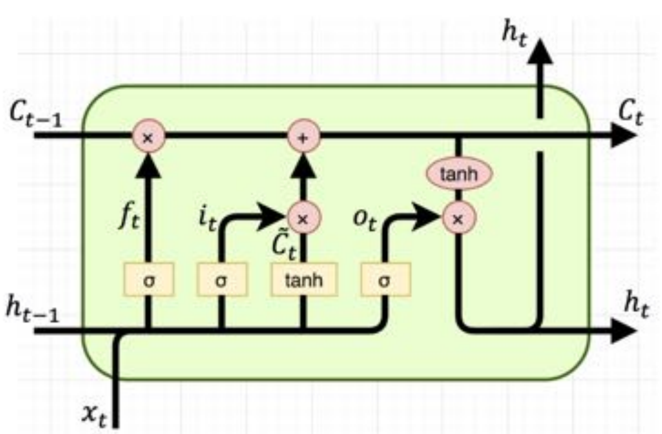


Micro Model

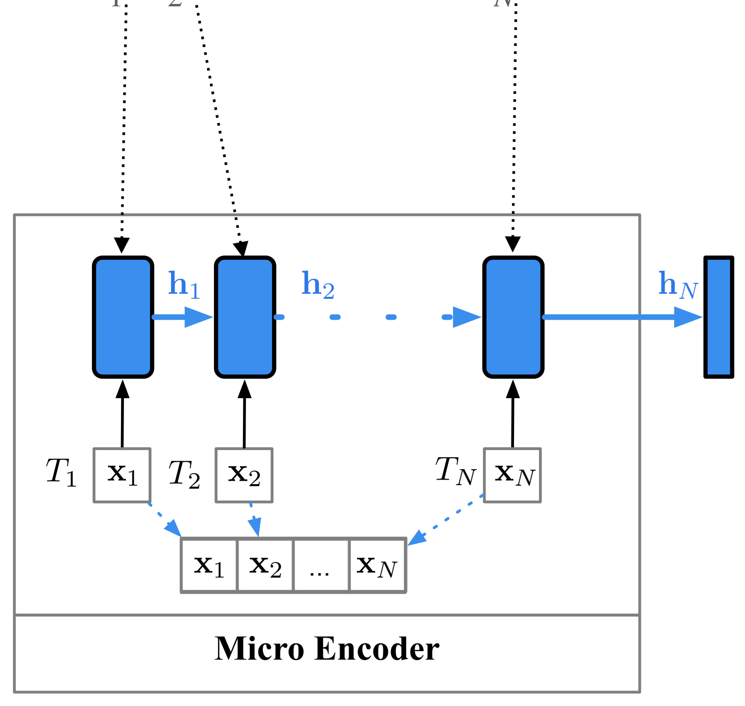
- **Micro Encoder**

  Encode the temporal sequence data in a certain period into one single dense vector.





