IDLE TIME DETECTION IN MANUFACTURING INDUSTRY-USING MACHINE LEARNING ALGORITHMS

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Abstract

Our day-to-day commodities truly depend on the industrial sector, which is expanding at a rapid rate along with the growing population. The production of goods needs to be accurate and rapid. Thus, for the present research, idle time detection in manufacturing industry using machine learning algorithms. When put into practice in the real world, predictive maintenance presents a set of challenges for fault detection and prognosis that are often overlooked in studies validated with data from controlled experiments, or numeric simulations. Smart manufacturing is reshaping the manufacturing industry by boosting the integration of information and communication technologies and manufacturing process. As a result, manufacturing companies generate large volumes of machine data which can be potentially used to make data-driven operational decisions using informative computerized algorithms. In the manufacturing domain, it is well-known that the productivity of a production line is constrained by throughput bottlenecks. The operational dynamics of the production system causes the bottlenecks to shift among the production resources between the production runs. Therefore, prediction of the throughput bottlenecks of future production runs allows the production and maintenance engineers to proactively plan for resources to effectively manage the bottlenecks and achieve higher throughput.

Keywords*: Machine learning algorithm, smart manufacturing, communication technologies, bottlenecks, operational decisions*

Introduction

For manufacturing companies, the management of machine failures is becoming increasingly important. Due to the increasing complexity of the machines, downtimes of any kind can affect the overall success of a company. Buying a spare system is not an alternative solution as the acquisition costs normally surpass the benefit of the spare system. In addition, most replacement systems also require regular maintenance, even if they are not used. That is why companies are looking for new ways to manage machine failures cost-effectively. Predictive Maintenance is one topical subject, among others, which is a promising direction to tackle machine failures before they actually occur. However, the selection of appropriate techniques from the field of Predictive Maintenance is challenging as numerous aspects have to be considered. In addition to Predictive Maintenance, there are many other approaches in this context for coping with machine failures such as Condition Monitoring or Continuous Improvements. Moreover, the trend towards machine learning raises the question of whether machine failures can be easily predicted. Although technical developments have improved the possibilities for manufacturing companies to cope with machine breakdowns, their practical application is still a challenging task for many reasons. On the basis of these considerations, the work at hand presents two real-world cases that were carried out in cooperation with manufacturing companies. For these companies, the detection of system errors is of utmost importance. In this context, it was shown that the detection of anomalies [of a machine is crucial for these companies. However, the meaningful detection of such anomalies is very complex. Interestingly, so far, many manufacturing companies often employ a selected choice of technical evangelists that are only able to detect anomalies based on their practical experiences over time. Such experts, in turn, are very expensive by design. To relieve them from manual decisions, this paper elaborates on how machine failures of these scenarios can be managed by analyzing sensor data of the production machines. In particular, the two examples will show that different types of sensor data, as well as detection techniques, should be considered. The first presented real-world setting is related to pharma packing machines. The latter machines wrap tablets into individual packaging units (i.e., blisters), and usually comprise several other components. For example, a product loader component pushes blisters and leaflets into cartons. This procedure, in turn, is prone to errors. Therefore, the packaging process needs to be continuously monitored to reduce costly downtimes as well as to comply with federal regulations. The continuous monitoring procedure, in turn, generates a large amount of sensor data coming from sensors that are related to the several components of the packaging machine. In addition, the pharma packing machine can be individualized for each customer, which might lead to many sensor parameter settings of the same machine type, including all obscured components.

Machine Learning Algorithms in Manufacturing

The quality-control process in manufacturing must ensure the product is free of defects and performs according to the customer's expectations. Maintaining the quality of a firm's products at the highest level is very important for keeping an edge over the competition. To maintain and enhance the quality of their products, manufacturers invest a lot of resources in quality control and quality assurance. During the assembly line, parts will arrive at a constant interval for assembly. The quality criteria must first be met before the parts are sent to the assembly line where the parts and subparts are assembled to get the final product. Once the product has been assembled, it is again inspected and tested before it is delivered to the customer. Because manufacturers are mostly focused on visual quality inspection, there can be bottlenecks before and after assembly. The manufacturer may suffer a loss if the assembly line is slowed down by this bottleneck. To improve quality, state-of-the-art sensors are being used to replace visual inspections and machine learning is used to help determine which part will fail.

