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Enhancing Large-Scale Production Scheduling Using Machine-Learning Techniques

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ABSTRACT

This study focuses on optimizing production scheduling in multi-product plants with shared resources and costly changeover operations. Specifically, two main challenges are addressed, the unknown changeover behavior of new products and the need for rapid schedule generation after unforeseen events. An innovative framework integrating Machine Learning (ML) techniques with Mixed-Integer Linear Programming (MILP) is proposed for single-stage production processes. Initially, a regression model predicts unknown changeover times based on key product attributes. Then, a representation where distances correlate with changeover times is compiled through multidimensional scaling, allowing constrained clustering to group production orders according to available packing lines. Ultimately, the MILP model generates the production schedule within a constrained solution space, utilizing optimal product-to-line allocation from cluster segmentation. A case study inspired by a Greek construction materials plant is used to validate the proposed approach. The results showed that this framework improves scheduling efficiency by providing rapid solutions, reducing downtime and facilitating the introduction of new products. Overall, a novel scheduling solution is proposed for manufacturing industries that face unknown production data and need quick schedule alternations.

Keywords: Scheduling, Optimization, Machine Learning, Industry 4.0, MILP

1. INTRODUCTION

As global competition rises and customer expectations increase, manufacturing industries must embrace digital technologies to remain competitive. Fluctuating demands, equipment breakdowns and raw material availability are some challenges that necessitate for schedules to be flexible and to adapt quickly to changing conditions without causing order delays or increased costs. This is particularly difficult in the presence of frequent and expensive product changeovers, since production schedules are typically handled manually and combinatorial complexity of real-life industrial instances does not allow exact methods to deliver optimal solutions quickly.

Recent breakthroughs in Artificial Intelligence (AI) and improvements in algorithms, computational capabilities and data accessibility, are opening up new ways to face challenges in manufacturing [1]. Today, industries have large amounts of data that are not being fully utilized. By applying techniques like ML, they could improve their decision-making processes. ML can help in demand forecasting, optimizing production schedules and managing the workforce efficiently.

Production scheduling is one of the major challenges in manufacturing environments. Fundamental research in production scheduling primarily focused on employing MILP and heuristic approaches. More specifically, Das et al. [2] and Georgiadis et al. [3] focused on reducing changeover times in flexible manufacturing systems. Notable contributions also include MILP formulations for handling sequence-dependent tasks in manufacturing environments [4,5] and decomposition strategies aimed at improving efficiency in scheduling [6,7]. While these scheduling approaches are effective for small and medium-sized problems, they often fail with larger, more complex ones, or when online scheduling is needed, highlighting the need for improvement and development of new rules to optimize solutions.

More recent studies have focused on integrating ML or Reinforcement Learning (RL) into scheduling systems.

Heger et al. [8] improved scheduling efficiency and reduced delays by dynamically adjusting dispatching rules with ML, while Gomes et al. [9] combined ML with optimization to enhance production. Additionally, studies like Hubbs et al. [10] have shown RL's effectiveness in dynamic scheduling environments. While promising, these methods have some critical limitations, including high complexity, overfitting, low data efficiency and long training times, suggesting the need to explore alternative ML approaches. Furthermore, although research on production scheduling has advanced significantly in recent years, its use in real-world industrial settings remains limited.

To overcome such restrictions, this work proposes a hybrid framework for optimizing production scheduling in multi-product, multi-line manufacturing plants that frequently require changeovers. The framework combines ML with a MILP model. Specifically, it creates a representation space where the distance between products correlates with their changeover times. Then the production orders are organized into clusters that match the available packing lines, using constrained k-means clustering. This assignment is introduced into the MILP model to restrict the solution space and allow for quicker schedule generation. Moreover, to address the problem of missing changeover data, the framework includes a ML model that predicts unknown changeover times and identifies infeasible transitions based on key product attributes. The framework is tested on a real-world scenario inspired by a Greek construction materials plant, demonstrating its effectiveness. The proposed approach improves scheduling efficiency, reduces downtime and helps facilities quickly adapt new products to the production.

2. PROBLEM STATEMENT

Production scheduling in multi-product industrial plants is a complex task characterized by demand variability and frequent changeovers, which can lead to substantial downtime, resource wastage and operational inefficiencies. For this reason, the establishment of effective scheduling strategies is essential.

