Schedulling Production Based on an Optimized Production Sequencer and Manufacturing Maps

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Abstract: In this article, we present an innovative application of manufacturing maps, specifically combining Petri Nets and Miniterms. Our proposed algorithm enables the determination of an optimal manufacturing sequence based on real-time information from the manufacturing line. The primary objective of this algorithm is to minimize the disparity in cycle times between different models, aiming to minimize the duration of workstations being stopped or blocked. This optimization leads to a reduction in total production time, accompanied by various benefits such as energy savings and increased production. To validate our approach, we implemented the algorithm using manufacturing maps and applied it to the 8XY line—a multimodel welding line located at the Ford factory in Almussafes, Valencia. We conducted simulations using actual production data from the Ford factory, considering three different types of order: random, optimal, and unfavorable. The goal was to compare the production time for each sequence. The results obtained from the simulations demonstrated a significant time improvement when employing the optimal sequence, as outlined in the article. A comprehensive analysis of the three sequences studied is provided. As a future direction of this research, we intend to explore additional applications that can leverage manufacturing maps for production line optimization. For instance, we plan to investigate the determination of optimal sequences for anomalies, where improvements in the line to reduce cycle time could yield greater profitability. Moreover, we aim to explore how production lines can be dynamically rebalanced in real-time to achieve energy savings and other advantages. These potential extensions highlight the versatility and practical implications of manufacturing maps in enhancing production line efficiency.

1 INTRODUCTION

Within the framework of Industry 4.0, the landscape of traditional manufacturing processes is undergoing a profound transformation driven by digitalization and advanced technologies. Industry 4.0 represents a paradigm shift characterized by the extensive adoption of state-of-the-art tools such as artificial intelligence (AI), the Industrial Internet of Things (IIoT), and big data analytics, fundamentally altering the landscape of goods and services production and delivery (Schwab, 2016).

Central to Industry 4.0 lies the optimization of production scheduling, a fundamental facet of manufacturing operations. The convergence of Big Data and IIoT has ushered in a revolutionary era in production scheduling, marked by dynamic scheduling strategies that permit real-time adjustments in production schedules to align with fluctuating conditions and demands. (Jiang et al., 2022)

The marriage of Big Data analytics with scheduling systems introduces the concept of predictive maintenance, effectively minimizing disruptions stemming from unforeseen equipment failures (Liu et al., 2023).

This strategic focus on Scheduling production within the Industry 4.0 paradigm holds the promise

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of substantial advantages. These encompass cost reduction, heightened operational efficiency, enhanced productivity, reduced errors, and bolstered security (Ghobakhloo, 2020). Furthermore, the amalgamation of these technologies contributes to sustainability efforts and bolsters environmental preservation.

Despite the undeniable benefits, the implementation of Industry 4.0 and advanced scheduling solutions is not without its challenges. Concerns span cybersecurity vulnerabilities (Rajalingham, 2020), skills and training deficits (Bauernhansl et al., 2014), interoperability issues (Wang et al., 2016), and substantial initial investments (Bauernhansl et al., 2014).

In this transformative landscape, sensorization, as a critical component of IIoT (Peinado-Asensi et al., 2023a), plays a pivotal role in redefining how production scheduling is executed using the philosophy and the results of our previous works (Garcia, 2022; Llopis, 2022). By enabling real-time data collection from various operational facets, sensorization empowers decision-makers with essential insights to optimize Production Scheduling processes efficiently. However, sensorization in IIoT is not without its challenges, including managing and analyzing vast volumes of data, industrial cybersecurity, and interoperability between systems and devices (Peinado-Asensi et al., 2023b).

1.1 Previous Works

In our previous works, (Peinado-Asensi et al., 2023a; Peinado-Asensi et al., 2023b), a new concept for generating industrializable IIoT applications, called *Industrializable Industrial Internet of Things (I3oT)* was presented. As we briefly explain in the introduction, there is an important limitation that is significantly slowing down its massive proliferation in the IIoT application industry. The installation of sensors, their wiring and data extraction through the IT network to the OT network, and the increasing number of machines or components to be sensorized prevent the proposed solutions from being applied in the industry in a massive way, due to the high cost involved in their implementation. The idea of the *(I3oT)* is to use the installation available in factories to develop IIoT applications from them. The machines installed in the industry operate automatically and have sensors that provide the information received by the PLC to control the lines.

