Using Business Analytics for Decision Support in Zero Defect Manufacturing of Composite Parts in the Aerospace Industry

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Abstract: In multi-staging manufacturing environments, more than necessary reworking at an early stage can prevent costly defects at later stages. One goal of the EU research project ZAero (Zero-defect manufacturing of composite parts in the aerospace industry) is to generate precious feature data by implementing an inline quality control for the manufacturing process of carbon fibre components of aircraft. However, for each feature detected by ZAero's inline quality control, operators must decide whether or not to rework that feature. Additional reworking of non defects can reduce expensive defects in later stages, but the increased effort should not have a significant impact on production. To help operators make the right decisions, an extensible hybrid decision support system (DSS) is proposed, which combines a software application that visualizes 3D-based process-specific feature data and supports the execution of rework decisions with web-based business analytics dashboards. The dashboards visualize data generated by part flow simulation experiments for various rework strategies, as well as valuable data from a manufacturing execution system (MES). The proposed DSS can be easily customized to integrate additional data treasures from the ever-increasing amount of data in the industrial sector.

Keywords: Decision Support Systems, Aerospace Engineering, Edge Computing, Fog-Based Analytics, Discrete Event Simulation, Industrial Internet of Things, Business Intelligence, Digital Twin, Zero-Defect Manufacturing.

1. INTRODUCTION

In the aerospace industry very high quality standards have to be met (Tomic et al., 2012). For the manufacturing of carbon fibre parts this is currently solved through extended end-of-line inspection (Capriotti et al., 2017) in combination with re-work processes to deal with defective parts. Also, in-situ visual inspection (Addepalli et al., 2017) is used for quality control, which is currently causing huge productivity losses during lay-up and has become a real bottleneck in carbon fibre parts manufacturing.

In the EU research project ZAero (Zero-defect manufacturing of composite parts in the aerospace industry) (Eitzinger, 2016) the future manufacturing of the A320neo wing covers provides the background for the developments. In the ZAero project a solution to reduce productivity losses by developing integrated inline quality control methods for the key process steps automatic fibre material lay-up and curing is provided.

This paper focuses on the lay-up inline quality control, that can detect features and additional data for these features on carbon fibre plies. Decision support systems (DSS) (Simon, 1960; Shim et al., 2002) support the cognitive processes of workers in decision processes. Simulation-based DSS are cited in many examples in literature (Mahdavi et al., 2010), (Salama and Eltawil, 2018) . . . , but less research focuses on visual design, the challenging integration into the concrete process and easy extensibility of the DSS. In our work, we implemented a DSS using a hybrid infrastructure that supports machine operators in deciding which features have to be reworked. We combine a specialized fat client software application that visualizes the current 3D based process-specific data from inline quality control and enables the execution of rework decisions, with web-based business analytics dashboards that support the decision-making task. The dashboards display data from a Manufacturing Execution System (MES) or a Production Data Acquisition (PDA) system and result data from part flow simulation (PFS) experiments with different rework strategies. We implemented these interactive dashboards using the business intelligence (BI) / data discovery product QlikView that also operates as a web server. Users can easily extended the dashboards to display additional data from other data sources in the future. Dashboards can also support line managers to analyze the performance of various production line part flow scenarios.

In (Döppner et al., 2018) the authors describe their research approach to elaborate the hitherto not investigated problem class of Empty Unit Load Device (ULD) repositioning (EUR) in air cargo. In their work they propose a web-based intelligent decision support system (IDSS) that combines a rule-based expert system with a good explanation facility and heuristics. Their multi-criteria decision making model takes into account costs, compliance and benefit. The performance of each individual criterion of an

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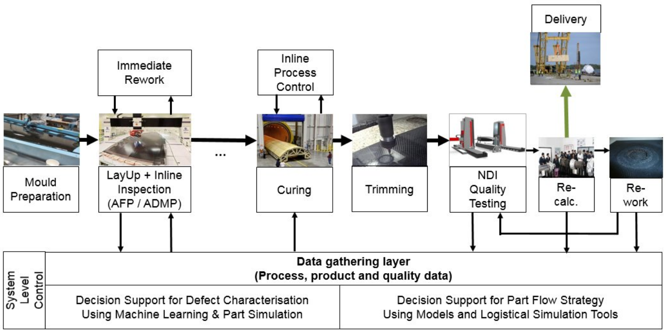

Fig. 1. ZAero - System Overview

alternative is displayed to the user with the help of a traffic light system. The overall score for each recommendation is then calculated by assigning numbers to the traffic light colors for each criterion and using a weighted sum method (WSM). Integrating additional 'non-rule-based' data was not an objective of this approach.

