Industrial 6G-IoT and Machine-Learning-Supported Intelligent Sensing Framework for Indicator Control Strategy in Sewage Treatment Process

Keping Yu, Graduate School of Science and Engineering, Hosei University, Japan

Motivation

- **Global Water Scarcity:** Rising water shortages demand efficient wastewater treatment and resource reuse.
- **Energy Wastage:** Traditional aeration processes waste over 60% of energy due to reliance on manual control.
- **Critical Role of Dissolved Oxygen (DO):** Accurate DO control is essential for effective and energy-efficient treatment.
- **6G-IoT Opportunity:** Advances in 6G-IoT and machine learning enable smarter, data-driven control strategies.
- **Research Goal:** Develop an intelligent framework to optimize DO levels, lowering carbon emissions from wastewater treatment plants.

Methodology

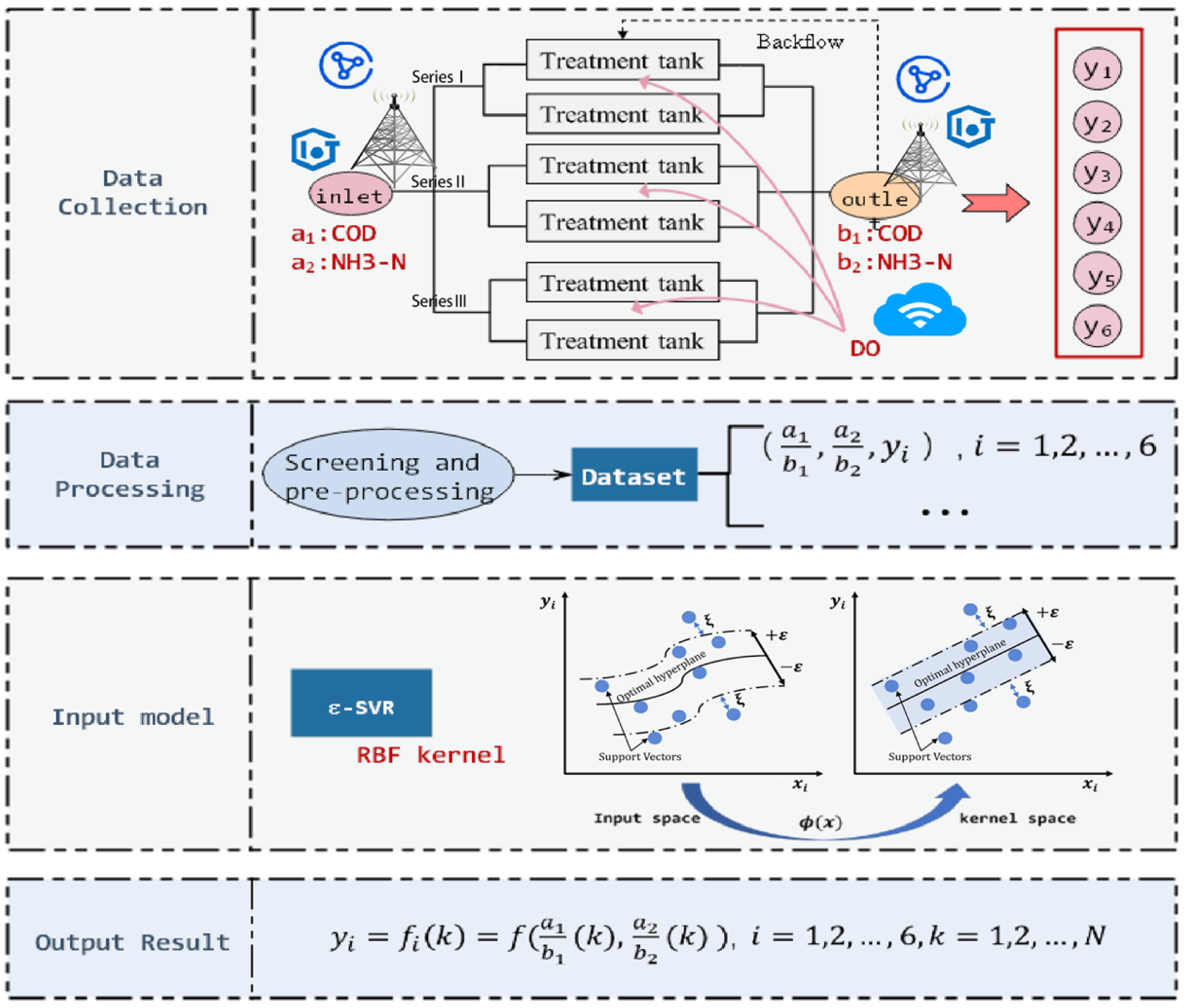

Fig. 1. System architecture of aeration research

1. **Data Collection:**

⇒**1.1 Source**: Data obtained from a sewage treatment plant.

