Production planning optimisation for composite aerospace manufacturing

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Composite materials proved highly successful for aerospace applications in the last decades, but increased cost pressure forces the composite industry to become more efficient. This requires new manufacturing technologies and optimised processes as raw material costs and labour costs are basically fixed when wanting to keep production on site. Probably the most defining process for aerospace composite production is manual layup of prepreg material with subsequent curing in an autoclave. From production planning view, this combination poses the challenge of transition from discrete layup manufacturing to batch curing processing with the restriction of limited allowed storage time of the prepreg material prior to cure. In this paper, a new approach for production order optimisation at the conjunction of discrete and batch processing is presented. The APOLLO named tool is designed to decrease throughput times, streamline production and increase autoclave utilisation in the composite aerospace industry.

Keywords: composite processing; production planning; aerospace; prepreg manufacturing; batch and discrete processing

1. Introduction

Modern commercial airliners are constructed using high-tech composite materials due to their favourable weight to strength/stiffness ration. The Ashby diagram in Figure 1 visualises the typical modulus to density range for different material classes showing the potential of composites. Their lower density offers decreased airframe weight in combination with increased mechanical properties and longer service-lifetime due to their superior fatigue resistance (Deo, Starnes, and Holzwarth 2001; Neitzel, Mitschang, and Breuer 2014). Therefore, it is no surprise that modern long range aircrafts like Airbus’ A350 XWB, A380 and Boing’s 787 feature more than 50% weight contribution of composite materials (Shehab, Ma, and Wasim 2013) as can be seen from the material distribution in Figure 1.

But these composite materials consisting of high-strength fibres embedded in polymeric matrix come at the price of significant higher manufacturing costs compared to more traditional metallic airframe materials. This is caused by their higher raw material costs and the more effort requiring manufacturing process, comprised of material layup, curing of the polymer matrix and final edge trimming.

Weight and weight reduction are the most important factors in space applications and are still two of the most defining factors for long range aircrafts. But acquisition cost and production quantity become ever more important for middle to short range planes. So in order for composites to continue their success story into applications for these smaller aircrafts major cuts in manufacturing costs and throughput times need to be realised. Project APOLLO is part of a three column concept for increased production efficiency in aerospace composite industry (Hueber and Schledjewski 2018). Autoclave production planning (APOLLO (Hueber, Fischer, and Schledjewski 2017)) together with continues cost estimation (ALPHA (Hueber, Horejsi, and Schledjewski 2016a; Hueber, Horejsi, and Schledjewski 2016b)) and process optimisation (ARTEMIS (Konstantopoulos et al. 2016; Hueber et al. 2017)) are considered key factors for improving production economic.

The typical/traditional aerospace composite manufacturing route consists of hand layup of prepreg fibre material on a one-sided mould, applying of a vacuum bagging and material curing in an autoclave under elevated pressure, vacuum and temperature (Bader 2002). Afterwards mechanical trimming, rigorous non-destructive testing (NDT) and final assembly are required. During the autoclave process, the polymer matrix is cured (McMillan et al. 2017), causing chemical crosslinks to form between the plastic molecules. Through this the liquid resin undergoes transition to a solid material embedding the...
fibres to ensure load distribution between them and protect them from environmental influences (Ehrenstein 2006; Neitzel, Mitschang, and Breuer 2014).

This autoclave processing is essential to the whole composite industry where it is used for manufacturing high performance composites parts especially for aerospace and motorsports applications. It is unmatched in its capability of providing high temperature and uniform pressure distribution to a wide range of part sizes and geometries.

On one side, these autoclaves need to be of considerable size to allow production of large parts, on the other side as little as possible volume should be left unused during each cycle to minimise costs (Witik et al. 2011). Now while the manual layup is a typical discrete manufacturing step, the autoclave curing resembles a batch process, where multiple small- to mid-sized parts are processed in one cycle.

The transition between these two production types together with the prepreg materials restricted out-life time between layup and autoclave processing poses severe challenges to production planning. On the one hand, autoclaves should always be loaded to their maximum capacity, requiring several uncured parts to be ready from layup at that time. On the other hand, layup capacity is limited and complex parts take up to several days in preparation, while the restricted out-life time does only allow very limited storage of layups prior to curing. Attempting to optimise the direct layup times is very difficult and jeopardy to process stability and final part quality, because hand layup of complex geometries is a tedious process that requires meticulous manual labour (Elkington et al. 2015). And part quality is highly sensitive to diligent execution while much of the process is not yet fully understood (Bloom et al. 2015). All this needs to be considered when trying to streamline aerospace production planning in order to maximise throughput and minimise autoclave cycles.