Applications of machine learning in manufacturing

Predictive maintenance is one of the key uses of ML in manufacturing because it can prevent the failure of critical machinery or components using algorithms.

- Significantly reducing planned and unplanned idle time and thereby costs.
- Providing technicians with centralized inspection, repair and practice requirements.
- Extend the remaining useful life of the machines by preventing any secondary damage during repairs.

- Reducing the size of the technical team needed to make repairs.

Advantages of machine learning for manufacturing

- More relevant data is being provided so that finance, operations and supply chain teams can better manage factory and demand-side constraints.
- Improving preventive maintenance and maintenance, repair and overhaul performance through high assessment accuracy at component and part levels.
- Provide manufacturers with a level of control over Overall Equipment Effectiveness at the plant level.
- Machine learning is changing relationship intelligence and rapidly establishing itself as a sales force market leader.
- Machine learning algorithms are revolutionizing product and service quality to predict which elements have a greater or lesser impact on company-wide quality.

Data Mining

Data mining is about explaining the past and predicting the future by means of data analysis. Data mining is a multidisciplinary field which combines statistics, machine learning, artificial intelligence and database technology. A manufacturing system exists to produce a group of parts, subassemblies, and/or products. As part of the ongoing digital revolution, it has become easy to capture and store a vast amount of data in a fairly inexpensive storage media. Data mining and knowledge discovery is an interdisciplinary field for uncovering hidden and useful knowledge from such large volumes of data.

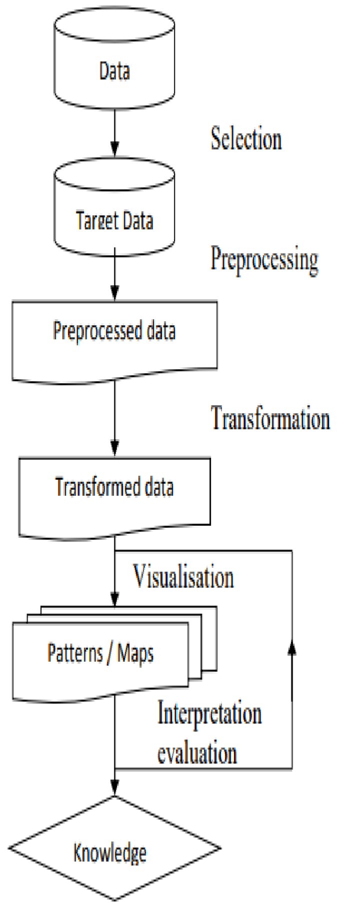

Figure: Knowledge Discovery Process

Machine learning :Machine learning systems automatically learn from data. This is often a very attractive alternative to manually constructing them, and in the last decade, the use of machine learning has spread rapidly throughout computer science and beyond. Among the different types of machine learning tasks a crucial distinction is drawn between supervised and unsupervised learning.

Methodology

The bottleneck machines were characterized by the presence of large waiting lines and these factors are used as predictor variables and the computed value k is the ratio of actual flow time that the job experiences in the system divided by the total processing time of that job.

Simulation has been commonly used to study the behavior of real-world manufacturing system to gain a better understanding of underlying problems and to provide recommendations to improve the systems. An enterprise will not easily open up its databases or data warehouse to any researcher, unless there is an implicit trust between them which usually takes time to develop. Two common approaches to getting around this data access problem are either using the open source data available in various repositories or by generating the data by building a simulation model. In the absence of such repositories in the domain of the researcher, a simulation model is an easier way to build up models for representing real life scenarios, to enhance system performance in terms of productivity , queues , resource utilization , cycle time, flow time , etc

Simulation Software

ARENA is built on the SIMAN simulation language. After creating a simulation model graphically ARENA automatically generates the underlying SIMAN model used to prepare simulation runs. The ARENA template is the core collection of more than 60 modules. It was designed to provide a general purpose collection of modeling features for all types of applications. In addition to providing core features for resources, queuing, inspection, system logic, and external file interface, the Arena template provides modules, specifically focused on aspects of manufacturing and material handling

Results and Discussion

Job Shop Simulation Model

the goal of the present research is to infer knowledge from data generated using the simulation model. This research uses a (10×10) benchmark problem from Lawrence. This problem has 10 jobs to be processed on 10 machines with unique routing and processing time. Table provides the data for the problem instance. The inter-arrival time generated from a negative exponential distribution is adjusted suitably to achieve utilization levels of 75% to represent moderately loaded shop and 85% to represent heavily loaded shop. Part type (a predetermined routing) is randomly assigned upon order's arrival. The probability of each part being chosen to be released into the shop is equal.

