




COMPLEX PRODUCTION SCHEDULING: METHODOLOGY AND CASE STUDIES



Introduction

Current *market forces* are putting *pressure on manufacturers* to *increase flexibility and customization*. Whether production is *make-to-order* or *make-to-stock*, the trend is towards *shorter production* runs and more *frequent product changeovers*, which increases the need for *better production scheduling* capabilities.

Companies whose *production costs* represent a *significant portion of the price* of their products can gain a source of *competitive advantage* by creating *optimal production schedules*. Complex manufacturing operations where multiple products often share *common infrastructure and resources* require *production schedules* on a timely and frequent basis. In addition, plant expansions are very expensive; *better production schedules* often allow companies to *increase throughput* without incurring large capital expenditures, resulting in *increased product gross margins*.

ERP, *production planning*, and several dedicated commercial *off-the-shelf (COTS)* solutions exist for *production scheduling*. However, these solutions *i)* only provide reasonable schedules at a coarse, weekly or monthly level, *ii)* produce schedules that are *not optimal* and/or require *ineffective manual manipulation* and/or *iii)* cannot be re-run daily, or ad-hoc, to address *immediate issues and priorities*. Further, while these solutions produce *working schedules*, they often *fail to accommodate related constraints* that can only be factored in by using a schedule evaluation or simulation solution. Examples of such constraints include *WIP inventory and related storage limitations*, sequencing conflicts on common machines, or resource-sharing restrictions.

The vast **production planning and production scheduling** literature includes many approaches based on **pure optimization**, simulation, and **hybrid simulation-optimization methods**. Recent surveys identify numerous implementations **involving discrete event simulation approaches**, with more than a dozen others involving **alternative types of simulation**. Numerous additional implementations involve **complex mathematics and metaheuristics** (i.e. designs or strategies to **efficiently explore all options** in order to find near-optimal solutions). However, these diverse implementations **share a common denominator** of exhibiting one of three conspicuous limitations: either they make **severe simplifications of the processes** they are trying to represent, or they only **consider portions of a complete process**, or they do not provide an integrated **system capacity** and job sequencing framework.

Existing solution approaches for **production process scheduling** characteristically focus on two basic questions:

- When should a **specific job be scheduled**?
- What **resources** should be **assigned** to perform the job?

In many cases, these questions can be answered by **applying simple rule-based mechanisms**, such as **sequencing tasks by Earliest-Due-Date (EDD)** or by the magnitude of their processing times. **More complex** rules can be derived by **combining two or more simple rules** into ratios or products, but the **basic concept remains the same**.

Although appealing for their **simplicity and intuitive nature**, these methods usually produce **inferior results** because they are static in nature and tend to **ignore relevant attributes of the tasks**, such as urgency to begin production, **penalties for tardiness**, interactions with other tasks, **availability of resources to perform all the work**, changeover and setup times and costs, etc. To address these limitations, optimization-based approaches can be used. These methods use **mathematical programming techniques** to find an **optimal solution** to maximize or minimize some metric, such as throughput, **capacity utilization**, makespan, or operating cost.

The **complexity of most real-world systems** involves **several decisions**, including:

- How to size a task (i.e., **job, batch, run, etc.**)
- How to **assign a task** to a production line
- How to sequence the tasks **on each production line**

Unfortunately, in **high product mix environments**, where product changeovers are **sequence-dependent**, the application of **exact mathematical optimization methods** is impractical, either because the **time** to obtain the **optimal solution** is **excessive**, or because such systems are **too complex to be mathematically formulated**. In these cases, what is needed is a **combination of mathematical methods with metaheuristic solution techniques** and, increasingly, simulation **modeling approaches**.

In response to this need, **OptPro** from **OptTek** provides a **sophisticated production scheduling solution** approach that **combines mathematical programming**, metaheuristic **optimization**, and **simulation** to craft **optimal or near-optimal production schedules** in a timely, **reliable**, and effective manner.

The modeling and **algorithmic designs** employed are especially suited to **complex situations**, with a **high production volume** and a high product mix, where **sequence-dependent constraints**, multiple line assignments, **scarce resources**, and **tight storage** and **WIP constraints** may be present. Such a **design structure** also proves **very effective** when a major disruption occurs in the plant, and there is an **urgent need** to quickly reoptimize the **production schedule**.





OptPro Methodology

The **OptPro** production scheduling approach 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*, metaheuristics, and the combination of *simulation and optimization*. **Figure 1** shows a *high-level representation* of the technology.

