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Developing manufacturing execution system with predictive analysis

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Abstract. Digitalisation is currently developing in many sectors of the economy. The success of a manufacturing enterprise requires a transition to digital control of production and business processes, to the greatest extent possible without human intervention using artificial intelligence technologies. This research applies a Manufacturing Execution System (MES) with Predictive Analysis to an automatic production line (Chemical Line) which contains sensors, actuators and pumps controlled by four Programmable Logic Controllers, linked together, and being monitored through a Supervisory Control and Data Acquisition system. The production line composed of four different subsystems, responsible for filtration to bottling the chemical product. This paper tries to join the MES system with Artificial Neural Networks (ANN) in order to not only monitor the system but having predictive analysis to plan the future. In such way we will take advantage of the benefits of the ANN, such as Long-Short Term Memory architectures. The experimental data will be compared with other usual platforms, such as the Master SCADA itself, through the course of this research.

1. Introduction and description of manufacturing execution system

A Manufacturing Execution System is a computerised system that tracks and monitors all the elements involved in the transformation of raw materials to the final product and documents these information in order to have full reports of all elements involved in the process.

MES are becoming an essential tool for operating Small and medium-sized enterprises (SME). With the rapid increase in technology, it is almost guaranteed that paper based operating systems that documents all assets of these enterprises will be replaced by more efficient and reliable smart MES [1]. MES system can help us to make decisions for the future in order to optimise our process to achieve better results.

These results can be obtained from the production line in real time, and can be plotted using various types of software, but in order to make prediction on them for the future prospect, we can take advantage of Artificial Neural Networks to make a perfectly good regression in order to actually see our gains and losses in the future, and be able to optimise our process.

2. Aim and solved problems

The aim of this research is to create a complete MES system for FESTO chemical line that can predict and analyse the predicted data.

Here are some of the problems and tasks that will be solved by this research:

- Sketches of all the production line
- Having the List of all the equipment in one place. (this will be useful also for creating a spare part list for the maintenance team)
- Reception of signals from the Programmable Logic Controllers (PLCs)
- Programming the dynamic production line in Master SCADA
- Programming the predictive part with ANN

3. Machine learning and MES

Machine learning (ML) is a very strong tool which can be used to analyse every form of data that will be obtained from the production process. We also know that MES can perform learning to apply on a wide range of production processes. Together ML and MES can be combined to extract various data and by analysing them they can find patterns and algorithms which can be used to optimise the production [2].

In the paper presented by S Mantravadi, C Li, CMøller on Multi-agent Manufacturing Execution System [2], they point out some examples from the literature that we can apply ML for manufacturing problems: optimising the process to achieve energy efficiency; developing analytical model that can predict the performance of rescheduling strategies and quantify the trade-offs between different performance measures for manufacturing system; developing a big data analytics platform for manufacturing system to increase sustainability performance in machining operations.

ML can also be used in order to detect abnormality in the production. And in such way we can estimate the quality of the product by integration of manufacturing, inspection and after-sales service data [3].

In the same paper presented by S Mantravadi, C Li, CMøller [2], there are several studies mentioned in the usage of ML in smart manufacturing:

So we can use ML not only for a better Business plan in the future or an optimised scheduling, we also can use ML for Quality improvement. But the best advantage is when we create a comprehensive MES that first, will do all the optimization and second, will decrease the amount of paid software in the process. This will focus on what actually matters in our task. Furthermore, we will have more control in personalising the MES for our use.

4. Concept and results

The concept of our MES is shown in the figure 1.

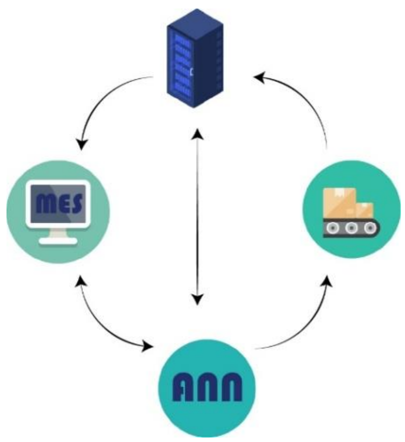

Figure 1. Concept MES.

Advantages of this implementation will be:

- No paid apps
- Narrowing the focus on what is important to us

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- Therefore, it will be user-friendly
- It will lower the cost of education of the staff

5. Monitoring task

For the state monitoring task of the system, we can take in account static and dynamic diagnostic. The static diagnostic is when all the requirements are known and stored as constants over time, whereas dynamic diagnostic is when the requirements are unknown and we have to compute them through formulas or other means.