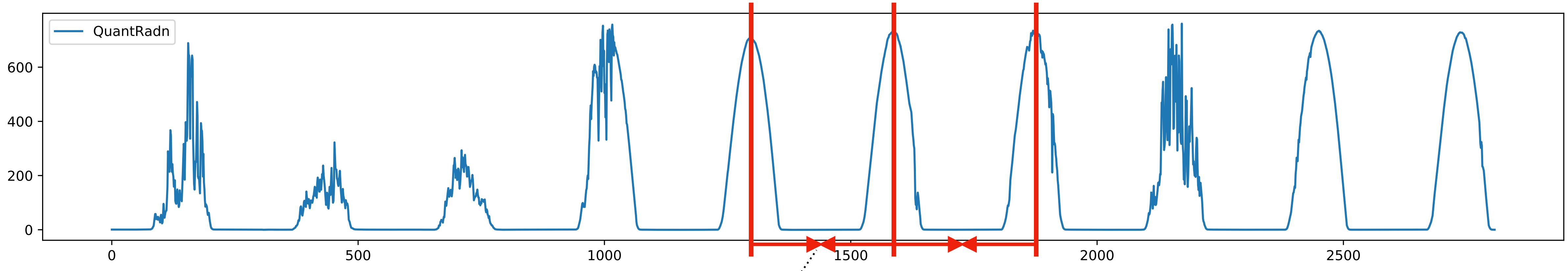
LSTM structure

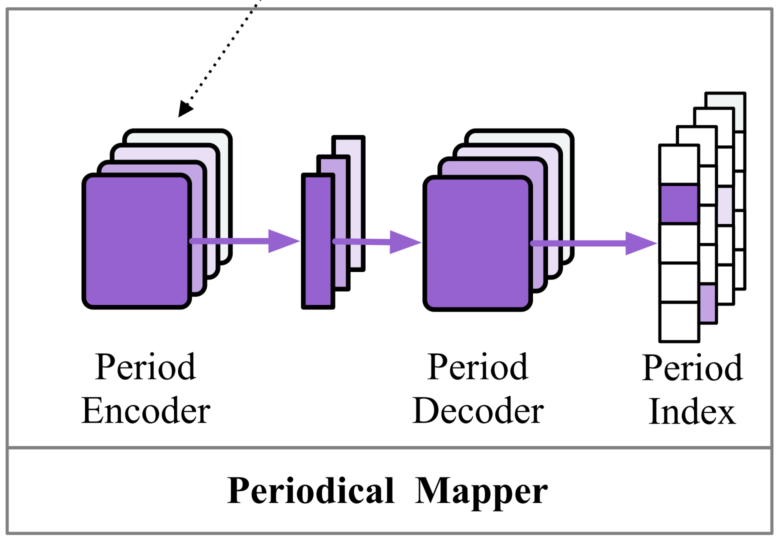


Micro Model

- **Periodical Mapper (1)**

  Extracting the periodical patterns

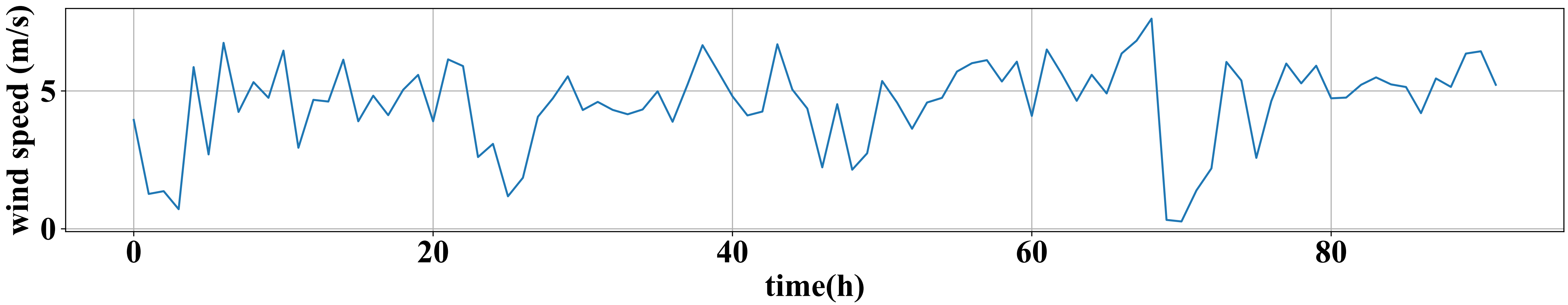




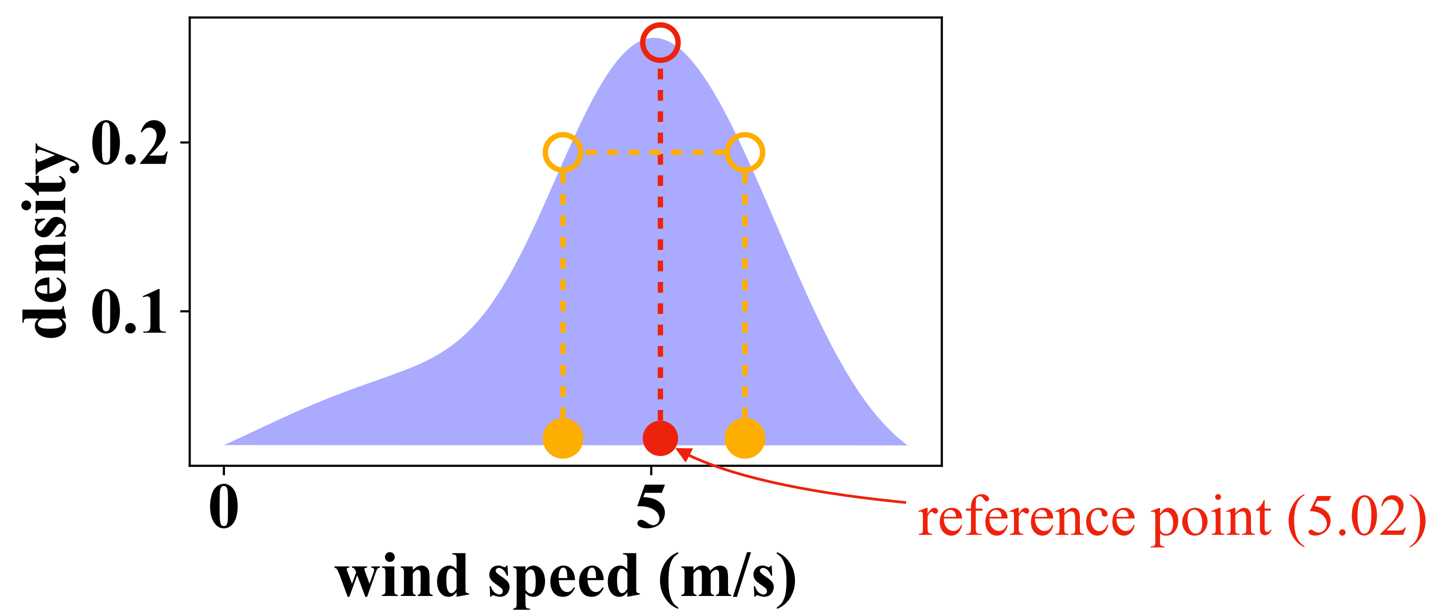
Micro Model

- **Periodical Mapper (2)**

  Reference points and reference area.



(a)

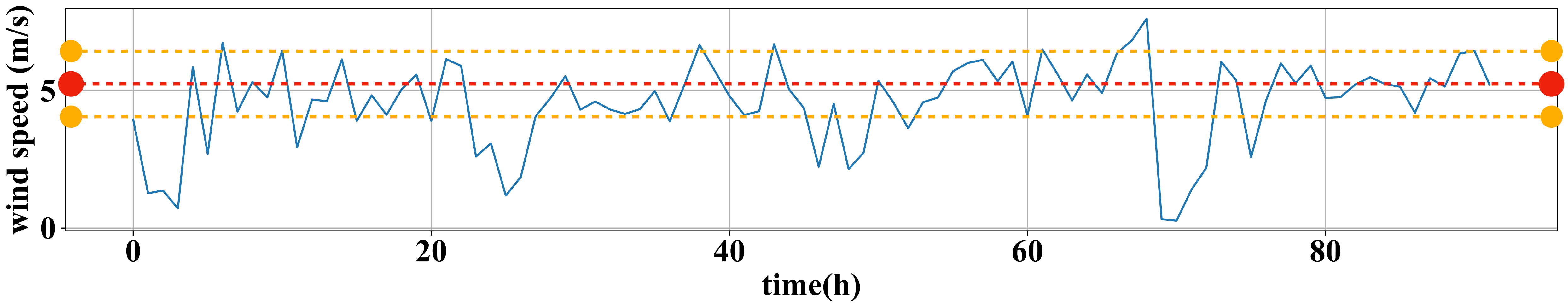


(b)

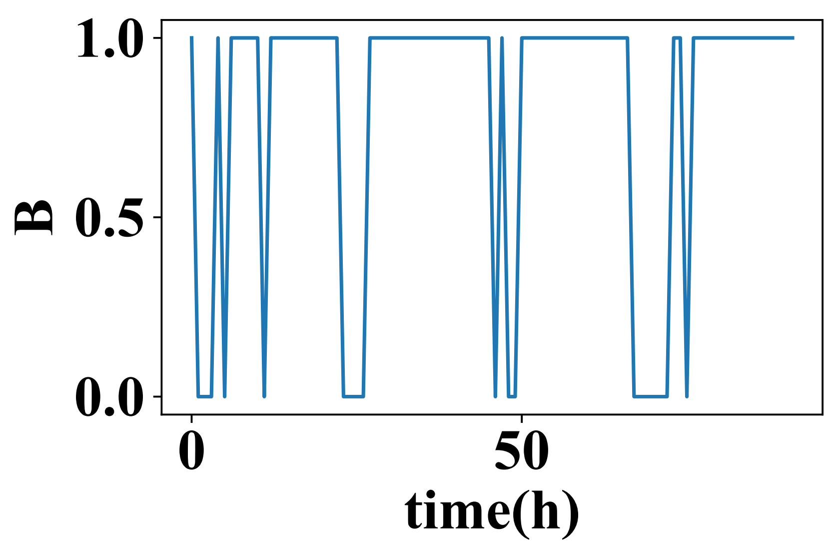
Micro Model

- **Periodical Mapper (3)**

  Binarization and Periodic Correlation.



(a)



