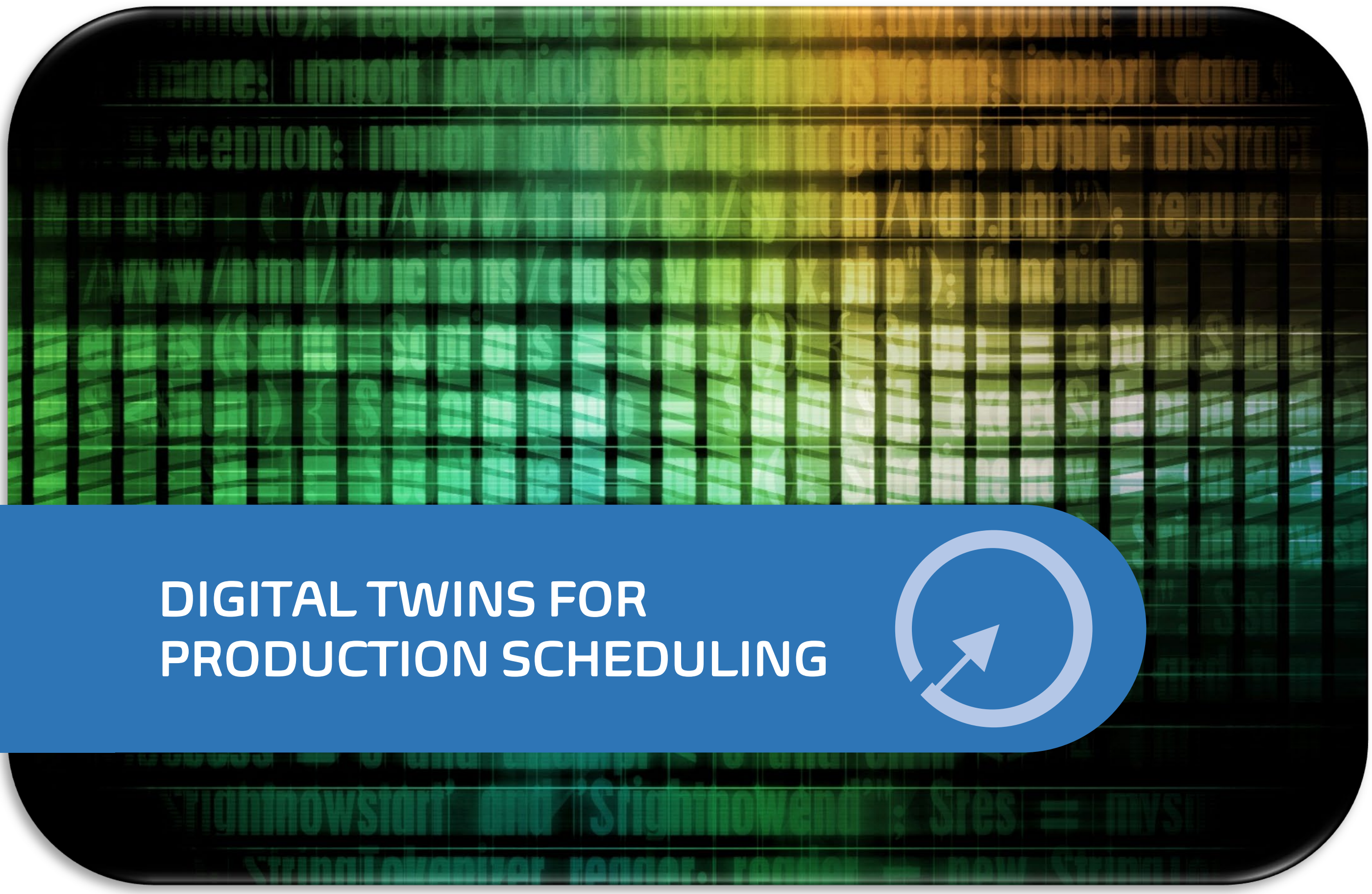
BETTER BUSINESS ANALYTICS



DIGITAL TWINS FOR PRODUCTION SCHEDULING

Introduction

Digital twins have garnered much attention lately, as trends like *"Industry 4.0"*, the *"Industrial Internet of Things"* (IIoT), and *"Smart Factory"* are coming into greater focus. However, general perception is that having a digital twin is expensive, usually entails large investments in equipment sensors and controls, and usually requires more effort than it is worth for a manufacturing company. In this paper, we debunk those myths.