2. Methods for production sequence problems

For solving production sequence problems two general approaches exist. The first class are mathematical analytic methods which aim to determine the exact optimal solution. The second class are heuristic concepts that sacrifice searching of the optimal solution for a faster and less complex attempt to find good, to near optimal solutions (Arnold et al. 2008). A comprehensive description of different planning methods can be further found for example in Buschkühl et al. (2010) or Herroelen (2005). Here only the two main classifications and the used Branch and Bound principle will be explained in short.

2.1. Mathematic analytic methods

The mathematic analytic methods always aim to find the exact global optimum of a sequence problem. To achieve this, they need to evaluate every possible solution of the problem according to defined boundary conditions and rate them for a target function. This means that the required calculation effort increases drastically with problem complexity. Consequently the analytic methods can become unsolvable or demand too many restrictions in boundary or problem definitions to provide meaningful results for complex problems (Domschke, Scholl, and Voß 1997; Arnold et al. 2008).
2.1.1. Branch and Bound

Branch and Bound (B & B) is the most widely used analytic method and follows the idea of dividing the problem into many ‘easier to solve’ sub-problems (Demeulemeester and Herroelen 1992). This ‘branching’ leads to the B & B characteristic tree like structure depicted in Figure 2 (Arnold et al. 2008). Every vertical path in the diagram represents one possible solution, in the case of production sequence, one possible production order. At each junction, the method evaluates the validity of the current path and either severs this branch or further extends it. Thus every path is analysed for its ability to provide a useful solution and its target function value is determined (Arnold et al. 2008). Important during the B & B process is that no possible solution of the original problem is lost during branching of the problem, while at the same time tight enough upper and lower bounds are defined to reduce calculation efforts (Buschkühl et al. 2010). Depending whether the problem is a minimisation or maximisation, the upper or respectively lower bound is the currently found best solution and is used to sever sub-optimal branches. Respectively the other bound represents a theoretical/hypothetical super-optimum which is normally calculated by purposely relaxing or ignoring one or more boundary conditions (Buschkühl et al. 2010). Actually reaching this bound during optimisation means the completion of the problem but also could indicate too weak boundaries. Further definitions and approaches of B &B can be found for example in (Brucker, Jurisch, and Sievers 1994; Mingozzi et al. 1998; Tanaka and Araki 2008).

2.2. Heuristic methods

The key difference between analytic and heuristic methods is that later do not aim to find the global optimum but instead accept a reasonable good local optimum in favour of reduced calculation time. This makes heuristics more suitable for large and complex problems which cannot be handled by analytic methods. The work principle of heuristics is to start from one possible solution of the problem, which needs to be found by other means than the heuristic itself, and the try to optimise it by slightly deviating from it. Once a better solution is found, this new one is taken as starting point and is again altered to see if an even better variation can be generated (Arnold et al. 2008).

The advantage of this procedure is that it takes significantly less calculation time in comparison to mathematic analytic methods and that it is far easier to implement (Biskup, Herrmann, and Gupta 2008). The main disadvantage is that the heuristic algorithm can easily get trapped in a local minimum, from which it is then unable to find better solutions or even the global optimum. Therefore, analytic and heuristic methods are sometimes combined to benefit from both the fast solving potential of heuristics and the global optimum of analytics. In conjunction with B & B heuristics can be facilitated as a very effective way for getting a very good initial upper or lower bound (Mingozzi et al. 1998).

3. APOLLO – Autoclave Production Order, Layup and Logistics Optimization

The APOLLO (Autoclave Production Order, Layup and Logistics Optimization) software is a self-written java program, which allows for complex production planning using a branch & bound algorithm. The aim of APOLLO is to find an ideal, or for complex problems a good, production order to minimise total production time at an optimised autoclave usage. At the moment this task is done manually by engineers resulting rather in easy to handle than optimised production orders. The idea of the program is to improve this process and enable more efficient production planning.
The tool permits the definition of several production projects each consisting of individual sub parts. Every part is assigned a layup station and layup time as well as the required autoclave cycle type. Based on part sizes autoclave loading scenarios for each cycle type are generated, considering a definable minimum loading requirement, e.g. 80% or 90%, of the available autoclave length. The aim of the program is to find the best combination of autoclave cycles and clean room manufacturing order to allow production of the desired quantity in the minimum amount of time. The possible variations are generated by the software during the optimisation as the open project structure hinders pre-definition while the limited out-life time of the layups presents a huge restriction to the optimisation potential.