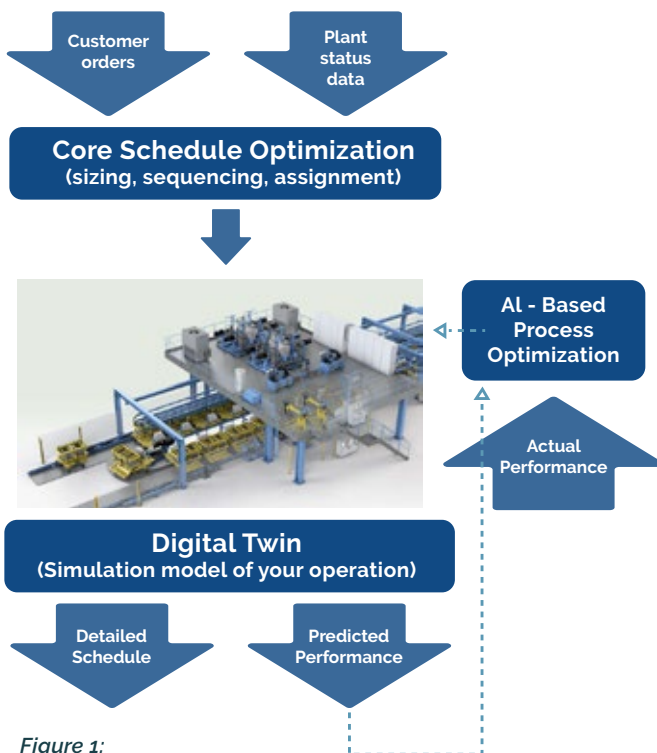


Figure 1:
High-level representation
of the technology
behind OptPro

Even *highly complex production environments* can sometimes be *tractable enough* that they can be *solved* with the *Core Schedule Optimization* alone. Examples are operations where *production lines are independent* of each other (i.e., there is little or

no interaction *between production lines*), and resources such as labor and physical assets are primarily *dedicated to each production line*. Most real-world systems, however, exhibit a degree of *complexity and interactivity* that makes it impossible to describe them with a set of *equations or mathematical expressions*. A good example of such a system is a *dairy foods production facility*. While it may be relatively simple to *optimize the schedule* of the filler machines and the packaging facility separately, *the schedules produced* without accounting for their interactions may *introduce conflicts in the upstream operations* of the process. Good coordination between *processing and packaging is critical*, so that the *scheduling* of the pasteurization step and the sterilization step, for example, are *well-synchronized with the scheduling of the filling and packaging operations*. To handle crucial interacting factors such as these, **OptPro** makes use of a *simulation model* called the **Schedule Evaluation Model (SEM)** – a *“digital twin” of the process*. The **SEM** is a realistic model of the *production facility*, which allows an iterative *evaluation of schedules* suggested by the *optimization engine*, in a *simulation optimization* sense. It is important to note that the **SEM** is only as detailed as is necessary to model the effects of *scheduling on a production process*.

Again, this approach is not needed in situations where *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 noted, *multiple products* compete for *common resources*, such as production *infrastructure and materials*, and where an *optimal production schedule* can drive *competitive advantage*. In general, this approach *finds application in organizations* that seek to *optimize and automate* their plant design and production schedule, or to *maximize the benefit* derived from their *operational processing decisions*. In manufacturing settings, *improved decision* making is enabled by *simultaneously optimizing scheduling*, sequencing, line-assignment, capacity, and layout decisions to meet forecasted *customer demands*.

The following *case studies* highlight the *benefits* of the **OptPro** approach.

Straightforward Pipe Insulation Manufacturing Case Study without need for a Schedule Evaluation Model



Consider a *large construction materials company* that produces *pipe insulation products* in one of its manufacturing facilities.

Prior to implementing **OptPro**, the company was *employing an advanced planning and scheduling (APS) system* that used a set of *dispatch rules*. While the system provided some *user-friendly capabilities*, the *complexity of the operation* had grown in recent years to the point that the *current system* was producing schedules that required *hours of manual "fixing"* to make them feasible.

The company *produces over a hundred different pipe insulation products*. Each product is described by the *type of material*, the internal diameter, and the thickness of the insulation, and is *manufactured on one or more of several available production lines*.