⇒**1.2 Indicators**: Chemical Oxygen Demand(COD),Ammonia Nitrogen(NH_3-N).

⇒**1.3 Monitoring points**: Data was collected at both inlet and outlet points to evaluate pollutant removal efficiency across the treatment process.

2. **Data Preprocessing:**

⇒ **2.1 Filtered**: Removed noisy and unstable data points to ensure data reliability.

⇒ **2.2 Derived**: Input variables as inlet-to-outlet **COD and NH_3-N ratios**.

⇒ **2.3 Normalized**: Standardized variables for model compatibility.

⇒ **2.4 Split**: **80%** dataset for training, **20%** for testing.

3. **Model Input and Training:**

⇒ **3.1 Input Features**: Ratios of COD and NH_3-N concentrations at inlet and outlet.

⇒ **3.2 Prediction Targets**: DO levels from the treatment plant's six zones, representing different aeration stages.

⇒ **3.3 Model**: Radial Basis Function Support Vector Regression (RBF-SVR), chosen for its ability to handle high-dimensional data and capture nonlinear relationships.

⇒ **3.4 Training Process**: The model learns to map input features to DO levels, aiming to support intelligent aeration control.

4. **Output:**

⇒ **4.1 Predicted Values**: The model predicts DO concentrations for six zones, providing data to optimize aeration control.

⇒ **4.2 Application**: Provides a foundation for implementing intelligent aeration strategies.

⇒ **4.3 Goal**: Enable energy-efficient operation by optimizing aeration control in wastewater treatment.

Dataset

(1). Source: Collected from a sewage treatment plant, **300,000 tons/day**, **8760 hours** of continuous monitoring data. **(2). Input**: COD Ratio: indicates the change in organic matter concentration $[2.4, 133.5]$. NH_3-N Ratio reflects nitrogen concentration changes $[1.3, 240.4]$. **Output**: Six zones of DO values for aeration control, $[0, 5]$.

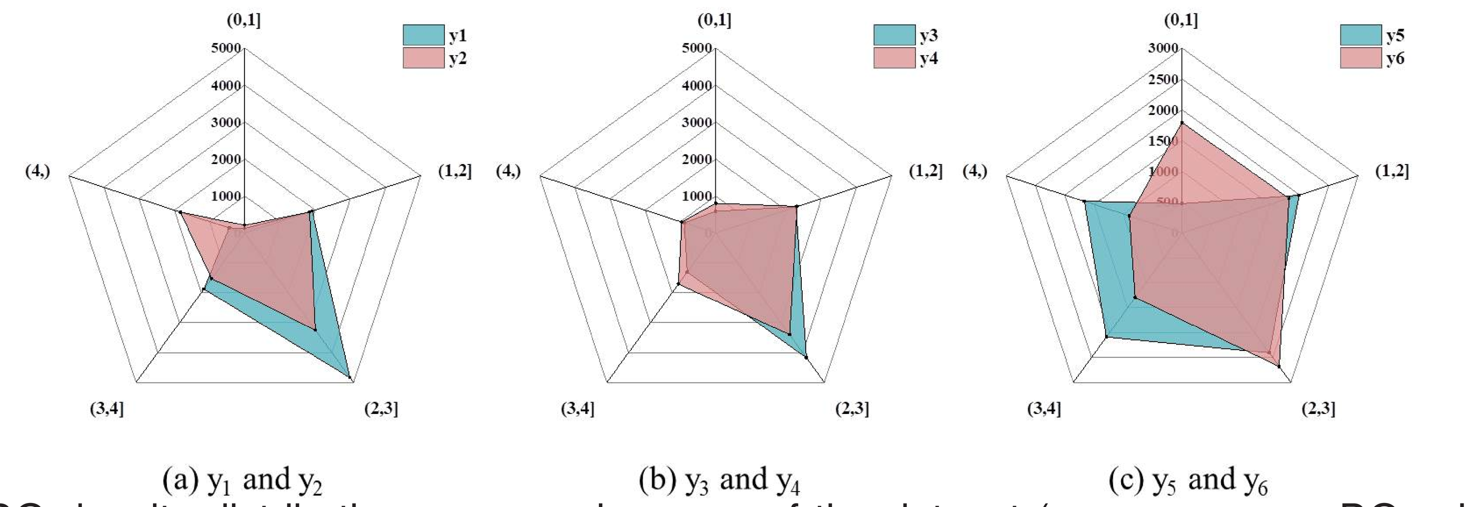

Fig.2. DO density distributions across six zones of the dataset ($y_1, \cdots, y_6$ are DO values for different tanks).

Results

1. Models and Metrics: **(1.1)**. **Ours**: RBF-SVR. **Baseline**: Liner-SVR, MLP, RFR. **(1.2)**. Mean Absolute Error **(MAE)**, Root Mean Square Error **(RMSE)**, Mean Absolute Percentage Error **(MAPE)**.