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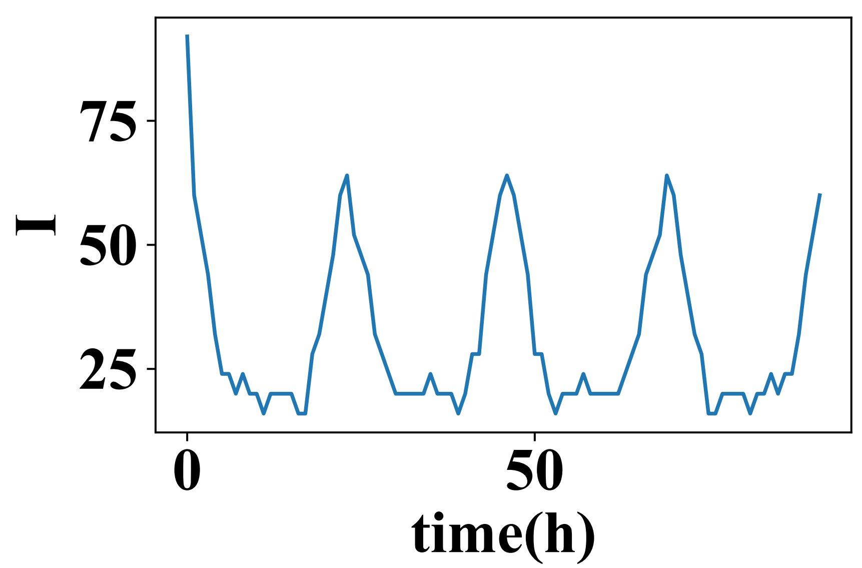
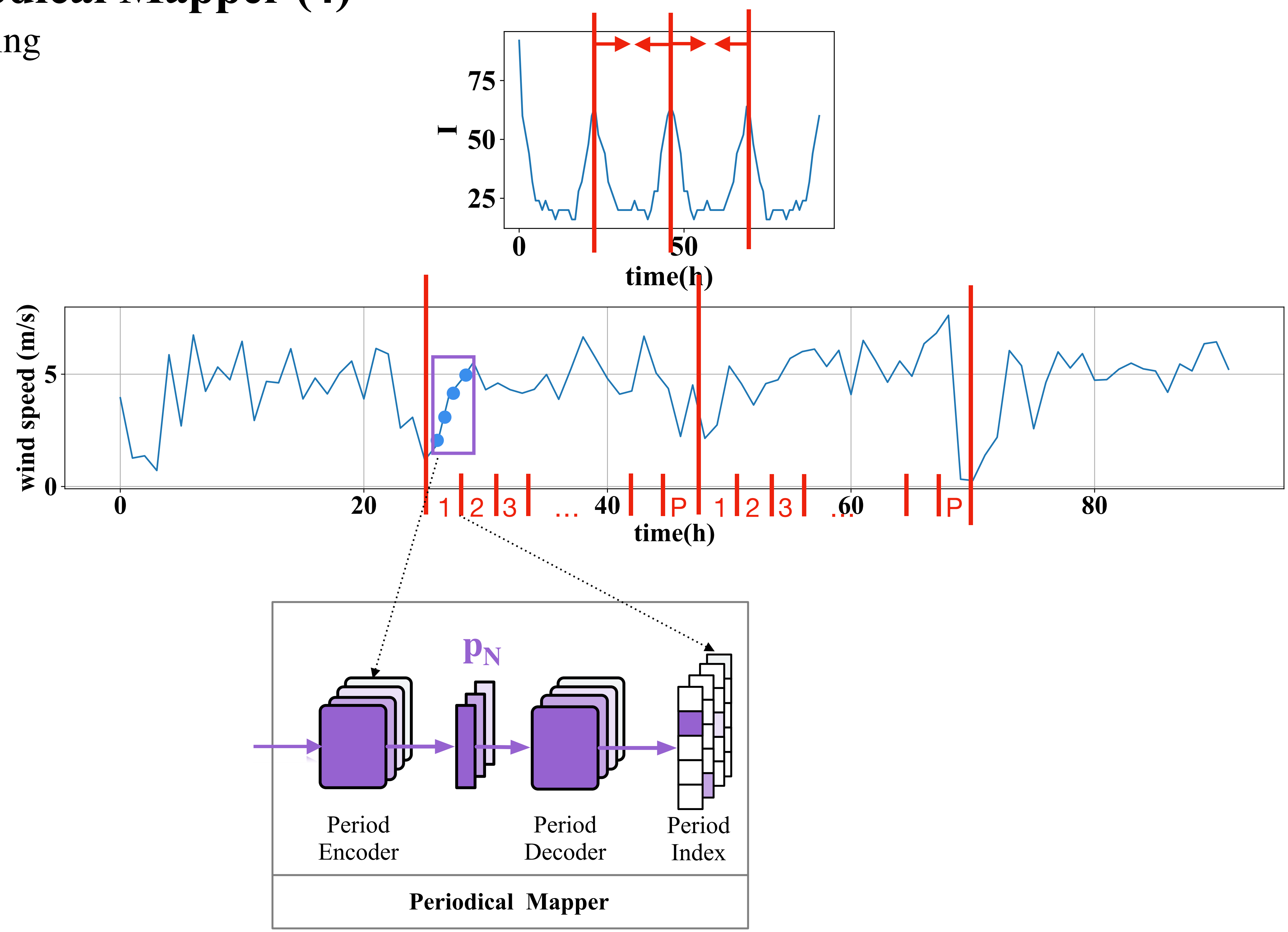


(c)