The *production facility* works on a *24/7 schedule* and the company's aim is to *schedule 30 days of production at a time*, with a detailed plan for the first *5-7 days* and a *less granular plan* for the remaining *23-25 days*. In this example, based on the *current conditions*, a *schedule is required for a single day of production* for five products on three available *production lines*.

The *schedule needs* to define:

- How much of each product must be *produced each day* on each line – i.e., what production *run size*, while *maximizing* total throughput
- What is the *best sequence of product* runs on each line to *minimize changeovers* and avoid overtime?

The *production requirements* for the day are shown as follows in **Table 1**:

SKU	Processing Rate (lbs/minute)	Possible Machine Assignments	Day's Demand (lbs)	Safety Stock Shortfall (Surplus)
1	150	1, 2	66,000	8,000
2	150	2, 3	27,000	0
3	75	1, 2, 3	90,000	4,500
4	75	1, 2, 3	48,000	(5,000)
5	75	2, 3	60,000	0

Table 1: Production requirements

In this case, the **quantity to produce** each SKU is the **Day's Demand** plus any shortfall (or, minus any surplus) in **safety stock**. The **total quantity to be produced** must, therefore, meet or exceed **298,500 pounds** of finished product (**the sum of the five SKU's Day's Demand**).

Additionally, the sequence-dependent **changeover times** incurred when **changing a machine** from production of **one product to another**, in minutes is as follows in **Table 2**:

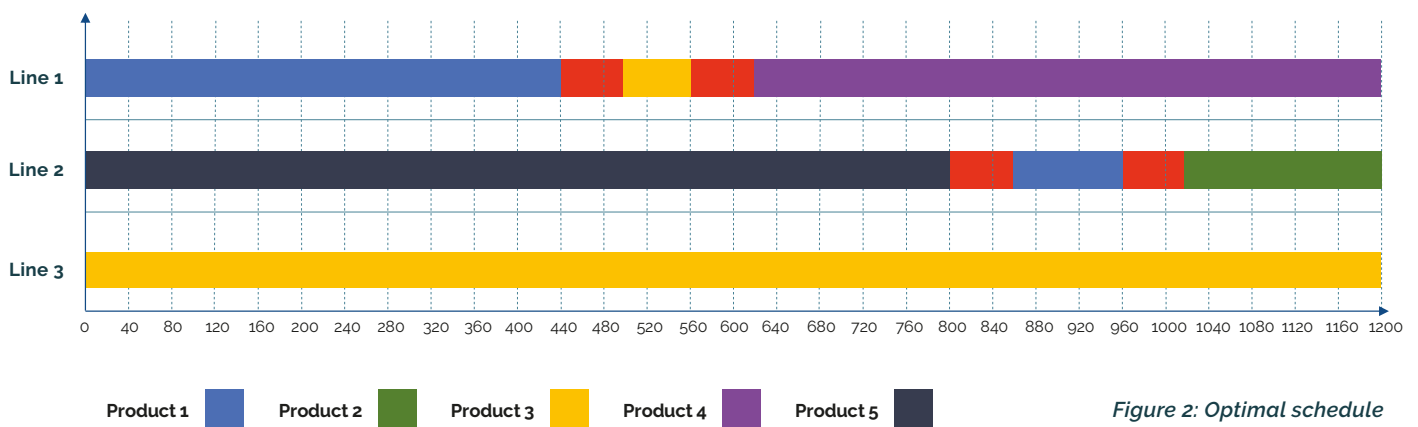
Product	1	2	3	4	5
1		60	60	60	60
2	60		60	60	180
3	180	120		60	120
4	180	180	120		120
5	60	180	120	120	

Table 2: changeover times

To **avoid paying its operators for overtime**, the plant must **finish production within 20 hours**. The additional 4 hours available at the end of the last shift are typically used for **preventative maintenance** and cleaning activities.

Optimal production schedule for Day 1

The optimal schedule is as follows in **figure 2**:



Perhaps not intuitively, but **optimally**, both Products 1 and 3 are **split into two batches**, to be **produced on different machines** to avoid incurring **overtime costs** (one of the key objectives). The **schedule maximizes throughput**, resulting in a total production of **306,500 pounds**, and **minimizes costs**, including changeover costs (**240 minutes**).

Rapid Re-Optimization

However, as a result of unforeseen *tool breakages*, the scheduler realized this *schedule cannot be put in practice* because of *tooling conflicts* in resource utilization; two batches of the same product cannot now be run in parallel (*Product 3 on Lines 1 and 3*), because they each require a mandrel of the same diameter and there is only one. In addition, *Products 2 and 4 also share a mandrel*, so those two cannot run in parallel either (*on Lines 2 and 3*).