Not enough focus was put on the human-centered aspects of interactivity say (Parsons et al., 2015). They describe their work on a tool named Visual Analytics of university Research networkS and IndusTrY (VARSITY) and discuss aspects such as interactivity, interaction and scoping using their tool. VARSITY also deploys the user frontend in HTML. But instead of using standard software, their backend system is implemented individually using Apache CouchDB, MySQL, Node.js, D3.js, JQuery and some individual connectors for necessary Web APIs, which seems to be more complex than using a BI standard solution.

The rest of the paper is structured as follows; Section 2 introduces the ZAero production process and the planning of the decision making process. Section 3 describes in detail the DSS implementation. Finally, section 4 presents conclusions and possible future extensions.

2. APPROACH

Figure 1 shows an overview of the ZAero system. After tooling preparation and Automated Dry Material Placement (ADMP®) or dry Automated Fibre Placement (AFP) lay-up of carbon fibre material for one layer (a complete part consists of multiple layers), two different non-contact sensors-types scan the carbon fibre surface of that ply in the inline inspection step for defect detection: A fibre orientation sensor (FScan) with 5 cameras that uses a reflection model of carbon fibre to measure fibre orientation (Zambal et al., 2015) and a laser profile scanner (LScan) with 3 cameras that acquires 3D profiles, to scan a ply. Figure 2 shows the lay-up and inspection system. The large data amount from both sensors then is aggregated by edge computing (Al-Fuqaha et al., 2015), and combined to identify features, their size and their location. Machine learning classifiers predict the type of the feature (angle deviation, gap, twist, . . .).

The overall inspection result then is written to an hierarchical data format file (HDF5) called the manufacturing database (MDB), that also contains the CAD-model for the part. In a next process step, a structural simulation (finite element simulation) is performed for all features found on a ply. The algorithm first calculates a margin of

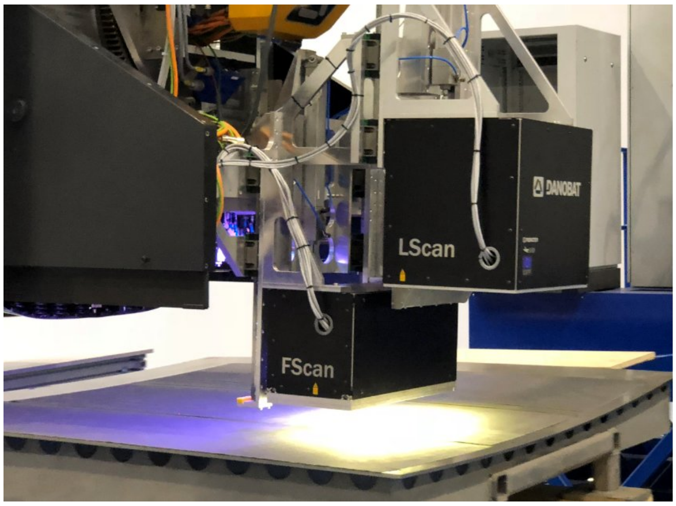

Fig. 2. ADMP LayUp + Inline Inspection for a Demo Part

safety (MoS) for each feature location without the defect and then repeats the calculation assuming a defect. The calculated values for MoS before and after defect then are appended to every feature of the current ply in the HDF5 file. The MDB and structural simulation together can thus serve as support for a digital twin of the ply.

In a next step, the decision makers must decide which features to rework and perform the rework before another ply can be placed over the current ply. After all plies of a wing are layered, next steps are curing the part in the oven and trimming. This is finally followed by an ultrasonic non destructive inspection (NDI) quality testing and some final recalculation and rework steps.

