SOLVING COMPLEX PRODUCTION SCHEDULING PROBLEM WITH MACHINE LEARNING | A CASE STUDY

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Abstract In this paper author investigates emerging trend of machine learning replacing proven industrial optimizer & heuristics to bring much needed flexibility and adaptability to dynamic business environment. While this optimizers & heuristics had been very successful in replacing manual intuition and experience based approach, the key challenges of this 'black-box' approach is lack of flexibility and adaptability to change in requirements and dynamic business environment. In this case study, a European component manufacturer was using manual scheduling of the moulds leading to significant down time & productivity loss due to suboptimal usage of Press & Moulds. The typical industrial optimizer is expensive & not able to cope up with dynamic demand supply situation of the polymer component manufacturing industry. This paper explores the solution approach using Machine Learning for the mould scheduling leading to optimal usage of moulds & pressing machines during manufacturing of molded components achieving significant reduction in machine down time, increase in productivity & reduction in cost of production.

***Keywords*: Production Scheduling, Scheduling Algorithms, Optimization, Heuristics, Machine Learning**

I. Introduction

IN this paper the author investigates emerging trend of machine learning replacing proven industrial optimizer & heuristics to bring much needed flexibility and adaptability to dynamic business environment. During the 90s, the traditional ERP system like SAP, BAAN etc. while being very successful in integrating business processes, were not capable of solving industry specific optimization requirements. These gaps were addressed by niche players like ILOG who defined Industry specific optimizers & heuristics. For example, steel manufacturing industry requires 'Coffin Optimizer' for the production scheduling of a hot rolling mill which must adapt to strict production rules derived from metallurgic and physical constraints. Similarly, paper industry requires complex "trim –loss' optimization for the paper cutting to minimize the cutting waste.

While these optimizers & heuristics had been successful in replacing manual intuition and experience based approach, the key challenges of this 'black-box' approach is lack of flexibility and adaptability to change in requirements in a dynamic business environment. Significant improvement in computing power, capability of processing big data & emergence of machine learning platforms like Google's Tensorflow® & SAP's Leonardo® open up the opportunity to employ machine learning and design learning optimization system which can be flexible & adaptable to address changing business environment while harnessing the power of big data.

This paper explores the solution approach using Machine Learning for the mould scheduling leading to optimal usage of moulds & pressing machines during manufacturing of molded components achieving significant reduction in machine down time, increase in productivity & reduction in cost of production.

II. Industrial Black Box Optimizers

In the 80s & 90-s, when many large businesses started implementing ERP-s from vendors like SAP, BAAN etc., they realized that the ERP system were not capable of solving complex production scheduling problems. At a later stage, software applications specializing in supply chain management, e.g., I2, APO etc. introduced certain 'off-the-shelf' optimizer & heuristics to solve these complex problems. However, these new applications, although more

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Note : Certain applications/products mentioned in this paper, e.g., SAP S/4HANA, SAP APO PPDS, SAP S/4HANA PPDS , SAP Leonardo, SAP HANA are products /applications owned by SAP SE while Tensorflow is an application owned by Google LLC /Alphabet Inc.

powerful than traditional ERP systems, were only partially capable to solve some of the scheduling problem.

At the same time, many researchers introduced mathematical models & algorithms to solve specific industry requirements. For example, 'Coffin Schedule' for steel hot rolling mills or 'Trim Loss Optimizer' for paper manufacturing industries. Following section elaborates traditional approach of solving some of the scheduling problems.

A. *Coffin Schedule for Hot Rolling Mills*

In production scheduling of hot rolling mill in a steel Plant, the production schedule must meet stringent production rules derived from metallurgical and physical constraints (typically Grade, Thickness & Width). In the conventional hot rolling of mixed grades, as many similar grades and thickness as possible need to be assembled and rolled in a single rolling schedule (one schedule, about 100 coils). In this system, the initial stage following a roll change consisted of the rolling of about 10 coils, starting with narrow widths (narrow gauge trip) and progressively shifting to greater widths (wide gauge strip) in order to stabilize thermal crown (roll crown caused by thermal expansion of the rolls). Thereafter the next 90 coils or so reduce steadily to narrower width.