The *appropriate tool constraints* are easily edited to *reflect shared resource conflicts*, the optimizer is very quickly re-run (*a matter of minutes*), and a new *optimal solution* is obtained as follows in **figure 3**:

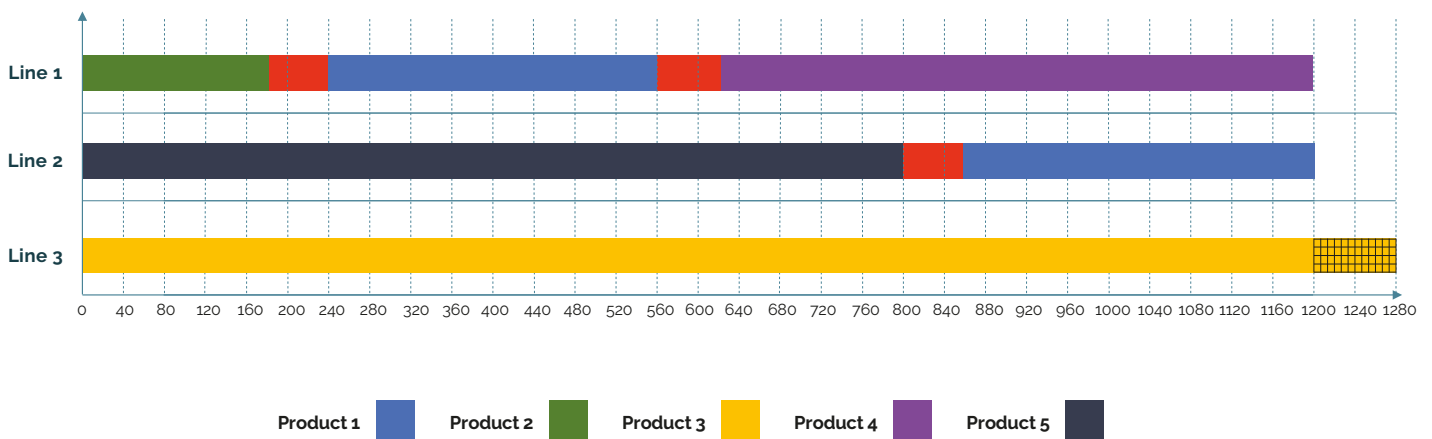
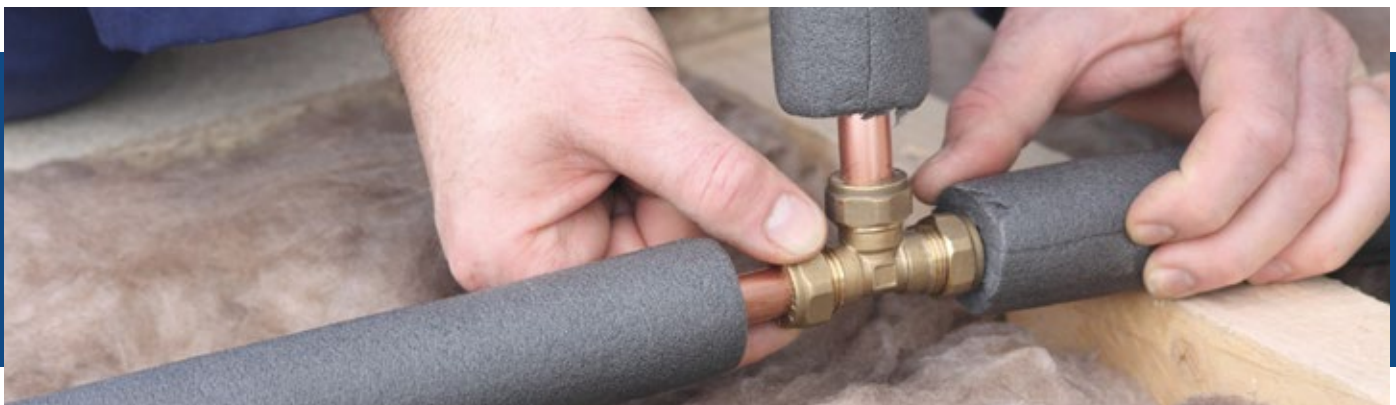


Figure 3: Optimal schedule after rapid re-optimization

This *new solution avoids* the *tool conflicts mentioned above*. Although this new solution does now incur 60 minutes of overtime on Line 3, it *reduces the total changeover time by 60 minutes*, practically *offsetting the cost of overtime with revenues* realized from additional throughput of 18,000 pounds of *finished Product 4*.