The duration of a changeover may vary depending on characteristics of the product such as formulation, quality requirements and physical properties. It is common that the production schedules are altered during the week, thus generating extra changeover operations. Furthermore, changeover data for specific products might be unavailable. Handling changeovers is a complex task, as it requires balancing the need to meet product demand with the goal of reducing inefficiencies and minimizing waste. In response to these dynamic conditions, scheduling approaches that quickly generate optimal solutions are needed.

To address these issues, the integration of ML techniques with MILP models presents a promising approach. Specifically, clustering methods can be utilized to group products with similar changeover requirements, thus narrowing the solution space for scheduling MILP models and facilitating its solution. Moreover, ML-based predictive models can predict changeover times even with incomplete data available. In this way, the production process can become more efficient and responsive.

In this study, a real-world scheduling scenario is examined, based on a construction materials plant in Greece. The facility produces around 240 final products through a two-stage continuous process, including mixing and packaging. There are 4 packing lines available in the facility, which operates 5 days a week. The production process is characterized by frequent changeovers, which vary due to products' properties, making their allocation to the packing lines a challenging task. The production is order driven and organized in a weekly basis.

Particularly, the production process includes the following steps. First, raw materials are weighed according to the product recipe. The weighed materials are fed into a mixing tank. After mixing takes place, the produced mixture is temporarily stored before being packaged by the available packing lines and transferred to the warehouse. It is noted that the whole production process operates in a continuous manner, therefore, production scheduling can be solely focused on the slowest stage, which is the packing stage. This allows for the reduction of the problem size and computational cost.

The problem described is solved using a novel solution framework which combines mathematical modeling and ML, aiming to rapidly create optimal schedules even in the presence of missing changeover data. The aim of this work is not to develop or compare machine learning algorithms but to propose an efficient scheduling solution that addresses the specific challenges of large-scale industries.

3. MATHEMATICAL FRAMEWORK

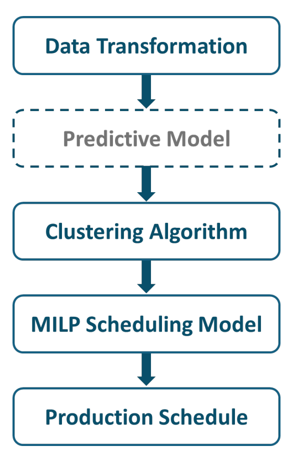

Figure 1. Solution strategy.

A hybrid scheduling solution is presented (Figure 1), for manufacturing industries that deal with unknown production data and need quick schedule adjustments. The detailed steps of the model are described in the following subsections.

3.1 Data Transformation

The production data must be properly formatted to be utilized in the proposed framework. The data transformation process involves the conversion of raw production data into a standardized format, using numerical and normalized values. Key product features, including raw material type, color, resin content and package size, are compiled into feature vectors, along with changeover duration data. All categorical features were converted into numerical values. For example, raw material type was transformed using one-hot encoding and colors were represented by their corresponding RGB codes. The transformed data serve as inputs for the next steps of the framework.

3.2 Predictive Model

This is an optional step, applicable in cases where there are missing data. Unknown changeover data, particularly when new products are introduced or when specific transitions have never been tested, should be predicted for smoother product transitions. ML forecasting models can be employed to estimate the unknown information. Specifically, a data-driven approach is used to predict missing changeover times. The approach uses a pair-based prediction method to estimate changeover times for any two products, whether or not they are part of the training set, based on the feature vectors of the product pair. The objective function for training the model is to minimize the difference between predicted and actual changeover times. To train the model, a regularized predictor is used, in particular Polynomial Regression with L2 Regularization, due to the small size of the dataset available. A third-order polynomial is chosen to capture the non-linear changeover behavior and to avoid excessive variance. L2 regularization is applied to penalize large coefficients and prevent overfitting. If more data were available, more advanced techniques like Deep Learning could be used, however, such models may not perform well with small datasets due to overfitting. The predicted changeover times are used to create practical production schedules.