With the rolling technologies used in past, when wide gauge strip was rolled subsequently to narrow gauge strip, the areas of the rolls that had been in contact with the edges of the narrow gauge strip showed greater wear than other areas. Accordingly, when rolling shifted to wide gauge strip, the marks in the worn areas of the rolls were imprinted onto the steel sheets, producing inferior products with abnormal sectional shapes. To avoid this, rolling of the remaining 90 coils shifted from wide gauges to progressively narrower gauges for which shape can be more easily controlled (principle of steadily decreasing strip width). This rolling sequence was called the "coffin schedule" because the configuration of the width changes resembled the shape of a coffin. [1]

Also orders in the hot rolling mill require to meet customer due dates or internal due dates, if the coils are to be further processed in other sections of the steel plant (e.g. cold rolling mill). In the latter case, the product mix in the hot rolling mill has to also be balanced in order to be able to "feed" different parallel down-stream processes and thus enable optimal capacity utilization.

Due to this complexity and the variety of plant designs in metals hot rolling, different mathematical programming approaches has been published. Lopez et al. [2] suggested a heuristic based on Tabu Search, which was successfully applied to Dofasco, a Canadian steel producer, but failed to be applied to other steel plants. In another research, Zhao et al. [3] applied a two-stage scheduling method to the hot rolling area of Baosteel, China. In another optimization-based approach, Biondi et al [4] first designed parts of the rolling programs using intelligent heuristics and composed these parts to fully feasible programs by solving a min-cost-flow problem. In second step, the built programs were scheduled using a mixed integer linear programming formulation in order to obtain an optimal schedule that violates as few order due dates as possible.

B. *Trim Loss Optimization for Paper Manufacturing*

In paper manufacturing, the paper rolls produced are required to be cut as per the customers' specification which vary from one customer to another. This leads to an inevitable loss of paper known as trim loss problem (TLP) or cutting stock problem (CSP). Since the paper industry operates under thin margin, it is the goal of every paper manufacturer to efficiently satisfy the customers while minimizing the wastage due to trim loss. The industries have to maintain an efficient production plan which is economical while meeting customer's specification & quality requirements.

Considering the financial impact and importance of the TLP, significant research has been carried out by several researchers [5,6,7] to develop models and recommend various methods to solve it efficiently. The TLP has been studied with different goals such as minimizing trim loss, minimizing the production costs, minimizing the number of patterns and minimizing the total length & overproduction.

TLP can be modelled as a global optimization problem with a complex formulation, and therefore efficient techniques are required for finding the solution. The solution approach for TLP problem can be categorized into three groups.

(i) Algorithmic methods: Although guarantee the best & optimal solution, but finds less industrial application due to high computational complexity.

(ii) Heuristic methods: Usually generate a faster acceptable solution although may not find the exact optimal solution. A drawback of these methods are their domain dependency that causes the limited application of apparently similar problems.

(iii) Metaheuristic methods: Guided by some lower level heuristic & have an ability of not being stuck in local optima that might happen with traditional heuristic techniques.

Many of this research has been converted to optimization & scheduling software and deployed in the industry as black box optimizer / scheduling tools.

C. *Challenges with Industrial Optimizers /Heuristics*

While the above mentioned optimizers & heuristics had been deployed by customers, there has been certain challenges which prevented wide acceptance of the applications. For example

- Prohibitive cost of the optimizers (including implementation cost) prevented small & medium industries from deploying the solutions
- The optimizer solutions were available only for specific industries, e.g. paper, steel etc. where the

production volume is significantly high & businesses can make large investments.

- Only the experts (typically PhD scholars & mathematicians) can customize, fine tune & deploy the solutions. The businesses who have deployed the solutions, do not have expertise to understand & interpret the results. As a result, they did not have choice to take informed decision but accept the output blindly.
- In many cases, the off-the-shelf optimizers /heuristics available could solve the scheduling problem partially.
- Not capable to adapt to dynamic business scenario-s. For example, if the product mix changed, the optimizers which were set up to solve scheduling problem for original product mix, were no more producing optimal result for the new product mix.

These challenges led many customers who had deployed off-the-shelf optimizers/heuristics to move back to manual scheduling using MS Excel.