The aim was not to develop a new algorithm or more efficient model for an already solved problem but to create an application-ready and fully operational software for a demanding, and previously unsolved, real-life problem. Although designed for the autoclave processing of aerospace composite parts, the APOLLO tool is suitable for many scenarios with the combination of discrete manufacturing followed by batch processing. Remotely similar two-stage optimisation problems can be found in Liu et al. (2017) and Meng et al. (2018).

3.1. Motivation, aims and boundary conditions

As mentioned before traditional composite manufacturing for aerospace involves individual production of different complex layups which are afterwards processed together for batch curing in an autoclave. For economic reasons, it is beneficial to use this kind of processing. First, a big autoclave gives more part design freedom as the part size is not restricted by manufacturing equipment, second, it allows for the large autoclave investment to be depreciated onto more parts. And last of all, one big autoclave takes up less space than an equivalent number of small ones. The downside on the other hand is the introduced complexity of production planning required for maximum utilisation of the equipment. (Ehrenstein 2006)

The main boundary condition for the APOLLO planning algorithm is the strictly limited out-life-time of the aerospace prepreg material. Due to its character of reinforcement fibre pre-impregnated with reactive polymeric matrix, hence the name ‘prepreg’, this commonly used material for aerospace composite can only be stored in frozen condition. For usage the material needs to be unfrozen before being cut into the required plies. Once unfrozen the out-life-time starts and must not be exceeded for a single ply in any part as material properties cannot be ensured afterwards, resulting in total loss of the part. While this is also an issue for non-aerospace applications, it is especially stringent in aircraft manufacturing. This limitation means that layup parts can only be stored for very limited period prior to curing as the sum of the parts layup time plus the pre-autoclave waiting time must not exceed the fixed, material specific, out-life-time (Ehrenstein 2006; Neitzel, Mitschang, and Breuer 2014).

This is similar to problems with perishable goods with an instant and total loss of value which can be found for example in Leung and Ng (2007); Amorim, Günther, and Almada-Lobo (2012); Farahani, Grunow, and Günther (2012); and Amorim et al. (2013). While the out-life time might not be a big planning restriction for goods infinitely available on short notice, the challenge in this scenario is that layup production is very time consuming (up to days for some parts) and limited by the amount of available layup stations.

3.2. Branch and Bound concept of APOLLO

The main challenge in the development of APOLLO was the idea of no or very little predefinitions making the tool as versatile and usable for real production environment as possible. In many studies the parts, their production amount and the whole manufacturing environment are fixed. This makes it easy to define all possible scenarios and combinations while in APOLLO none of the above is predefined and each project can in theory be as complex as desired. Meaning the algorithm is not limited to only consider one or two parallel machines. It allows the user to define the project size, how many parts to be considered and the number of available layup stations and autoclaves.

This requires a much more flexible algorithm capable of generating all B & B combinations which then need to be checked against the defined project boundaries for their validity. Another highly important difference of the APOLLO project to typical B & B is that it is not a classic n-job scheduling scenario of either the identical parallel (Nessah, Yalaoui, and Chu 2008; Ranjbar, Davari, and Leus 2012; Gökgür, Hnich, and Özpeynirci 2018) or different sequential machines type (Brucker, Jurisch, and Sievers 1994; Mingozzi et al. 1998; Brucker, Hilbig, and Hurink 1999; Detienne, Sadykov, and Tanaka 2016).

Both Neufeld, Gupta, and Buscher (2016) and Janiak et al. (2015) provide very good and recent reviews of this classic Resource Constrained Project Scheduling Problems with detailed comparison of the different problems and used algorithms. Early descriptions of these problems can for example be found in Ignall and Schrage (1965); Graham et al. (1979); Adams, Balas, and Zawack (1988); and Demeulemeester and Herroelen (1992).
Placing APOLLO among these known problem categories proved practically unfeasible as it is far more complex and to our knowledge unique in its form. This also made it impossible to benchmark or compare it to other existing algorithms.

In APOLLO, the discrete production of several perishable goods on different workstations is scheduled to minimise total production time while ensuring maximum usage of the batch autoclave process. This results in two competing target functions and hence in a two-level optimisation scenario. The interaction of autoclave loading and layup manufacturing order is schematically depicted in Figure 3. To further add complications different autoclave cycles might be required for different layups, forbidding the combination of some parts in the same cycle. With this set-up Project APOLLO takes on two major challenges in production planning that were found often missing in research and academic developments; a real industrial application and two combined business functions (Pahl and Voß 2014).