Micro Model

- **Periodical Mapper (4)**

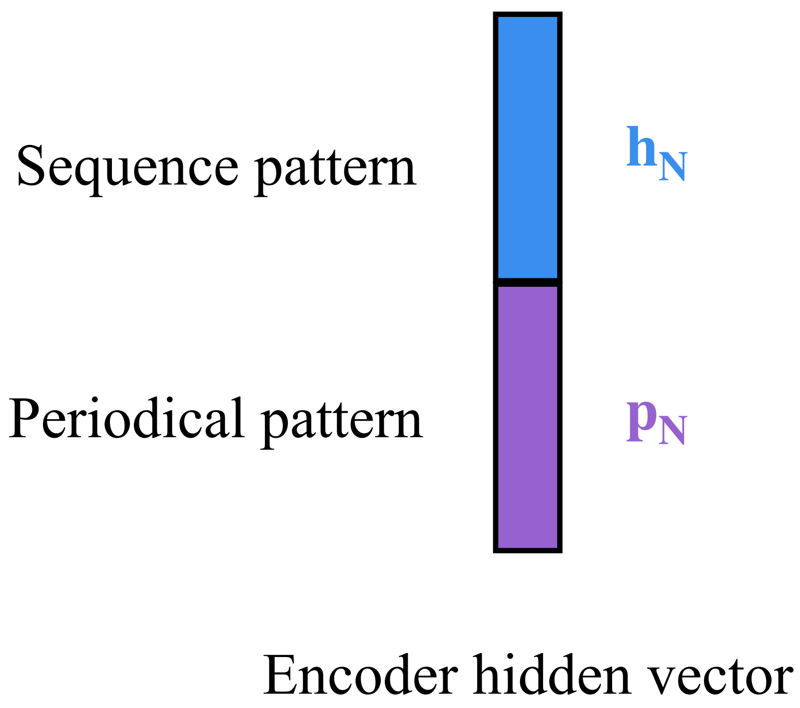
  Indexing

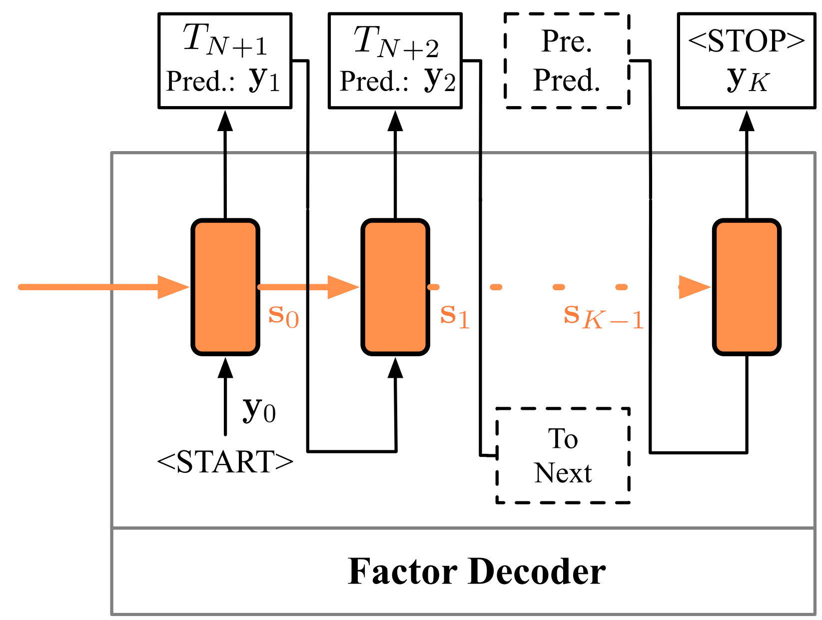


Micro Model

- **Micro Decoder**

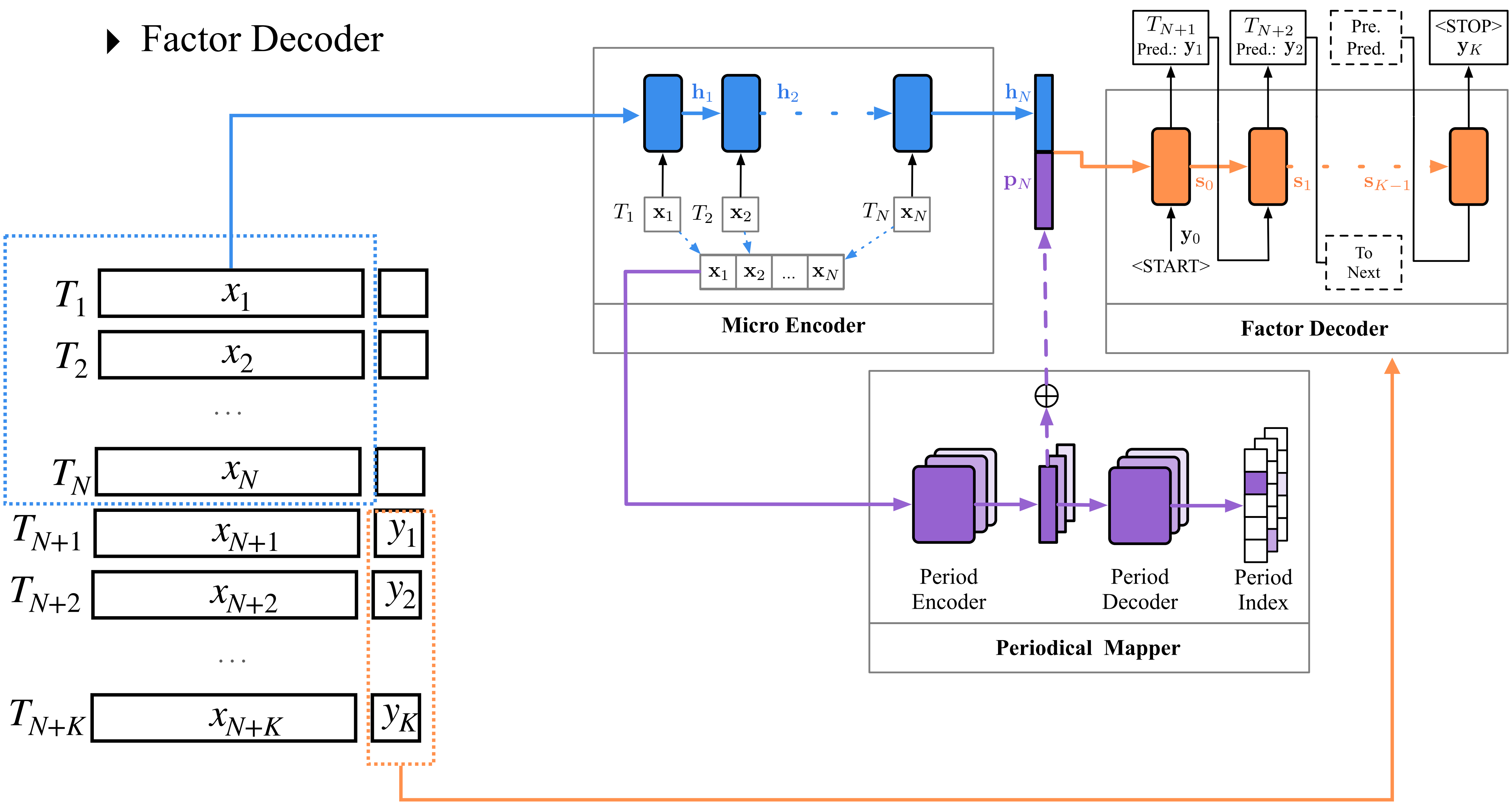
  Predict weather parameters.





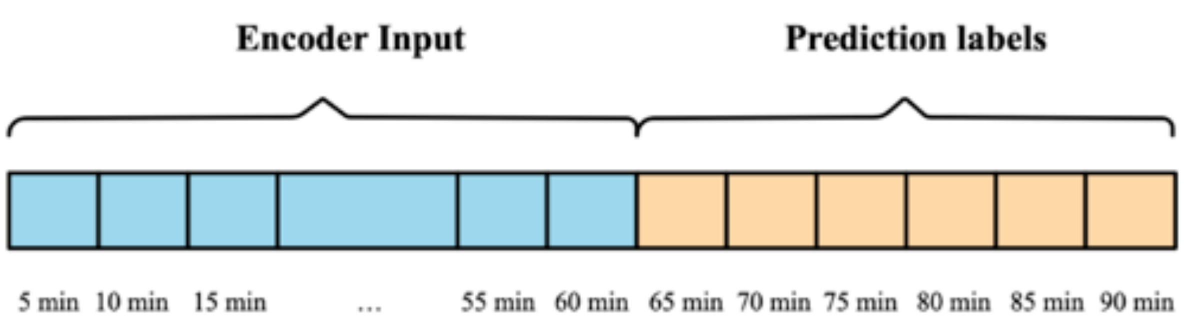
Micro Model

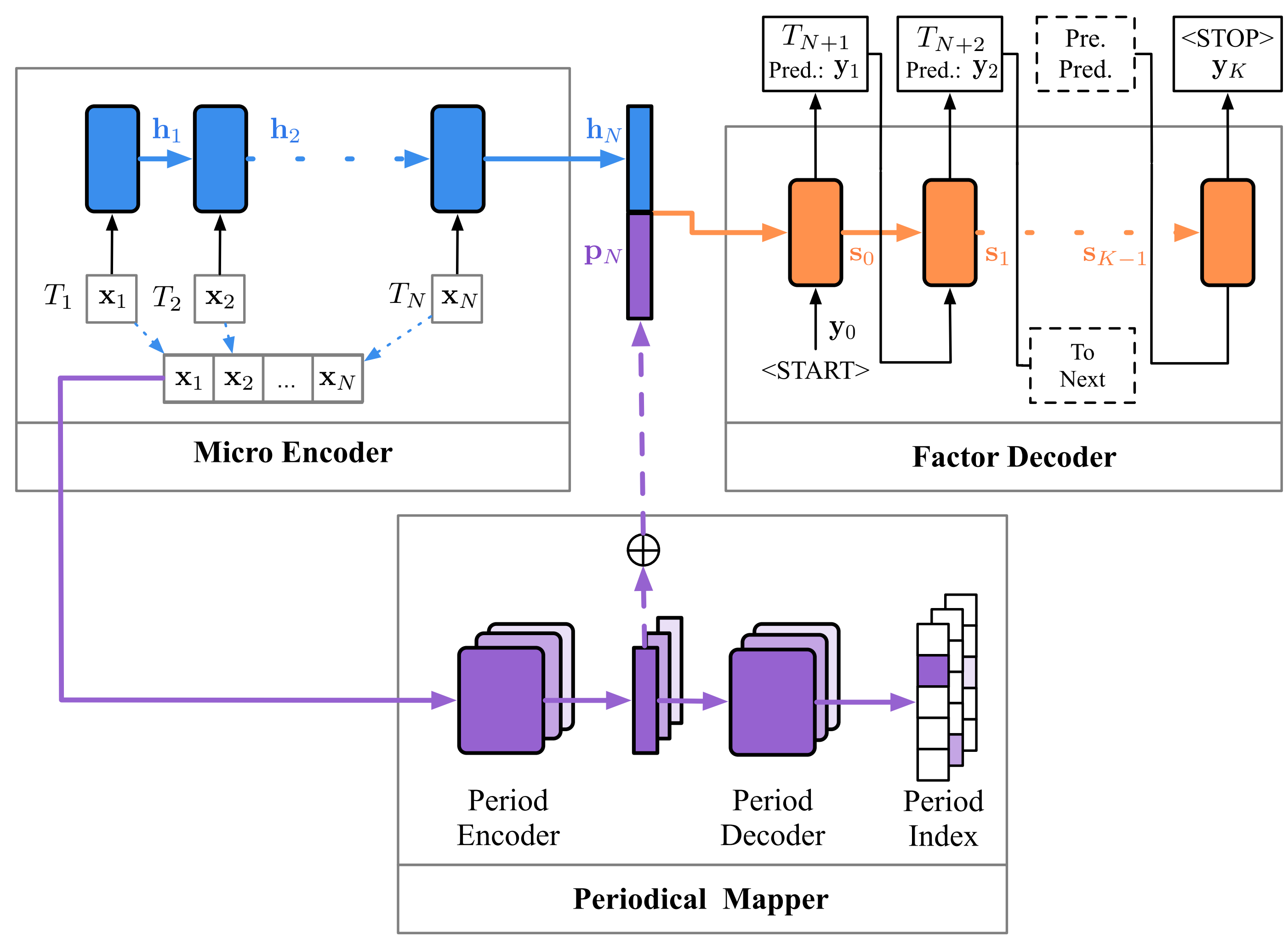
- **Micro Model**
  - Micro Encoder
  - Periodical Mapper
  - Factor Decoder



