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FRAMEWORK FOR NON-CONTINUOUS SPACIOUS MECHANISM WITH TECHNICAL BEGATS

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ABSTRACT

In this application we proposed non linearity have introduced new challenges in Hospital resource monitoring and scheduling. First, a stacked auto encoder is used to extract dominant representations of each local process unit and establish the local inner monitor. Second, mutual information (MI) is used to determine the neighbour-hood variables of a local unit. Finally, the outer-related representations from all process units are used to establish global monitoring systems. Every resource is important in hospital sector, while oxygen cylinder plays an important role as it is used for emergency purpose. There should be a proper monitor and control over this integrated system so that any fatal deaths can be mitigated by providing cylinders whenever it's needed most. A large number of variables, complex relations between units, and process non linearity contribute to the difficulty in developing first principle-model of processes and prevent the use of model-based monitoring methods. Then the owner pays the cost for the defect parts. After buying the parts office manager sends to the employee. Then employees replace the defects parts. The admin maintains the payment detail of buying parts.

Keywords : Non-Continuous Spacious, resource monitoring, scheduling

INTRODUCTION

In any sector resource allocation plays a vital role to improve their service, it is true in Health-care sector too, oxygen cylinders are no less important than other resource. There are multiple deaths happening when cylinders are not shared to patients when they needed most. Proper monitoring and scheduling the cylinders in a hospital can mitigate this problem, yet these can be effectively applied when multiple hospitals are integrated in the process. The distributed monitoring scheme is more efficient in detecting a local fault (a fault that affects only a local part of a process) than the centralized monitoring scheme. Machine learning is a growing technology which enables computers to learn automatically from past data. Machine learning uses various algorithms for building mathematical models and making predictions using historical data or information. with the help of sample historical data, which is known as training data, machine learning algorithms build a mathematical model that helps in making predictions or decisions without being explicitly programmed. Machine learning gives the high accuracy, it gives output optimally. Eventually efficient monitoring and scheduling can be achieved by using machine learning algorithm.

ITERATURE REVIEW

Canonical correlation analysis-based fault detection methods with application to alumina evaporation process.

In this paper, canonical correlation analysis (CCA)-based fault detection methods are proposed for both static and dynamic processes. Different from the well-established process monitoring and fault diagnosis systems based on multivariate analysis techniques. CCA-based FD schemes have been proposed for linear static and dynamic processes. Compared with common multivariate analysis-based methods, e.g. PCA and PLS based, the proposed methods, which consider input and output variables in both off-line training and on-line monitoring phases, are an improvement. less robustness of the method against drift. 2.doesn't suitable for non-continuous linear process.[2]Fault detection for non-gaussian processes using generalized canonical correlation analysis and randomized algorithms.

A generalized Canonical Correlation Analysis (CCA)-based fault detection method aiming at maximizing the fault detectability under an acceptable false alarm rate. More specifically, two residual signals are generated for detecting of false in input and output subspaces, respectively. The optimality of its fault detectability has been analysed with respect to the minimum covariance of residual signals. It is not suitable for the generalized CCA- based method with Gaussian assumption.

A spare modelling and dictionary learning method This study focuses on the performance monitoring of a non-Gaussian process with multiple operation conditions. By utilising the Bayesian inference technique, the proposed method, Locality Preserving Sparse Modelling (LPSM), can automatically identify the current operation condition.[3]Sparse coding and dictionary learning provide a beneficial paradigm to represent raw data in feature space appropriately and helps to discriminate the faulty sample from the samples under normal condition. High computational cost and less data correlation. It has to improve as Super-large scale multimode process with highly data correlation.

Multivariate statistical process monitoring involves dimension reduction and latent feature extraction in large-scale processes, and typically incorporates all measured variables. However, involving variables without beneficial information may degrade monitoring performance. This study analyses the effect of variable selection on principal component analysis (PCA) monitoring performance. [4] In this study, the behaviour of PCA-based monitoring was analysed and the effect of variable selection on monitoring performance was further explored. Considering the significant effect of variable selection on process monitoring performance, a fault-relevant variable selection integrated with Bayesian inference method was developed to achieve the best possible performance of PCA-based monitoring**.** only the fault detection and isolation have been discussed in this. The fault diagnosis and prognosis is cannot be done.

This paper proposes a new fault detector based on a recently developed unsupervised learning method, denoising autoencoder (DAE), which offers the learning of robust nonlinear representations from data against noise and input fluctuation. DAE is used to build a robust multivariate reconstruction model on raw time series data from multiple sensors, and then the reconstruction error of the DAE trained with normal data is analysed for fault detection.[5]

The proposed approach is able to detect faults without any explicit knowledge of the faults and model uncertainties or external disturbances. Incorporating the temporal information has greatly improved the fault detection performance, which indicates the importance of temporal dependency in time series data in the design of fault-detection algorithms.