Of course for the inline layup inspection all critical features (defects) must be reworked - but what features are critical? Usually, operators configure this by setting rework rules based on some property values for e.g. the extent value of a special feature type (e.g. rework all fuzzballs >= 2mm). In general, the inspection software could only forward those features that correspond to this rigid set of rules. However, one would deprive oneself of the possibility of detecting possible trends in the overall process (creeping deterioration). More efficient is also to provide non defect features and later to determine which of them must be classified as to be reworked by using rework rules. This procedure now offers the possibility of reworking more than the minimum required by the process. Any additional rework will of course also result in increased correction time. But the usage of hard limits within rework rules does not seem to be perfect, and additional rework can help to reduce defects that occur at later stages in the process (e.g. NDI quality testing) and thus help to reduce future rework times.

2.1 Planning the Decision Making Process

Two roles are assumed to be involved in optimizing a plant: The machine operator and the line manager.

The line manager is responsible for delivery of all orders in time. His job is to ensure that resources are available to match the demand (number of moulds, number of fibre placement machines, number of active mould preparation

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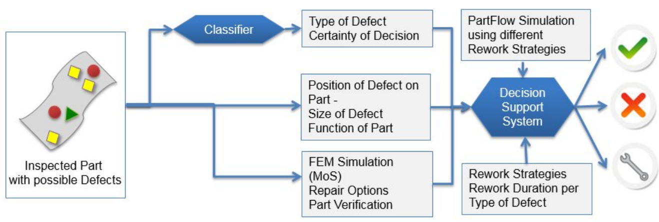

Fig. 3. DSS Overview

stations, shift plans). He uses PFS to ensure proper order fulfillment and is more likely to need support with tactical decisions.

The machine operator uses the decision support tool operationally to decide whether features need to be reworked or not, and is interested in the estimated order delivery information for his current order.

In the first phase of the project, the DSS shall support the machine operator in his decision-making process. According to (Anthony, 1965) in this case the unstructured decision to be taken is what features to rework. The operator can use the essential characteristics of the feature (location, size, extent, ...) to manually define for each feature if this has to be reworked or not. Additionally, the event type, the MoS calculated by structural simulation and a calculated severity value is supported.

But manually clicking for any feature would be too time intensive and erroneous. A faster way for the operator is to select an alternative from pre-definable rework strategies depending on suitable rules, which then rapidly sets an appropriate *IsRework* flag value for any corresponding feature. The operator then should use the default rework strategy suggested by the line manager, but has to rework at least all features the minimum rework strategy *Rework NIO* (= rework all defects) defines to be reworked. For each existing alternative, the DSS provides information on how many features would be reworked and how long the rework time would then take.

Information about the current order timeliness help in this task too; thus visualizations from results of PFS runs that execute for the whole plant those rework strategies are integrated. If PFS results show that there is enough time for the concrete order, the operator maybe decides to rework some features more, to hopefully get less rework to do in later process stages. Figure 3 shows the most relevant parts of the DSS.

3. IMPLEMENTATION

The decision to rework also non defects can be made more easily if decision makers know more about the additional rework times required and the delay in the delivery of their specific order. In the ZAero project a system-level DSS was developed that assists human decision-making in assessing defects and part flow planning through the production line. The tool is supported by a model built using the discrete event simulation tool "Tecnomatix Plant Simulation" from Siemens for part verification and logistical planning. Simulation model experiments are performed periodically; the potential future data from simulation runs is stored and used for predictive analytics later.

Inspection systems and generally all production / industrial I4 environments generate a multitude of data: "The next wave of IoT innovation will be driven by data analytics" say (Patel et al., 2017). There are also trends in DSS areas to use Business Intelligence (BI) Tools (Felsberger et al., 2017) to cope with the ever-increasing amount of data.

On one hand, the DSS shall visualize all individual process-relevant data as well as possible and also requires corresponding functions in the software solution in order to take over the desired decisions of the user and thus adapt processes accordingly. On the other hand, in order to support decision-making as much as possible, the DSS should be able to present relevant information from as many different data sources as possible. Since the second part seems to be more volatile, due to the constantly changing processes in production environment, a split approach was implemented. In principle, web solutions are of course always to be preferred. However, they usually also require higher development costs. To create a web solution for the first more stable part seemed to be too costly, therefore a typical fat-client architecture was chosen.