Given this is a *real-world example*, the approach illustrated here resulted in an **8% increase in throughput compared to a manual approach** being used beforehand, with an overall **10% cost savings** from changeovers and still *reduced overtime*.





DAIRY INDUSTRY CASE STUDY WITH A SCHEDULE EVALUATION MODEL



OptPro was implemented for a *dairy processing and packaging plant* design and equipment manufacturer, with an *implementation carried out at a medium-sized dairy production facility* with one pasteurizer/separator, one sterilizer and six filling machines (*a simplified schematic of the facility is provided in Figure 4*). The facility had a *difficult time creating a schedule* that would produce *enough product to meet demand*, without the need for *overtime* and without the current *corner-cutting on cleaning and maintenance*.

The *challenge* was to create a *schedule* that would:

- *Minimize the time* to produce SKUs – keeping *below 100%* indicating *no need for overtime*, and *allowing time for cleaning & maintenance*
- *Maximize the existing utilization*, but keeping below 100% indicating no need for additional capacity/infrastructure
- Produce a schedule, and *be able to reschedule*, quickly

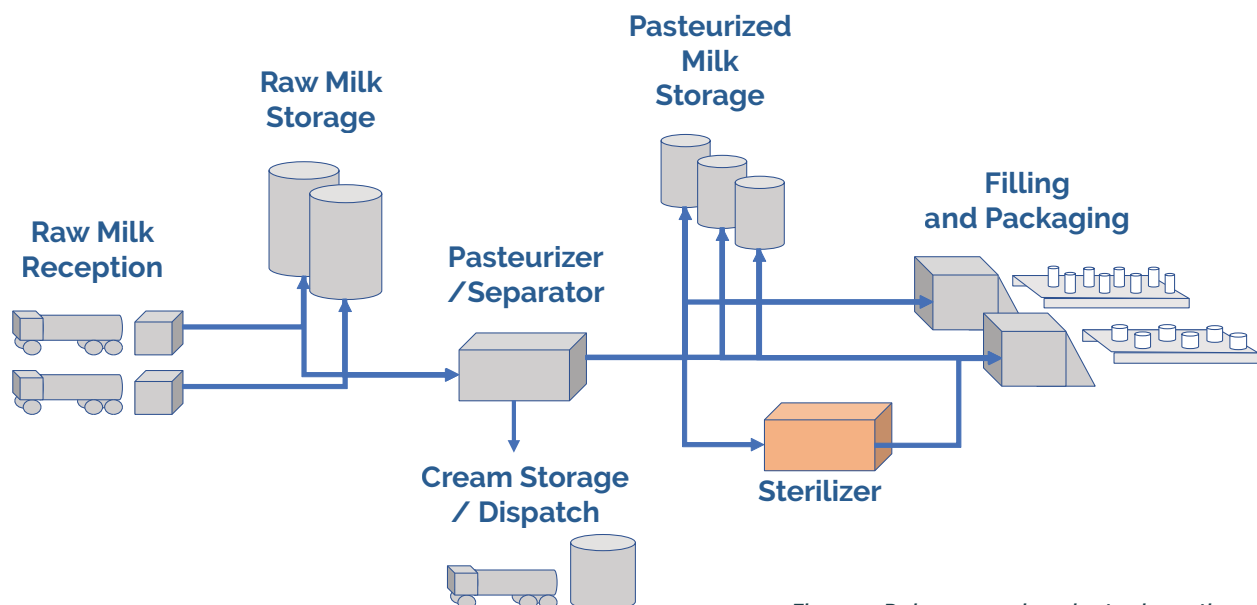


Figure 4: Dairy processing plant schematic

Demand is specified by 17 SKUs of different dairy product types and package sizes. In the plant, *raw milk reception occurs daily*, with raw milk storage silos *directly filled by pipes* from the reception area. Siloes are then *pumped through to the pasteurizer/separator* where the *raw milk is separated into pasteurized milk* with different fat content specifications, and a cream byproduct. *The cream is stored until it can be dispatched* at the end of the day. *Pasteurized milk is stored until a filling machine is available*, and then it is either filled as *fresh product*, mixed with flavoring and filled as flavored product, or sterilized and *filled as ultra-high temperature (UHT) product*. In the final step of the process, filling machines fill containers of a prespecified size with the appropriate final product. *A SKU is defined by the combination of finished product type and container size.*