Micro — Training Phase

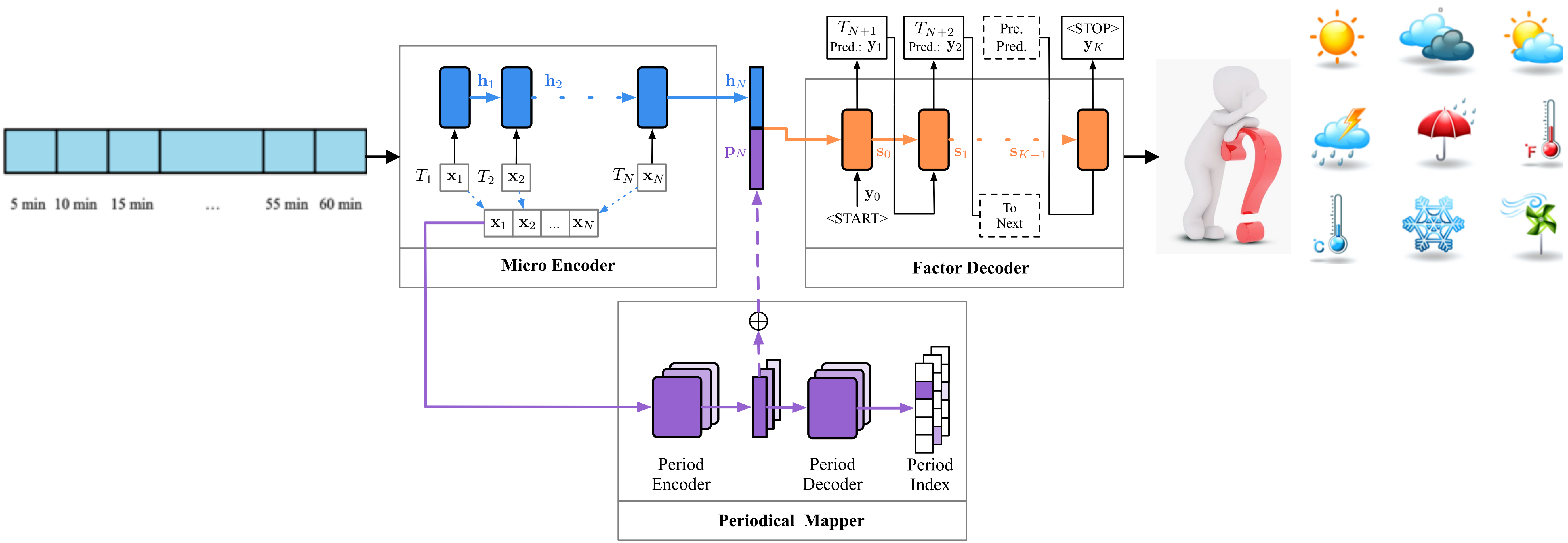
- **Data Labeling**
    - Select the most relevant parameters for predicting each specific weather parameter
    - Take previous years' measurements as the ground truth
    - Take each (N x T)-minute data as inputs and label the data in the subsequent M time interval





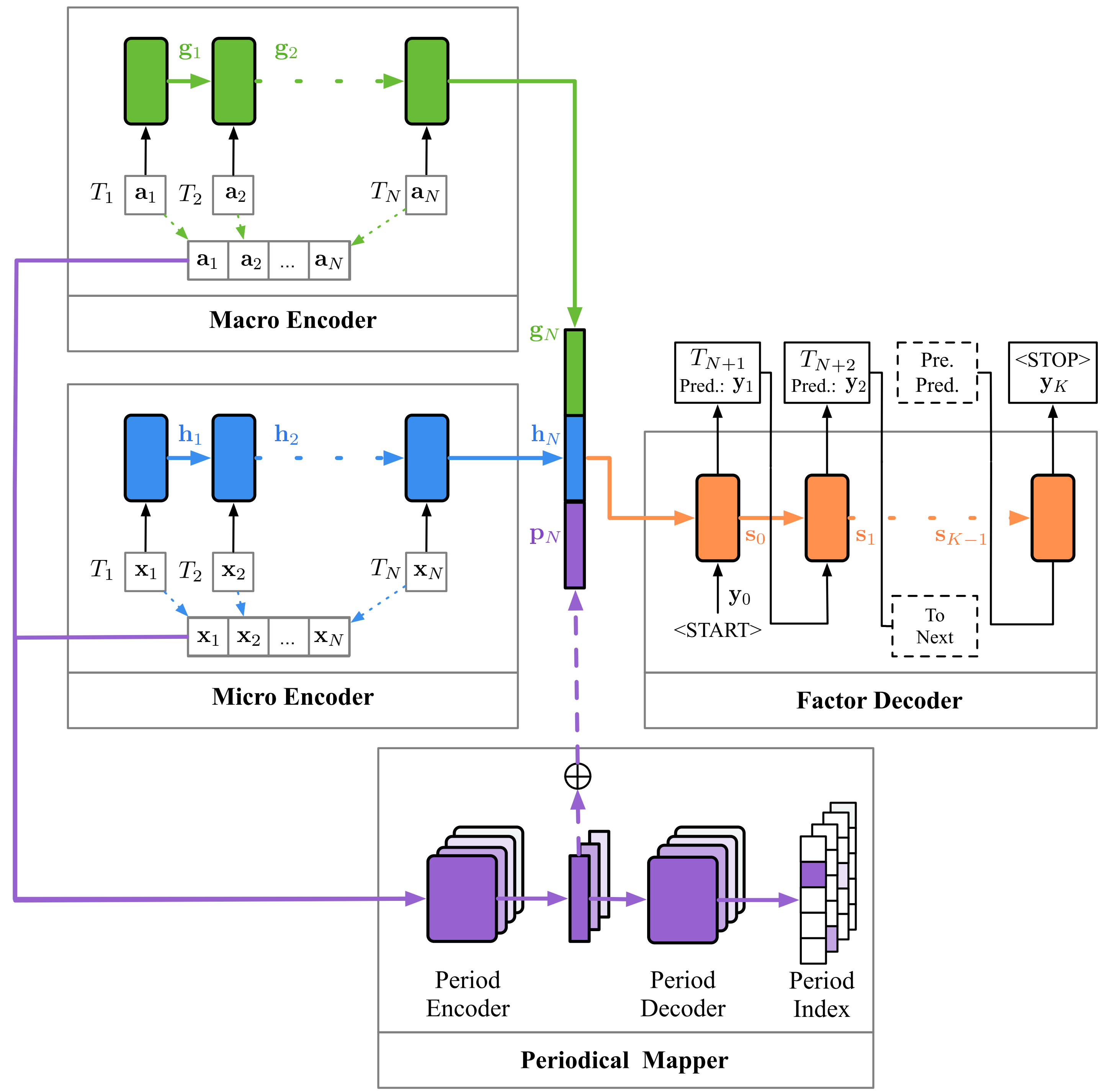
Micro — Prediction Phase

- **Data Processing**
  - Take the previous (N x T)-minute data, as input
  - Prediction: 



