International Journal of Science and Research (IJSR)
ISSN: 2319-7064
ResearchGate Impact Factor (2018): 0.28 | SJIF (2019): 7.583

Recent Information Technology Trend of Using Machine Learning in Manufacturing Scheduling

Dhanesh Thatikonda

Sprint Telecommunications, Department of Information Technology, Naperville, IL, USA

Abstract: ***Production Scheduling is the process of arranging, controlling and optimizing work and workloads in a production process or manufacturing process. Scheduling is used to allocate plant and machinery resources, plan human resources, plan production processes and purchase materials. It is a key tool for manufacturing and engineering, where it can have a major impact on the productivity of a process. Scheduling jobs in a manufacturing system is by implementing Job release rules. Performance of the Job release rules depends on the state of the system in at each moment and anideal rule that caters to all states in the system doesn't exist. To improve performance of scheduling plan that caters to dynamic demands, ascheduling approach that uses machine learning can be used. Machine learning algorithms by analyzing the historicaldemand, forecast and performance of the system (including simulation runs) can decide which is the most appropriate dispatching rule at each moment in time.***

Keywords: Dynamic Scheduling, Production scheduling, Machine Learning

1. Introduction

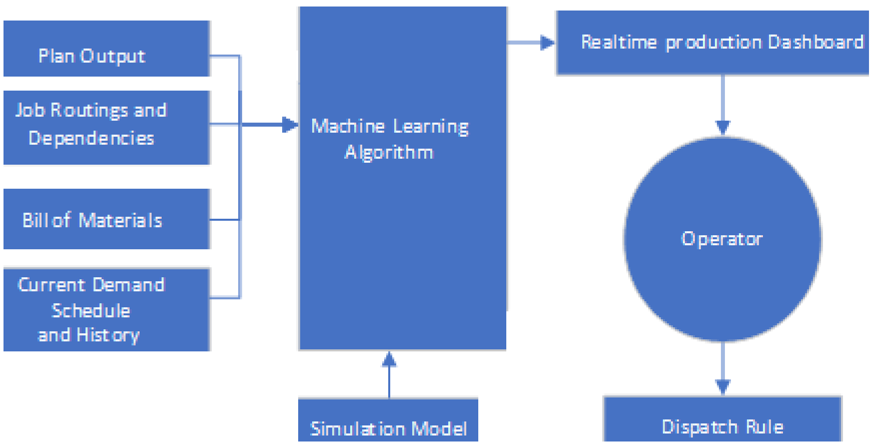
The chosen enterprise for this case study is a leader in thegaming industry that is producing the most innovative and engaging cabinets. The chose enterprise employs cellular manufacturing system. The production is configure to order, anddemand is irregular.Job sequencing and replenishment tasks need changes throughout the day to cater to urgent orders and field breakdown orders. Thisarticle focuses on the need for Machine learning algorithms that feedProduction scheduling dashboard. Operators use the production scheduling dashboard to determine the loading sequence of discrete jobs onto the production line.

Scheduling is the process of arranging, controlling and optimizing work and workloads in a production process. Companies use backward and forward scheduling to allocate plant and machinery resources, plan human resources, plan production processes and purchase materials.

- Forward scheduling is planning the tasks from the date resources become available to determine the shipping date or the due date.
- Backward scheduling is planning the tasks from the due date or required-by date to determine the start date and/or any changes in capacity required.

The goal of manufacturing scheduling optimization is to efficiently allocate machines and other resources to jobs, or operations within jobs, and then carry out the subsequent time phasing of these jobs on individual cells.
Scheduling problems include inherent job characteristics (due to mixed mode production), Constraints on resources, material and optimization criteria.

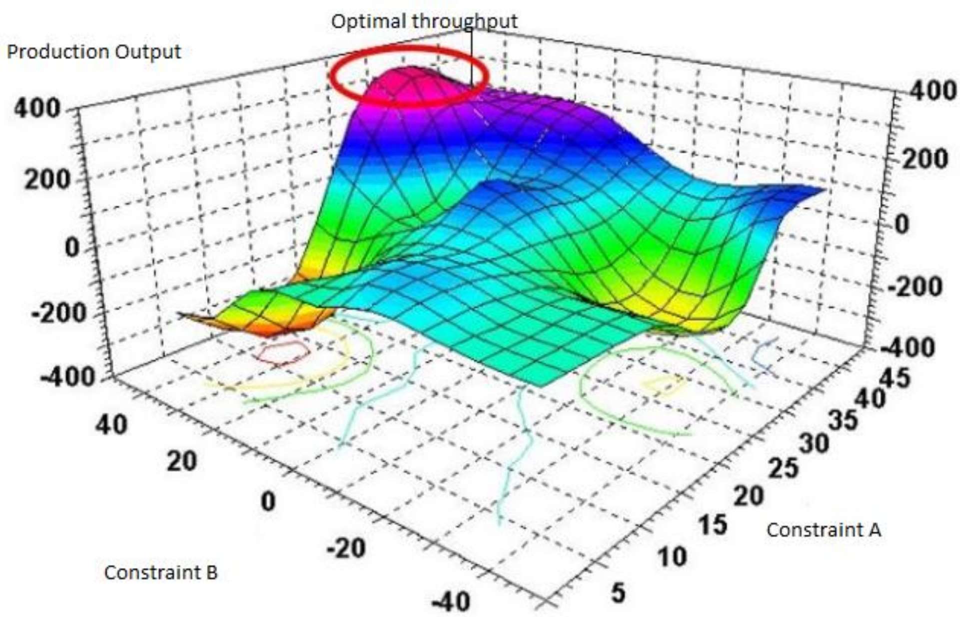
The chosen manufacturing system operate in dynamic environments where unanticipated events (like urgent jobs, customer requirement date changes) can cause a change in the schedule, and a previously approved schedule loses its optimality. Predictive–reactive scheduling approach is used forchanging the schedules in response to unforeseen events.
The algorithm interprets a scheduling problem as an optimization model with certain constraints, in terms of an objective function and explicit constraints.