We will describe how **OptPro™** uses a digital twin to aid in optimal production scheduling (OPS), which:

1. Is affordable for almost any manufacturer.
2. Can be used effectively, even for operations without sophisticated ERP and MAS systems.
3. Does not require the company to invest in expensive equipment sensors and controls.

What is a "digital twin"?

Borrowing from several sources, we can define a Digital Twin as a software representation: a digital replica – of a physical asset, a process, a system, or a device, which can be used for various purposes. In general, the digital twin should help us analyze the past, understand the present, and plan for the future.

While the above definition is vague, we will apply it to our area of interest: optimal production scheduling. In this context, we refocus our definition as follows:

> **Digital Twin:** *a software representation of the manufacturing process to analyze root causes of past scheduling successes and failures, understand the current state of the process, and obtain production scheduling plans to efficiently satisfy upcoming customer demand.*

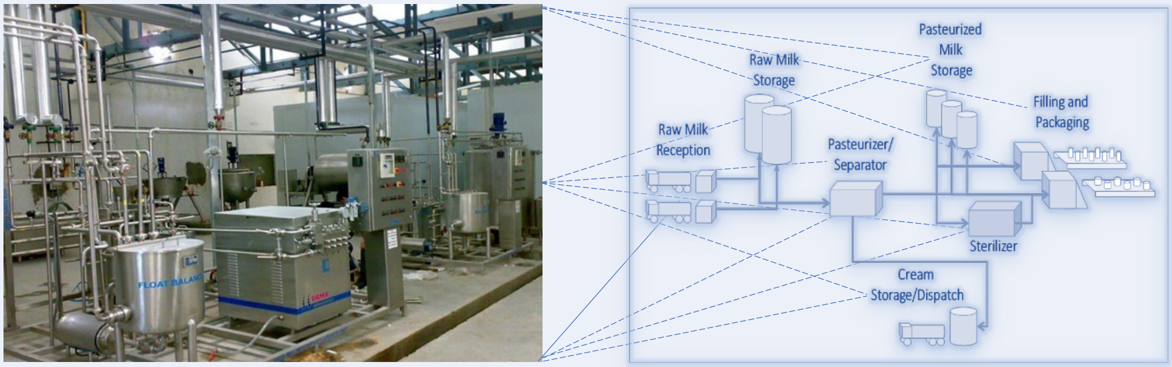
With this definition, we can now dispel the myths mentioned earlier.

Myth 1: Digital twins are too expensive

If we consider that a digital twin can refer to any software representation of our manufacturing process, and that such representation is meant to aid in creating better production schedules, then we can conclude that a digital twin can be a detailed simulation model of the process.

To build such a simulation model can be rather inexpensive. Off-the-shelf discrete event simulation software licenses may require a one-time license fee of $15,000 to $20,000 plus 20% maintenance. Factoring the wages of a full-time simulation analyst results in an annual cost of about $200,000.

A better approach is to obtain a system that combines an optimizer with a simulation model that is already configured for your operation. For an initial investment between $50 to $250K – depending on the complexity of the operation – or a monthly subscription of about $25,000, you can acquire a system that includes a digital twin tailored to your needs, integrates with your existing data input and output capabilities, and produces optimal schedules for your production requirements. Although this approach may require a considerable initial investment, the recurring annual cost to update and maintain the model is much lower.