1.1.1 Miniterm-Based Big Data for Predictive Maintenance

Previous works carried out by the research group following the *(I3oT)* philosophy was in (Garcia, 2022)where we have presented an innovative solution for the early detection of faults in industrial machinery by using a virtual sensor called Mini-term defined in (García, 2016), see figure 1. The mathematical model proposed in (García, 2016) was reformulated in (García and Montés, 2017), by using tensor algebra, which reduces the computational cost of the model, especially when the number of mini-terms and micro-terms is high. The Miniterm is based on the measurement of the technical cycle time as a parameter to predict failure. When the component is approaching the end of its useful life, the cycle time increases alerting that it must be replaced. The great advantage of the miniterm is that it does not require the installation of any additional sensor, but uses the sensorization of the machine's own automatic system and only requires the programming of a timer in the PLC. In (Garcia, 2022) a case study was presented in which the Miniterm was implemented in a production line of a vehicle manufacturing company, in particular, in the Ford factory based in Almussafes (Valencia). In this factory there are more than 24,000 mini-terms monitoring cylinders, clamps, elevators, screwdrivers, etc. The results showed that the virtual sensor could detect anomalies, which allowed the maintenance team to take preventive measures in order to avoid the stoppage of the production line. This fact has made that different indicators of the plant, among which is the TAV (Technical Availability), increased significantly, see (Garcia, 2022).

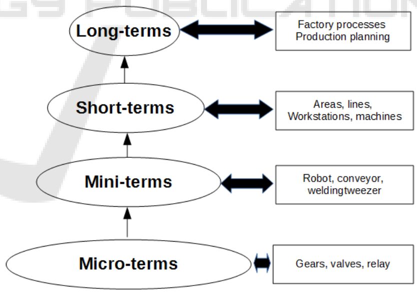

Figure 1: From the micro-term to the long-term.

1.1.2 Manufacturing Maps for Smart Factory Management

In the study by (Llopis, 2022) a new tool called Manufacturing Maps is described which is a smart factory management tool that relies on the combination of Petri nets and big data mini-terms.

A manufacturing map is a hierarchical construction of Petri nets in which the lowest level net is a temporary Petri net based on mini-terms, and in which the highest level is a global view of the entire plant. The manufacturing map is fed by Big Data based on miniterms, which allows it to have in real time the current status of the components that make up the production chain, see figure 2

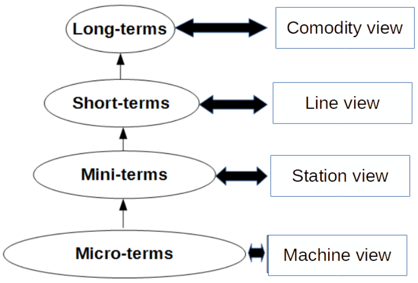

Figure 2: From the micro-term to the long-term in a Manufacturing Map

Once the petri net model is built, the user of the Manufacturing Map can select which view of the plant he/she wants, being able to select the lowest level view, machine view, or a global view of the plant, commodity view. The navigation through the different levels is done as in google maps, see (Llopis, 2022).

2 OUTLINE OF OBJECTIVES

The previous modelling and simulation work of the Manufacturing Maps, combined with the real-time measurements of the miniterms can generate countless new applications. The present article seeks to explore one such application, namely, to seek the optimal manufacturing sequence in real time in order to minimize manufacturing time.

This objective is one of the topics explored in the literature, as for example in (Jiang et al., 2018), in which a production programming system based on the Internet of Things (IoT) was proposed in order to optimize the production sequence in real time. The system used sensors and IoT devices to collect real-time data on production and quality, and then used optimization algorithms to generate the optimal manufacturing sequence. In this article, Manufacturing Maps (Petri nets + Miniterms) will be used to generate the optimal manufacturing sequence based on the current state of the line measured with the miniterms. Without loss of generality, the present article focuses on the optimization of manufacturing sequences for the automotive sector where the use of flexible manufacturing lines is quite widespread.