III. Machine Learning & AI as New Frontier

The emergence of Machine Learning & AI brought a new opportunity to re-look at these industrial problems. [8] The key advantages of ML & AI compared to the traditional industrial black-box optimizers are:

- Machine Learning algorithms are dynamic in nature and inherent capability to learn can help them not only to improve over time, but also to adapt to changing business scenario-s more effectively.
- Advent of open source programing languages like *Python* & platforms like Google's *TensorFlow®*, which had two benefits
  - Low cost of ownership due to open source technologies
  - Easy to consume built in libraries of algorithms & mathematical models
- Ever growing pool of experts for companies to set up their own competencies. No more dependencies on expensive product companies.
- Many startups are working in ML & AI space and able to address these white space at competitive price

IV. Scheduling Optimization for an European Speciality Component Manufacturer

Rubber component manufacturing has certain scheduling challenges which requires complex mathematical modeling. In this section, how machine learning can be leveraged to solve the industry problem will be discussed using the case of a leading European Automotive & Pharmaceutical Component Manufacturer.

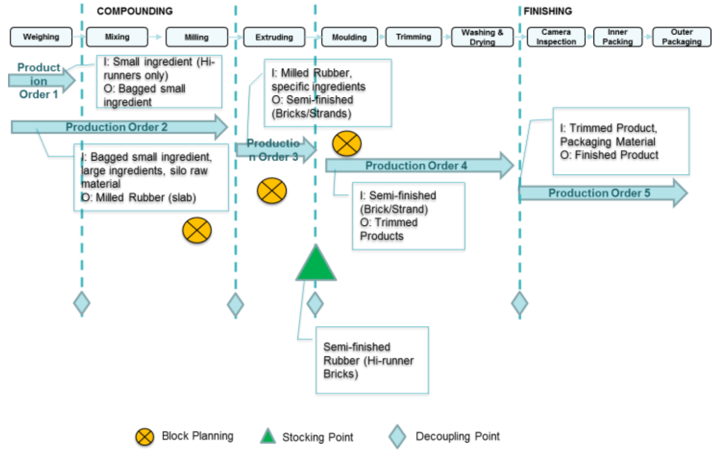

Fig. 1. Component Manufacturing Process

A. *Component Manufacturing Process*

The manufacturing process of component manufacturing [9] is depicted in Fig 1. Following are the major processes in component manufacturing:

- **Weighing**: The different components are weighted and prepared for manufacturing
- **Compounding:** The components are mixed and milled at this stage for the next step
- **Extrusion**: The extrusion process produces processed rubber bricks which are input material for moulding.
- **Pressing & Moulding**: In this stage, the rubber bricks are fed to the pressing machine for moulding. The moulds are prepared based on the customer orders which decides the shape of the final product. Each press holds two moulds for simultaneous production. The moulds can be for two different products but the input raw material has to be same to avoid contamination. There are two types of products – high runners (high volume products) & low runners (low volume special products).
- **Finishing:** The final stage where quality inspection is carried out before packaging the materials.

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B. *The Scheduling Constraints at Pressing & Moulding*

In rubber or polymer based component manufacturing, Pressing & Moulding is the bottleneck process. The key constraints in the process are:

- Multiple 2 layer Presses need to operate 24x7. Each press contains two moulds which can be used for same product or different sets of products. However, the input rubber bricks have to be same to avoid contamination and quality problems.
- Restricted set of Molds available – sometimes with reduced number of cavities (that produce final product from rubber)
- Brick-weight difference & compound color rule to prevent cross-contamination among input materials

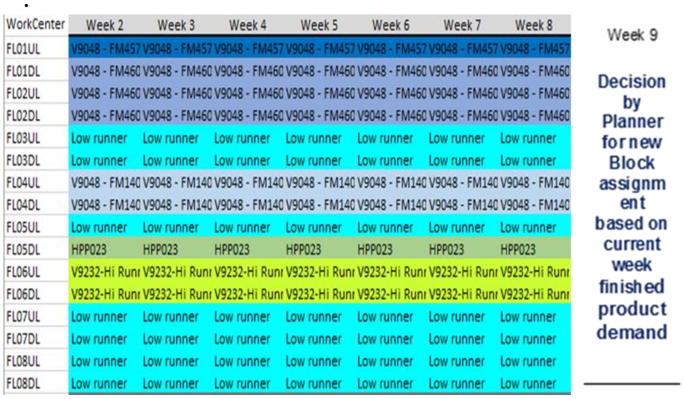
- Planning Process:
  - Hi-runner product Molds are pre-assigned to presses every month
  - Lo-runner product Moulds to be assigned to remaining presses based on delivery date and order priority
  - Change-over of moulds to be minimized, takes 4 hours i.e. 1/2 shift per setup
  - Sheets per shift is computed by Planner - maximum number of sheets limited by lower rate of both molds
  - Planner tries to run same mold type in both upper and lower layer of presses for maximum production rate

C. *Current Solution Approach*

The current solution uses SAP APO PPDS integrated with SAP S/4HANA (ERP System) for scheduling optimization. The approach is summarized below:

- Classify Products as High and Low-Runners based on Sales Orders demand
- Use PPDS Block Planning capability of S/4HANA Advanced Planning to create Compound – Mould characteristic combination as Block buckets on resources
- Optimization using APO PPDS Black Box Optimizer. The optimizer parameters were set using trial & error method to deliver optimal result with sample data

Fig 2. Provides the sample output from the block planning.