On the one side, the autoclave cycles and loadouts need to be arranged in a way to ensure maximum usage of the available process volume and reduce the total number of needed cycles. This Autoclave solver provides a list of proposed cycles with corresponding loadings and creates a scheduled production demand for the CleanRoom solver. On the other side, the CleanRoom solver needs to find the best production order for the layups in order to keep total production time to a minimum. It gives back the availability of layups and the Autoclave solver then needs to make sure to not exceed the allowed out-life-time for the parts.

APOLLO is the combination of parallel machine job shops in CleanRoom with perishable goods and lot size planning in Autoclave. This development is the first step towards advanced computational process planning at this critical composite production step. It is of non-linear integer programming and the overall computational complexity depends on the individual project definition, but for the described scenario, it is NP-hard.

3.3. Working principle

While on principle, the APOLLO program is built on Branch & Bound, it is not strictly pure B & B. The reason is pure B & B requires all solutions of the problem to be evaluated or the lower bound to be reached. But for complex problems, the APOLLO optimisation algorithm is not able to calculate all possibilities of larger projects within an acceptable period. Therefore, at the moment the algorithm needs to be stopped by a timer, rendering the outcome a heuristic instead of an analytic one in most cases (Rocha et al. 2008).

The principle work flow of the APOLLO optimisation algorithm is described in Figure 4 where it can be seen that autoclave cycles represent the main level of the B & B solver. For easier understanding all objectives, variables and parameters used by the algorithm are summarised in Table 1. The algorithm starts by creating the first autoclave cycle level, generates different possible loadouts for this cycle and checks if no boundary condition was violated.

If boundaries were violated, the solver looks for different variations within the current autoclave cycle level and goes back up one level if none can be found, cutting that branch. Except when being already in the top level, in this case, all possibilities have been evaluated and the optimisation is considered finished. The two main boundaries are the allowed out-life-time of each layup and the required minimum autoclave loadout.

If no boundary was violated and parts of the project are still unproduced, another autoclave cycle level is added. This depth-first strategy for the B & B optimisation ensures a quick finding of a first solution and thus upper bound for the problem (Shim and Kim 2007; Arnold et al. 2008; Tanaka and Araki 2008).
Figure 4. Work flow of APOLLO optimisation algorithm (Hueber, Fischer, and Schledjewski 2017).

For every autoclave cycle loadout scenario, the availability of the required layups from the cleanroom is checked and if unavailable at time, either waiting time is added or a different loadout scenario is chosen. Once all parts are manufactured, the total production time of the current process order is compared to the upper and lower boundary of the branch and bound system. Depending on this outcome and the availability of different variations on the current autoclave (AC) cycle level, the process is now either finished or repeated for other loadout variations.

Once the first valid solution of the problem is generated, the found production time is kept as upper bound of the problem and added to the boundary conditions. It is updated whenever a better solution is found. From now on any new branch exceeding this upper limit at any time can be cut off without further examination as its outcome can no longer be an optimum.
Table 1. List of objectives, variables and parameters in APOLLO.

| Class                  | Type                          | Entry                                      |
|-----------------------|-------------------------------|--------------------------------------------|
| Objectives            | Primary                       | Production time                            |
|                       | Secondary (passive)           | Autoclave usage                            |
| Decision variables    | Autoclave                     | Loadout of every cycle                     |
|                       |                               | Start time of every cycle                  |
|                       | Cleanroom                     | Start time of every layup                  |
| Parameters            | Project                       | Planning scope (production lot size)       |
|                       |                               | Project part list                          |
|                       |                               | Out-life-time                              |
|                       |                               | Total allowed autoclave waiting time       |
|                       |                               | Possible autoclave cycles                  |
|                       | Part                          | Autoclave cycle times                      |
|                       |                               | Layup time                                 |
|                       | Layup station                 | Available stations                         |
|                       | Autoclave                     | Allowed parts                              |
|                       |                               | Autoclave length                           |
|                       |                               | Allowed autoclave cycles                   |

In order to achieve the desired versatility of the tool, the integrated automatic variations generator is allowed to loosen the minimum AC loading boundary condition and to include waiting periods between AC cycles. This procedure ensures that APOLLO is able to find solutions in all cases, at the cost of increasing the amount of possible variations.

3.4. Mathematic model

More generally the APOLLO model can be described mathematically by the equations in this section.

