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DIPARTIMENTO DI MECCANICA

Risk-based scheduling in the remanufacturing of turbine blades

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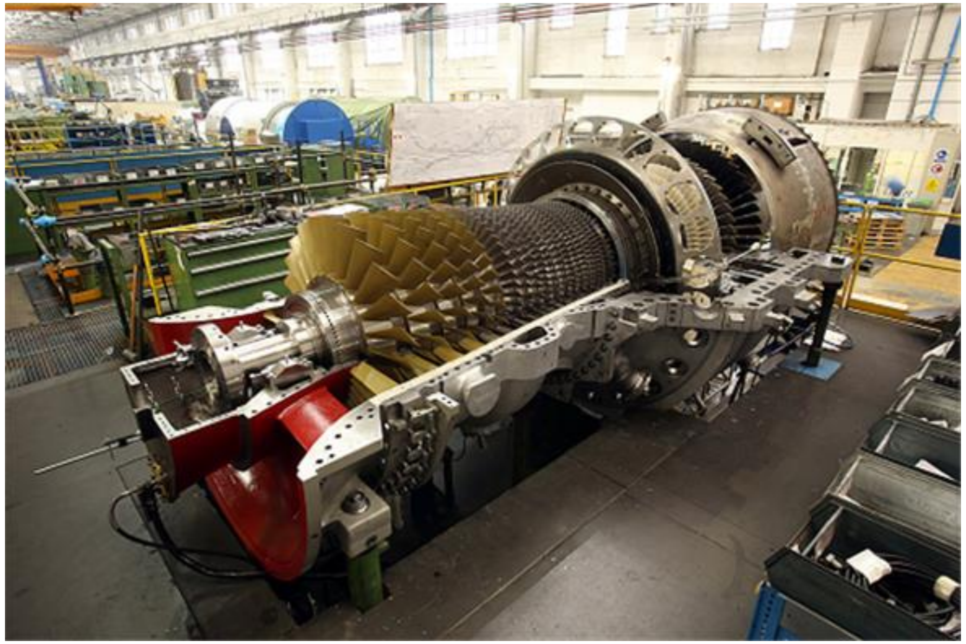
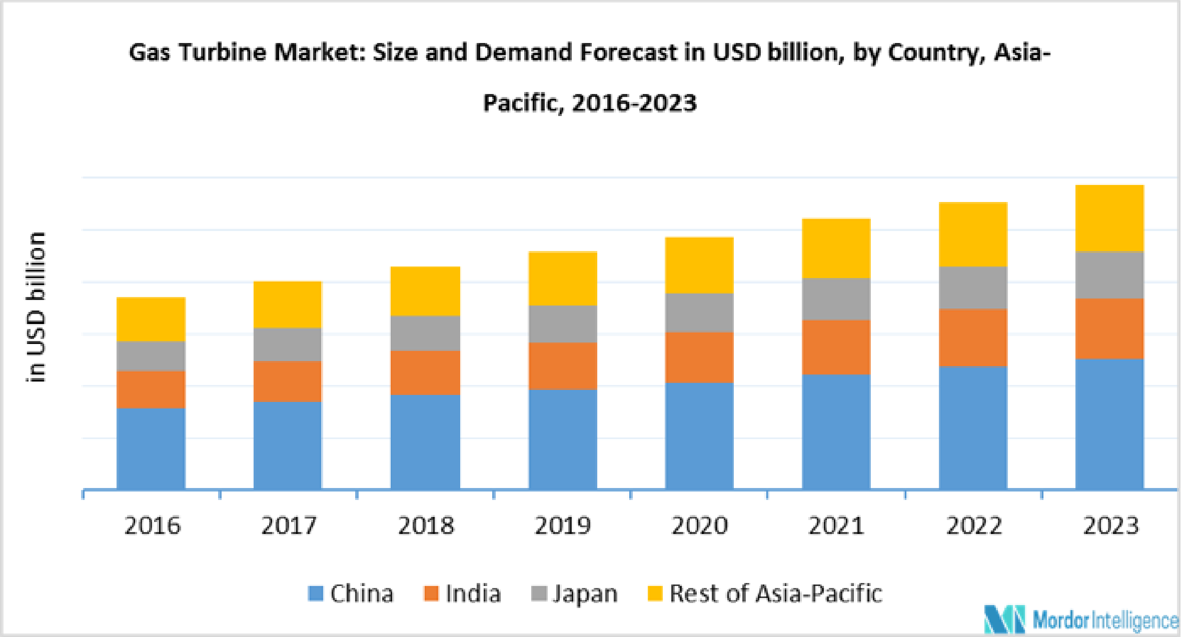
Gas Turbine





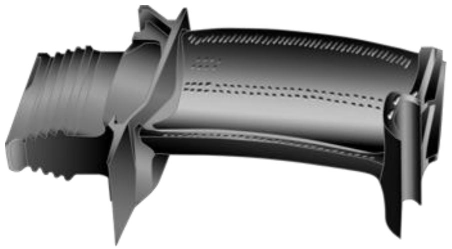
Gas Turbine: most efficient power generation plant
Leading Manufacturers: GE, Siemens, Ansaldo, Mitsubishi

