Multi-agent Manufacturing Execution System (MES): Concept, Architecture & ML Algorithm for a Smart Factory Case

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Abstract: Smart factory of the future is expected to support interoperability on the shop floor, where information systems are pivotal in enabling interconnectivity between its physical assets. In this era of digital transformation, manufacturing execution system (MES) is emerging as a critical software tool to support production planning and control while accessing the shop floor data. However, application of MES as an enterprise information system still lacks the decision support capabilities on the shop floor. As an attempt to design intelligent MES, this paper demonstrates one of the artificial intelligence (AI) applications in the manufacturing domain by presenting a decision support mechanism for MES aimed at production coordination. Machine learning (ML) was used to develop an anomaly detection algorithm for multi-agent based MES to facilitate autonomous production execution and process optimization (in this paper switching the machine off after anomaly detection on the production line). Thus, MES executes the 'turning off' of the machine without human intervention. The contribution of the paper includes a concept of next-generation MES that has embedded AI, i.e., a MES system architecture combined with machine learning (ML) technique for multi-agent MES. Future research directions are also put forward in this position paper.

1 INTRODUCTION

Context-aware Manufacturing Systems. Automated operations in a manufacturing enterprise require both plant control systems as well as enterprise software. In the era of digital transformation, smart factories can automate manufacturing operations by being context-aware. Given that smart factories are key components of Industry 4.0 (Kagermann *et al.*, 2013), it is essential to develop manufacturing information systems that can assist humans and machines in the execution of their tasks on the shop floor. Manufacturing execution system (MES) is an information system and a real-time compliant software, which is identified to enable smart factories due to its ability to act as a digital twin (Mantravadi and Møller, 2019). It supports shop floor as well as the supply chain level activities of a manufacturing enterprise (Mantravadi *et al.*, 2018) (Mantravadi *et al.*, 2018).

The revolutionary wave of computing (Internet of Things, IoT) which is the phenomenon of connecting objects over the internet, has enabled us to have intelligent manufacturing systems. As a core of any manufacturing system, MES controls production process that involves the physically connected production units/physical assets/equipment. Modern factories generate massive amounts of production data during the production process, where MES faces certain challenges such as:

- Make best use of ever-increasing amounts of logged production data to find meaning, dependencies, relations and problems in production which are not apparent upfront

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- Possess analytical solutions to support extracting, storing and analyzing the data to obtain an optimized decision for MES

This paper is motivated by the need on how to share and process valuable information in a much more efficient and flexible way to solve the above two challenges and fill the gap of lacking decision support capability of MES (Li, 2012).

Machine Learning for Manufacturing Execution System. Machine learning (ML) is an important toolbox which can be used to make sense of the data generated from the production and ML is already known to serve the purpose of knowledge synthesis in engineering automation (Lu, 1990). MES can perform learning to apply on a wide range of production processes, including optimization of individual module behavior, optimization across each module or one or more production lines (Gröger *et al.*, 2012). ML can help MES to export valuable information from the production modules and feed it to the modern computing power and learning algorithms. This will consequently result in exploring new opportunities, business models and solving the challenges that were not possible before.

Some examples from the literature that apply ML for manufacturing problems:

1. For optimizing the process to achieve energy efficiency, Palensky P et.al. suggested that time periods need to be around 15-30 minutes to switch off the equipment if the energy consumption beyond the upper bound according to the production scheduling of MES (Palensky and Dietrich, 2011).
2. Vieira et al. proposed an analytical model that can predict the performance of rescheduling strategies and quantify the trade-offs between different performance measures for manufacturing system (Vieira *et al.*, 2003).
3. In order to build prediction models to increase sustainability performance in machining operations, Woo et al. developed a big data analytics platform for manufacturing system (Woo *et al.*, 2016).