A dairy processing plant

The digital twin (simulation model)

Figure 1. A dairy processing plant and its digital twin

Myth 2: Digital twins involve huge data requirements

In general, it is true that the more *useful* data you have, the better. Having real-time, accurate data about the status of every piece of equipment in your plant is great if you want to monitor the factory for potential equipment failures or other disruption. However, such data fidelity would be overkill for a master production schedule or a detailed schedule of next week's, or even next day's, production. For such needs, having certain information about the process would be sufficient. For example, the digital twin would need:

- A process map, by product or SKU, that represents the possible routings and sequence of steps – with corresponding resources – required to process each SKU.
- The time required to process each SKU on each piece of equipment in the SKU's process map, and the due date (or due time) for each SKU, as shown in Table 1.
- The time required to set up the equipment and to change over from producing one SKU to producing another SKU, as shown in Table 2.
- The upcoming customer demand (or production orders), by SKU, for the planning horizon desired.

The data should be readily available in most manufacturing facilities without the need to invest in sophisticated sensor and control systems. This data is sufficient to build a digital twin of the process, in the form of a simulation model, as a critical element to optimize production schedules. If the company is interested in continuing to improve the process by moving to more sophisticated, real-time optimization capabilities, the investment should be justified by the incremental value obtained.

Table 1. SKU processing data

SKU	Processing Time	Due Date	Lateness Penalty
1	30	80	7
2	40	100	8
3	10	120	2
4	40	170	3
5	50	190	5

Table 2. Change over data

SKU	1	2	3	4	5
1	-	13	7	12	11
2	9	-	11	13	6
3	9	10	-	20	7
4	10	7	8	-	6
5	14	13	12	13	-

OptPro: using the digital twin

OptPro is a state-of-the-art production scheduling solution developed to address the complexities found in many manufacturing operations:

- Costly setups and changeovers
- Large product variety, shared resources and equipment, infrastructure, and labor
- Production costs that represent a large portion of the product's price
- The need to increase production without incurring large capital expenditures
- High product losses and waste

The production scheduling approach in OptPro makes use of multiple technologies, either alone or in combination, tailored to the situation at hand. What every implementation has in common, regardless of the individual technologies employed, is a technological framework that coordinates and unifies the function of its components. This framework can be described as a scheduling optimization engine, which draws on a diverse set of techniques to obtain an optimal or near-optimal production schedule. These techniques include mathematical programming, metaheuristic optimization, and the combination of simulation and optimization. Figure 2 shows a high-level representation of the technology.

In the figure, we show a loop that iterates between an optimization engine and a schedule evaluation model (SEM), i.e., the digital twin of your operation. This loop, called a simulation optimization iteration, works as follows:

Step 1: based on the characteristics of the operation, the optimization engine suggests a schedule to the digital twin

Step 2: the digital twin runs a simulation of the suggested schedule

Step 3: the digital twin outputs a set of performance metrics about the schedule (e.g., total make span, capacity utilization, operating costs, etc.)

Step 4: if a prespecified stopping criterion has been reached, STOP; otherwise, go to Step 1

Of course, there are advanced methodologies that govern this loop, especially in Steps 1 and 2.

