Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering)

A novel time-span input neural network for accurate municipal solid waste incineration boiler steam temperature prediction

Qin-xuan Hu

Cite this as: Qin-xuan Hu, Ji-sheng Long, Shou-kang Wang, Jun-jie He, Li Bai, Hai-liang Du, Qun-xing Huang, 2021. A novel time-span input neural network for accurate municipal solid waste incineration boiler steam temperature prediction. *Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering)*, 22(10):777-791.

https://doi.org/10.1631/jzus.A2000529

Combustion characteristics in waste incineration furnace

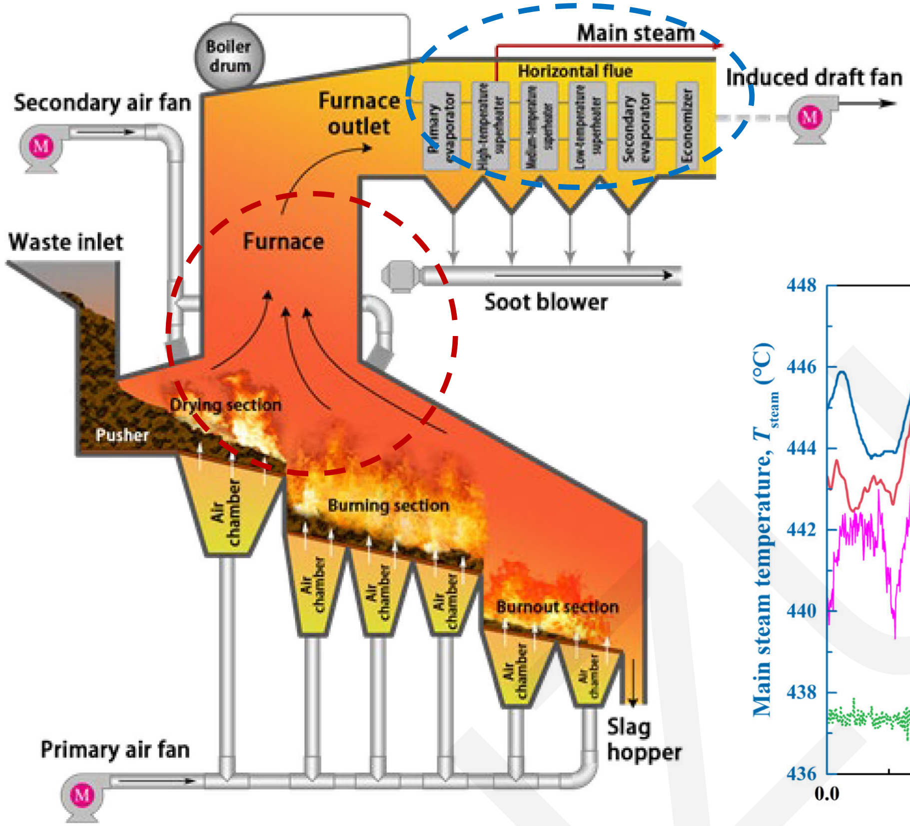

Fig. 1 Structure of the waste incineration grate furnace

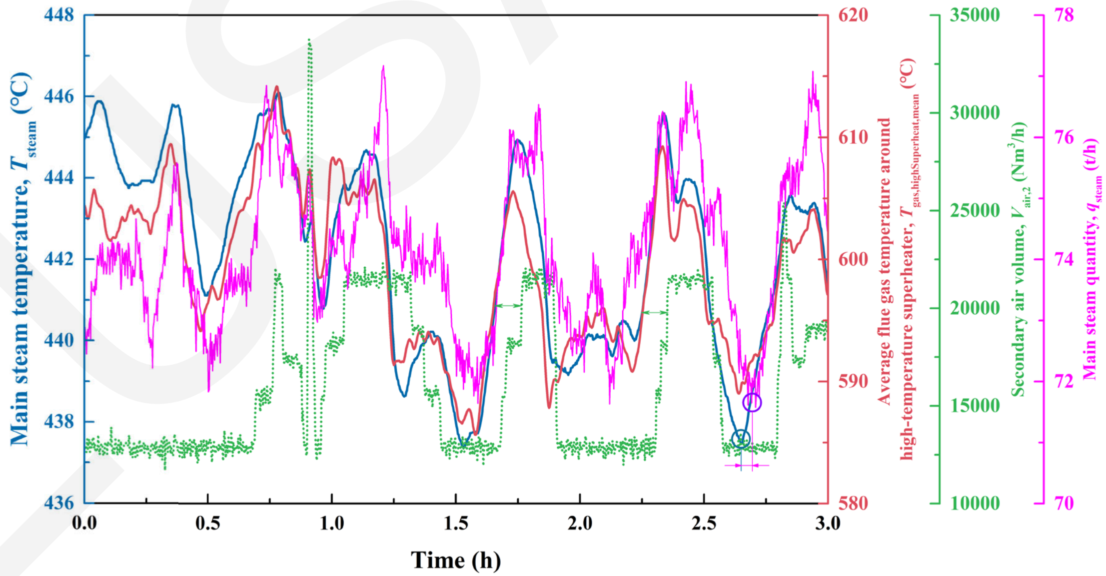

Fig. 3 Time variation of the major variables as recorded by the DCS

- Multiple variables, large capacity, complex system, coupling effects between variables
- **Time-lag** between variables makes the neural network difficult to predict the trend of parameters.

Method - Time-span input framework neural network

- The current-time input framework neural network (**C-T model**), basic model.
- The time-span input framework neural network (**T-S model**). T-S model contains the characteristic of **time-lag** between different variables.