The global gas turbine market size

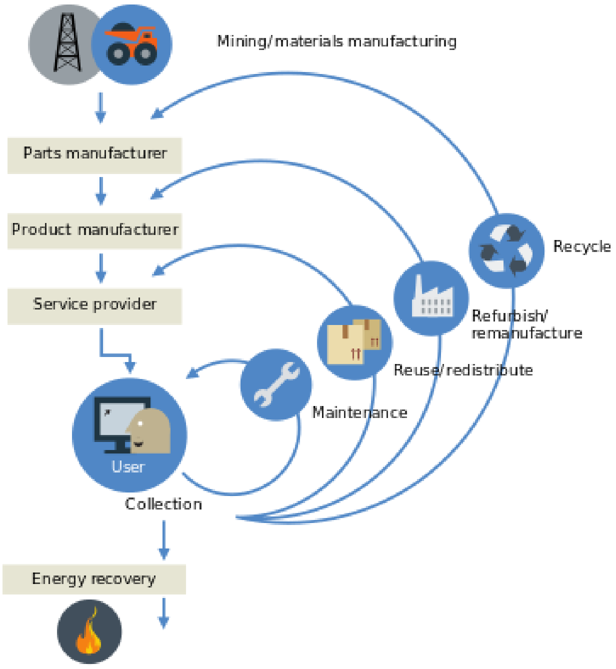
- Estimated at US $5.89 billion in 2019[1]
- Expected to US $12.03 billion by 2027
- Predicted annual growth rate 7.4%[2]

1. https://www.mordorintelligence.com/industry-reports/gas-turbine-market
2. https://www.globenewswire.com/news-release/2020/10/06/2104651/0/en/Gas-Turbine-Market-Size-Worth-Around-US-12-03-Billion-by-2027.html

Gas Turbine Blade



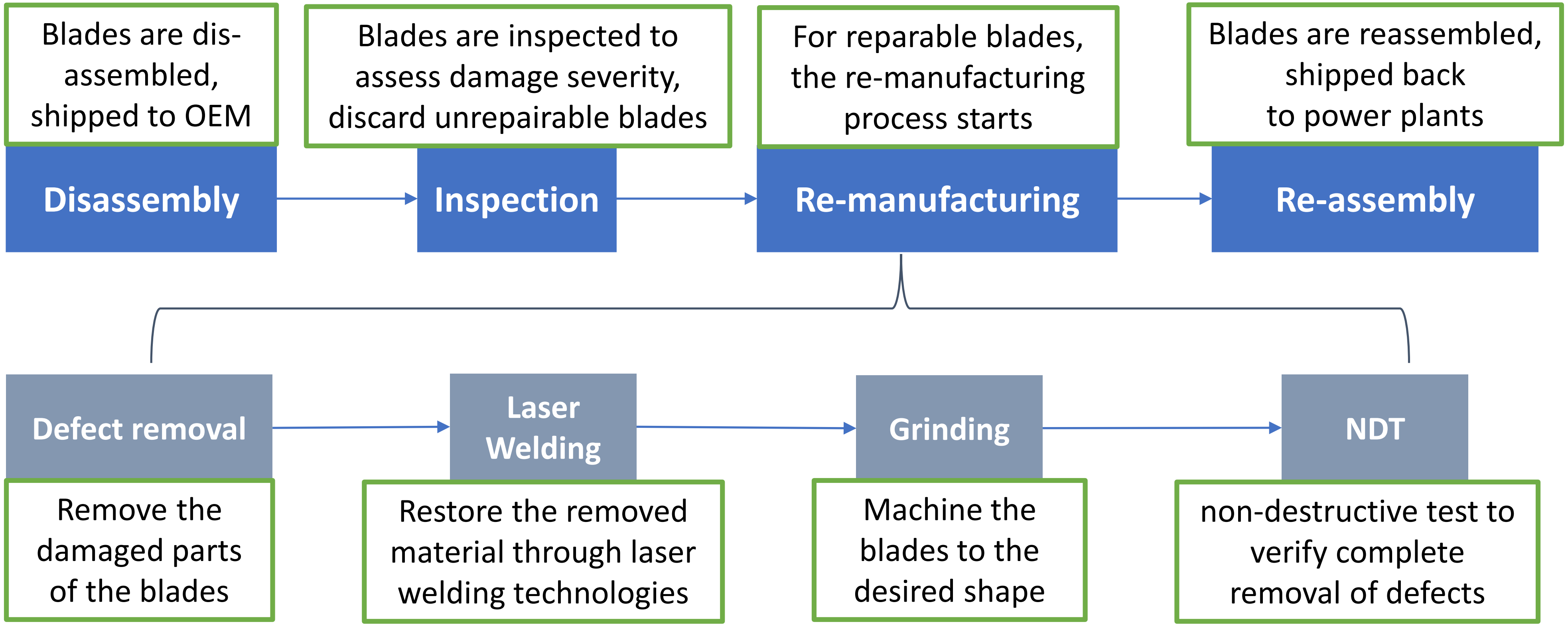
25,000 hours



- **High-value** product (single blade ≈ 10,000 euro)
- The life cycle of gas turbine is 25,000 hours, after this, blades need to be disassembled and maintained
- Due to the high value, the power plants often require **refurbished** blades
- Matching the typical characteristic of **remanufacturing** and circular economy business model