In order to optimize a desired performance criterion, scheduling sequence of the job as well as start time of the job in each cell need to be calculated. Constraints on the operation floorinclude no two different jobs may be performed simultaneously in the same cell, operation timings at each cell is dependent on the type of assembly.

To overcome these limitations, a set of earlier system simulations is used to determine which rule is the best for each possible system state. These simulation cases are used to train a machine learning module to gain knowledge about the cellular manufacturing system. Gained knowledge is then used by the Machine learning module to make decisions on Job sequencing and release rules.

The simulation set contain all the possible data casesover a period. This may not include all scenarios and new constraints and scenarios may occur. Scheduling system recommendations may not be optimal always. A production job sequence may perform well in a simulation for a given set of attributes, but it may perform poorly when applied dynamically. The feedback from implementation is again added to simulation history and fed to Machine learning algorithm as Knowledge. With this process recommendations keep improving over time. An example of production rate based on two constraints is shown below.



The optimization problem is to find the optimal combination of these parameters in order to maximize the production output. Given example is complicated enough with two constraints.Without machine learning Operators are trying to dynamically decide the job sequenceto optimize production based on previous experience. This knowledge from previous experience in the form of production history is exactly what is fed as an inputto machine learning algorithms. By analyzing vast amounts of historical data, the algorithms can learn to understand complex relations between the various parameters and their effect on the production.

The fact that the algorithms learn from experience, in principle resembles the way operators learn to control the process. However, unlike a human operator, the machine learning algorithms have no problems analyzing the full historical datasets for hundreds of sensors over a period of several years.Different kinds of machine learning algorithms can be applied, and the outcome varies based on the algorithm chosen. Learning accuracy of the network is dependent on training examples. For example, learning accuracy achieved using functional virtual population is 24.6%.

Optimization algorithm

Machine learning algorithm capable of predicting the production rate based on the job parameters that we can modify, is a valuable tool. The multi-dimensional optimization algorithm looks for the highest peak representing the highest possible production rate. The algorithm can give recommendations on how to best reach this peak, i.e. which control variables to adjust and how much to adjust them. Such a machine learning-based production optimization thus consists of three main components:

Prediction algorithm

A machine-learning algorithm that can successfully predict the correct production rates based on multiple feeds of historic data and simulation plans.

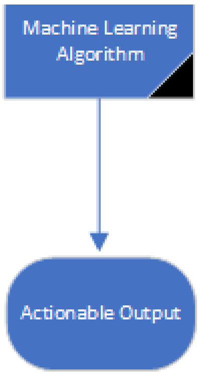
Multi variable optimization

Prediction algorithm then actsas the base of optimization algorithm that explores the Job schedule and sequencing.

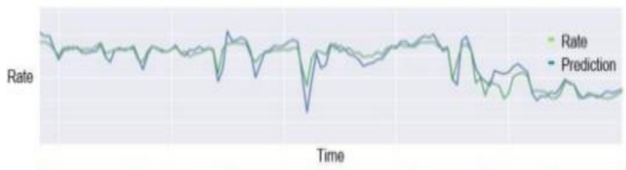
Actionable output

Recommendations include Jobs start dates that need to be changed, Production line the Jobs need to be loaded and the sequence in which the jobs can be loaded.

Production Scheduling Dashboard					
Job Number	Assembly	Production Line	Due Date	New Due Date	Sequence
346271	Test Assembly1	Line 1	15-Jan-20	15-Jan-20	1
345945	Test Assembly1	Line 1	16-Jan-20	15-Jan-20	2
937291	Test Assembly3	Line 2	15-Jan-20	15-Jan-20	1



On Comparisonof the Manual Operation selection and algorithm output, the enterprise can achieve 1.5% increase in individual production line throughput.



Above graph compares production rate with Algorithm prediction over a period of 1 month. The variance in actual through put is much less compared to the earlier static production plan model.

2. Conclusion

This paper provides a review on the use of machine learningin dynamic scheduling of manufacturing systems. It also discusses about various constraints in productions scheduling and ways to overcome using Machine learning algorithms. The algorithm output is presented as a dashboard and implementation is still the choice of the production planner. This dashboard removes the guess workout of the production planning with estimated through put numbers with each change. Finally, the point is made that in future, a scheduling module that would incorporate the machine learning algorithms will be able to achieve better through put with same production framework.

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