Electrical-STGCN: An Electrical Spatio-Temporal Graph Convolutional Network for Intelligent Predictive Maintenance

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研究背景与研究意义

研究背景:

- 预防性维修（Predictive maintenance ，PdM）是一种数据驱动的设备健康预测策略，广泛用于各行各业。
- 然而，当前基于 AI 的预测策略缺乏考虑工业设备之间的相互作用。

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研究意义：

- 提出了 Electrical-STGCN 模型，同时考虑到了设备相互作用和时间序列特性
- 提出了新的核函数解决图卷积过平滑问题
- 通过实验验证 Electrical-STGCN 有效性

相关工作

PdM 采用的 ML 算法分为四块：Supporting Vector Machines (SVM), K-Means, Ensemble Learning (EL), and Artificial Neural Network (ANN).

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- K-Means：需要提取指定聚类个数；数据顺序敏感；不同数据标准化方法影响预测结果。
- EL algorithms：模型复杂；计算时间长
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4 类模型共同缺点，缺乏考虑时间依赖。所以提出了 Electrical-STGCN，既考虑设备相互作用和时间依赖。

模型数据集

数据来自于卧式加工中心（horizontal machining center）的三相电路。$shape == 5 * 3 * 34394$

TABLE II
SPECIFICATIONS OF THE TOTAL 34394 RECORDS.

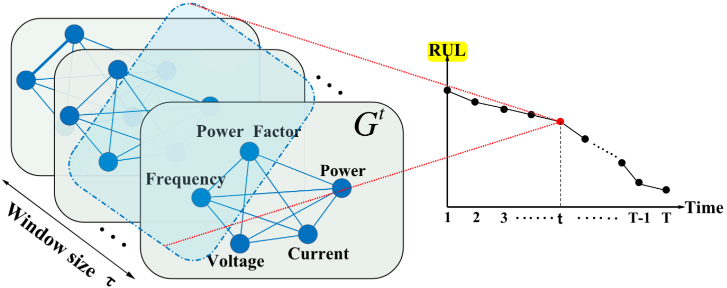
Attribute	Variable	Range	Mean/Standard Deviation
A phase power factor	$\cos\varphi_A$	0.40-1	0.84/0.17
B phase power factor	$\cos\varphi_B$	0.27-1	0.82/0.20
C phase power factor	$\cos\varphi_C$	0.31-1	0.78/0.23
A phase reactive power	Q_A	1-133 W	25.21/25.11
B phase reactive power	Q_B	3-152 W	32.76/32.05
C phase reactive power	Q_C	1-137 W	30.79/33.02
A phase current	I_A	0-34.8 A	6.58/7.05
B phase current	I_B	0.4-40 A	8.03/8.69
C phase current	I_C	0-38 A	7.11/7.83
A phase voltage	U_A	213.2-229.9 V	223.20/3.03
B phase voltage	U_B	217.6-231.7 V	226.74/2.39
C phase voltage	U_C	217.9-231.4 V	226.34/2.53
A phase frequency	f_A	49.96-50.03 Hz	49.99/0.02
B phase frequency	f_B	25.02-50.03 Hz	49.99/0.14
C phase frequency	f_C	49.96-50.03 Hz	49.99/0.02

问题阐述

已知序列，$\mathbf{X}_\tau = \{\mathbf{X}^{t-\tau+1}, \ldots, \mathbf{X}^t\} \in \mathbb{R}^{\tau\times 15}$

其中 $\mathbf{X}^i =$
$(\cos\varphi^i_A, \cos\varphi^i_B, \cos\varphi^i_C, Q^i_A, Q^i_B, Q^i_C, I^i_A, I^i_B, I^i_C, U^i_A, U^i_B\ U^i_C, f^i_A, f^i_B, f^i_C) \in \mathbb{R}^{1\times 15}, i \in \{t-\tau+1, \ldots, t\}$

求 $\hat{RUL}^t$



图定义

图公式： $G^t = (V^t, E^t, \mathbf{A}^t)$

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$$\text{其中：}\ \mathbf{V}^t = \begin{pmatrix} \cos\varphi_A^t & \cos\varphi_B^t & \cos\varphi_C^t \\ Q_A^t & Q_B^t & Q_C^t \\ I_A^t & I_B^t & I_C^t \\ U_A^t & U_B^t & U_C^t \\ f_A^t & f_B^t & f_C^t \end{pmatrix} \in \mathbb{R}^{5\times 3},\ E^t = \mathbf{1}$$

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$\mathbf{A}^t$ 有两种方法：

- 相似度法 $a_{sim(j,k)}^t = \begin{cases} 1/\left\|\boldsymbol{v}_j^t - \boldsymbol{v}_k^t\right\|_2, & \left\|\boldsymbol{v}_j^t - \boldsymbol{v}_k^t\right\|_2 \neq 0 \\ 0, & \text{otherwise} \end{cases}$