3 METHODOLOGY

3.1 Ordering a Production Stack

When ordering a Production Stack for the automotive sector, we start from the fact that our stack will include the vehicles to be produced. Not all vehicles are the same, there are different models of the same vehicle with different characteristics. The same model can have 3 or 5 doors, may or may not have a sunroof, etc., which generates significant variability between models. Let's define $\{1...m\}$ as the different models or variants.

The manufacturing line will be composed of workstations and where in each of them a specific work will be carried out to manufacture the vehicle. We assume in this case that we will have $\{1...n\}$ workstations on the manufacturing line on which the ordering of the production stack will be carried out.

Be $a_{i,j}$ the TcT (Cycle Time) of the model i in the station j. We can consider matrix W as the matrix that provides us with information about the Cycle Times (TcT) of each model (rows) at each station (columns).

$$M_{i,j} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix} \quad (1)$$

From this matrix, we can obtain two types of matrices, the matrix of minimum weights and/or the matrix of maximum weights, which will allow us to determine the most favourable and unfavourable ordering possible.

3.1.1 Minimum Weights Matrix

We start from the M matrix calculated above and we want to find the lowest diference TcT between different models or rows of the M matrix.

We will get a matrix N of mxm where each element $n_{i,j}$ as the minimum absolute value of the difference between the elements of the row i and the row j.

$$N(i,j) = \min |M(i,k) - M(j,k)| \quad (2)$$

for all k=*1,2,...,n*

This new N matrix will enable us to identify the shortest Cycle Time (TcT) among various models or rows in the N matrix. Each element of the textitN matrix represents the minimum variation between rows i and j in the M matrix.

$$N_{i,j} = \begin{bmatrix} 1000 & n_{1,2} & \dots & n_{1,m} \\ n_{2,1} & 1000 & \dots & n_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ n_{m,1} & n_{m,2} & \dots & 1000 \end{bmatrix} \quad (3)$$

3.1.2 Algorithm for Determining Optimal Ordering Sequence

- Initialization: The initial element of the optimal ordering sequence is identified as the row containing the first model to be manufactured.
- Second Element: The second element of the optimal ordering sequence corresponds to the column associated with the first element in the sequence.
- Iterative Process: To determine the remaining elements of the optimal ordering sequence, we follow an iterative process:

  . Selection: From the set of remaining models (m-2), we select the row that corresponds to the column of the previous element in the optimal sequence.

  Minimum Search: Subsequently, we identify the minimum value within that selected row.

  Next Element: The column corresponding to this minimum value is designated as the next element in the optimal ordering sequence.
- Completion: We repeat this iterative process until all elements of the optimal ordering sequence have been determined.

This algorithmic approach facilitates the systematic determination of the optimal ordering sequence for the manufacturing process according to their minimum total cycle time (*TcT*).

3.1.3 Maximum Weights Matrix

During the comparison of production times based on different orderings, we conducted an analysis that aimed to maximize the Cycle time (TcT), focusing on the worst-case scenario. This particular ordering strategy is built upon a weighted matrix, in which we calculate the largest *TcT* when transitioning from one model to another.

Our starting point is the previously computed matrix M, and our objective is to identify the maximum *TcT* difference between various models or rows within matrix M.

$$D(i,j) = \max |M(i,k) - M(j,k)| \quad (4)$$

for all k=1,2,...,n

To achieve this, we construct a matrix D with dimensions mxm, where each element $d_{i,j}$ represents the maximum absolute difference in *TcT* between row i and column j in matrix M.

$$D_{i,j} = \begin{bmatrix} -1 & d_{1,2} & \dots & d_{1,m} \\ d_{2,1} & -1 & \dots & d_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m,1} & d_{m,2} & \dots & -1 \end{bmatrix} \quad (5)$$

This approach allows us to effectively maximize the *TcT* difference among the different models to be produced, all of which are represented by the rows within matrix D.

3.1.4 Algorithm for Determining the Most Unfavorable Sequence of Manufacturing Models

To identify the most unfavorable sequence for the production of various models, we begin with the matrix D, which encapsulates the maximum Cycle time (TcT) incurred when transitioning between different models during manufacturing.