Table 10×10 Job shop problem data

Operation										
Job	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**5,18**	**8,21**	**10,41**	**3,.45**	**4,38**	**9,50**	**6,84**	**7,29**	**2,23**	**1,82**
2	**9,57**	**6,16**	**2,52**	**8,74**	**3,38**	**4,54**	**7,62**	**10,37**	**5,54**	**1,52**
3	**3,30**	**5,79**	**4,68**	**2,61**	**9,11**	**7,89**	**8,89**	**1,81**	**10,81**	**6,57**
4	**1,91**	**9,8**	**4,33**	**8,55**	**6,20**	**3,20**	**5,32**	**7,84**	**2,66**	**10,24**
5	**10,40**	**1,7**	**5,19**	**9,7**	**7.83**	**3,64**	**6,56**	**4,54**	**8,8**	**2,39**
6	**4,91**	**3,64**	**6,40**	**1,63**	**8,98**	**5,74**	**9,61**	**2,6**	**7,42**	**10,15**
7	**2,**	**8**	**9,**	**4**	**5,**	**6**	**7**	**1,**	**3,**	**1**

	80	,39	24	,75	75	,6	,44	26	87	0,22
8	2,15	8,43	3,20	1,12	9,26	7,61	4,79	10,22	6,8	5,80
9	3,62	4,96	5,22	10,5	1,63	7,33	8,10	9,18	2,36	6,40
10	2,96	1,89	6,64	4,95	10,23	8,18	9,15	3,64	7,38	5,8

assumptions are made about the operation of the job shop

- Pre-emption is not allowed once an operation is started on the machine it must be completed before another operation can begin on that machine.
- Machines never break down and are available throughout the run period.
- Each machine is continuously available for assignment, without significant division of the time scale into shifts or days and without consideration of temporary unavailability such as breakdown or maintenance. Machines may be idle.
- Processing time on the machines are known, finite and independent of the sequence of the jobs to be processed.
- Each of the jobs is processed through each of the 10 machines once and only once. Furthermore, a job does not become available to the next machine until and unless processing on the current machine is completed i.e., splitting of job or job cancellation is not allowed.
- In-process inventory is allowed. If the next machine on the sequence needed by a job is not available, the job can wait and joins the queue at that machine.

Job arrival section

In the job arrival section, entities are created and some attributes are assigned. After assigning the attributes, depending on the attribute, the batching module starts batching and batch size is randomly assigned a number between 1 and 9. Once a batch is ready, it is routed to the first machine in the sequence assigned for that job type. Machining sequences are taken from "SEQUENCE" module of ARENA. The following parameters are recorded at this moment.

- Entity serial number
- Part type
- Job arrival time
- Number of jobs waiting in front of all jobs
- Cumulative processing time of all jobs waiting in front of all machines.

Validation and verification

The model was validated by running a test simulation run by setting the inter-arrival time of jobs slightly higher level than the maximum cumulative processing time for all jobs. The underlying assumption is that if there is no waiting time the cumulative processing time for each job type should equal the flow time for the job. The computed flow time for each job was tallied with manually computed cumulative processing time for each job and thus the model was validated.

Simulation Output

Ten replications of the experiment was carried out for each of the three dispatch rules (First come First Served, Shortest Processing Time and Earliest Due date) and the experiment was repeated for 75% and 85% utilization levels.

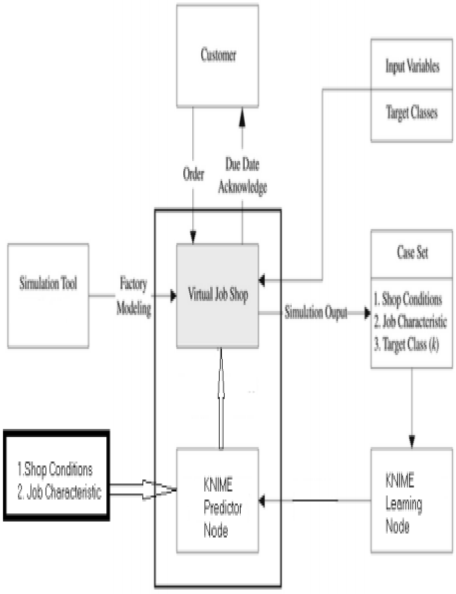

Figure: Proposed MT-TWK Model

Table Sample input data for MT-TWK Model (learning mode)