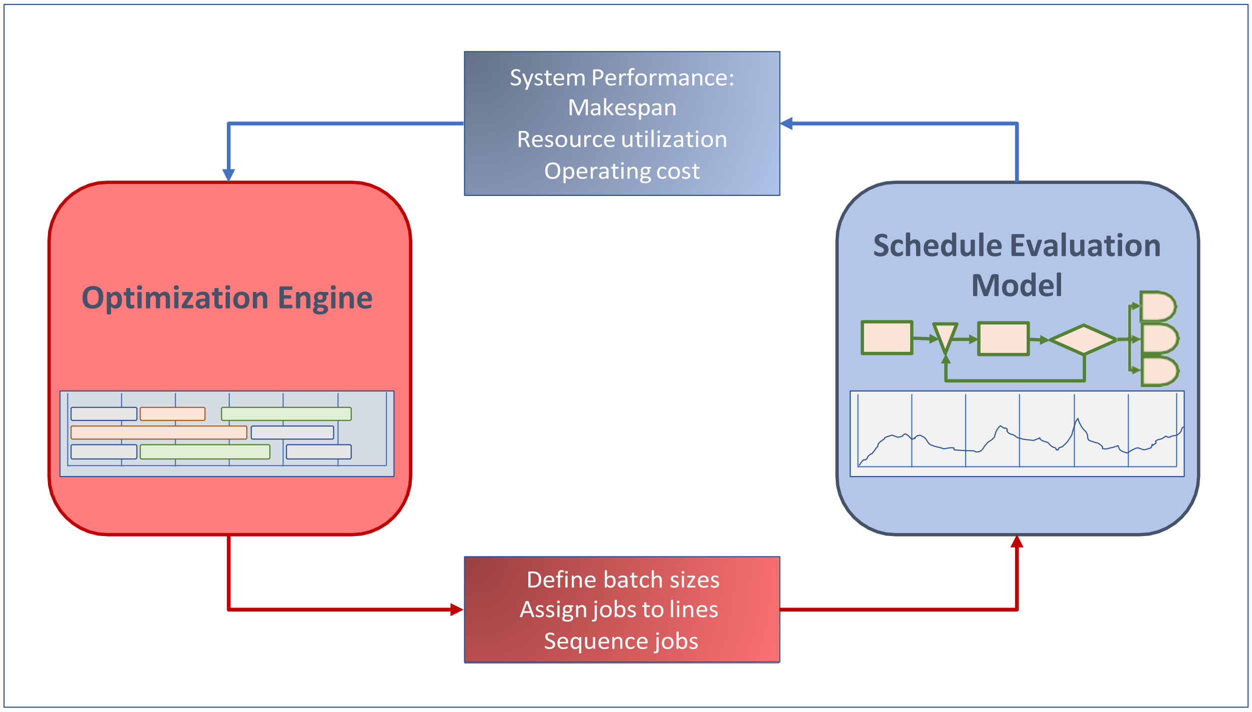


Figure 2. The simulation optimization loop in OptPro

In Step 2, the digital twin predicts the performance of the real system, given the inputs suggested by the optimizer in Step 1. For this, the digital twin must be detailed enough to capture the aspects of the real system that are relevant to the production schedule, such as processing times, changeover times, and the process map for each SKU. In turn, the optimizer in Step 1 uses information that is fed back by the digital twin, from the results of the simulation, to learn from the process and make better decisions. These decisions are made with the objective to optimize one or more performance metrics, such as maximizing throughput, maximizing on-time fulfillment of production orders, or minimizing production costs, and can be summarized as follows:

- Create batches of optimal size for each SKU
- Assign those batches to a production line (i.e., a set of machines)
- Sequence those batches optimally on each production line

As the iterative process advances forward, this feedback loop becomes more important. The optimizer learns from the results of simulations it has previously suggested to the digital twin and adjusts accordingly to produce better and better schedules. The loop runs until at least one of three stopping conditions are satisfied: (1) the prespecified run time has been reached; (2) the prespecified number of iterations has been reached; or (3) there has been no additional improvement in the results for a prespecified number of iterations.

This approach is not needed in situations where using straight-forward rules such as first in, first out (FIFO) or earliest due date (EDD) would suffice. Instead, it is designed for those operations where, as we have noted, multiple products compete for common resources, and where improved production schedules can be a source for competitive advantage.

A small, real-world example

To illustrate the approach within OptPro, let us look at a small example from a real-world operation. The operation in question is an industrial print shop that takes on-line orders via its website for a myriad of printed products. One of the most popular products this company offers is photobooks. The company receives more than 50,000 photobook orders per day. The overall photobook production process is depicted in Figure 3.
At a high level, this process involves six steps: (1) batching and sequencing of customer orders, (2) printing, (3) cutting, (4) matching, (5) binding, and (6) shipping. Customer orders are first placed into batches of books of the same size and paper type. Next, batches are released to the printing step in a prespecified sequence. Then, the books are printed, in their batches, on one of three available printers. The book covers and the corresponding contents are printed separately. After printing, the batches are cut to the correct size, then the covers and content are matched before being bound in batches again. Once binding is complete, the batches are separated into individual customer orders, boxed, and shipped to the customer.