C-T model input algorithm:

$$\boldsymbol{x}^{(i)} = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix}^T \quad \text{single sample}$$

$$X = \begin{bmatrix} — & (\boldsymbol{x}^{(1)})^T & — \\ — & (\boldsymbol{x}^{(2)})^T & — \\ \vdots & \vdots & \vdots \\ — & (\boldsymbol{x}^{(m)})^T & — \end{bmatrix} \quad \text{sample space}$$

T-S model input algorithm: single sample

$$\boldsymbol{X}^{(i)} = \begin{bmatrix} x_1^{(i-d)} & x_2^{(i-d)} & \cdots & x_n^{(i-d)} \\ \vdots & \vdots & & \vdots \\ x_1^{(i-1)} & x_2^{(i-1)} & \cdots & x_n^{(i-1)} \\ x_1^{(i)} & x_2^{(i)} & \cdots & x_n^{(i)} \end{bmatrix} = \begin{bmatrix} | & | & \cdots & | \\ \boldsymbol{x}_1^{(i)} & \boldsymbol{x}_2^{(i)} & \cdots & \boldsymbol{x}_n^{(i)} \\ | & | & \cdots & | \end{bmatrix}$$

sample space

$$\boldsymbol{X} = \begin{bmatrix} — & (\boldsymbol{x}_1^{(1+d)})^T & — & — & (\boldsymbol{x}_2^{(1+d)})^T & — & \cdots & — & (\boldsymbol{x}_n^{(1+d)})^T & — \\ — & (\boldsymbol{x}_1^{(2+d)})^T & — & — & (\boldsymbol{x}_2^{(2+d)})^T & — & \cdots & — & (\boldsymbol{x}_n^{(2+d)})^T & — \\ & \vdots & & & \vdots & & & & \vdots & \\ — & (\boldsymbol{x}_1^{(m)})^T & — & — & (\boldsymbol{x}_2^{(m)})^T & — & \cdots & — & (\boldsymbol{x}_n^{(m)})^T & — \end{bmatrix}$$