Less reliability, availability, and productivity of WT's. Less efficient solution to integrate fault detection and FTC in the data-driven framework. Deep Canonical Correlation Analysis (DCCA), a method to learn complex nonlinear transformations of two views of data such that the resulting representations are highly linearly correlated [6]. In experiments on two real-world datasets, we find that DCCA learns representations with significantly higher correlation than those learned by CCA and KCCA.

RESULT: We have shown that deep CCA can obtain improved representations with respect to the correlation objective measured on unseen data. DCCA provides a flexible nonlinear alternative to KCCA.

DISADVANTAGES: Unable to test the representations produced by deep CCA in the context of prediction tasks and to compare against other nonlinear multi-view representation learning approaches that optimize other objectives.

In this paper, A deep stacked autoencoder (SAE) is introduced for soft sensor. A novel variable-wise weighted stacked autoencoder (VW-SAE) is proposed for hierarchical output related feature representation layer by layer. An industrial application shows that the proposed VW-SAE can give better prediction performance than the traditional multilayer neural networks and SAE.[7]

A novel VW-SAE model is proposed for high-level output-related feature extraction. VW-SAE are designed and stacked to form deep networks. The effectiveness of the proposed VW-SAE is validated on an industrial application.

The proposed VW-SAE cannot be used for pattern recognition for classification problems. It is a linear correlation measurement. Hence, the correlation is not mined sufficiently.

It describes an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data[8]

A nonlinear generalization of PCA that uses an adaptive, multilayer encoder network to transform the high-dimensional data into a low-dimensional code and a similar decoder network to recover the data from the code is achieved. The very limited information in the labels is used only to slightly adjust the weights found by pretraining.

A kernel independent component analysis (KICA) is widely regarded as an effective approach for nonlinear and non-Gaussian process monitoring. A nonlinear contribution plots method is also developed based on the idea of a sensitivity analysis to help identifying the fault variables after a fault is detected. A monitoring method for nonlinear and non-Gaussian processes have been proposed using the novel GMM-based WKICA approach. In our WKICA method, KICA is used to extract the KICs from the process data. [9]. It Doesn't provide theoretical direction and practical implementation.

In this work, a novel condition-driven data analytics method is developed to handle the problem of frequent and wide changes in operation conditions. A condition-driven data analytics and monitoring method is developed for wide range nonstationary and transient continuous processes. The proposed method provides a novel analytics viewpoint for continuous process monitoring with typical nonstationary and transient characteristics which reveals promising extension to other applications. It Cannot be conduct condition-driven fault variable isolation and root cause analysis in particular for fault diagnosis with no historical fault samples.[10]

SYSTEM DESIGN

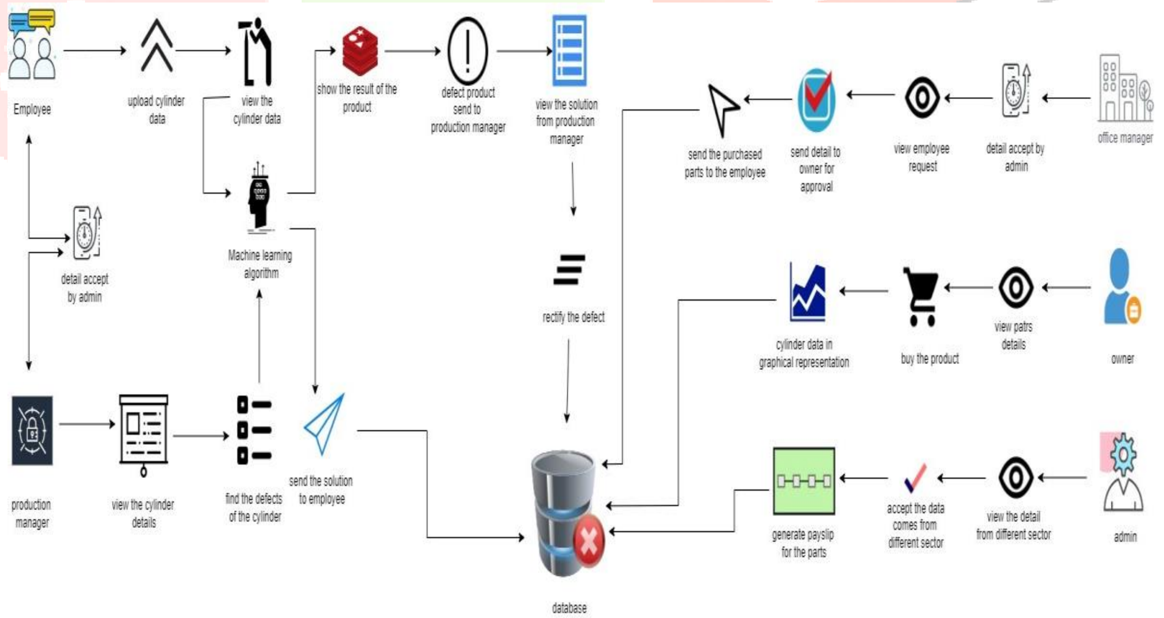

Fig 1: system design

MODULES

- Data collection and defect detection
- Validation Analysis
- Validating request and product status
- Cash transaction
- Permission Access