Static diagnostic

In first step we have to read the input data that define the characteristics of the system such as pressure from sensors or databases and feed it into our OPC server. Then we have to read the pre-set key performance indicators (KPI) to define the boundary for our inputs.

Then we have to access our knowledge base which contains a set of rules to make our knowledge base management system to be able to produce controlling signals in order to monitor the state of our system.

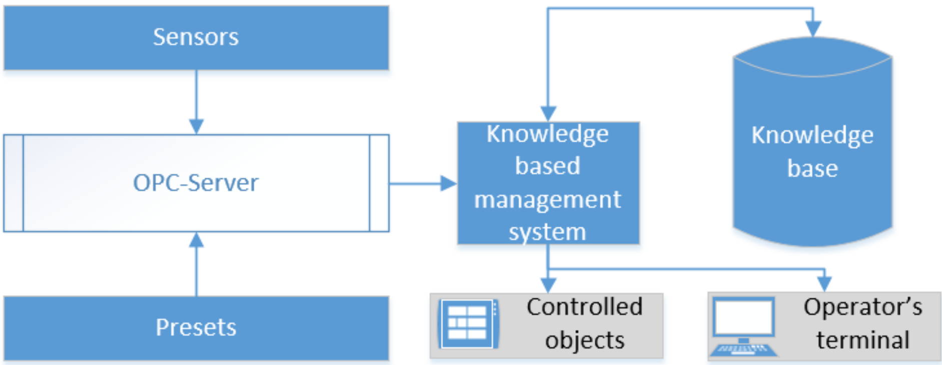

Figure 2. Static diagnostic scheme.

For example, for monitoring the state of our system based on the air pressure of the pneumatic system, we have a knowledge base which part is shown as bellow using Resource description framework (RDF)[4]:

```
:kpi1 a classes:KPI;
rdfs:label'PressureSensor';
prop:hasInter ind:Interval2;
prop:hasInter ind:Interval3.
:Interval2 a classes:Interval;
prop:causesind:alarm;
prop:hasMin'0';
prop:hasMax'4'.
:Interval3 a classes:Interval;
prop:causesind:warning;
prop:hasMin'6.5'.
:alarm a classes:state.
:warning a classes:state.
```

The knowledge base entries for the pressure monitoring can be presented as a set of IF-THEN statements:

- If Current_Pressure<Preset_Pressure_Min (4 bar) then alarm.
- If Current_Pressure>Preset_Pressure_Max (6.5 bar) then emergency warning.

Then we need to send a query to the knowledge base to find the malfunction and monitor our system.

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Dynamic diagnostic

Now for the situation that we need to change something in the production line or equipment or changing the materials, we do not have control on the changing itself. For this reason, the key performance indicators (KPI) should be computed. In order to do it, we offer to use cooperative work of following elements: digital model, execution environment, Database management system and control system block.

In order to get data from control plant we can use Distributed Control System (DCS) or Improved Control System (ICS). They are directly connected to the control plant, so they can send control signals to it. We also presume that a Protective Safety System (PSS) is also placed there.

In order to calculate KPI in situation of task, source material or equipment changing we propose to use compositional program-analytic models (CPAM), which are models of different level KPIs connection. They are actually expressions, explaining how KPI depends on another one or on control parameters.

So, data measured by sensors is sent to the database management system (DBMS). Then we should use Execution environment to run digital models (particularly CPAM) in order to compute KPI corresponding to relevant situation. Thus, execution environment also needs relevant data from control plant.

Then the execution environment computes the relevant KPI, basing on current data and CPAM. So, reference data is computed and then it should be sent back to DBMS in order to match and to check if current data meets KPI's limitations (Figure 3). It is quite similar with the previous task. After the evaluation and comparison, set points go back to DCS to provide control signals, based on modelling values. At the same time the data from execution environment is displayed with human-machine interface (HMI) to show the difference between set-point and current values. CPAM can be represented in different ways: formula-based models, neural-network model, analytical models [5].