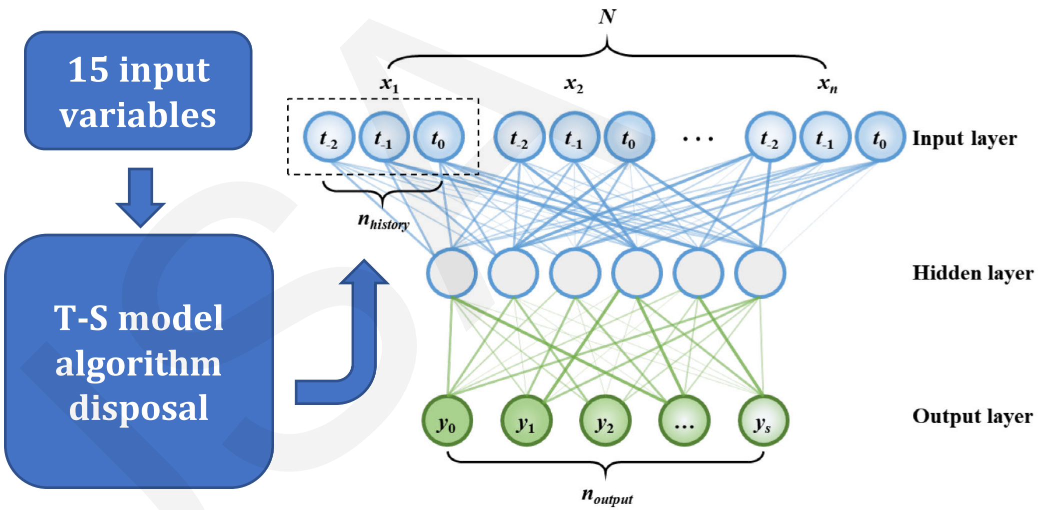

Fig. 4 Structure of neural network

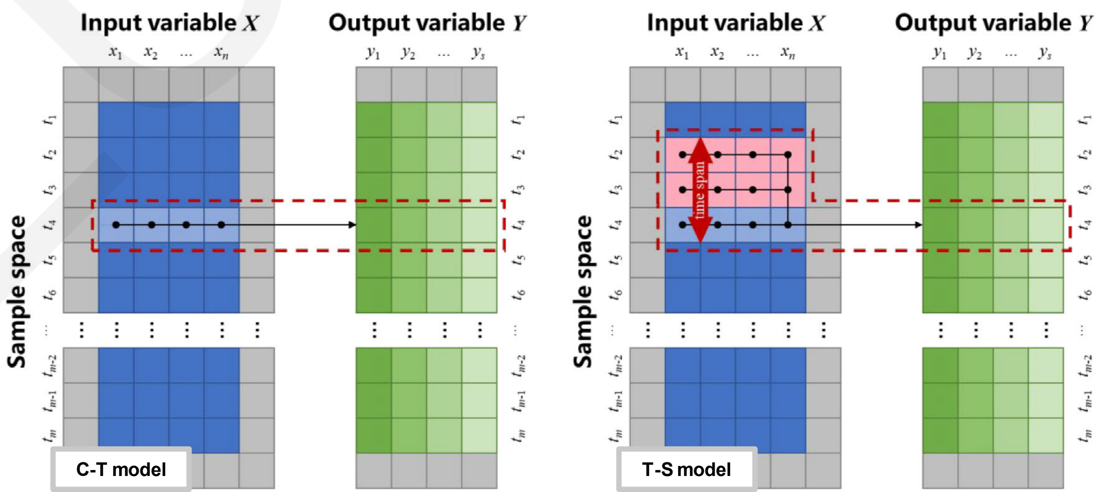

Fig. 5 Input-output mapping relation

Results and Conclusion

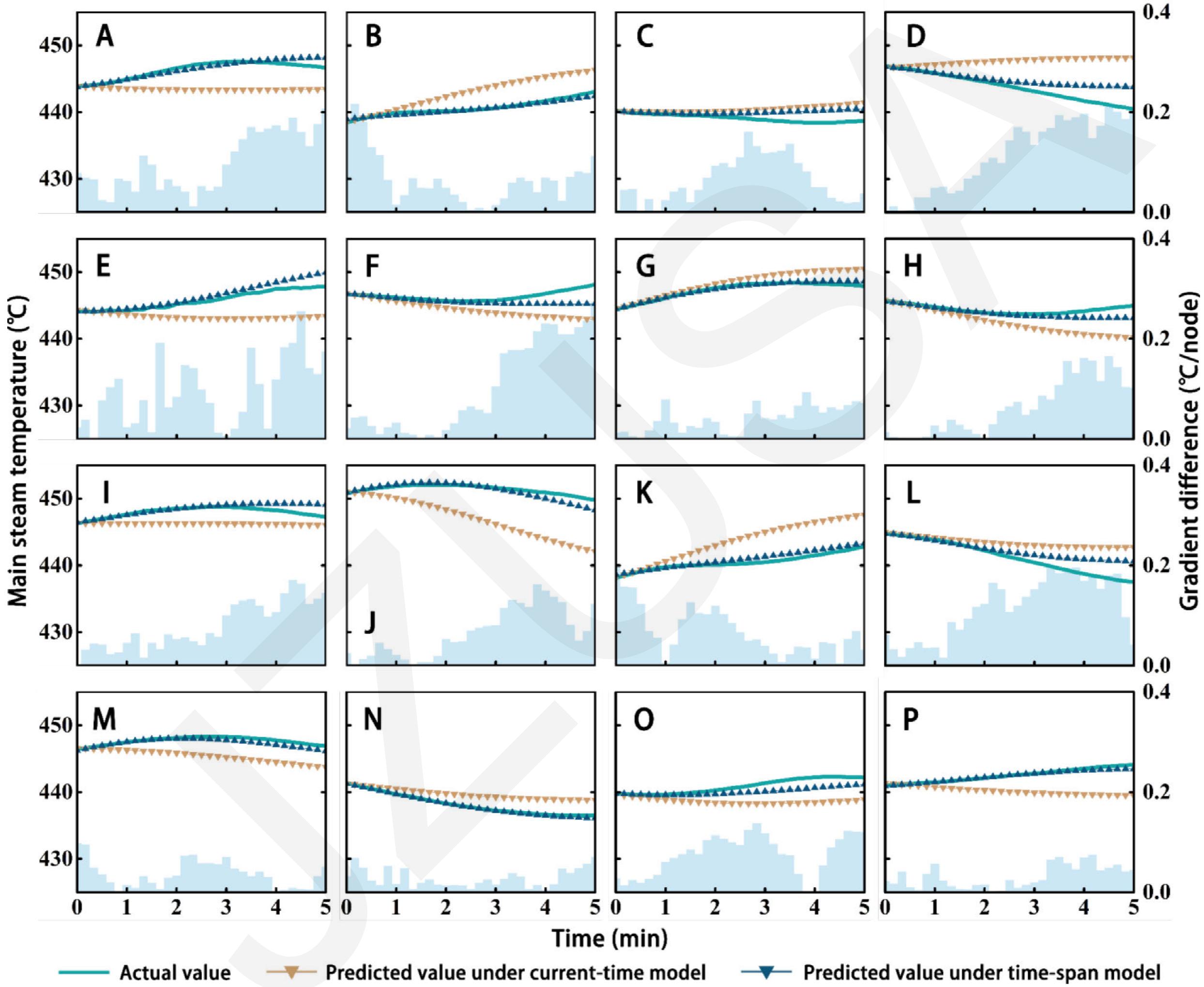

Fig. 7 Prediction of the main steam temperature under two different input framework