3.3 Clustering Algorithm

The aim is to simplify the complex scheduling problem by decomposing it into smaller sub-problems. This is achieved by clustering products into groups corresponding to the available packing lines. The goal is to identify clusters that minimize the total expected within-cluster changeover time T_i, given by equation (1).

$$T_i = \frac{1}{|\mathcal{C}_i|} \sum_{p \in \mathcal{C}_i} \sum_{\substack{p' \in \mathcal{C}_i, \\ p' \neq p}} \min(ch_{p,p'}, ch_{p',p}) \tag{1}$$

Where $|\mathcal{C}_i|$ is the number of products in the i^{th} cluster, and the minimum of $ch_{p,p'}$ and $ch_{p',p}$ represents the best-case changeover time between two products *p* and *p*′, when changeovers are not symmetrical. Using the average changeover time could overestimate distances, leading to less efficient clustering, whereas using the best-case scenario results in more compact, homogeneous clusters. While T_i does not represent actual changeover times for specific schedules, it serves as an estimator for the average expected changeover time within each cluster.

To facilitate the clustering process, a structured approach is proposed, inspired by clustering-oriented representation learning methods [11]. A new representation space z_p is compiled for each product, where the distance between products reflects their changeover time. Particularly, a distance metric $d(z_p, z_p')$ is learned to approximate the changeover time between two products. In this representation, products closer to each other have smaller changeover times, making it easier to group them effectively for scheduling purposes. The Euclidean distance is used as the distance metric. Since Euclidean distance is symmetric and cannot handle asymmetry, the approach focuses on the expected changeover time, which is calculated as the minimum changeover time between two products.

The learning objective minimizes the difference between the distance in the new representation space and the expected changeover time as shown in (2).

$$\min \sum_{p \in P} \sum_{\substack{p' \in P \\ p' \neq p}} \left(d(z_p, z_p') - \min(ch_{p,p'}, ch_{p',p}) \right)^2 \tag{2}$$

This can be interpreted a classical Multidimensional Scaling (MDS) problem with distance targets equal to $\min(ch_{p,p'}, ch_{p',p})$. The application of this method produces a changeover-time driven representation space. K-means clustering can be applied on this space to group the products based on their new representations, minimizing the within-cluster distances D_i, which is equivalent to minimizing the expected changeover time T_i within each cluster, as explained in (3).

$$D_i = \frac{1}{|\mathcal{C}_i|} \sum_{p \in \mathcal{C}_i} \sum_{\substack{p' \in \mathcal{C}_i, \\ p' \neq p}} \left\| z_p - z_{p'} \right\|_2^2 = T_i \tag{3}$$

By grouping products into clusters with small changeover time values, the complexity of the scheduling problem is significantly reduced. In this way, clusters can be assigned to specific production lines and sequencing decisions are only made for the products within a cluster. This approach enhances computational efficiency while ensuring practical and effective production schedules.

It is noted that the clustering solution also respects production time constraints by ensuring that all products within a cluster can be produced within the available time on each production line. This is done using a constrained k-means approach. To account for the sensitivity of k-means to initial cluster centers, the algorithm is run multiple times with different random initializations, and the best clustering solution is selected after evaluating the total expected within-cluster changeover time.

3.4 MILP Scheduling Model

To address the production scheduling challenges described, an immediate precedence MILP model developed within our group [12] is employed. The model incorporates mass balance, assignment, timing and sequencing constraints, using a continuous time frame for precise timing decisions. The objective of the model is to minimize the production's total changeover time. The allocation of products to packing lines given from the previous step of the framework is inserted as a fixed decision into the scheduling model, thus reducing its complexity and facilitating its solution. The mathematical model is implemented in GAMS 42.5.0 and solved using CPLEX 12.0. The following represent the key constraints included in the mathematical model.

$$\sum_{j \in Pj} Y_{p,j} = 1 \quad \forall p \tag{4}$$

$$\sum_{p' \neq p, p' \in Pj} X_{p',p,j} \leq Y_{p,j} \quad \forall j, p \in Pj \tag{5}$$

$$\sum_{p' \neq p, p' \in Pj} X_{p,p',j} \leq Y_{p,j} \quad \forall j, p \in Pj \tag{6}$$

$$\sum_{p \in Pj} \sum_{p' \neq p, p' \in Pj} X_{p,p',j} + 1 = \sum_{p \in Pj} Y_{p,j} \quad \forall j \tag{7}$$

$$C_{p,j} + ch_{p,p'} \cdot X_{p,p',j} \leq C_{p',j} - r_{p'} . Y_{p,j} + \omega \left(1 - X_{p,p',j}\right) \quad \forall j, p \in Pj, p' \in Pj, p' \neq p \tag{8}$$

$$C_{p,j} \geq (s + r_p) \cdot Y_{p,j} + \sum_{p' \neq p, p' \in Pj} ch_{p',p,j} \cdot X_{p',p,j} \quad \forall j, p \in P_j \tag{9}$$

$$C_{p,j} \leq \omega \cdot Y_{p,j} \quad \forall j, p \in P_j \tag{10}$$

$$\min \sum_{j, p \in Pj} \sum_{p' \neq p, p' \in Pj} ch_{p,p',j} \cdot X_{p,p',j} \tag{11}$$