Micro-Macro Model

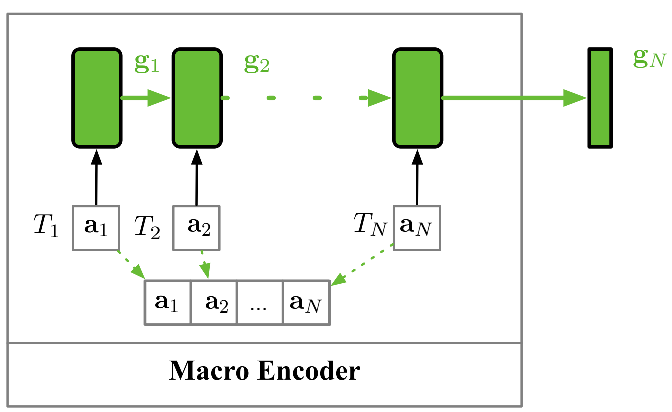
- **Micro-Macro Model**
  - Micro Encoder
  - Macro Encoder
  - Periodical Mapper
  - Factor Decoder

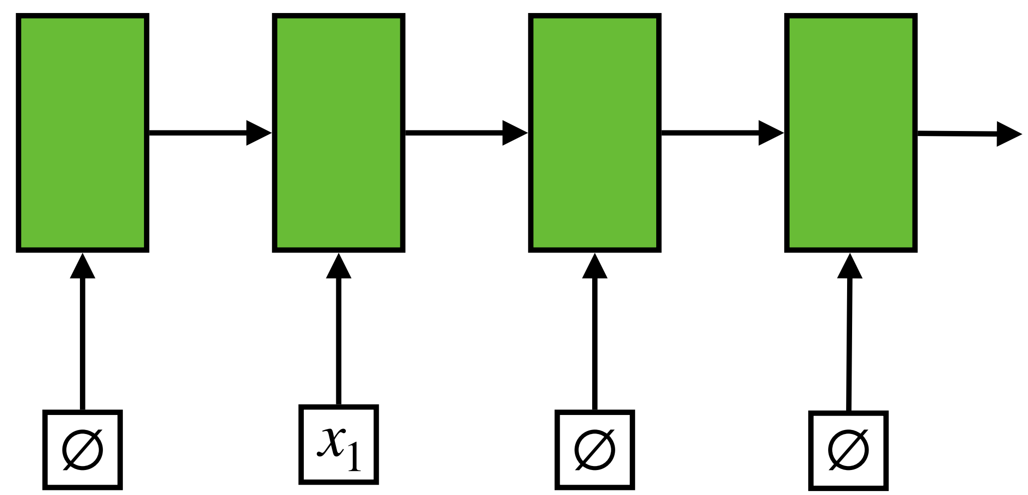


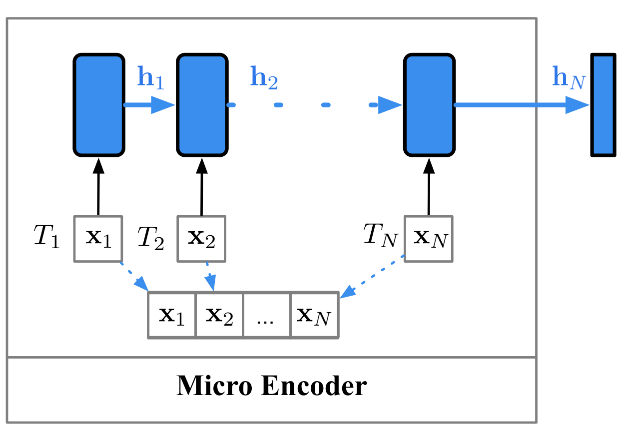
Micro-Macro Model

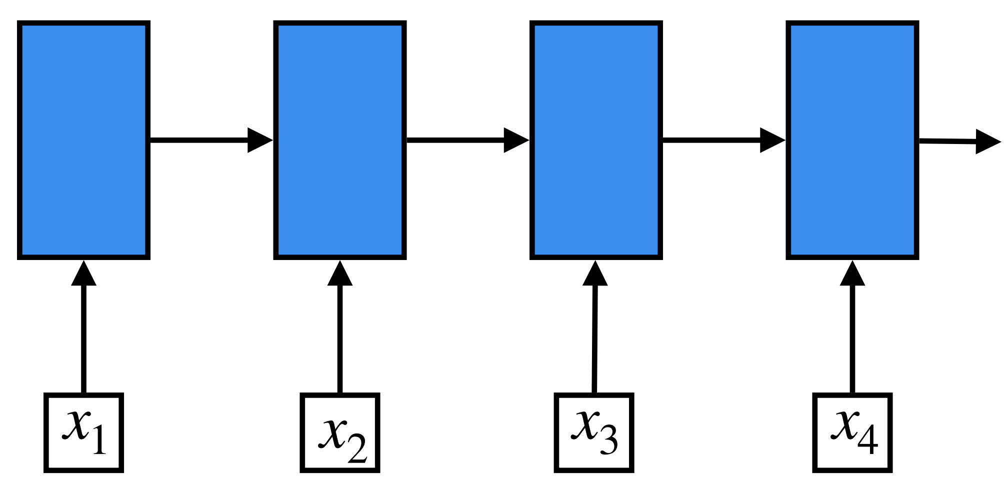
- **Macro Encoder**

  Downscaling



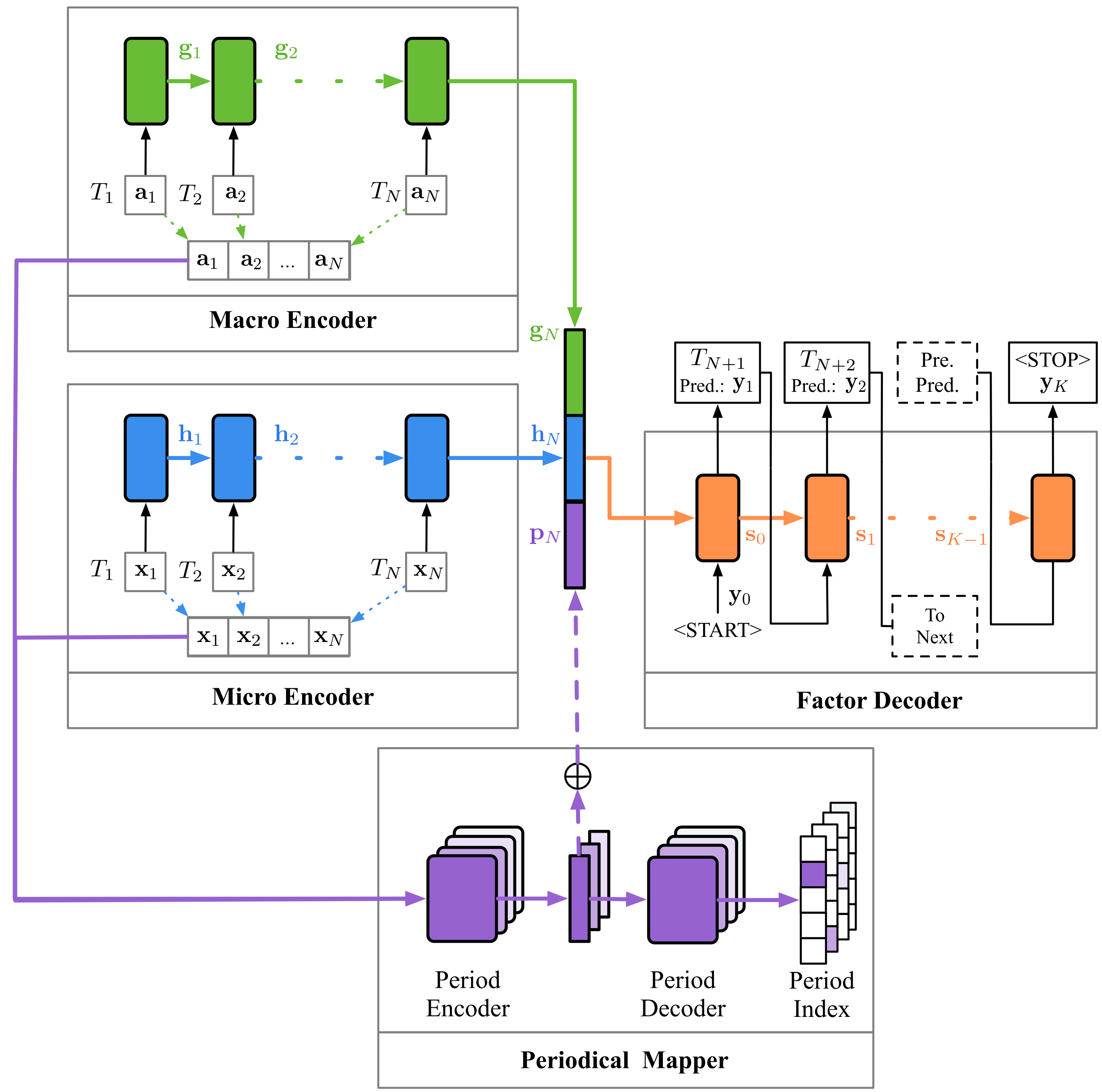






Micro-Macro Model

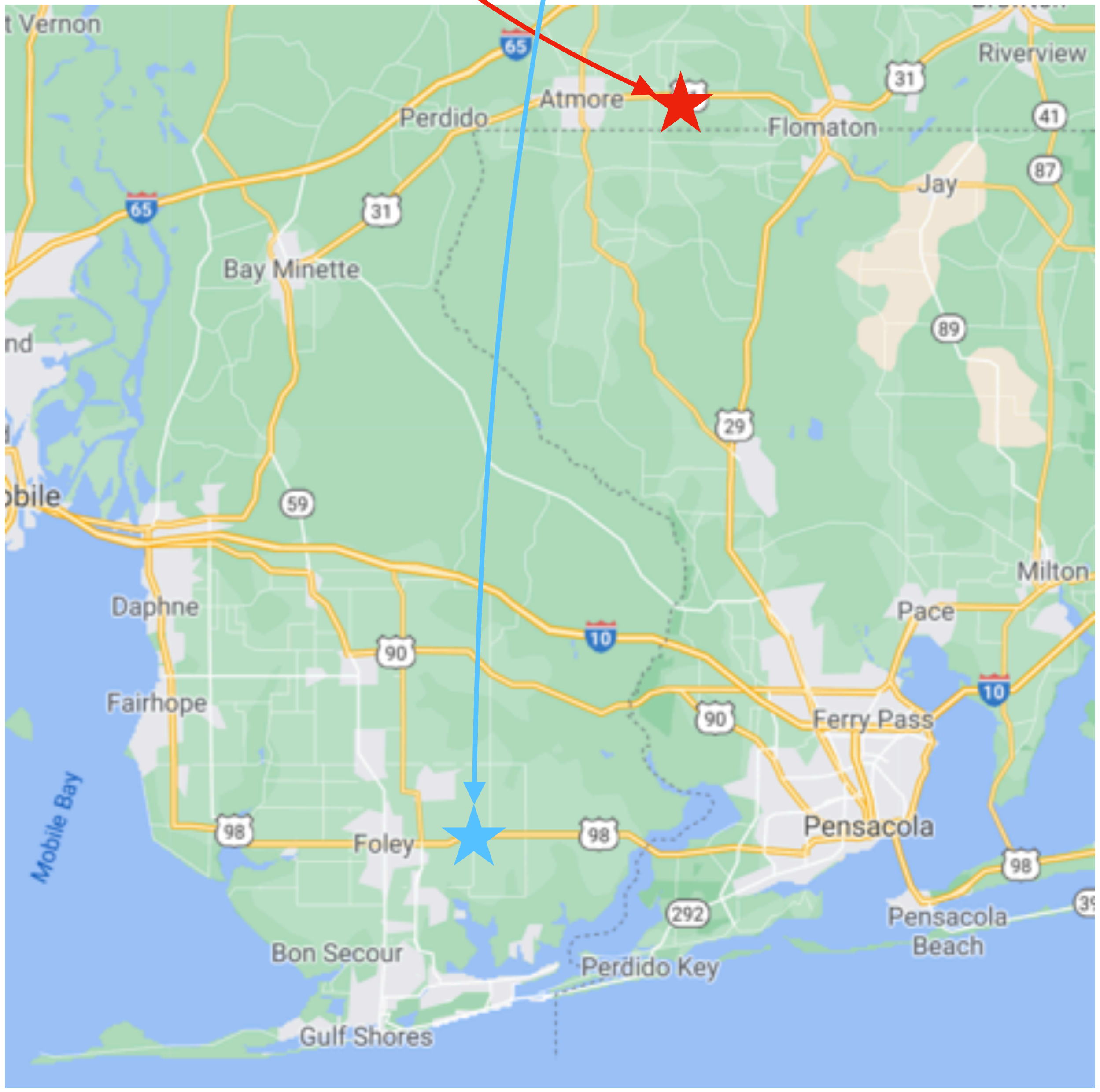
- **Micro-Macro Model**
  - Micro Encoder
  - Macro Encoder
  - Periodical Mapper
  - Factor Decoder



Experiments

- **Dataset**
  - SA Mesonet (26 automated weather stations, Atmore and Elberta in this experiment)
  - WRF-HRRR
  - Training: 2017, 2018
  - Test: 2019

Temperature,
Humidity,
Pressure,
Wind speed



Relevant Parameters

Predictions	Measurement parameters
TEMP	Vitel_100cm_d, IRTS_Body, SoilCond, SoilWaCond_tc, Vitel_100cm_b, eR, wfv, Vitel_100cm_a, SoilCond_tc, RH_10m
HUMI	Temp_C, Vitel_100cm_d, Vitel_100cm_a, Vitel_100cm_b, AirT_2m, AirT_10m WndSpd_Vert_Min, SoilT_5cm,Pressure_1, PTemp, IRTS