neural network models. The light blue bars show the absolute value of the gradient difference between the curve of the time-span model and the actual value.

Results and Conclusion

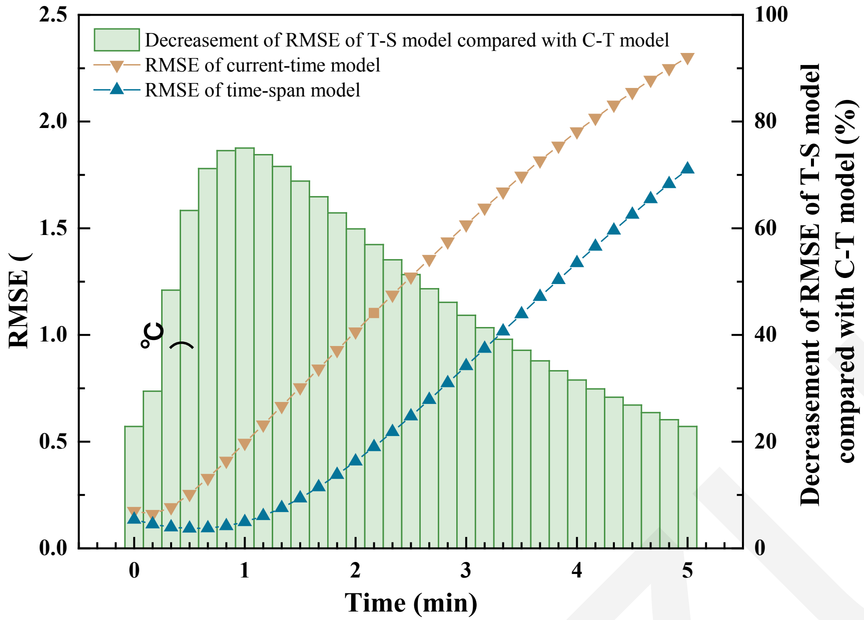

Fig. 8 Prediction RMSE of the C-T model and the T-S model in each future time node

