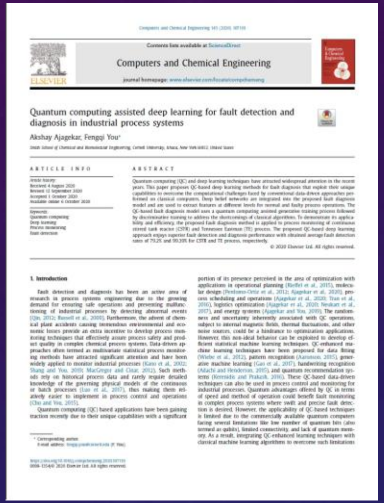
Computers and Chemical Engineering

Quantum computing assisted deep learning for fault detection and diagnosis in industrial process systems

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INTRODUCTION

Background

Growing demand for ensuring safe operations and preventing malfunctioning by detecting abnormal events.

Preventing plant accidents causing environmental and economical losses.

Computational limitation of classical training algorithm for deep learning model.

Objective

To propose a quantum computing-based fault diagnosis model for complex industrial chemical process systems.

Demonstrate the applicability of the proposed model through two case studies on a CSTR and TE process.

Optimizes the training part with the help of quantum computing as compared to traditional data driven approach.

Literature Gaps

Applicability of QC based techniques

The applicability of QC-based techniques is limited due to the commercially available quantum computers have low number of quantum bits, limited connectivity and lack of quantum memory.

Ref. Wiebe et al., 2012

PCA Limitations

PCA-based methods do not take into account the temporal correlations between process data and information between classes when determining the lower dimensional representations.

Ref. Venkatasubramanian et al.,2003

Linear Methods

Most of the analytical approaches are limited to linear and some specific nonlinear models, hence need for complex methods for detection system.

Ref. Lee et al., 2006

Literature Comparison

Applicability of QC based techniques

Overcomes current quantum hardware limitations by proposing a hybrid approach that leverages both classical and quantum resources effectively.

Ref. Wiebe et al., 2012

PCA Limitations

The use of deep learning allows the model to capture temporal dependencies and class-specific information, improving the accuracy of fault detection.

Ref. Venkatasubramanian et al.,2003

Linear Methods

The paper leverages deep learning, which is well-suited for handling complex, nonlinear relationships within the data.

Ref. Lee et al., 2006

METHODS

Methodological Approach

Classical Data-Driven Methods

- Principal Component Analysis (PCA)
- Partial Least Squares (PLS)
- Independent Component Analysis (ICA)
- Fisher Discriminant Analysis (FDA)

RBM and Quantum Techniques

- Restricted Boltzmann Machines (RBMs)
- Adiabatic Quantum Computing
- RBMs as the initial data interaction with the proposed QC model.

Quantum-Powered Fault Diagnosis

Proposed QC-Based Deep Learning Model

- Quantum computing techniques for improved fault detection.
- Trained using historical process data.
- Tested on separate datasets with normal and faulty states.

Industrial Validation

- Application of QC-based model for fault detection and evaluation on:
  1. Tennessee Eastman (TE) chemical process.
  2. Continuous Stirred Tank Reactor (CSTR) process.

Quantum Advantage and Experiment Details

Quantum Advantage

- Enhanced fault detection rates in case studies.
- Reduced false positives compared to classical techniques.

Experimental Settings (TE Process and CSTR Process)

- Continuous and real-valued historical process data.
- Normalization of training data.
- Utilization of all 52 process variables as input for the QC-based model.

RESULTS AND DISCUSSION

Fault Detection with Local Classifier:

- Local classifier outputs probabilities between 0 and 1 for normal or faulty states.
- Threshold probability of 0.5 determines sample state (normal or faulty).
- The average False Detection Rates for training is 99.57% and validation is 99.39%.

Fault Identification with QC-Based Model:

- Repeating sub-network utilizes deep belief networks (DBN) and local classifier.
- Output probabilities from the sub-network serve as inputs for the global classification network.
- Abstractions of normal and faulty states are merged to diagnose new process data samples.

Performance Comparison:

- QC-based model achieves 99.39% average detection rate and 5.25% false positive rate.
- Outperforms PCA and DBN-based models in fault detection rates.
- Demonstrates high efficiency in distinguishing normal and faulty state.

Quantum Processing Unit:

- AQC-based device with 2,048 qubits and 5,600 couplers.
- Limits RBM energy function size to 52 units per layer.
- Weight and bias updates computed using samples from the quantum processing unit.

Learning Algorithm:

- Contrastive divergence (CD) learning algorithm for RBM training.
- CD-k learning with Gibbs chain for k steps to generate training samples.
- Modified variation for RBMs with Gaussian visible units.

Model Parameters and Trade-off:

- DBN-based sub-network parameters fine-tuned with backpropagation.
- Gradients of loss function estimated for iterative parameter updates.
- Minimization of categorical cross-entropy loss for maximum likelihood estimates.
- QC-based model achieves a balance between high FDR (99.39%) and low FAR (5.25%), efficient in distinguishing faulty data from normal operation states.

SUMMARY

Conclusion

Quantum computing reduces computation effort and combines quantum and deep neural networks to offer a competitive edge.

Competitive performance against classical methods as we get average Fault Detection Rate (FDR) of 80% and total average False Alarm Rate (FAR) of 1.3% for rare fault detection.

Demonstrates robust generalization, even without feature screening and achieves higher accuracy in classifying different fault states.

Future Research Avenues

Scaling Quantum Computing:

- Explore quantum computing scalability for complex industrial chemical processes.
- Investigate performance with a growing number of process variables.
- Assess quantum computing's potential compared to classical techniques as systems become larger and more complex.

Improving Quantum Generative Training:

- Enhance quantum generative training techniques.
- Explore different quantum algorithms for improved sampling abilities.
- Aim for faster convergence and superior deep learning model performance.

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THANK YOU