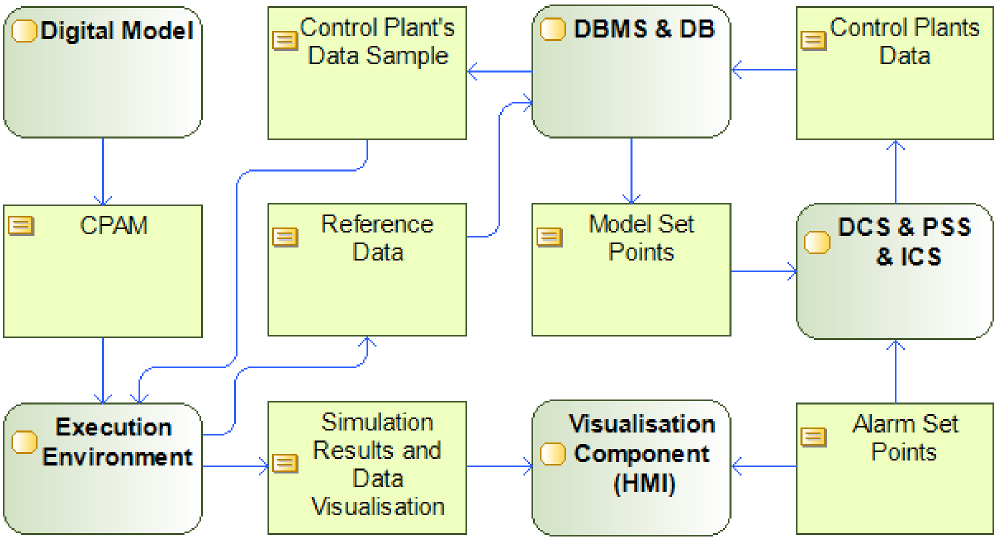

Figure 3. Functional scheme of system dynamic diagnostics.

6. Adaptive control system

The idea of development of an adaptive control system for complex object is to determine the complexity at the first step. After that we transfer complexity values into control system requirements. In this paper we describe the objects which contain the high grade of all of the complexity features. In this way, the complexity of manufacturing process can be rated due to next features, shown below.

Multi-variable or multi-connected control object. Such systems in which control is carried out to several connected variables. Moreover, all input variables have a significant effect on the state of the entire object, and their interaction is manifested in all output parameters of the object.

Let us assume that in usual strait objects, dependence between input Xn and output Yk can be described by Wnk transmission function. At the same time Y in musty-connected control object description is more complex. On the Figure4 such connection is shown.

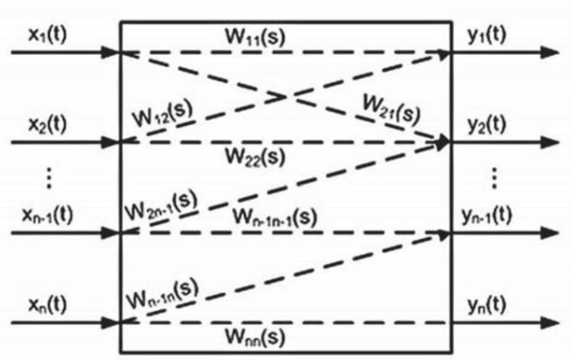

Figure4. Multi-variable control object.

Here we can see that Y2, for example depends on X1, X2, Xn-1 inputs and W12, W22, Wn-1n-1 transmission functions. Because of described features, arises the complexity of management of such systems. It appears an additional control tasks, such as:

- Negative relative value influence elimination.
- Dynamic diagnostics of an object characteristic or system state.
- Control parameters optimization, according to set points [6].

7. Computer vision in quality control

Computer vision is one of the main means for quality control in industrial production lines. The typical procedure is inspecting a product with a camera and then controlling the entire production with the result of the analysis of this inspection. The problem is that most of the time this inspection is being done by human but it is really difficult to detect if there is no algorithm for the detection, so not only doing this inspection by human can be not true, it also can be time consuming. Another problem is to achieve sufficient camera measurement for feature extraction. Once sufficient measurements and features are obtained, however, a machine vision system can replace a human observer successfully. So, we also can apply computer vision to our MES in order to come up with a system which can prevent inadvertent errors. Such as detecting defected bottles before feeding them into the system or even for packaging [7].

8. Conclusion

The concept in this paper acts like a client-server system where the main part of it is the MES. ML will be a tool to help the MES be more efficient. This system will be easier to use than other systems currently available and this allow to monitor the production as well as management. Because concept is based on ML then you can just document the results of the ANN for management and business plans.

9. Future developments

The next steps of this project are to develop the MES system for other production lines. Production lines can be far away from each other and not connected physically and the MES system can be cross-platform.

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