ML is also able to identify the anomaly behavior in a production line, which has been a hot topic in recent years, i.e., anomaly detection. It has become a manufacturing imperative for high velocity real-time production to analyze patterns of data streams and look for anomalies that can reveal something unexpected on the production line. Ko et al., use ML based anomaly detection to estimate the products' quality by integrating manufacturing, inspection and after-sales service data (Ko *et al.*, 2017). Liu J et al., developed a structured neural networks which efficiently reduces anomaly detection misclassification for a manufacturing system (Liu *et al.*, 2018). Van Stein et al., proposed a GLOSS anomaly detection algorithm which helps to detect anomalies in high dimensional mixed data sets of manufacturing process (Van Stein *et al.*, 2017). Vodencarevic et al. presented anomaly detection algorithm, AN-ODA, to detect anomalies in the cyber-physical systems (Asmir Vodencarevic *et al.*, 2011). Windmann et al. identify the abnormal behavior, OTALA and QRM were developed for modeling learning of discrete states and continuous behavior (Windmann *et al.*, 2015).

There are several other studies that also show how ML was used for solving/improving a specific task on the shop floor. All these studies also indicate the fact that using ML in manufacturing has been studied extensively and that it is a well-established research line. However, not many studies address the benefit utilization aspect of existing manufacturing information systems that could use toolboxes such as ML.

Against this backdrop, we argue that larger impact is created for a manufacturing enterprise when researchers can maximize the value of existing MES with systems thinking approach to address a bigger problem for the enterprise. Such approach can be realized by deploying MES with collaborating technologies. A collaboration system, which is a combination of different elements such as hardware, software, organizational practices and other tool boxes like ML could include MES software as a main actor. Such a collaborating system, designed based on an information system (MES) can derive significant benefit for the overall enterprise. Whereas a single task solving approach might not derive maximum value from the existing IT assets in a factory. A similar concept of 'Work System Theory' proposed by Alter also advocates linking people, processes and IT tools for improving business performance (Alter, 2011).

In this paper, a smart factory scenario of detecting anamoly using multi-agent MES is outlined as an example. It supports the enquiry on how to provide decision making for MES using ML techniques to detect the abnormal behaviors on the production line; a question that was not widely researched before.

Section 2 introduces the theoretical framing to the MES research, section 3 describes the approach followed by a proposal of a system architecture and an algorithm to support the concept. Section 4 concludes the position and presents the future work.

2 CONCEPT OF 'AI EMBEDDED MES FOR A SMART FACTORY'

The Intelligent Manufacturing Systems (IMS) were first outlined in 1978 (Hatvany and Nemes, 1978). AI research results are highlighted as promising tools for managing complexity, uncertainty, unforeseen problems, dynamic changes and disturbances in manufacturing systems (Hatvany and Lettner, 1983) (Monostori and Prohaszka, 1993) (Shen *et al.*, 2000).

Holonic manufacturing and multi-agent based manufacturing control are two popular approaches for distributed intelligent manufacturing control. Since multi-agent based control systems are pure software environments unlike holonic manufacturing systems (McFarlane *et al.*, 2003), an agent based approach is more suitable for implementation on a software like MES to improve process performance.

Requirements of Future Factories. Two of the few design principles of Industry 4.0 are 'interconnection' and 'decentralized decisions' (Hermann *et al.*, 2016) that require smart factories to use MES to implement production scheduling in real-time via intelligent data acquisition and analysis (Chen *et al.*, 2017). For this, OPC UA based interaction in multi-agent systems is a recommended technology (Chen *et al.*, 2017). With the changing manufacturing requirements, MES too needs rethinking and MES research needs to combine the aspects of AI.

3 APPROACH

The proposed multi-agent MES consists sub-agents (that run on Raspberry pi platform) and central agent (a middle-ware running on MES server). The agent is designed as a virtual digital shell of each physical asset of the production line. The main idea behind this agent-based approach is to use a sub-agent as an assistant to collect the data which is generated by the asset during the production, and leverage central agent to identify the abnormal behavior and aid MES to execute. The extension of this work would be to test and implement such software system. The proposed software falls under the category of centralized multi-agent system (Kamdar *et al.*, 2018).