3.4.1. Project

\[ P(1, 2, 3, \ldots, p) \] Parts in project, \((P1, P2_a, P2_b, \ldots, )\),

\[ N_i(1, 2, 3, \ldots, n_i) \] Jobs (Layup manufacturing) per part, \((\text{amount of part } P1, P2_a, P2_b, \ldots, ); i[1, 2, 3, \ldots \leq p]\), (2)

\[ M_j(1, 2, 3, \ldots, m_j) \] \(m_j\) identical machines (Layup stations) of type \(j, j[1, 2, 3, \ldots \leq p]\); can produce a set of parts \(P_j \in P\), (3)

\[ T_i \] Job process time of part \(i\), (4)

3.4.2. Reactor (Autoclave)

\[ R(1, 2, 3, \ldots, r) \] Reactors (Autoclaves) in Project,

\[ CT(1, 2, 3, \ldots, c) \] \(CT\) Cycle types in project; \(CT_K\) available cycle types for Reactor \(K\); \(CT_K \in CT; K \leq r\), (5)

\[ cycle_f \in c \] \(c\) all cycles in project\(1, 2, 3, \ldots\),

\[ l_i \] Length of part \(i\) in reactor,

\[ L_K \] Usable length of reactor \(K\),

\[ A_{fi} \] Loading scenario. Number of parts \(i\) in cycle \(f\); \(i \in p\). (10)
3.4.3. Boundary conditions

Through the boundary conditions, the generation and validation of the possible problem solutions are controlled and defined.

\[ L_K \geq \sum_{i=1}^{p} A_{i} \cdot l_{P_i} \geq \text{minLoading} \]

Cycle loading of reactor \( K \) for cycle \( f \); all cycles (except last cycle of every type) must be utilized above \( \text{min Loading} \).

\[ ST_K(f \ni N_i) \geq ST_{N_i} + T_i, \forall N_i \in A_{i} \]

Start time of cycle \( f \) in reactor \( K \) containing part \( N_i \) must not start before part production is finished.

\[ ST_K(f) \geq ST_{K}(f - 1) + CT(f) \]

New cycle in reactor \( K \) can only start after previous cycle of same reactor is finished.

\[ ST_{M,l} \geq ST_{M,l-1} + T_l, \forall l \in N_i \cap \forall i \in P_j; \forall j \in m_l; l \geq 2 \]

Start time of job \( l \) on machine \( M_j \) cannot start before job \( l - 1 \) on the same machine is finished.

If no cycle with \( \text{minLoading} \) is possible at current start time, add wait time until \( \text{minLoading} \) can be achieved or one of the boundary conditions below is violated.

\[ ST_K(f) = ST_K(f^0) + WT_K(f) + \text{StepWT} \]

Start time \( ST_K(f) \) for cycle \( f \) in reactor \( K \) equals earliest possible Start time \( ST_K(f^0) \) plus current wait time \( WT_K(f) \) plus one additional wait increment \( \text{StepWT} \).

\[ \sum_r \sum_c WT_K(f) \leq WT_{\text{max}} \]

The total wait time of all cycles \( c \) in all reactors \( r \) is not allowed to exceed a defined max wait time.

\[ T_i + WT_{N_i} \leq OT \forall N_i \]

Process time \( T_i \) plus wait time \( WT_{N_i} \) before processing in reactor, must not exceeding allowed out-life-time \( OT \) for any job \( N_i \).

\[ WT_{N_i} = ST_K(f \ni N_i) - (ST_{N_i} + T_i) \]

The wait time for the job \( N_i \) is start time of the cycle containing the part minus end time of part processing (start time \( ST_{N_i} \) plus production time \( T_i \)).

If a boundary condition is violated, the current cycle loading \( A_{i} \) is replaced by new iteration, which is again checked for possibility. If no valid solution for cycle \( f \) can be found, the loadout of previous cycle \( f-1 \) is altered. If \( f-1 = 0 \) and absolutely no solution with current parameters could be found, \( \text{minLoading} \) is reduced by incremental steps until a solution for the problem is found.

\[ \text{minLoading} - \text{StepLoading} \]

Reduce autoclave utilisation limit by one increment.

3.4.4. All parts produced

The criteria for an iteration to be a solution to the optimisation problem is that it is capable of producing all required parts without violating any of the above boundary conditions.

\[ \sum_{i=1}^{p} N_{P_i} = \sum_{c=1}^{p} \sum_{i=1}^{p} A_{i} \]

Sum of all jobs per parts in project must equal the sum of all parts process in all cycles.
3.4.5. Main objective

The main objective of APOLLO is to minimise the total time required to produce all needed parts, while keeping reactor usage, the secondary objective, as high as possible.

\[
\min \left( \max_{f} (ST(f) + CT(f)) \right) \quad \text{Main objective function: minimise the finishing time of the last finishing cycle in the project.}
\]

(21)

4. Case study

To prove the working capability and usefulness of the developed APOLLO algorithm, it was tested on a complex aerospace part constructed out of several sub parts. The part itself and most used parameters are taken directly from industry. But while in reality, the part is manufactured within a larger production environment with more products sharing resources and capacities, in this work only the part itself is analysed as if it were the single part being produced in the case study environment.