For the second, more data-intensive part, the integration of the display of relevant data into the overall solution via a configurable, a more easily adaptable BI Web solution was decided. On the tool market there exist a lot of solutions that can be used for implementing BI solutions. Some of the most used Big Data visualization tools (Minelli et al., 2013) are:

- Tableau, www.tableausoftware.com
- QlikView, www.qlikview.com
- MicroStrategy, www.microstrategy.com
- D3JS, Data Driven Documents java script library, http://d3js.org
- SAS, www.sas.com ...

QlikView was chosen for this project, because of the integrated support for simple extract transfom load (ETL) tasks (Inmon, 1992). In our environment clean data can be accessed; Therefore, the need for sophisticated transformation scripts is low, which saves the cost of using an often expensive data warehouse (Inmon, 1992).

Thanks to its in-memory architecture QlikView also convinces with good performance (Rantung et al., 2018) and enables easy ad-hoc data filtering as well as fast drilldown possibilities, which thus also offers a good user experience when testing hypotheses. Analytics experienced users can quickly create BI dashboards. Even inexperienced users can then analyze data with those dashboards created. QlikView thus already supports the broad spectrum of features of a data-driven DSS demanded by (Power, 2008). The Developer Edition from QlikView enables rapid development and first initial testing. A QlikView server is available for integrated use, which then also provides features such as the permanent time-controlled loading of data and functions as a web server, via which dashboards can be made easily accessible to end-users.

The final DSS infrastructure shown in Figure 4 therefore uses a combination of a fat client Decision Support Tool and BI web-dashboards built using QlikView.

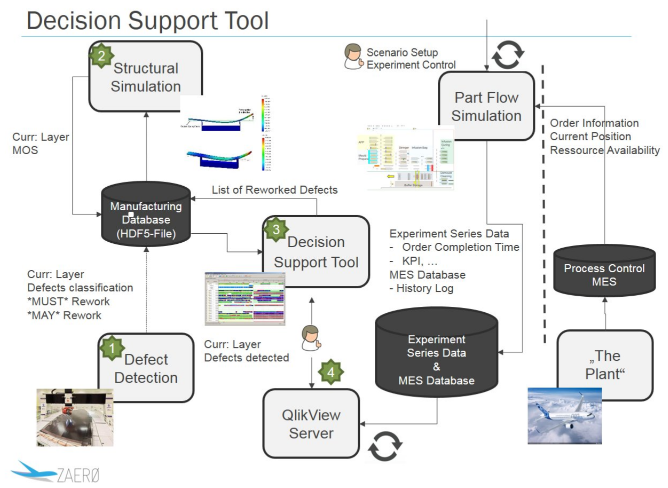

Fig. 4. DSS Infrastructure and HDF5 file (MDB) usage

Table 1. Results from Plant Simulation Experiments

Experiment Duration	Observations	24		48		96		120		144	
	Strategies	3	4	3	4	3	4	3	4	3	4
		(min)									
35 days		1,56	1,63	1,57	1,78	1,68	2,24	1,85	2,41	1,93	2,55
63 days		1,61	1,92	1,67	2,22	2,12	2,78	2,31	3,05	2,50	3,35
91 days		1,66	2,02	2,17	2,43	2,41	3,25	2,69	3,75	3,48	4,02

3.1 Tecnomatix Plant Simulation + Database + QlikView

As shown in Figure 4, the PFS model is used in multiple ways: For calculating experiment series for different rework strategies and to generate data the way a MES system would normally generate it. On each experiment series run, the PFS initializes with the current plant status first and then executes multiple series of experiments using different rework strategies. For the MES part, Plant Simulation is executed sometimes (identified by an ever incrementing *RunId* value) and then writes history information of orders and machines data into an MS-SQL server database. This order history information was used to examine whether the MES data that can later be expected in real production can also be helpful to support decision making (= data from the past for descriptive analytics).

In order to obtain a suitable stochastic for the rework strategies experiment series (identified by an ever incrementing $ExperimentSeriesId$ value), several runs are carried out for each strategy in parallel. To see how much time is needed to compute the series, some experiments were carried out. As hardware an Intel Xeon Gold 6136 CPU@3GHZ, 192GB memory and 2*12 Cores was used. The Results of the experiments are depicted in Table 1. Finally, the setting was chosen, that executes 4 strategies with each 96 observations to simulate 63 days in future; This takes less then 3 minutes to execute.