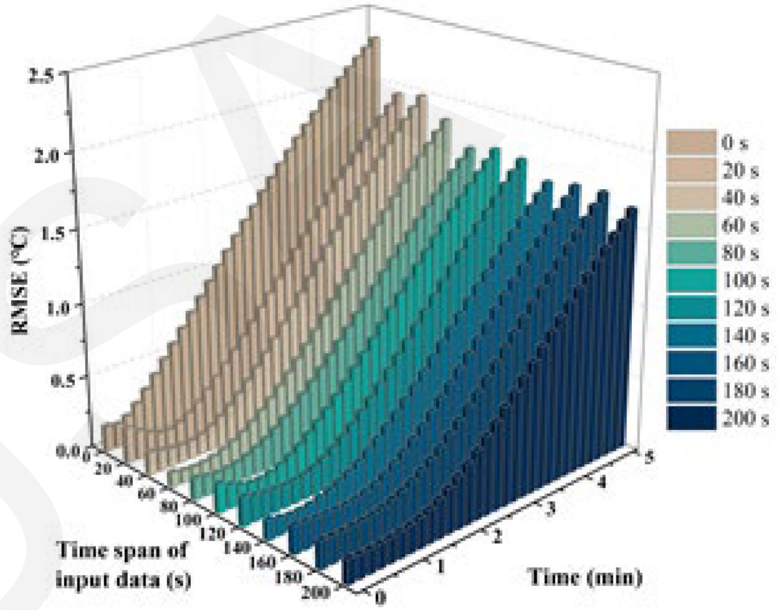

Fig. 13 Prediction RMSE of each future time node of the model with different time spans of input data

- T-S model had a lower prediction error than C-T model, and could achieve a near zero prediction error in the first one minute.
- The RMSE of the model with only a 20 s time span of input was significantly reduced by 28.2% compared with the current-time model.

Results and Conclusion

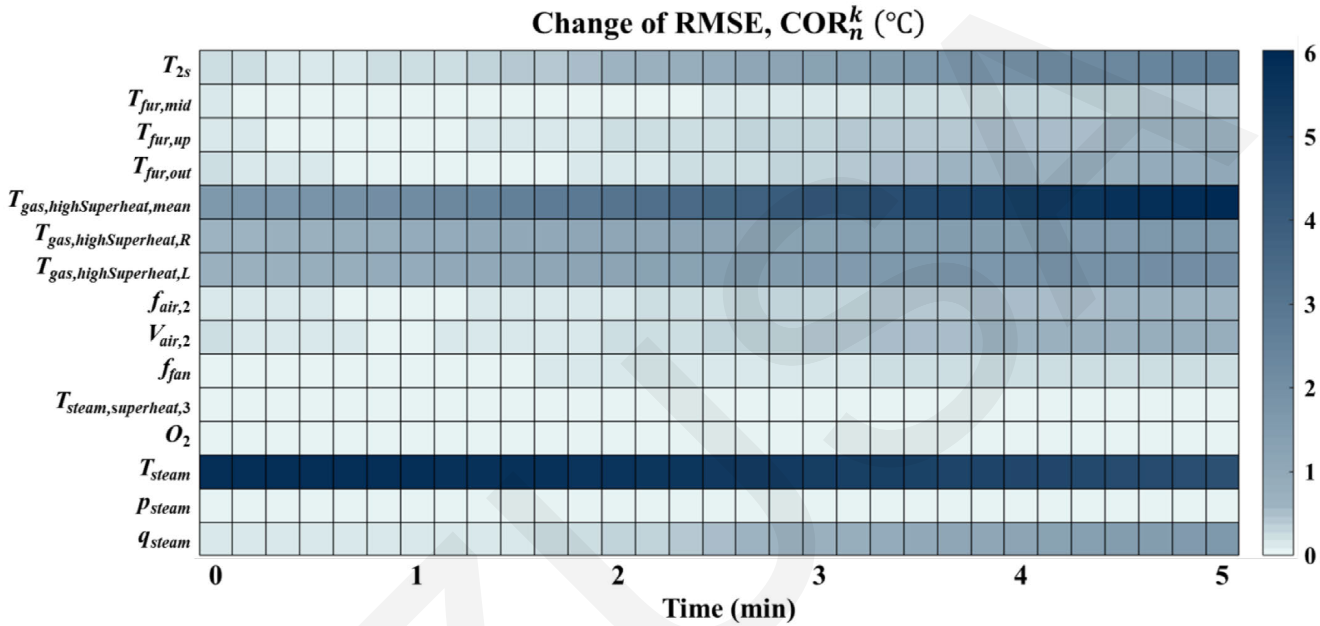

Fig. 14 COR of prediction of the main steam temperature at each future time node after removing different variables

- The sensitivity analysis shows that the ***main steam temperature*** itself and the ***average flue gas temperature around high-temperature superheater*** are the two most important parameters impacting on the prediction.
- the **T-S model has a better prediction performance and generalization ability**, with the prediction error reaching near zero in the first 60 seconds, and the maximum prediction error can also be reduced to nearly 1.5℃.