OptPro first applied a *sequencing and assignment algorithm to the process* at the filling step. *Four distinct tests were then executed*, and the *time was measured for completion*, along with the *quality of the solution* in terms of makespan and equipment utilization. *The tests and their respective quality results are described in Table 3.*



#	Type	Obj	Time	Mksp	Util
1	A	U	7s	99.1%	95%
2	AE	U	15s	99.1%	96%
3	M	M	11s	97.4%	85%
4	ME	M	9s	97.4%	85%

Table 3: Evaluation tests

In Column 2 of Table 3, the “Type” of test is defined as follows:

A: Average: → weekly production is averaged over 7 days, such that one-seventh of the weekly demand must be completed in each day.

M: Makespan minimizing schedule → total weekly production *must be completed* as soon as possible.

E: Expanded → the *number of SKUs is doubled to 34*, but the *demand per SKU is halved*, to test the *flexibility of the algorithm to larger quantities of SKUs*, while *guaranteeing that a feasible schedule exists*.

Thus, *if Column 2 contains the abbreviation: “AE,”* it means that the test is of type “Average, Expanded”. This means that the test involves a *daily average demand* equal to one-seventh of the *total weekly demand for each SKU*, and the number of SKUs will be 34, *but the demand for a SKU will be half that of the original SKU*.

Column 3 shows the primary objective(s) of the test case, either *U = equipment utilization (maximized) or M = makespan (minimized)*. Time, in Column 4, reflects the *computer run time* – in seconds – to obtain the *best solution*. *Columns 5 and 6 display the resulting values of Makespan and Utilization*, respectively. These are all expressed as percentages. Thus, makespan is reported as a percentage of the *maximum allowable production time* (i.e., 1,440 minutes per day for *tests involving an “Average” production requirement*, and 10,080 minutes per week for *tests involving a “Makespan-minimizing” production requirement*).

The *results indicate* that *all schedule options were viable*, and all executed quickly. None showed *Utilization > 100%*, indicating *no need for additional capacity*. All showed *Makespan < 100%*, indicating *no need for overtime*, and leaving time for *cleaning and maintenance*.

Need for Schedule Evaluation Model or SEM (simulation)

It currently takes an *experienced process engineer* over five hours to obtain a *good scheduling solution for the week*. Part of the reason is that a *filler schedule must consider the coordination between the filler schedule and the activities* at the upstream equipment – namely the sterilizer and the pasteurizer. If these are not in *step with the fillers*, then the filler *schedule can be greatly disrupted* by long idle times or costly and *untimely changeovers*. Although **OptPro** produced *excellent solutions for the fillers in a very short computational time*, it was necessary to *verify that the upstream equipment could also be scheduled* in a way that *minimized disruption of the fillers' schedule*. This proved *challenging*, especially in the case of the *sterilizer whose operation is more constrained in terms of buffer capacity* - whereas the pasteurizer relies on large, relatively *non-expensive storage tanks*, the sterilized product must either be *fed directly to the filler*, or it must be *stored in relatively small, expensive aseptic tanks*.

To address this issue, a detailed **SEM** of the dairy plant *was modeled*. After initial testing, it was *necessary to modify the initial solution generator* in the **OptPro** algorithm *to eliminate much of the reliance on randomization*. The *new solution construction method* then *selected SKU sizes* and filler machine assignments in close coordination with the sterilizer to *avoid periods of idle time at the fillers*, ensure *continuous operation of the sterilizer*, and *minimize changeovers*. This new approach was *successful* and although the *total run time* for each of the test cases described earlier (*see Table 1*) now took *between 1 and 4 minutes*, the *schedule options were again all viable* and this increase in time still represents a *great improvement compared to the 5 hours* it currently takes *the engineer*.



A High-Volume eCommerce Printshop Operation with Schedule Evaluation Model



The *final case* refers to a *high-volume printing operation*. Customers *upload a design* and then *order products* such as *photobooks, calendars, and other personalized items* from the company's *online store*. The company receives *several thousands of orders each day* during peak periods. Each different item in an order is *assigned a production ticket ID*. Thus, some orders may be *associated with a single production ticket*, and some with *several tickets*. On average, the company *generates over 50 thousand production tickets per day*.