The procedure for finding this sequence closely parallels the method used to identify the most favorable sequence:

- Initialization: We commence by selecting the first element of the most unfavorable ordering sequence, which corresponds to the row containing the first model to be manufactured.
- Second Element: The second element of this sequence corresponds to the column associated with the first element selected.
- Iterative Process: To determine the remaining elements of the most unfavorable ordering sequence, we employ an iterative process:

  Selection: From the set of remaining (m-2) models, we choose the row corresponding to the column of the preceding element in the sequence.

  Maximum Search: Subsequently, we identify the maximum value within that selected row.

  Next Element: The column corresponding to this maximum value is designated as the next element in the sequence.
- Completion: We repeat this iterative process until all elements of the ordering sequence have been determined.

As a result, this algorithm produces a vector representing the most unfavorable sequence for ordering different models based on their accumulated maximum total cycle time (TcT).

4 EXAMPLE OF APPLICATION ON A REAL LINE

4.1 Definition of the Welding Line and the Manufacturing Maps Model

Previous works by the (Llopis, 2022) research group have used the welding line as an example, which is a line of multiple models where 68 different models and variants are manufactured. The line consists of eight workstations where three of them have six welding units, four stations have four welding units and one station has a welding unit as shown in Figure 3.

The Petri net is built from real-time information of three mini-terms at each station, which measure the sub-cycle time for robot arm movement, welding clamp movement and welding task. The welding line is modelled from the plane of view of the manufacturing map line and divided into three layers: the *A* layer shows the eight stations connected in series, the *B* layer covers each station with six, four or one welding unit, and the *C* layer models the process of a divided welding unit in its mini-terms as seen in Figure 4.

There are two ways to interpret process modelling by using the Petri net: considering transitions as actions and places as states, or considering transitions as a set of actions and places as states. In this case, the transition is understood as an action and an example of substitution transition is used to introduce subnets into the hierarchical network.

Once the modelling of the main Petri net corresponding to the *A* layer has been carried out, each of the transitions is deepened in a subnet that includes all the actions carried out within the corresponding station. Each subnet contains subnets, which gives the hierarchical network a deeper structure. In each subnet corresponding to a station, there is a transition including a subnet for each robot.

The *C* layer is fed directly by the Miniterms Big Data, in which sub-cycle times are available for the robot arm movement, the welding clamp movement and the welding task in real time. The *A* layer model is obtained by the flattening technique, see (Llopis, 2022).

4.2 Data

When performing the simulation of the welding line, the first thing to be done is the generation of the production stack, in our case the stack has a size of 10,000 vehicles. The generation of the production stack is based on the actual production of the Ford factory in Almussafes in March 2015, from these production data the probability of manufacturing each of the models is calculated and the 10,000 cars to be manufactured are generated with their different models based on the previously calculated probability. The actual production stack is not random since it is based on the processing of orders placed at the factory, but depending on the orders there is no specific sorting sequence so it could be considered random.

4.3 Production Stack Ordering

In order to carry out a comparative study of the production time, which is the time used to manufacture the same production stack, three types of ordering of the production stack have been carried out:

- Random sequence, the manufacturing sorting sequence is completely random and is based on the fact that it is manufactured according to the order placed so it is also considered random.
- Optimal ordering based on the minimum path previously explained.
- Unfavourable ordering, this type of ordering is based on the maximum path explained in the previous point.

4.3.1 The Most Favourable Sequence

This type of ordering is completely straightforward, we take the optimal ordering sequence and the vector to be ordered (Production Stack) and return the ordered vector according to the optimal sequence. One of the characteristics of this sequence is that those same models are manufactured together, that is, the set of vehicles belonging to the same model are manufactured in a block (one after another).

4.3.2 The Most Unfavourable Sequence

The function implemented to sort the production stack, as in the optimal sequence, uses an iterative approach that follows the previously obtained optimal sorting path.