Serial Number	F1	F2	F3	F4	F5	F6	Computed K factor	Assigned Class
3510	1	6.4	24.5	19.1	6	50	2	B
3511	3	0	28	19.1	6	47.1	2.2	C
3512	8	14.5	27	18.2	8	61.7	1.4	B
3513	8	14.5	27	18.2	8	61.7	1.7	B
3514	10	4.4	17.5	6.6	4	28.5	1	A
3515	4	0	0	0	0	0	2.2	C
3516	6	0	0	0	0	0	1.2	A
3517	9	0	7.9	0	1	7.9	3.9	E
3518	9	0	7.9	0	1	7.9	4	E
3519	9	0	7.9	6.2	2	14.1	4.5	E
3520	9	0	12.4	7.9	3	20.3	5	E
3521	2	0	18.6	4	4	22.6	1.6	B
3522	2	0	18.6	4	4	22.6	1.7	B
3523	2	4	18.6	9.1	5	31.7	1.7	B
3524	2	4	18.6	18.2	6	40.8	2.2	C

Legend

F1 – Job Type

F2 – Work Content of jobs in 2nd second bottleneck machine

F3 – Work content of jobs in 1st bottleneck machine

F4 – Work content of jobs in 3rd bottleneck machine

F5 – Number of jobs waiting in all queues in the shop

F6 – Sum of remaining processing time of all jobs in the shop.

A rule set was generated from the decision tree. It may be observed that, in certain cases, several of the rules are applicable, and to overcome this problem rules are sorted by confidence. The rule that reduces the error rate the most appears first and the rule that has the lowest confidence appear last. The first rule that covers the new order is applied and the rule consequent is used to arrive at the due date. There is also a default class that is used when none of the rules apply.

Sample output with predicted flow time

Serial number	F1	F2	F3	F4	F5	F6	Computed K factor	Assigned Class	Predicted Class	K Factor for the predicted class	MT-TWK flow time
3510	1	6.4	24.5	19.1	6	50	2	B	C	2.6	112.58
3511	3	0	28	19.1	6	47.1	2.2	C	B	2	73.2
3512	8	14.5	27	18.2	8	61.7	1.4	B	B	2	95.6
3513	8	14.5	27	18.2	8	61.7	1.7	B	B	2	95.6
3514	10	4.4	17.5	6.6	4	28.5	1	A	B	2	99.2
3515	4	0	0	0	0	0	2.2	C	A	1.3	66.3
3516	6	0	0	0	0	0	1.2	A	A	1.3	83.98
3517	9	0	7.9	0	1	7.9	3.9	E	A	1.3	50.05
3518	9	0	7.9	0	1	7.9	4	E	A	1.3	50.05
3519	9	0	7.9	6.2	2	14.1	4.5	E	B	2	77
3520	9	0	12.4	7.9	3	20.3	5	E	C	2.6	100.1
3521	2	0	18.6	4	4	22.6	1.6	B	B	2	110.8
352	2	0	18.	4	4	22.	1.7	B	B	2	110

2			6			6					.8
3523	2	4	18.6	9.1	5	31.7	1.7	B	C	2.6	144.04
3524	2	4	18.6	18.2	6	40.8	2.2	C	B	2	110.08

The most significant advantage of this approach is the prediction of target class is handled by the algorithm and regression equations algorithm is not explicitly generated. The predictor module uses the model tree generated for prediction of target class thus enabling automation of decision process.

Conclusion

This study is an attempt to explore the application of machine-learning techniques in manufacturing and indicate that the factors considered for flow time estimation that can easily be obtained from any reasonably good manufacturing information system will help managers to predict a due date for delivery more accurately compared to traditional methods. The performance of the manufacturing management systems can be improved considerably by using information intensive methods rather than by using simple methods. Even though, TWK method is commonly used in industry for quoting due dates. The problems of assigning a value to 'k' the factor by which the processing time is multiplied to arrive at flow time flow time was hitherto a matter of opinion of production manager. The MT-TWK method proposed automates the process of assignment of value to 'k' by tapping into the knowledge stored in data repositories. With growing interest in data and organizations carrying huge repository of all kind of manufacturing data author foresees a need for methods that will take advantage of this in helping organizations to quote lead times that are realistic and achievable.

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