For this paper the problem is chosen to be the anomaly behavior on current production line of AAU Smart lab (Madsen and Møller, 2017) where the two anomalies are identified as:

(1) Unusual drilling speeds (too high or too low) and (2) Unusual number of parts finished per minute

The main approach can be described in the following steps:

- **Monitoring** - This step is performed by the sub-agent of each asset. The data is generated during the production process monitored by the sub-agent.
- **Data Collection** - The production data will be collected and stored by sub-agent during the production. The selected features of the data will be used for building the behavior model.
- **Modelling** - In order to learn the behavior model of the system, the sub-agents push the data sample to the central agent that is running on server. Based on the above identified two features, the data on drilling speed and the processing time will be extracted from the production data. The extracted data will be fed into the formulae (see the following formula in section 4) to obtain the mean and variance for building the normal behavior model. To distinguish an abnormal behavior, a statistical model is used to detect the normal behavior of the system based on the collected data metrics.
- **Anomaly Detection** - The central agent applies a statistical test to detect whether it is a normal or abnormal behavior according to the data point.
- **Group Decision Making** - If the anomaly is detected, the central agent needs to quickly identify the cause of the abnormal behavior, flag the corresponding sub-agent(s) and generate a new decision for adjusting the behavior of the physical assets through the sub-agent(s). The server also holds a repository for storing the system topology. If the decision requires reconstructing the system topology, the topology repository also needs to be updated.
- **Behavior Adjustment** - The central agent will send the commands to the sub-agent which is involved in causing the anomaly. The current behavior adjustment considered in this case is switching the machine off if the abnormal behavior is detected.

This approach to the situation helps us in presenting the architecture and an algorithm in section 4.

4 SYSTEM ARCHITECTURE AND ALGORITHM

The system architecture can be represented as Fig.1.

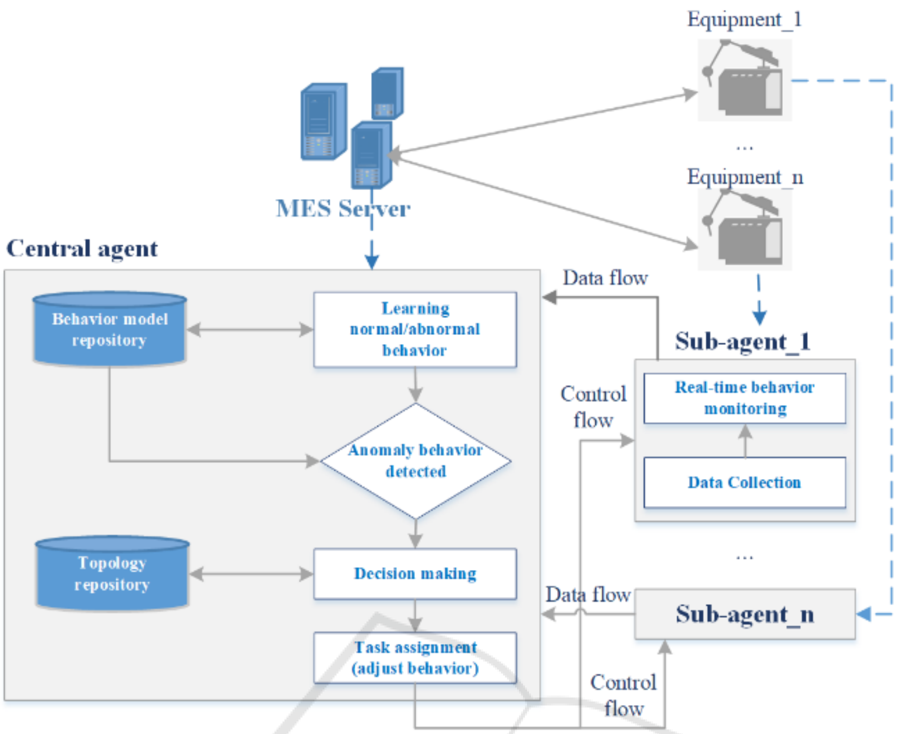

Figure 1: System architecture of ML based multi-agent manufacturing execution system.