DATA COLLECTIOM AND DEFECT DETECTION

In this module the employee can register the details for the login purpose once the complete the registration the employee didn't login without approval of admin, once the employee can approved by the employee the approval message can be send via mail then employee login means then they upload the cylinder details and image they upload means then view the cylinder details such as temperature , pressure filled type, state, refilling date , expiry date and check the cylinder status it such as product has no defect and if the product has defect it send to the production manager once cylinder defect is analysed then check the status if the production manager is send via mail then the employee will change the cylinder details then it check the cylinder it will satisfied means it use for the purpose and if cylinder get damaged then the employee also purchase the parts of the specified material then data is send to the office manager for the approval.

VALIDATING ANALYSIS

In this module the production manager has to register his details for the registration once his register then it can't log in because once admin will approve only the production manager can log and the approval message can send by the admin via mail. Once the approval has satisfied then the production manager can log in to the profile then they can check cylinder details send by the employee they can check the cylinder data one by one i.e., temperature, pressure, refilling date, filling type, expiry date. Which data has defect send defect parts to the employee via mail.

VALIDATING REQUEST

In this module then office manager can register his details once they registered, they wait for the admin approval for login. Once the admin can approve then the office manager can login to this portal then they view the request of the parts send by the employee, then send the data to the owner to buy the parts, once the product bought by the owner show the purchased part details send the request to the employee.

CASH TRANSACTION

In this module owner log in to his portal the view the request buying parts send by the office manager once they verified then they proceed the payment for the parts buying once the payment can be done then the details can be sent too admin and office manager and oxygen cylinder production data or information can be represented in the form of graph.

PERMISSION ACCESS

In this module admin can login to his portal then approve the details of the employee, production manager, office manager will register details send by the respective person and also maintain the details of selected employee, production manager, office manager will register details then they generate the pay slip for the parts can be purchase by the owner and send the pay slip details via mail. Each and every detail can be stored in Database.

IMPLEMENTATION

ALGORITHMS

Algorithm 1: Distributed Modeling and Computing Framework for Nonlinear Process Monitoring.

OFFLINE MONITORING

Step 1: Determine the inner unit variables of each unit and the neighborhood variables from other units using MI-based variable selection.

Step 2: Establish the local unit monitors.

2.1 Train an SAE for the bth unit using the bth CPU;

2.2 Add a full-layer neural network to the SAE to reconstruct the inner unit variables.

2.2 Calculate the T 2 hb and Qb statistics;

2.3 Determine the threshold T 2 hb,th and Qb,th ;

2.4 Perform DCCA between the bth unit and neighborhood variables and obtain the correlated representations using the bth CPU;

2.5 Calculate the T 2 ub statistics;

2.6 Calculate the threshold T 2 ub,th for T 2 ub;

Step 3: Establish the global monitoring statistic.

3.1 Collect the obtained outer-related representations from all local units as z;

3.2 Calculate the T 2 z statistic;

3.3 Determine the threshold T 2 z,th for the T 2 z .

Step 4: Construct the comprehensive monitoring statistic of local unit Jcomp and determine the threshold.

ONLINE MONITORING

Once a new sample is obtained, the following three-step procedure is performed to identify the process status and fault location.

Step 1: Examine the global and comprehensive local unit monitoring statistics.

1.1 If T 2 z exceeds the control limit, then the fault is a global fault that generally affects several operation units;

1.2 If Jcomp exceeds the control limit, then a fault that affects some local units exists.

Step 2: Examine the monitoring matrix of local unit.

2.1 Once T 2 z or Jcomp exceeds the control limit, analyze the monitoring statistics of local unit to localize the fault unit.

2.2 If an outer-related monitor for the local unit with statistic T 2 ub exceeds the control limit, then a fault in the local unit affecting the neighboring units exists;

2.3 If only an inner monitor for the local unit indicates a fault, then the fault is a local fault affecting the local unit only.

Step 3: Examine the variable contribution plot to locate the faulty variables. Once a fault is detected, calculate the contribution of variables to the fault.

CONCLUSION

A local–global modelling and distributed computing framework for efficient monitoring of nonlinear plant-wide processes with industrial big data are proposed in this article. The distributed monitoring framework incorporates SAE based DNN to characterize the complex variable relationship within a local unit and uses the selection of MI-based relevant variables and DCCA neural network to characterize the relationship between a local unit and its neighbouring units. Outer-related representations for each unit are generated to establish a global monitoring model. Given that the distributed monitoring framework involves information from only local and neighbouring units, the modelling task can be divided and completed by using different CPUs to make the process. In future wide variety of area can be covered to monitor and schedule multiple resources and allocate them effectively.

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