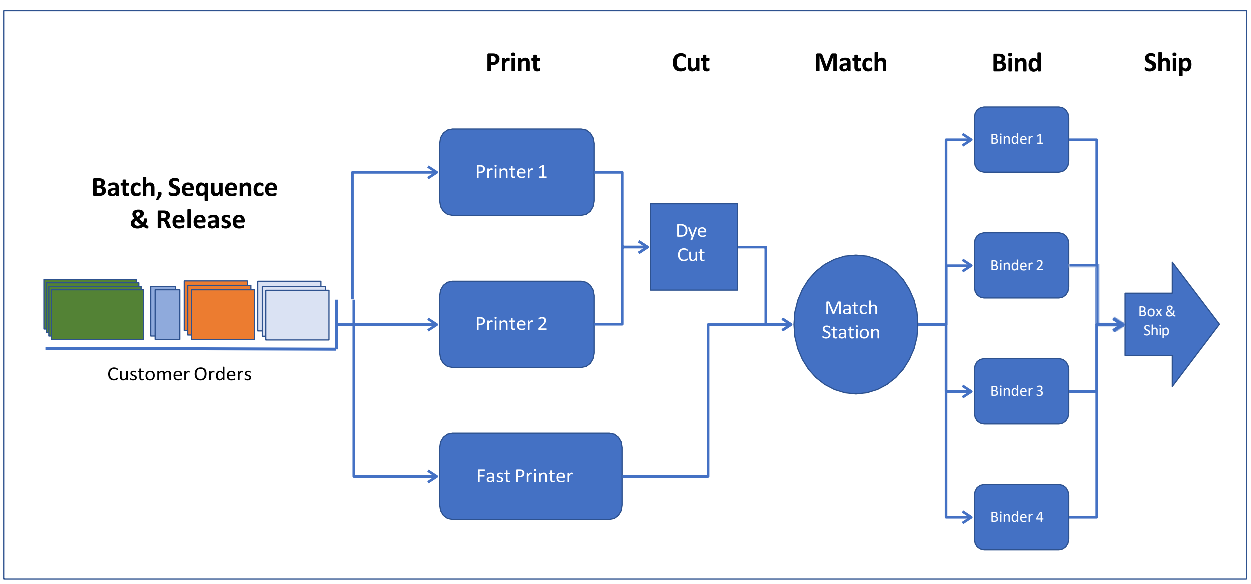


Figure 3. The photobook production process

Due to the high volume of orders the company receives, it is necessary to batch and sequence customer orders periodically during the day; otherwise, the backlog of orders can become too large to handle efficiently. Defining the time interval for this batching and sequencing activity is one of the decisions of interest. Production management also wanted to decide how to batch orders at different steps in the process, and how to sequence these batches to reduce changeovers and setup times, with two main objectives:

- Reduce order cycle time
- Improve on-time shipment of its customer orders

To achieve these objectives, we created a digital twin of the production process using the simulation capability within OptPro. Then, we used the digital twin to process their historical data spanning a period of 90 days. By processing their historical customer orders, we could run different scenarios and compare to the way the company processed those orders in the plant. We compared three scenarios:

1. Batch and process customer orders in the order in which they arrive (historical actuals)
2. Batch and sequence orders optimally at the printing step, and process them in that same order in every subsequent step
3. Batch and sequence orders optimally at the printing step and re-sequence optimally at the binding step

The results of these scenarios are summarized in Table 3.