4.1. Problem description

The generic aerospace assembly reviewed in this case study consists of a total of five sub parts (P1–P5) as listed in Table 2. Those labelled Px_a and Px_b (P2_a, P2_b, P5_a, and P5_b) are two-production-step parts. This means that after completion of Px_a, the part needs to be processed a second time in the CleanRoom and autoclave. This is necessary due to intermediate tasks that need to be performed on the Px_a parts prior to finishing the whole layup in Px_b. These tasks are not taken into consideration in APOLLO as they are logistically separated processes and do not directly interact with the considered process chain. Also as the Px_a parts are fully cured, there are no technical limitations for having them on buffer storage. In order to produce one piece of final product a total amount of 11 sub parts need to be manufactured within a minimum time period to avoid intermediate storage and thus fixed capital and to improve total production output.

The attachment parts sets consist of 12 pieces that are manufactured and processed as set together. A similar approach was taken for the small parts assortment which consists of several small parts but will be considered as one in this study. This was done under the knowledge that none of these parts is the bottle neck in the production.

The described production flow is graphically shown in Figure 5, with the displayed numbers being representative for a production volume of eight final assemblies. Raw prepreg material is distributed from the cutter to the CleanRoom as plies. There the layup manufacturing happens according to the available number of layup stations, before the finished uncured layups are moved on to the autoclave area. The autoclave section considers different cycle requirements and multiple autoclaves. The dotted lines represent the flow of the cured Px_a parts from the autoclave back into the clean room for secondary layup.

Figure 6 represents a graphic summary of the parts needed for eight final assemblies and their distribution to the two different autoclave cycle types which are necessary due to different required processing parameters.

4.2. Results

For the described case study, general planning parameters were analysed for their influence on production time together with possible production environment optimisation strategies. In this section, the obtained results using the APOLLO software are shown.

| Part name | Sub part description | Production quantity | Layup time [min] | Available layup stations | Autoclave cycle type |
|-----------|----------------------|---------------------|------------------|-------------------------|----------------------|
| P1        | Large sub parts      | 2                   | 2400             | 4                       | 2                    |
| P2_a      |                      | 2                   | 960              | 4                       | 1                    |
| P2_b      |                      | 2                   | 1440             | 4                       | 2                    |
| P3        | Medium sub part      | 2                   | 480              | 2                       | 2                    |
| P4        | Small parts assortment | 1                   | 360              | 2                       | 1                    |
| P5_a      | Attachment parts sets | 1 (12 pieces)       | 96               | 18                      | 1                    |
| P5_b      |                      | 1 (12 pieces)       | 288              | 18                      | 2                    |
The APOLLO software’s output consists of two parts: total production time and manufacturing order, which is exemplarily shown in the following two tables. The first (Table 3) is the CleanRoom production plan containing the production order for every available layup station and the individual layup production starting times. The second (Table 4) is the Autoclave plan including all needed cycles of every type and the corresponding loading for every autoclave included in the manufacturing scenario.

4.2.1. Planning scope
The first aspect evaluated in the case study was the influence of the planning scope on the mean production time per part. The planning scope is the number of parts considered as one production lot, which is subject to the optimisation.
Table 3. Optimisation result CleanRoom: layup plan, station usage and start times.

| Layup station | Start time | Part name | Layup station | Start time | Part name |
|---------------|------------|-----------|---------------|------------|-----------|
| 1             | 0          | P2_a      | ...           | 1920       | P2_a      |
|               | 2880       | P2_a      | 96            | 5280       | P2_b      |
|               | 3840       | P2_b      | 192           | 6720       | P2_b      |
|               | 5280       | P2_a      | 288           | 8160       | P2_b      |
|               | 6720       | P2_b      | 384           | ...        | 1980      |
|               | 8160       | P2_b      |                | 5          | P1        |
|               | 2400       | P1        | 2340          | 4800       | P1        |
|               | 4800       | P1        |                | 7200       | P1        |

Table 4. Optimisation result Autoclave: autoclave cycle times and loading plans.

| Autoclave | Start time | Cycle type | Loading |
|-----------|------------|------------|---------|
| 1         | 480        | 1          | P5_a, P5_a, P5_a, P5_a, P4 |
| 1         | 960        | 1          | P2_a, P2_a, P2_a, P2_a, P5_a |
| 1         | 1920       | 1          | P2_a, P2_a, P2_a, P2_a, P5_a |
| 1         | 2400       | 2          | P1, P1, P1, P1, P3 |

Figure 7. Influence of planning scope on the mean production time (Hueber and Schledewski 2018).