The purpose of this work is to integrate the ML into multi-agent MES for detecting the anomaly behaviors in a supervised fashion. In order to achieve that, we chose the client-server (CS) style architecture.

Anomaly detection algorithm helps central agent to distinguish the abnormal behavior from the normal production activities of the production. We assume that the features of the production data follow the Gaussian (Normal) distribution. The main algorithm is described as:

Feature Selection. Two features are selected for our example, drilling speed (x1) and number of parts finished per minute (x2).

Fit Parameters. Given the number m sample data where μ1 and μ2 represent the mean of the feature x1 and x2 of sample data separately, and σ1 and σ2 stands for the variance of the feature x1 and x2 of sample data separately.

$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} x_j^i$$

$$\sigma_j^2 = \frac{1}{m}\sum_{i=1}^{m}\left(x_j^i - \mu_j\right)^2$$

Calculating p(x): Calculating the probability p(x) of the new production data x to see if it is lower than the predefined lower bound ε, where the anomaly is detected if p(x) < ε (predefined as a threshold).

$$\mathrm{p(x)} = \prod_{j=1}^{n} p\left(x_j; \mu_j, \sigma_j^2\right)$$

$$= \prod_{j=1}^{n} \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left(-\frac{(x_j-\mu_j)^2}{2\sigma_j^2}\right)$$

Below is the partial python code to calculate the mean μ, co-variance σ and probability density p:

```
import numpy as np
from scipy.stats import
     multivariate_normal
from sklearn.metrics import f1_score

# This function estimates the
  parameters: mu and sigma
# input: X - data sample X
# output: mu: the mean of the data
```

```
# set X; sigma: Covariance
def estimate_gaussian(X):
    mu = np.mean(X, axis=0)
    sigma = np.cov(X.T)
    return mu, sigma

# This function is to calculate the
  probability density function

def multivariateGaussian(X, mu,
    sigma):
    pro =
    multivariate_normal(X,mean=mu,
    cov=sigma)
    return pro
```

5 CONCLUSIONS & FUTURE WORK

The following contribution of the paper is directed to improve MES by combining its deployment with AI techniques:

- A perspective on carrying out high impact research for a manufacturing enterprise is put forward. Given that information systems research concerns socio-technical and organizational aspects, a position was taken that future research on benefit utilization of MES and deploying it with collaborating systems (such as agent-based systems or prediction systems etc.) can improve business performance of a manufacturing enterprise, which ultimately aligns with strategic and functional objectives of a smart factory.
- The study inferred that existing MES literature lacked attention on its benefit realization using decision support mechanisms. It established the potential in applying AI to the factory floor to leverage the existing manufacturing IT tools of MOM layer (as per ISA 95 standard).
- Agent based approach is suitable for MES implementation in the smart factory context.
- A concept was developed to establish the future research agenda on the topic of combining AI with MES. To verify the concept, system architecture and anomaly detection algorithm that can run on top of MES to execute decision on the production line, were proposed. Based on this proposal, an artifact: a smart factory with multi-agent MES could be designed in the future.

As far as we know, it is the first time combining the anomaly detection machine learning algorithm with agent based MES in manufacturing.

Currently, the authors' team is working on implementing this approach at AAU Smart lab's production line. The project "AAU Open Source MES Framework" undertaken by the authors', aims to design and develop an open platform (an open source software stack) for smart factory solutions. The project contributes to the manufacturing digitalization using "Odoo" open source enterprise resource planning (ERP) system to achieve interoperability through vertical integration of the factory floor.

The future work intends to develop a toolchain that builds the communication channel for exchanging the operational commands and production data between MES and sub agents that run on programmable logic controllers and raspberry-pi. This multi-agent setup works in real-time to improve the process performance in the factories.

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