The *company provides* the customer with a *planned ship date for each order*, determined by the *type and number of associated production tickets*. For example, an order that contains *multiple and complex types of items* may be assigned an *expected ship date* that corresponds to *5 workdays after the order was received*, whereas an order with a *single, and simple, item* might be assigned a *ship date* corresponding to only *2 days after the order was received*. The *primary goal* of the company is to *maximize on-time-shipment*, measured as the percentage of orders that *ship on or before the planned ship date*.

Current *scheduling is, to a large extent, performed following a First-Come-First-Serve (FCFS) approach*. The only *"intelligence"* added to *FCFS* is that for a *given backlog of production tickets*, similar items are *processed together as batches*, to minimize changeovers. By and large, the biggest *bottleneck in the process is the printing step* which occurs first for *most products*. This step involves both the *longest processing times* and the *longest changeover times* of any step in the process. As a result, *jobs can be sequenced at the printers*, ignoring any of the steps occurring downstream - the problem is then effectively reduced to a sequencing problem. A *Schedule Evaluation Model (SEM)* of the plant is *used to simulate the optimal sequence* and collect detailed metrics. The *SEM* models each *step of the process*.

A *high-level process* of the plant is depicted in the *flow chart of Figure 5*. The multiple machine sequencing problem with *sequence-dependent setups* can likewise be *formulated with an objective* that can be expressed as *minimizing the number of tardy jobs*, such that a *complete formulation* can be computed.

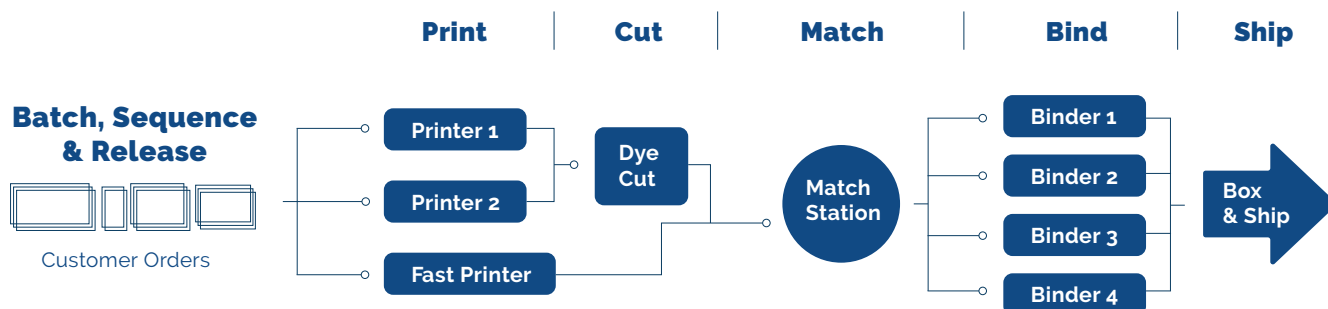


Figure 5: High level flow chart of printing process

The *solution approach* involves a *unique search procedure* with a “*greedy*” *heuristic construction method* (i.e., the *locally optimal choice* is made at each stage) and *efficient neighborhood search*. The greedy constructor is *based on the Apparent Tardiness Cost with Setups (ATCS) rule*, applied to the *total weighted tardiness* on a single machine where *jobs are sequenced* in descending order of a priority index.

To illustrate this method, *consider a set of 5 jobs* as shown in **Table 4**.

Job	Proc. Time	Weight	Due Date
1	30	7	80
2	40	8	100
3	10	2	120
4	40	3	170
5	50	5	190

Table 4: Jobs data

Setup times for these products are shown in **Table 5**.

Setup Time	1	2	3	4	5
0	9	6	8	8	12
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	

Table 5: Setup times, including initial setup

The priority *indexing calculations and resulting sequence* for jobs yet to be selected at each time interval are shown in **Table 6**.

t	1	2	3	4	5	Sequence
0	0.01565	0.02822	0.01231	0.00410	0.00177	2
46	0.02051		0.00723	0.00141	0.01155	1
85			0.02653	0.00232	0.00381	3
102				0.00030	0.01229	5
159				0.00231		4

Table 6: Applying ATCS indexing to the set of 5 jobs

The total *weighted tardiness metric* for this sequence is shown in **Table 7**. This method *compares favorably* to other *well-known* dispatch rules. It outperformed an *Earliest-Due-Date (EDD)* method by 21% (total weighted tardiness = 204), *shortest processing time* by 33% (total weighted tardiness = 240) and does only *1% worse than Moore's algorithm* (total weighted tardiness = 159). The latter is well known as an *algorithm that minimizes the total number of tardy jobs*, but it cannot directly address changeovers or weighted tardiness metrics. The fact that *ATCS does comparably well leads* us to the conjecture that ATCS is *well-suited as an initial sequence constructor* for the case of *minimizing the total number of tardy jobs* and weighted tardiness.