The DSS infrastructure now uses a scheduler to launch the simulation tool any 15 minutes execute this setting and write data; And the QlikView Server was configured to load this data also in 15 minutes intervals, but always starts 5 minutes later.

3.2 Decision Support Tool

The .NET based Rapid Application Development (RAD) tool PPOpt (Project Planning and Optimization) from Profactor was used, to implement a software solution to support decision making in our environment. This GUI (graphical user interface) tool helps the machine operator to decide which of the features need to be reworked. The developed solution solves the following tasks among others:

- Read and write HDF5 files.
- Show the inspection results for a ply as a list and per click show features and their location in 3D space.
- On mouse over a feature in 3D space, a tool tip is displayed. If users click on a feature in 3D space, the corresponding feature in the list will be selected.
- Enables to set the $IsRework$ flag for individual features of a ply.
- A module named *ReworkStrategies* enables to define rework strategies (see Figure 6). Theses strategies can be executed by users, to fasten the process to define what features shall be reworked. Rules can be attached to strategies to define what features to rework (e.g. rework all fuzzballs >= 2mm). If a single strategy is later applied, all the rules of the strategy are reviewed. If at least one rule matches, the $IsRework$ flag is set for this feature.
- One special strategy can be marked as IsSeverityCalculator. An algorithm then uses the n rules limits (=CompareValue) to calculate a single severity value to express the magnitude of the problem:
  $Severity = \max(\frac{FeaturePropertyValue_j}{CompareValue_j})\Big|_{j=1}^{n}$
  $\rightarrow Severity \geq 1.0$ (=defect) must be reworked
  $\rightarrow Severity < 1.0$ could be additionally reworked
- Using the module *ReworkDuration* operators can configure how long a special feature type needs to be reworked.
- Enables access to further analytical QlikView data (PFS results, current ERP/PPS/MES data ...) using deep hyperlinks to support the decision making process.

The tool periodically checks the HDF5 file of the current part in production. If a *PLY_DEFECTS_VERIFIED* event from structural simulation is detected, all features and also the properties of the ply inspection are displayed to the operator. Figure 5 shows the GUI. To decide whether to rework a particular feature or not, users may consider the following properties of the feature:

- $Type$ (angle deviation, gap, twist, overlap, foreign object, fuzzball, early/late cut, ...)
- $Severity$
- $Area$, $Length$, $Width$
- MR = MoS reduction
- MoS - before and after defect (for quick and detailed analysis)

The operator can use the predefined *ReworkStrategies* to reduce the time needed to decide which features to rework and which not. (e.g. 'Rework NIO + 25% IO' = the worst 25% (depending on $Severity$) of non-defective features should also be reworked)

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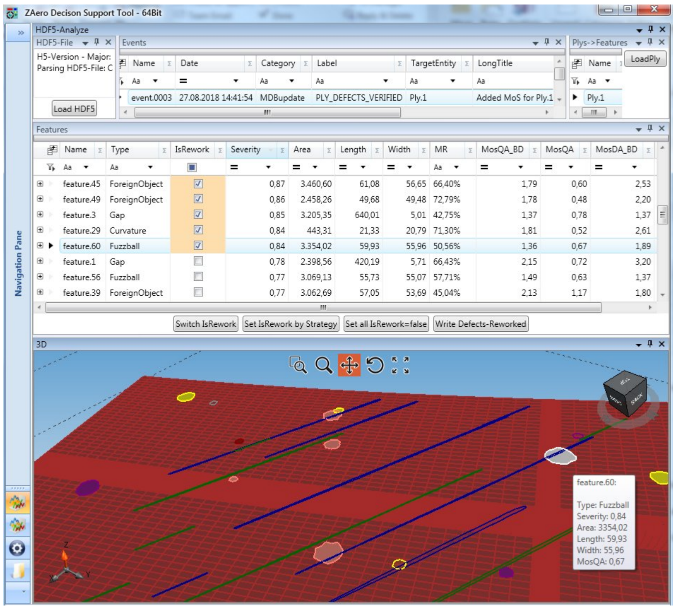