Constraints (4) guarantee that each product *p* is assigned to a single packing line *j* through the binary allocation variable $Y_{p,j}$. The set Pj introduces the potential assignment of products to processing lines. Constraints (5) and (6) ensure that each product assigned to a processing unit *j* has only one direct predecessor and successor *p′* in the production sequence, using the sequence binary variable $X_{p,p',j}$. Constraints (7) require that the total number of active allocation variables for the packing line must be one greater than the sum of all active sequence binary variables. Constraints (8) dictate that if two products are processed consecutively in a unit, the completion time of the second product $C_{p',j}$ minus its processing time $r_{p'}$ must be greater than the completion time of the first product plus the required changeover time between them $ch_{p,p'}$. Constraints (9) and (10) establish that the completion time of a product is greater than the sum of its setup time s, processing time and the required changeover time but does not exceed the available production horizon. Lastly, constraint (11) represents the objective function of the model, which is to minimize the total changeover time across all production lines.

3.5 Production Schedule

By implementing data preprocessing, unknown data regression and clustering, the production orders are organized into clusters with minimal changeover times. This assignment is then input into the scheduling MILP model and production schedules characterized by minimum changeover times and efficient use of packing lines are generated. The employment of this framework results in time-efficient production schedules for multi-product industrial plants with frequent changeover operations.

4. RESULTS & DISCUSSION

Initially, the prediction of missing changeover data was examined. This is something which can occur either when certain product-to-product transitions have not been tested or when new products are introduced into production. Accurately predicting these changeover times is essential, as selecting an unfavorable or infeasible production sequence can lead to downtime and waste.

To achieve this, key factors that influence changeover times, such as raw material type, color, resin content and package size are used as features in a predictive model. A cubic polynomial regression model is used, with a regularization hyperparameter λ set to 0.01, as it was found to provide the best fit to the data. To prevent overfitting, L2 regularization is applied.

Eight case studies were conducted to evaluate the performance of the predictive model (Table 1). In each case, 10-12 products were removed from the initial dataset to serve as the test data, while the remaining data was used for training. Only a small proportion was chosen for testing due to the limited size of the dataset. Testing with larger proportions could potentially compromise the model's ability to learn generalizable patterns.

The model's performance was assessed based on its ability to accurately predict infeasible changeovers (Infeasible Changeover Accuracy % – ICA), as well as its

Mean Squared Error (MSE) and Mean Absolute Error (MAE). As shown in Table 1, the model exhibits high prediction accuracy across both training and testing datasets. On the training data, the model achieves an average ICA of 99.71%, with a MSE of 0.022 and a MAE of 0.072. On the testing data, it demonstrates an ICA of 99.90%, with a MSE of 0.018 and a MAE of 0.074.

Table 1: Predictive model metrics.

	ICA %		MSE		MAE	
Case	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
1	99.65	99.77	0.024	0.023	0.071	0.081
2	99.75	100.00	0.020	0.010	0.073	0.064
3	99.75	99.89	0.020	0.019	0.072	0.079
4	99.76	100.00	0.020	0.020	0.073	0.080
5	99.75	99.87	0.019	0.020	0.071	0.078
6	99.64	99.85	0.025	0.021	0.073	0.072
7	99.64	99.85	0.025	0.019	0.073	0.070
8	99.76	100.00	0.020	0.013	0.073	0.071
Avg	99.71	99.90	0.022	0.018	0.072	0.074

With the problem of unknown production data solved, the next part of the study focuses on improving scheduling efficiency by minimizing total changeover time across packing lines in shorter timeframes. In fast-paced industrial settings, production schedules often need to be quickly adjusted multiple times a day due to unforeseen changes. For this reason, the proposed approach was applied to assess the produced schedules and the computational times.