PRES	RH_10m, SoilCond, Temp_C, Vitel_100cm_d, AirT_1pt5m, IRTS_Trgt, PTemp, Vitel_100cm_b, SoilSfcT, AirT_10m
WSPD	WndSpd_2m_WVc_1, WndSpd_10m, WndSpd_2m_Max, WndSpd_Vert_Tot, WndSpd_2m_Std, QuantRadn, WndSpd_2m_WVc_2, WndSpd_Vert, WndSpd_10m_Max, WndDir_2m

From Mesonet Observation

Feature ID	Description
9	250hpa U-component of wind (m/s)
10	250hpa V-component of wind (m/s)
55	80 meters U-component of wind (m/s)
56	80 meters V-component of wind (m/s)
61	Ground moisture (%)
71	10 meters U-component of wind (m/s)
72	10 meters V-component of wind (m/s)
102	Cloud base pressure (Pa)
105	Cloud top pressure (Pa)
116	1000m storm relative helicity (%)

From WRF-HRRR Output

Overall Performance

		0 to 5 min	5 to 10 min	10 to 15 min	15 to 20 min	20 to 25 min	25 to 30 min
	TEMP	0.502	0.531	0.564	0.601	0.632	0.670
	HUMI	4.431	4.507	4.552	4.707	5.122	5.802
Atmore	PRES	1.087	1.133	1.139	1.156	1.184	1.235
	WSPD	0.396	0.552	0.572	0.658	0.709	0.833
	TEMP	0.424	0.468	0.471	0.475	0.479	0.485
	HUMI	1.852	1.873	1.893	1.905	1.933	2.015
Elberta	PRES	1.075	1.213	1.245	1.309	1.452	1.607
	WSPD	0.492	0.528	0.556	0.584	0.614	0.656