Fig. 5. ZAero DSS Tool - displaying Sample Data

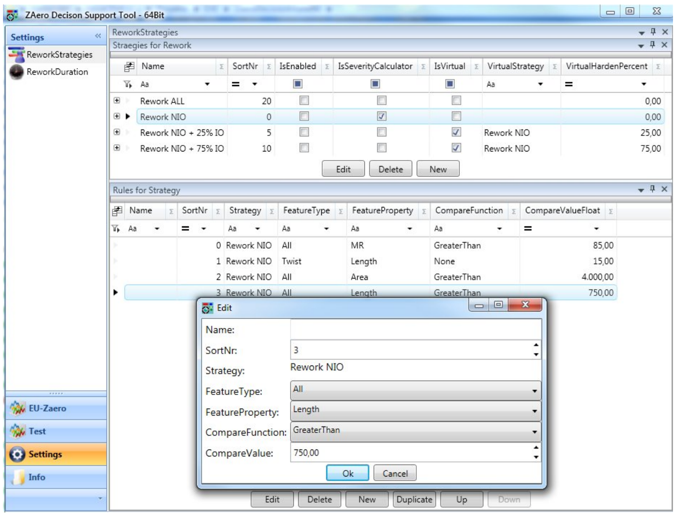

Fig. 6. DSS - Rework Strategies and Rules

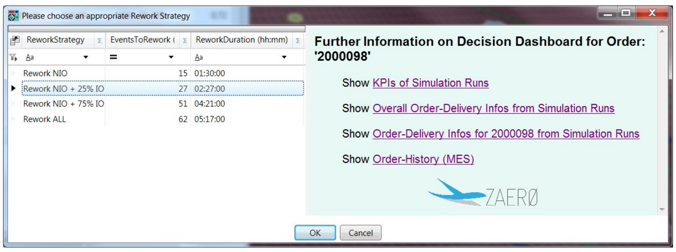

Fig. 7. DSS Dialog to choose a Rework Strategy + Hyperlinks to QlikView Dashboards

A click on the 'Set IsRework by Strategy' button opens an additional DSS-dialog as shown in Figure 7 that uses this information. For each rework strategy the dialog indicates how many features have to be reworked and gives an estimate of how long the rework would take then.

This dialog also serves as a bridge to access results of detailed PFS runs for different rework strategies. The operator can choose the hyperlinks to access the appropriate QlikView dashboards shown in Figures 8, 9, 10.

Simulation Duration: 63 Days | Observations per RepairStrategy: 96

Avg. of KPI per Rework Strategy

KPI	Rework Strategy	Rework NIO	Rework NIO + 25% IO	Rework NIO + 75% IO	Rework All
# parts out		122,00	122,00	119,94	118,07
# Throughput per Day		2,18	2,18	2,14	2,11
AGV 1 traveled Distance [m]		113 605,32	106 626,13	96 970,88	96 602,79
AGV 2 traveled Distance [m]		152 408,72	141 333,31	129 038,18	127 712,33
avg deviation of order completion time (Full Orders)		-18 784,38	-18 397,76	-9 731,79	3 398,95
avg deviation of order completion time (Partial Orders)		30 497,75	30 221,65	30 221,85	30 235,45
avg Leadtime (order - Life-Time)		1 384 996,36	1 273 217,82	1 153 881,18	1 143 932,41
avg ocupation PC_Storage_01		0,26	0,17	0,09	0,09
Indicator #1.1 number of parts per month		61,00	61,00	59,97	59,04
Indicator #1.2 avg lead time		1 426 756,61	1 274 327,25	1 116 939,43	1 100 748,14
Indicator #1.3 avg total rework time		24 742,69	38 928,49	57 261,50	60 998,13
Indicator #2.1 avg Floor to Floor (lay-up) time per part		272 869,35	293 038,29	319 505,94	323 503,20
Indicator #2.3 avg AFP Rework time		11 308,16	25 267,70	43 594,33	47 394,40
Indicator #2.5 avg re-work time		253,32	253,42	253,48	253,33
Indicator #2.7 count of rework operations		97,87	197,36	240,69	253,33
Indicator #3.2 time in oven		92 055,36	92 961,79	91 310,99	91 504,70
max Leadtime (order - Life-Time)		1 581 938,14	1 555 066,71	1 526 566,41	1 515 006,98
Weighted (+ only) deviation of order completion time (Full Orders)		7 447,82	8 071,44	13 112,94	23 554,49
Weighted (+ only) deviation of order completion time (Partial Orders)		66 044,74	65 760,29	65 743,33	65 752,28