Four scenarios involving 100 to 130 production orders over a 120-hour horizon were investigated, since the problem size and order mixture are expected to have an impact on the production schedules obtained. First, the monolithic MILP model was used to solve the problem, with a CPU time limit of 2 hours. This time restriction was introduced due to the practical limitations of computationally expensive methods in real-world applications. For cases where the MILP model failed to find an optimal solution within this time, the best solution obtained during this period was recorded.

The proposed solution framework (PROP) was then applied to the same scenarios. The framework initially grouped production orders into clusters using the representation and clustering step, ensuring that each packing line handled products with minimal changeover times. Employing the representation step helps to separate the clusters more clearly, as shown in Figure 2. The axes represent the two dimensions of the reduced space obtained through MDS. The product mixture may lead to more dispersed clusters in some case studies, affecting clustering time, which remains minimal, but with little to no impact on optimality.

It is noted that some points may appear to fit better in a different cluster, but they were placed in neighboring clusters due to production line operating time constraints. The allocations were subsequently input into the MILP scheduling model, to reduce the solution space, improving computational efficiency.

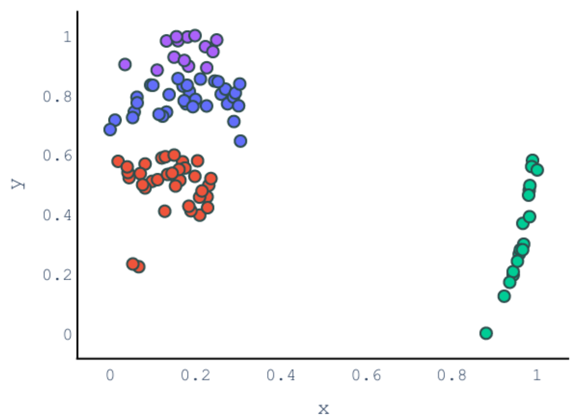

Figure 2. Clusters of production orders for case study A.

Table 2 summarizes the results of the case studies examined, organized by the number of weekly orders in ascending order. The two approaches are assessed based on their computational cost and the objective values.

Table 2: Comparison between the two approaches.

	Objective			CPU (s)	
Case	**MILP**	**PROP**	**Diff%**	**MILP**	**PROP**
A	17.41	14.66	-15.8	7200	27.4
B	19.87	15.54	-21.8	7200	4.1
C	24.13	17.54	-27.3	7200	8.0
D	25.76	18.62	-27.7	7200	3.4

Combining clustering techniques with optimization methods significantly improved computational efficiency, generating high-quality schedules with the smallest objective values within seconds across all case studies. While the monolithic MILP model failed to find optimal solutions within a 2-hour limit, the proposed framework consistently delivered efficient results, especially for more complex problems which showcased greater improvements. The framework seems to effectively reduce problem complexity, demonstrating its suitability for dynamic industrial environments.

5. CONCLUSIONS

This study proposed a framework to optimize production scheduling in multi-product manufacturing plants with parallel production lines, shared resources and frequent changeover operations. The framework integrates ML techniques with MILP to address two main challenges, minimizing product changeover times and predicting unknown changeover durations.

The ML-based predictive model addressed the issue of missing changeover data by achieving high accuracy in its predictions. It identified infeasible transitions with over 99.6% accuracy and achieved a low prediction error, with an average MSE of 0.02 and MAE of 0.07. These outcomes make it easier to integrate new products into production schedules while minimizing disruptions and inefficiencies. Additionally, the results of the presented framework showed significant improvements in scheduling efficiency. The computational time was cut down by two orders of magnitude. Furthermore, across different case studies, the objective value was reduced by 16% to 28%, highlighting the framework's ability to generate more effective schedules.

The results indicate that the proposed approach is suitable for dynamic real-world industrial environments where changeovers are a major source of downtime and waste. However, the framework does have limitations. Since the approach is not exact, the results can vary depending on the initial clustering configuration and production order combinations. Future work could focus on taking into consideration additional plant constraints, such as due dates and raw material availability, to further improve its applicability. Furthermore, it could focus on extending the model to account for multi-stage production processes and investigating alternative objective functions. Finally, testing advanced ML techniques, like neural network-based solutions, could enhance prediction accuracy and error minimization.

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