Each element of the production stack is checked one by one, in each iteration of the loop, the current element of the production stack is compared with the elements of the optimal ordering sequence according to the established maximum. If they are equal, the next element of the optimal sequence is saved and that next element is searched in the Production Stack and if it is found, it is added to the ordered Stack and removed from the Production Stack. If not found, the current Production Stack item is added to the sorted Stack.

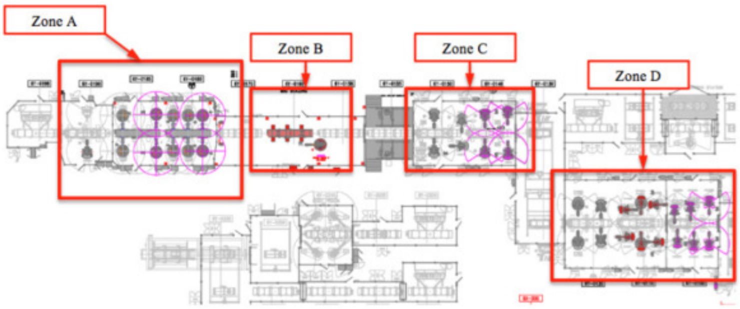

Figure 3: Layout welding line.

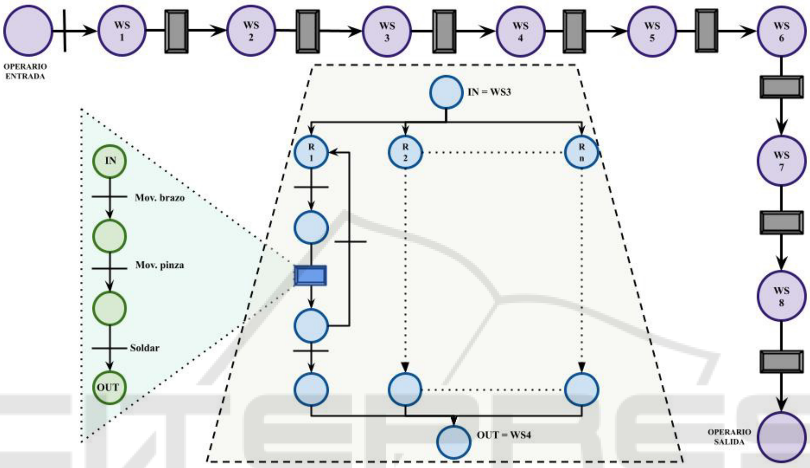

Figure 4: Hierarchical Petri net of the 8XY line.

At the end, the function returns the vector with the sorted stack, which contains the elements of the Production Stack ordered according to the optimal sequence with a set maximum. The reason why this type of ordering is carried out is because we do not want vehicles of the same model one after the other, that is, behind a specific vehicle will always follow the one that has a worse time, therefore, the most unfavourable one.

4.4 Results

Once we have implemented the simulation of the welding line with the Petri nets and the production data based on the real production of the Ford factory in Almussafes that we use to simulate the manufacture of 10,000 cars, we proceed to simulate said manufacture. The same Production Stack will be simulated with the 3 ordering sequences described above:

- Random
- Optimal
- Unfavourable

As seen in figure 5, we have generated 25 different data sets (production stacks), using the manufacturing probability from the month of March 2015 and we have simulated them using the three pre-set sorting sequences in order to obtain a more detailed analysis of production times and obtain more precise and reliable results. As a summary of the previous figure, we can calculate the average production times in hours of the 25 stacks generated with each of the ordering sequences studied as shown in table1:

Table 1: Average production time according to the ordering sequence in hours.

Random	Optimal	Unfavourable
306.40	291.35	314.49

As seen in table 1, the production time is being improved if the production stack is ordered. Next, we go on to comment in more detail on the results obtained.