WorkCenter	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
FL01UL	V9048 - FM457	V9048 - FM457	V9048 - FM457	V9048 - FM457	V9048 - FM457	V9048 - FM457	V9048 - FM457
FL01DL	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460
FL02UL	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460
FL02DL	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460	V9048 - FM460
FL03UL	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner
FL03DL	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner
FL04UL	V9048 - FM140	V9048 - FM140	V9048 - FM140	V9048 - FM140	V9048 - FM140	V9048 - FM140	V9048 - FM140
FL04DL	V9048 - FM140	V9048 - FM140	V9048 - FM140	V9048 - FM140	V9048 - FM140	V9048 - FM140	V9048 - FM140
FL05UL	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner
FL05DL	HPP023	HPP023	HPP023	HPP023	HPP023	HPP023	HPP023
FL06UL	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr
FL06DL	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr	V9232-Hi Runr
FL07UL	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner
FL07DL	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner
FL08UL	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner
FL08DL	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner	Low runner

Week 9

Decision by Planner for new Block assignment based on current week finished product demand

Fig. 2. Block Planning Output

D. *Solution Approach using Machine Learning*

The alternative approach for optimization using Machine Learning [10] to improve utilization of Press /Moulds is explained below.

Task T: Optimize the Schedule by optimum sequencing of moulds

Performance Measure P: (i) % Efficiency Gain, (ii) % Reduction in change over time

Target Function V:

Target Function representation: V = w(0) + w(1).X(1) +w(2).X(2)+……

Where X(i) is the type of mould & press combination while V is the changeover /waiting time.

The objective is to reduce Target Function V through training experience and derive optimal value of weightage w(i).

In addition to above, following constraints need to be taken into consideration:

- Delivery Date constraints
- Input Material constraints (Only same input material can go to any given press for a particular run)
- Input material availability
- Availability of Moulds & Mould life (Every mould has predefined life /maximum number of runs)

Training Experience E:

Stage 1. Compete against manual solutions (experience based)

Stage 2. Compete against own solutions

Following diagram (Fig 3) explains the entire information & process flow and the reference architecture for machine learning platform to deliver optimized schedule.

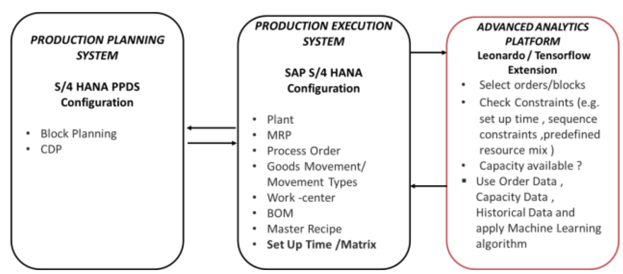


Fig. 3. Reference Architecture

E. *Key Learning*

While the model is still under trial run, there are few learning that needs to be taken into consideration:

- Data Quality is extremely important. The historical data available may not be of good quality & training result can get impacted by same.
- The manual scheduling output was taken for initial training. However manual scheduling can be driven by personal experience & hence can vary from planner to planner. Hence this can be at best used for initial training.
- A parallel run is recommended to compare the

results

- Machine Learning is still an emerging field in shop floor scheduling. Hence stakeholder management & change management is a critical building block for success.

V. Conclusion

While the current Machine Learning based approach is still under lab trial, the initial result is encouraging. The Implementation of Machine Learning instead of static industry specific optimizer addresses the dynamic business environment better. This will lead to

- Scheduling based on dynamic business environment
- Significant improvement of productivity & machine utilization
- Optimization of machine changeover time
- Optimum utilization of moulds leading to better quality & less wastage

The framework also helps achieving ‘OTIF’ (On Time In Full) targets better and meet customer requirements better, Machine Learning can take into consideration customer priority, machine break down, non-availability of raw materials based on real time data.

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