Sequence	Setup Time	Start Time	Completion	Tardiness	Weighted tardiness
2	6	6	46	0	0
1	9	55	85	5	35
3	12	92	102	0	0
5	6	109	159	0	0
4	12	172	212	42	126
Total					161

Table 7: Computing total weighted tardiness

Implementation complexity

In our implementation, *the ATCS rule* had to be *modified in two fundamental ways* in order to: **(1) handle multiple machines**; and **(2) appropriately time the release of "related" items**. The first modification is *obtained by changing the ATCS indexing function* to represent the time at which the *first feasible machine will become available*. (Some machines may *not be able to process a job*, so they are not feasible for that job.) The second modification was necessary because of a *process particularity*: the company *consolidated all items in an order into a single shipment*. That meant that, oftentimes, items with significantly different processing times *had to be shipped together*. *In order to limit WIP inventory*, the release of items in a *given*

customer order with much *shorter processing times* had to be timed in such a way that they would *finish processing* at approximately the same time as those with *longer processing times*.

For this implementation, **OptPro** again used a **Schedule Evaluation Model (SEM)** to *evaluate solutions*. In this case, the **SEM** models the full plant, which *provides a more precise measure of the performance* of the system than the *estimated factors in the ATCS* (modified to manage multiple machines). This proved essential because *WIP inventory can build up in different areas of the plant*, causing *wait times* that are not addressed in the *ATCS indexing rule*.

Due to the *large volume of incoming orders*, the procedure is *repeated at various intervals* during the day, or whenever a *major disruption occurs in the plant*. This is necessary to *avoid excessively large volumes of backlogged orders*, which ensures that the *optimization runs quickly enough*, and produces *high-quality results*. On the other hand, running the procedure too often makes it impossible for *enough items to be batched into large enough chunks*. There are certain batch processes in the plant, where *producing a single item* requires the *same processing time* as processing a batch of 50 items. Thus, the “chunking” step is critical in *ensuring the efficiency of the solution by creating batches of similar jobs* (i.e., jobs with characteristics similar enough that there is *no changeover or setup time* incurred between them).

Based on *preliminary testing and simulations* conducted on historic data, during *normal months of operation* (January through September), the **OptPro** implementation typically *improves on-time shipment of customer orders* from a current average of **91% to between 98% and 99%**. However, the *solution is most valuable during the peak holiday months* between October and the end of December, when the current *on-time shipment metric is only 75%*. During these periods, the *solution approach typically yields on-time shipment performance* between **92% and 96%** (a *significant improvement of 23% to 28%*). These outcomes are *expressed as ranges due to variability in the results* at different *time intervals*, determined by the *average complexity and volume of the orders* in the backlog at different times.





CONCLUSIONS

The *combination* of *custom mathematics, metaheuristic-based algorithms, and simulation evaluation models* has proven *very effective in a wide variety of complex production scheduling applications* – where *ERP, planning and COTS scheduling solutions are challenged in handling the complexity* and other requirements.

The *efficiency and quality of solutions* obtained by the **OptPro** method makes it *well-suited for handling problems* not only in *strategic production design and planning situations*, but in *real-time, operational scheduling*.

Often, *effective scheduling solutions* require a *combination* of *mathematical methods* with *metaheuristic solution techniques* coupled with *simulation modeling approaches*; **OptPro's** ability in this regard makes it an *ideal solution for many complex scheduling challenges*.

OptPro also *proves useful for re-optimizing a schedule in the event of a major disruption in production* (e.g., a machine breakdown). This *re-optimization* has a *crucial role* in many settings, where the *usual reaction is to continue with the planned schedule* and “*work around*” the *disruption*, which often leads to *increased operating costs and excess product waste*. By enabling the schedule to be *re-optimized in a matter of seconds*, the disruption and its estimated duration can be *addressed directly in the new schedule* – thus minimizing these negative effects – *and production can resume immediately*.



4684 S Hampton Cir
Boulder, CO 80301

 720.987.6111

www.bettersolv.com