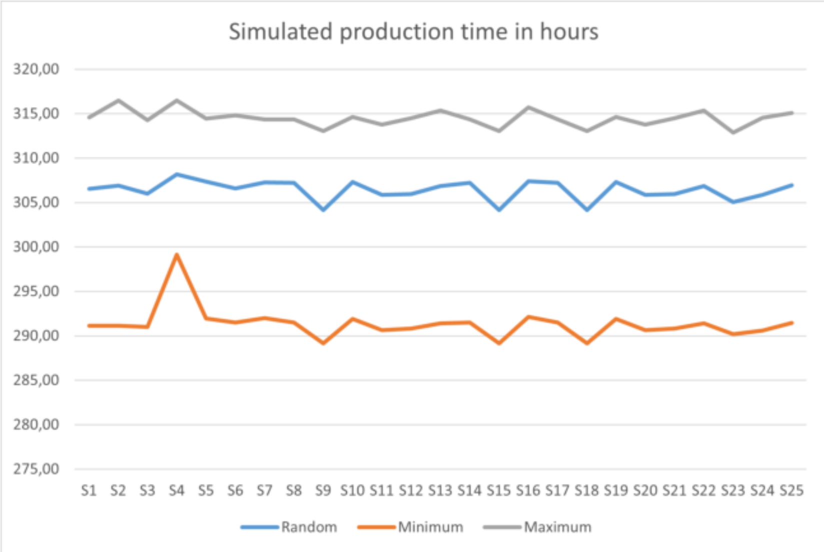

Figure 5: Results.

5 DISCUSSION

In view of the results obtained in the previous section, we can observe an improvement in production times when ordering the stack of cars to be manufactured following the optimal sequence based on the minimum accumulated TcT.

In this way we can study how much we are improving with respect to the random sequence of the production stack and we can also compare the data with the most unfavourable sequence.

From these data we have studied the percentage of improvement in production times for 10 of the 25 production stacks generated as shown in table 2:

Table 2: Percentages of improvement ordering the production according to optimal sequence.

Production Stack	Improvement percentages
Stack 1	5.0%
Stack 2	5.1%
Stack 3	4.9%
Stack 4	5.5%
Stack 5	5.3%
Stack 6	5.0%
Stack 7	5.3%
Stack 8	5.2%
Stack 9	4.3%
Stack 10	5.3%

If we calculate the average percentage of improvement by ordering the production stack with the optimal sequence, there is an average improvement of about 5.1% of the production time, which means that in the case of manufacturing 10,000 cars, 5.1% extra cars could be produced in the same time, which is equivalent to producing 510 extra cars.

In the case of studying the worst possible case, which means that we are ordering following the most unfavourable sequence without the possibility of car model repetition, the results would be as follows comparing the worsening with respect to the ordering with the optimal sequence as shown in table 3 and with the production stack using a random order as shown in table 4.

Table 3: Worsering percentages ordering the production according to optimal sequence.

Production Stack	Worsening percentages
Stack 1	8.1%
Stack 2	8.7%
Stack 3	8.0%
Stack 4	5.8%
Stack 5	7.7%
Stack 6	8.0%
Stack 7	7.7%
Stack 8	7.8%
Stack 9	8.3%
Stack 10	7.8%

If we calculate from table 3 the average percentage of production time that is getting worse if we compare with the optimal sequence, we observe that the average percentage is 7.8%, which means that in the same time we are manufacturing about 780 fewer vehicles if we compare with the optimal sequence.

Table 4: Worsening percentages ordering the production according to random sequence.

Production Stack	Worsering percentages
Stack 1	2.6%
Stack 2	3.1%
Stack 3	2.7%
Stack 4	2.7%
Stack 5	2.3%
Stack 6	2.7%
Stack 7	2.3%
Stack 8	2.3%
Stack 9	2.9%
Stack 10	2.4%

In this case the production time worsens on average by 2.6% when compared to the random production stack, actually the percentage is not very high compared to the randomization. The results show us that the improvement in production time when ordering the production stack from an optimal sequence based on the minimum accumulated TcT between the different models is significant.

6 CONCLUSIONS

In this article we have proposed an application to manufacturing maps (Petri Nets+Miniterms) by generating an algorithm that allows to determine the optimal manufacturing sequence with the real-time status of the manufacturing line. As demonstrated in this article, there is a considerable gain in time. In our future works we will try to study new applications that manufacturing maps can offer for the optimization of production lines such as, for example, finding out the optimal sequence for an anomaly, where could be more profitable the applications of improvements in the line to reduce cycle time or how to rebalance in real time the lines to save energy, etc.

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