Table 1: Performance of RBF-SVR model on different datasets(tanks).

Dataset	MAE (↓)	RMSE (↓)	MAPE (↓)
Y1 (y_1)	0.5047	0.7733	21.44%
Y2 (y_2)	0.7079	0.9807	29.82%
Y3 (y_3)	0.5127	0.7783	22.07%
Y4 (y_4)	0.5878	0.7926	23.16%
Y5 (y_5)	0.6254	0.9273	25.66%
Y6 (y_6)	0.5927	0.8283	24.80%

2. Main Results on RBF-SVR(Table 1): **(2.1)**. Best Performance on Y1: The RBF-SVR model achieves the lowest MAE (0.5047), RMSE (0.7733), and MAPE (21.44%) on the Y1 dataset. **(2.2)**. Poor Performance on Y2: Y2 has the highest MAE (0.7079), RMSE (0.9807), and MAPE (29.82%) due to inconsistencies in input data increasing model fitting difficulty. **(2.3)**.The RBF-SVR model demonstrates good predictive performance across all datasets.

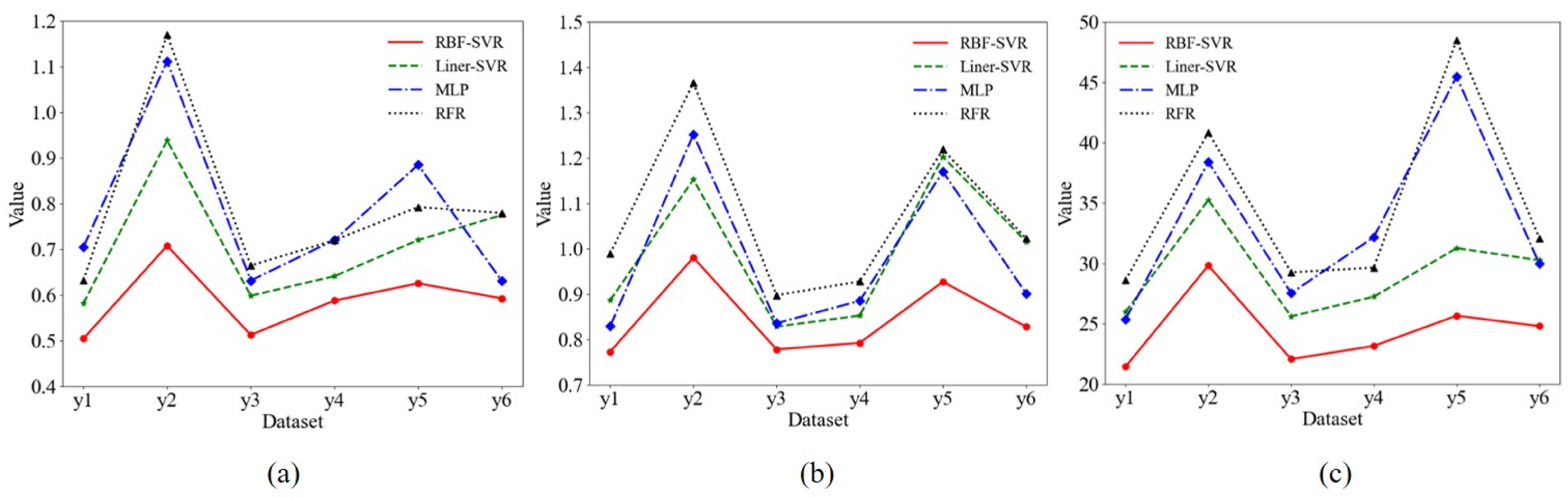

Fig. 3. Models with different series of DO datasets: (a) MAE, (b) RMSE, (c) MAPE.

3. Main Results on Models (Fig.3): **(3.1)**. The RBF-SVR model consistently outperforms all baselines (MLP, Linear-SVR, RFR) across MAE, RMSE, and MAPE metrics. **(3.2)**. The proposed method achieves the best performance, with an average MAE improvement of 0.2, and excels particularly when using the y_1 or y_3 series as input. **(3.3)**. MLP and Linear-SVR occasionally outperform RFR, but **RBF-SVR is the most effective model overall.**

Conclusions

- **Innovative Control:** Proposed an RBF-SVR-based intelligent sensing model for precise DO prediction in wastewater treatment.
- **Superior Performance:** RBF-SVR outperforms baseline models with a 5% improvement and prediction deviation below 0.6.
- **Energy Efficiency:** Accurate DO prediction enables optimized aeration control, leading to energy-efficient operation.

Key References

[1] Z. Guo, Y. Shen, C. Chakraborty, F. Alblehai and K. Yu, "Industrial 6G-IoT and Machine-Learning-Supported Intelligent Sensing Framework for Indicator Control Strategy in Sewage Treatment Process," in IEEE Internet of Things Journal, vol. 11, no. 18, pp. 29308-29320, 15 Sept.15, 2024,