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- 特征值法 $\mathbf{L}^t_{norm} = (\mathbf{D}^t)^{-\frac{1}{2}} (\mathbf{D}^t - \mathbf{E}^t) (\mathbf{D}^t)^{-\frac{1}{2}} \in \mathbb{R}^{5\times5}$

$a^t_{\phi_1(j,k)} = \begin{cases} \phi^t_{1(j)} - \phi^t_{1(k)}, & e_{jk} = 1 \\ 0, & \text{otherwise} \end{cases}$

模型框架

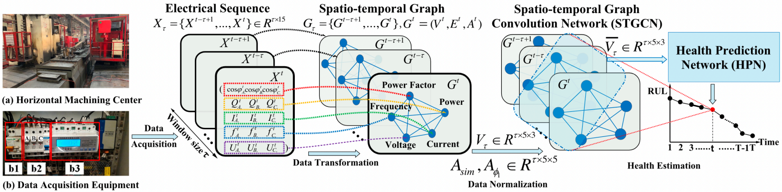

Fig. 5. **Working procedure of the Electrical-STGCN.** Given τ electrical records $\mathbf{X}_\tau$, we first transform this sequence to the constructed spatio-temporal graph $G_\tau = (V_\tau, E_\tau, \mathbf{A}_\tau)$. Then G_τ is forwarded through the Spatio-Temporal Graph Convolution Network (**STGCN**) to create feature $\overline{\mathbf{V}}_\tau$, which involves both attribute interactions and temporal dependency. After that, the $\overline{\mathbf{V}}_\tau$ is fed into the Health Prediction Network (**HPN**) for current health estimation. **(a)** is the monitored industrial equipment. **(b)** is the power supply circuit of the electrical sensor: **b1** is the leakage protector; **b2** is the three phase fuse; **b3** is the electrical sensor.

step 1. 数据规范化

- $\mathbf{A}_{\text{sim}}$ is a stack of $\left\{\mathbf{A}_{\text{sim}}^{t-\tau+1}, \ldots, \mathbf{A}_{\text{sim}}^{t}\right\}$
- $\mathbf{A}_{\phi_1}$ is a stack of $\left\{\mathbf{A}_{\phi_1}^{t-\tau+1}, \ldots, \mathbf{A}_{\phi_1}^{t}\right\}$
- $\mathbf{A}_{\text{sim}}, \mathbf{A}_{\phi_1} \in \mathbb{R}^{\tau \times 5 \times 5}$

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- $\mathbf{A}_{\mathsf{sim}}, \mathbf{A}_{\phi_1} \in \mathbb{R}^{\tau\times5\times5}$
- $\mathbf{A}_{sim}^{t} = \left(\mathbf{\Lambda}_{sim}^{t}\right)^{-\frac{1}{2}} \mathbf{A}_{sim}^{t} \left(\mathbf{\Lambda}_{sim}^{t}\right)^{-\frac{1}{2}}$
- $\mathbf{A}_{\phi_1}^{t} = \frac{\left|\mathbf{A}_{\phi_1}^{t}(n,:)\right|}{\left\|\mathbf{A}_{\phi_1}^{t}(n,:)\right\| + \epsilon}$

step 2. Electrical-STGCN and step 3. HPN

空间卷积

- $\widetilde{\mathbf{V}}^t = \gamma \mathbf{A}^t_{\phi_1} \mathbf{V}^t + (1-\gamma)\mathbf{A}^t_{sim}\mathbf{V}^t$
- 其中，$\mathbf{V}_\tau \in \mathbb{R}^{\tau\times5\times3}$, $\overline{\mathbf{V}_\tau} \in \mathbb{R}^{\tau\times5\times3}$, γ 为超参数，$\widetilde{\mathbf{V}_\tau} = \left\{\widetilde{\mathbf{V}^{t-\tau+1}}, \ldots, \widetilde{\mathbf{V}^t}\right\} \in \mathbb{R}^{\tau\times5\times3}$

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时间卷积和残差网络

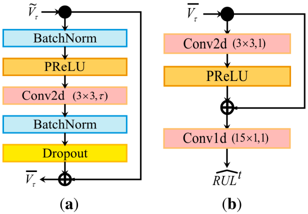

Fig. 6. **(a) Overview of the 5-layer temporal residual block.** Given the $\widetilde{\mathbf{V}_\tau} \in \mathbb{R}^{\tau\times5\times3}$, the output is $\overline{\mathbf{V}_\tau} \in \mathbb{R}^{\tau\times5\times3}$. **(b) The HPN architecture.** The HPN is made up of a residual connection and a convolution layer. Given the $\overline{\mathbf{V}_\tau} \in \mathbb{R}^{\tau\times5\times3}$, the output is $\widehat{\boldsymbol{RUL}}^t$.