A larger planning scope allows more combinatorial possibilities but reduces short time planning flexibility. The findings of this study are shown in Figure 7. A clear and significant reduction in production time can be seen for larger planning scopes. The increased number of desired parts increases the optimisation possibilities for the algorithm allowing a higher utilisation and reduced production time. Generally longer planning scopes provide more degrees of freedom to find optimal production combinations. Caused by the ratio of demanded parts to available layup stations the production of odd numbers is less effective as can also be seen in Figure 7. The decrease on production time is largest for few parts and gets less with increasing planning scope with very little gain from 8 to 10 parts.

The benefit of larger planning scopes, although quite expected, is probably the most important finding of the APOLLO project. Because it fundamentally highlights the benefit of computational production planning as larger planning scopes are preferable, but can only be optimised by software solutions like the developed APOLLO tool.

4.2.2. Optimisation of production environment

Beside simple production planning APOLLO is also extremely useful for production environment optimisation. During the studies, the layup of P1 was recognised as the bottle neck of the current production layout. A series with increasing
number of P1 layup stations was conducted therefor with the results shown in Figure 8. An initial drop in production time for additional P1 layup stations can be seen. But after one the benefit of additional stations is cancelled, because at this point the bottle neck is shifted from P1 layup to P2 layup. For further decrease of manufacturing time beyond this point, a parallel increase in available P2 layup stations, as is shown by the second graph in Figure 8, is necessary.

Building up on the bottle neck examination, Figure 9 shows the single influence of the autoclave capacity on the manufacturing times. While additional capacity provides very little benefit, it can be seen that the analysed environment, on the other hand, is very sensitive to autoclave capacity reduction. Yet the data also indicates that one big autoclave is better than an equal capacity split on two smaller one, because it allows better usage of the available space (compare 1 × 12 m and 2 × 6 m).
Although individually additional autoclave capacity does not provide much benefit, in combination with extra P1&P2 layup stations large improvement is achievable. Figure 10 summarises the effect of different production environment optimisation approaches. It shows the importance of the layup capacity for the production time and the potential of the combined approach with an additional autoclave.

4.2.3. Initial variation of the combination seed

Big influence on the initial results and the speed of convergence towards the final optimum were found for the initial order of the produced parts. This initial variation seed poses as the starting point for the following optimisation. Figure 11 shows the found results after 1000, 10,000 and 1,00,000 iterations for different starting combinations. It has to be mentioned that only a random selection of the total 5040 possible initial variations were analysed in the depicted manor. The concept was implemented as ‘Initial Variation’ into an algorithm improvement where the shown effect is utilised to check all possible variations before using the best one for the following optimisation. This drastically improved the results found for complex problems within limited calculation times.

While checking for the ideal Initial Variation causes additional calculation time to be required at the optimisation start, the improved results easily compensate for it. Figure 12 shows the improvement achieved through this implementation in comparing the results of both with or without Initial Variation. Originally both algorithm versions were given 2 min optimisation time, but as the Initial Variation takes up additional calculation time, the original algorithm was run a second time. This time, it was allowed the same total time as the new algorithm needed with Initial Variation. As can be seen even with equal total times, the Initial Variation results are significantly better. This finding proves the usefulness of the Initial Variation implementation and the improved optimisation more than justifies the additional calculation requirement.

Figure 11. Influence of initial variation seed on the optimisation convergences.

Figure 12. Comparison of found results after fixed times with and without Initial Variation.
4.3. Problems and possible improvements

It was found both by the authors and in literature (Herroelen 2005; Shim and Kim 2007; Pahl and Voß 2014) that most research focuses on idealised academic examples while fairly limited work on application relevant scenarios is available. Especially, the classic identical machines job-shop example has been a focus of work for decades with many improvements of algorithm effectiveness for the specific task. As impressive as these developments are, the focused research onto this specific scenario leaves out many real production constellations. APOLLO is an attempt to provide a solution for the specific planning problem of interacting discrete and batch production as it occurs in composite aerospace manufacturing. The program is explicitly designed to fulfill industry needs and represent real production environments.