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}}$$

Table 1: Parameter information

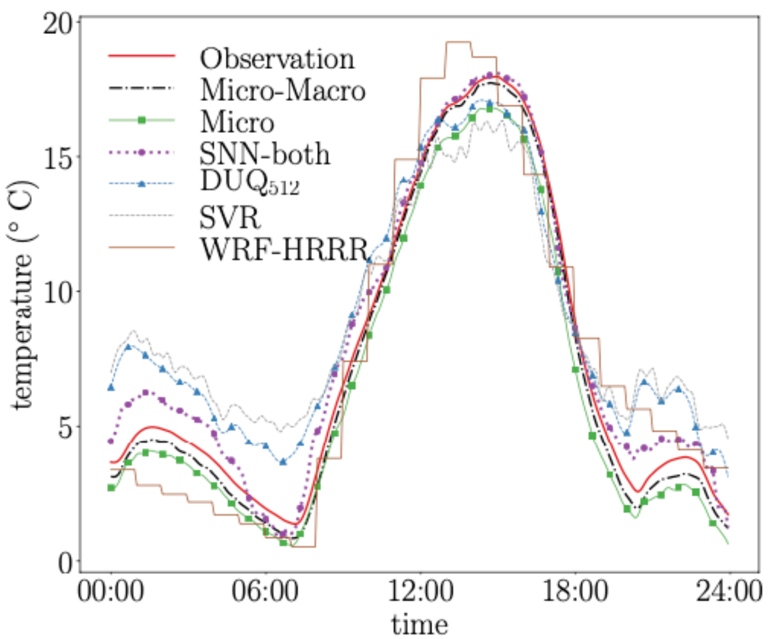
Parameter	Measurement	Mounting Height	Measuring Range
TEMP	Air Temperature	2 m	-40 to 60°C
HUMI	Relative Humidity	2 m	0 to 100%
PRES	Atmospheric Pressure	1.5m	600 to 1060mb
WSPD	Wind Speed	2 m	0 to 100 m/s

Comparisons

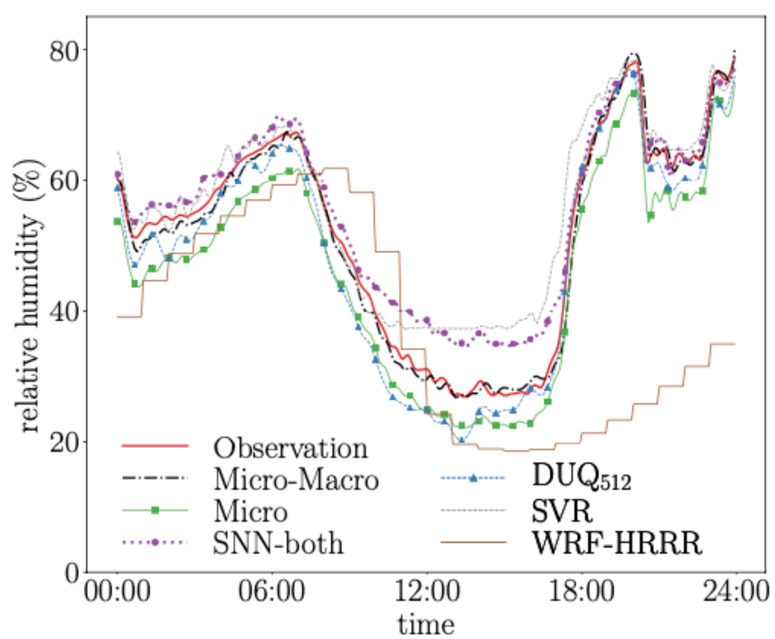
	Atmore				Elberta			
	TEMP	HUMI	PRES	WSPD	TEMP	HUMI	PRES	WSPD
WRF-HRRR	2.412	20.471	1.648	1.112	1.633	14.296	1.554	1.412
SVR	3.581	20.507	5.209	1.306	1.734	22.953	6.752	1.887
SNN-Micro	0.668	9.137	5.373	0.354	1.381	4.387	4.927	0.265
SNN-both	0.619	7.611	4.959	**0.330**	0.804	4.250	4.337	**0.264**
DUQ_{512}	0.812	5.668	2.714	0.592	0.645	3.524	3.513	0.541
$DUQ_{512-512}$	0.657	5.354	2.667	0.585	0.632	3.326	3.225	0.489
Micro-Macro	**0.502**	**4.431**	**1.087**	0.396	**0.424**	**1.852**	**1.075**	0.492

RMSE values of different methods for 5-minute prediction

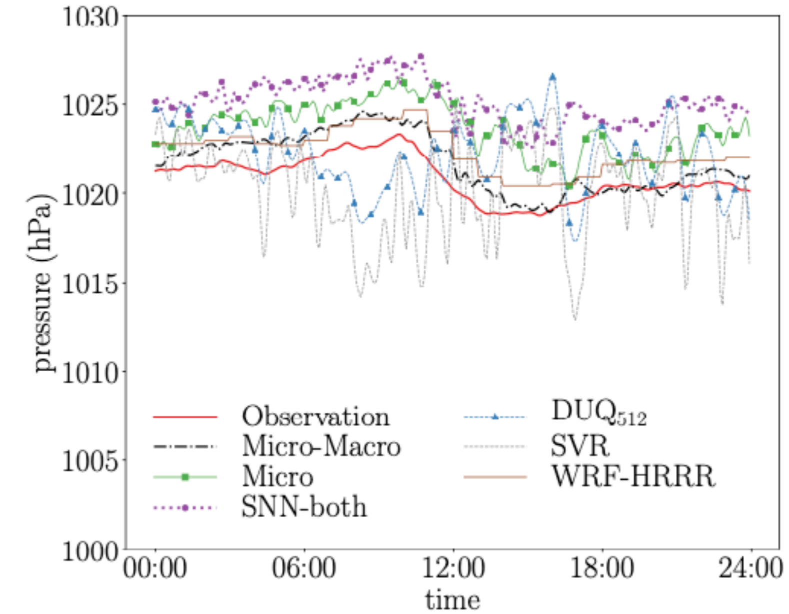
One-day Prediction



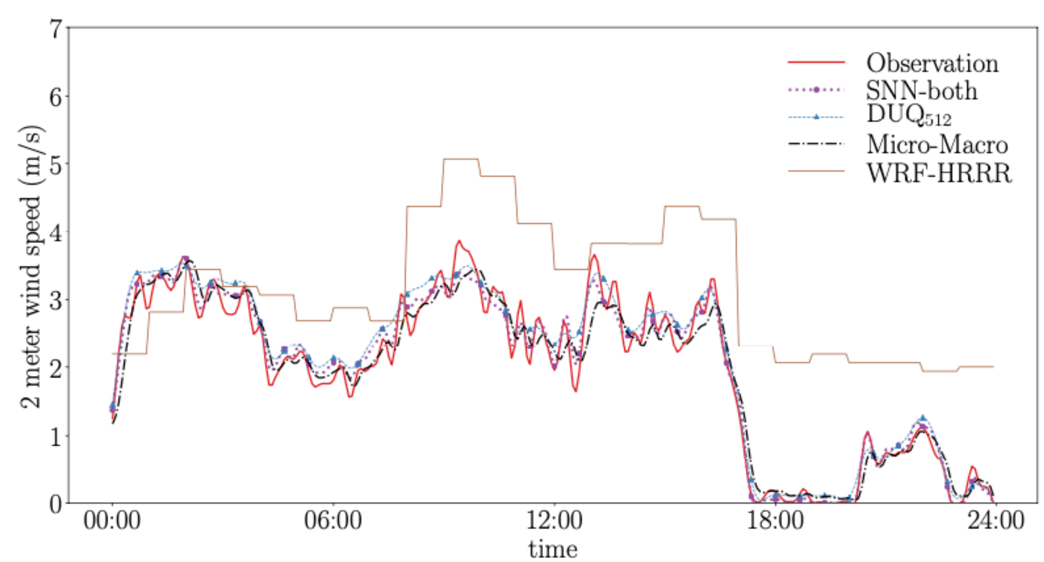
(a) temperature



(b) humidity



(c) pressure



(d) Wind speed

Please see our article for details

https://prefer-nsf.org/pdf/PREFER_Modelet_Evaluation.pdf