Table 3. Summary production scheduling results

Scenario	1	2	3
On-time shipment (%)	67.2%	81.3%	83.6%
Average Cycle Time (days)	4.58	4.26	4.30

The summarized results show statistical significance for on-time shipment at a 95% level of confidence; however, the difference in average cycle time between scenarios 2 and 3 is not statistically significant. From these results we can conclude that, with respect to Scenario 1, optimizing the schedule of batches released to the printers results in a 21% improvement (14 percentage points) in on-time shipment. By optimizing again at the binding step, and additional 3% improvement is possible. In both scenarios, cycle time is reduced by about 7% with respect to their existing method.

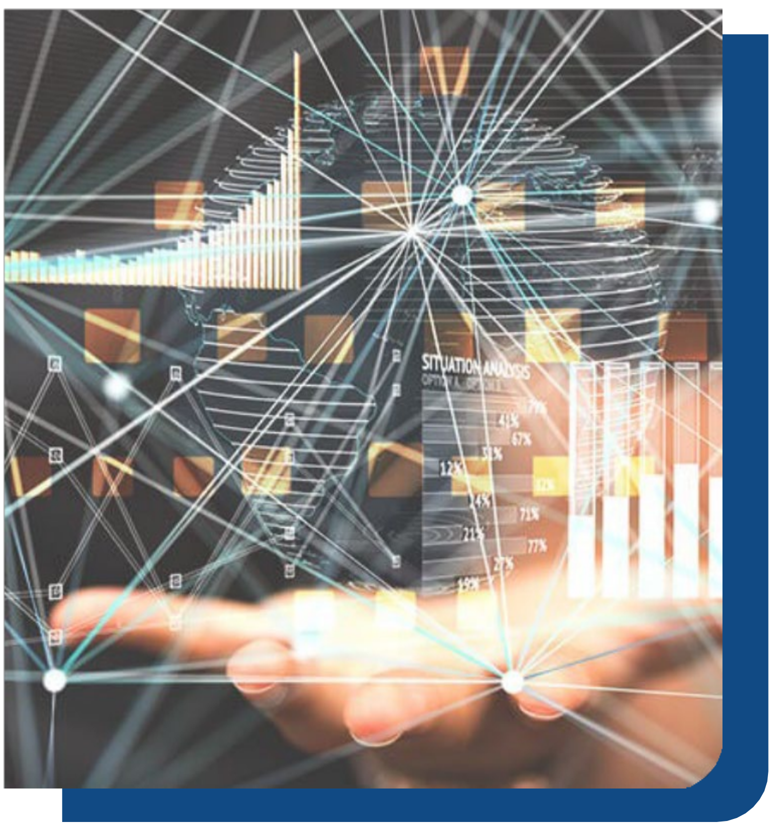
Rapid re-optimization capability

Let us suppose that one of the printers is down for part of the planning horizon. Instead of waiting for the printer to be back up and running to process all batches assigned to it, or having to spend hours on a revised plan, plant managers would like to be able to quickly re-optimize the schedule. The algorithms in OptPro are capable of rapid re-optimization, helping to create a new schedule that minimizes the changes with respect to the original plan, therefore limiting the overall disruption to the plant operations.

To illustrate this, we re-ran Scenario 3 above, but included a 5-day shutdown of Printer #3 in the simulation of the operation. After running a 30-day simulation, we found that on-time shipment decreased slightly, from 83.6% to 82.7%, while average cycle time increased from 4.3 days to 4.7 days.

Despite this increase in average cycle time, the total number of orders expected to be processed remained the same, and only about 0.9% more orders were forecasted to be shipped late.

This small example is indicative of the power behind OptPro and the use of a process simulation model as digital twin – which does not have to be expensive nor data-prohibitive. For additional information about OptPro and the benefits other customers have derived from applying optimal production scheduling in their manufacturing environments, please visit www.bettersolv.com, or get in touch with us at the contact provided below.



BBA

4684 S Hampton Cir
Boulder, CO 80301

720.987.6111

www.bettersolv.com