Fig. 8. Dashboard: KPIs of Simulation Runs

Simulation Duration: 63 Days | Observations per RepairStrategy: 96 | #Orders: 1

PlanFinishTime

OrderId	ExpNoName	PlanFinishTime	95th Percentile FinishTime	InTime
2000098	Rework NIO	2018-10-31 12:08:38	2018-10-31 06:54:42	
	Rework NIO + 25% IO	2018-10-31 12:08:38	2018-10-31 07:04:54	
	Rework NIO + 75% IO	2018-10-31 12:08:38	2018-11-01 09:24:41	
	Rework All	2018-10-31 12:08:38	2018-11-01 15:40:15	

Fig. 9. Dashboard: Order-Delivery Info for 2000098 from Simulation Runs

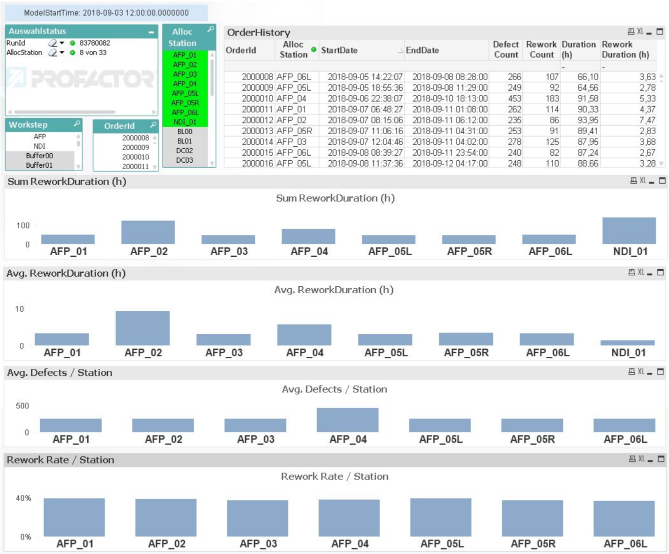

Fig. 10. Dashboard: Order-History (MES/PDA)

The Dashboard in Figure 9 shows e.g. for each rework strategy if the 95th percentile finish time for this order is in time or delayed provided that all lay-up stations would use this rework strategy.

All this information helps the operator to choose a concrete rework strategy which then defines all features that have to be reworked. If there is enough time, more rework should be planned to hopefully get fewer defects in later stages.

After rework is done, a click on the 'Write Defects-Reworked' button sets the flag *IsRework* for all reworked features in the MDB too. Structural simulation therefore can also consider effects over several layers in the next run for all not reworked features. This button click also writes an appropriate event into the MDB, to trigger the lay-up to continue work.

The proposed DSS infrastructure can easily be adapted to display additional data, as the visualization of simulated MES/PDA data in the solution has proven. MES data e.g. provides helpful hints for optimizing production. For one simulation experiment *AFP_04* station was set to produce more features and the workers of the lay-up machine *AFP_02* were configured to rework slower. Operators can see this clearly in the "Avg. ReworkDuration" and "Avg. Defects/Station" charts depicted in Figure 10 and thus respond in a timely manner (e.g. perform preventive maintenance on *AFP_04*).

4. CONCLUSIONS AND FUTURE WORK

The presented hybrid decision support system infrastructure provides machine operators with all information / visualization they need for the decision-making process of planning necessary rework tasks in production. Users can also easily extend BI dashboards to integrate additional valuable data sources in the future.

In a next work step, the PFS and dashboards will be further developed, to better support line managers that want to analyze the performance of different production line part flow scenarios (e.g. add additional lay-up machines). The current simulation model also does not take into account the fact that more rework in earlier phases will lead to less rework in later phases of production. In a next work step, the model will be updated to respect an appropriate *NDI-Rework Decrease Factor*. Correct settings for this factor can be determined during real production then using DoE (Design of Experiments) (Box et al., 1978). The simulation experiments showed that *NDI-Rework* can be a bottleneck in some situations, so reducing rework there may help to optimize the whole plant.

Future research can use the location information of the feature to guide the worker to this location on the ply e.g. by using a beamer/laser that projects the location of the erroneous feature on the ply. Alternatively, a suitable augmented reality technology can support the worker with suggestions for the necessary rework tasks.

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