损失函数

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(RUL - \widehat{RUL})^2$$

其中，$RUL = \frac{\text{Time to failure - Current time}}{\text{Time to failure}}$

1. Introduction
2. ELECTRICAL-STGCN
3. Experiment

探索实验

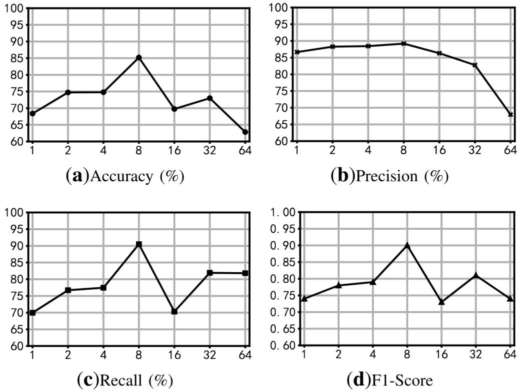

Fig. 7. **Evaluation metrics of the Electrical-STGCN at different window size τ.** The Electrical-STGCN performs the best when $\tau = 8$, i.e., Accuracy= **85.20±0.21**%, Precision= **89.20±0.41**%, Recall= **90.51±0.25**%, and F1-Score= **0.90±0.01**.

探索实验

TABLE III

ABLATION STUDY ON γ WITH $\tau = 8$.

γ	Accuracy [%]	Precision [%]	Recall [%]	F1-Score
0.2	75.77±1.42	79.53±0.87	91.38±4.17	0.83±0.02
0.3	73.76±0.56	80.97±1.20	86.37±3.51	0.81±0.01
0.4	**85.20±0.21**	**89.20±0.41**	90.51±0.25	**0.90±0.01**
0.5	76.98±0.94	79.89±0.71	**92.67±3.08**	0.84±0.01
0.6	76.14±1.30	81.62±0.89	88.56±4.70	0.82±0.02

探索实验

TABLE IV
THE EFFECT OF DIFFERENT KERNEL FUNCTIONS WITH $\tau = 8$ AND $\gamma = 0.4$.

Kernel Functions	Accuracy [%]	Precision [%]	Recall [%]	F1-Score
Baseline [32]	77.32±1.24	83.88±1.11	87.75±4.43	0.83±0.02
$a^t_{L_2(j,k)}$	84.19±0.28	87.60±0.82	90.63±0.48	0.88±0.01
$a^t_{exp(j,k)}$ [31]	81.37±0.28	85.48±0.65	90.25±0.99	0.87±0.01
$a^t_{sim(j,k)}$ & $a^t_{\phi_1(j,k)}$	**85.20±0.21**	**89.20±0.41**	**90.51±0.25**	**0.90±0.01**

实验结果

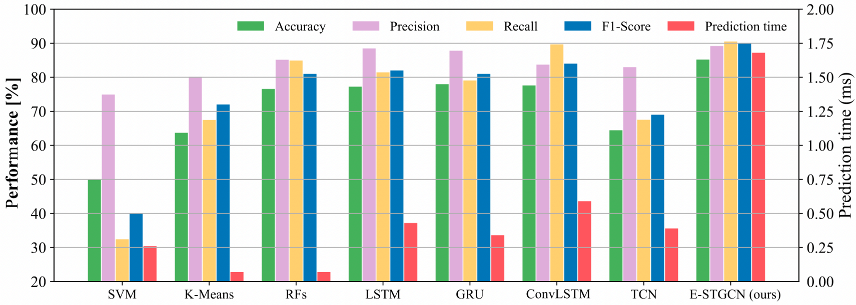

Fig. 9. **Comparison with different ML algorithms in terms of Accuracy, Precision, Recall, F1-Score, and Prediction time.** We conduc
ML algorithms on the testing data and calculate the average processing time for each record.

实验结果

TABLE V
COMPARISON WITH OTHER ML ALGORITHMS IN TERMS OF WILCOXON SIGNED-RANK TEST.

Competitors	Accuracy [%]	Precision [%]	Recall [%]	F1-Score
SVM [20]	49.85±3.56(+)	74.92±15.79(≡)	32.42±9.93(+)	0.40±0.10(+)
K-Means [23]	63.69±4.28(+)	80.15±4.05(≡)	67.47±3.87(+)	0.72±0.02(+)
RFs [25]	76.57±1.23(+)	85.15±1.19(≡)	84.92±5.17(≡)	0.81±0.02(+)
LSTM [27]	77.25±2.02(≡)	88.48±1.70(≡)	81.44±6.05(≡)	0.82±0.03(≡)
GRU [28]	77.98±1.66(+)	87.81±1.41(≡)	79.06±5.59(≡)	0.81±0.02(+)
ConvLSTM [29]	77.60±1.11(+)	83.73±1.66(≡)	89.67±2.75(≡)	0.84±0.01(+)
TCN [30]	64.43±2.62(+)	82.99±2.65(≡)	67.51±9.55(≡)	0.69±0.04(+)
E-STGCN(ours)	**85.20±0.21**	**89.20±0.41**	**90.51±0.25**	**0.90±0.01**

$^{+}$ means that Electrical-STGCN is significantly better than other competitors.
$^{\equiv}$ means that there is no significant difference between Electrical-STGCN and others based on Wilcoxon signed-test with the significance level of 0.05.

Thank You