At the moment the main drawback of APOLLO are the long required calculation times. This stems mostly from the tremendous increase in variations associated with project complexity. For example, while the algorithm is able to solve the problem for three parts within a few hours, it is unable to consider all possible variations for four parts within a time frame of 5 days. Although the program is fully designed and ready for full-scale production optimisation, the current long calculation times partly limit its application. Reducing calculation time per variation and especially improving the branch cutting capabilities of the algorithm would highly increase the program’s usability (Herroelen 2005). Although aerospace industry does not have the issue of short time demand changes, production deviations can still occur due to part failure or scrap. In the simplest way, the production plan is adapted accordingly by reactive scheduling (Herroelen and Leus 2004, 2005; Valledor et al. 2018). Further approaches for handling disruption in production planning can be found in Belassiria et al. (2018); and Yue et al. (2018). But optimisation times must not be too long therefor. The focus for future improvement of the program should thus be in ways to effectively reduce the number of variations that need to be evaluated. Additionally, the number of evaluations per second could be increased by further streamlining the code and by implement multi-threading to allow usage of more CPU cores.

The use of more advanced, intelligent solvers would be the logical next step now that the current APOLLO version has proven its usefulness and the potential of production planning software in complex industry environment.

In the development of APOLLO realisation of a working software and prove of concept to show its effectiveness and usefulness to industry were prioritised over algorithm and run-time optimisation. It is probably not the most refined tool, but a well working attempt at a challenging problem, trying to close the gap between academic efforts and industrial needs. We are aware that a manifold of mathematically far more developed production planning approaches and models exist in research, also for combined batch and discrete manufacturing, as can be found in Amorim, Günther, and Almada-Lobo (2012); Farahani, Grunow, and Günther (2012); and Amorim et al. (2013). But as these are for different scenarios, APOLLO is to our knowledge the first attempt on computerised optimisation for this specific application of interacting discrete and batch production, typical for aerospace composite manufacturing.

Although the case study parts and all parameters are directly taken from industry, it was not possible to compare the reached optimisation results to the industrial production times. This is because the here discussed assembly is part of a bigger production environment with four parallel autoclaves and additional assemblies with varying production amounts. Unfortunately, we were neither able to simulate this full environment at this point nor single out the real production times of only the case study assembly from the available production information.

But APOLLO is still a certain improvement to the current status as there is no comparable solution available and planning is done manually on weakly basis (planning scope of 4) right now. With APOLLO increased planning scopes become possible, which were shown in this work to be highly beneficial.

As a next evolution of the program, the combination of the implemented B & B algorithm with a heuristic method could be highly beneficial (Shim and Kim 2007). Or like shown in Rocha et al. (2008), where the combination of B & B with a GRASP (greedy randomised adaptive search procedure) metaheuristic showed extremely promising results. For longer planning periods and high complexity scenarios the rolling horizon approach described in (Jans and Degraeve 2008; Lobos and Vera 2016; Rodriguez et al. 2017; Ziarnetzky, Mönch, and Uzsoy 2018) could be a very valuable implementation to enhance usability of the APOLLO tool. The idea is to split the optimisation horizon into a detailed and an aggregated period. Through iteration the border between these two periods is continuously shifted forward until detailed planning is achieved for the full planning horizon.

A desirable extension of APOLLOs planning capabilities would be towards raw material provision and scheduling of the afterwards needed NDT and CNC trimming. Both additions would fall under the classic job-shop scenarios. The material preparation would fit the most basic problem with defined jobs needing to be scheduled and distributed onto parallel identical machines to achieve zero tardiness for all jobs. The job due dates would be subject to the APOLLO autoclave and layup planning result. The usefulness of NDT and CNC inclusion would depend on the allowed intermediate storage size before these steps and the gain must be counterbalanced against the increased tied-up capital. To avoid unnecessary complexity growth, both proposed expansions should be implemented as independent secondary optimisations.
5. Conclusion
Advanced production planning is a necessity, not only for composite industry, but is especially challenging for complex manufacturing environments. One of which is the combination of discrete layup production with subsequent autoclave batch curing found in the prepreg aerospace industry. Project APOLLO was created to prove the usefulness of computational tools in production planning at the interface of discrete layup manufacturing and autoclave batch processing. In its development, great emphasis was placed on allowing a highest degree on versatility and ease of use. Through the successful implementation of B & B optimisation promising results were found highlighting the large financial benefit of computational production planning for the composite aerospace industry. This in our view makes the APOLLO development a powerful tool and valuable research contribution for this specific, but complex production planning problem. While specifically designed for it, the combination is probably not exclusive for the composite aerospace industry, making the concept also interesting for a wide field of industry besides prepreg autoclave manufacturing.

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Note
1. Prepreg: semi-finished production where the reinforcement fibers (woven or non-woven fabrics or tapes) are pre-impregnated with the reactive polymer resin. In order to prevent unwanted curing reactions, the material needs to be stored in frozen condition. After unfreezing prior to processing it only has a limited out-life-time.

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