Remanufacturing of turbine blades

The blades are processed in **batches**



Disassembly

Blades are dis-assembled, shipped to OEM

Inspection

Blades are inspected to assess damage severity, discard unrepairable blades

Re-manufacturing

For reparable blades, the re-manufacturing process starts

Re-assembly

Blades are reassembled, shipped back to power plants

Defect removal

Remove the damaged parts of the blades

Laser Welding

Restore the removed material through laser welding technologies

Grinding

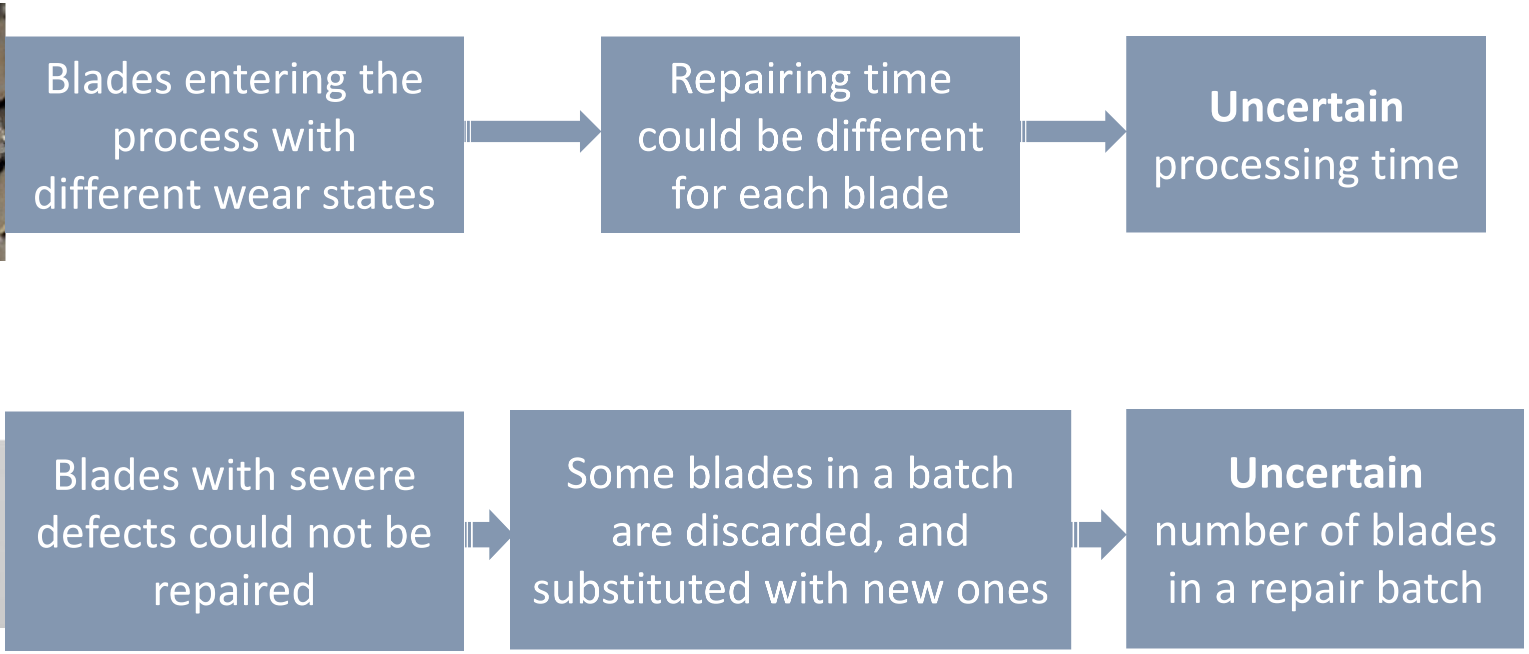
Machine the blades to the desired shape

NDT

non-destructive test to verify complete removal of defects

Uncertainty

The repair process is affected by a significant degree of uncertainty



Blades entering the process with different wear states

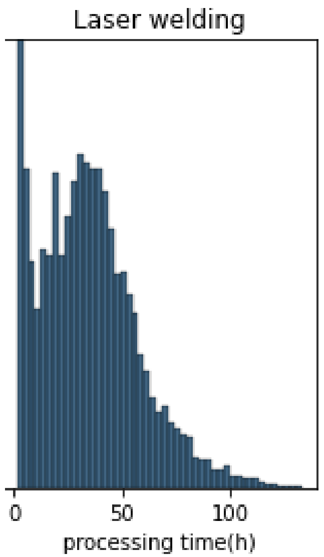
Repairing time could be different for each blade

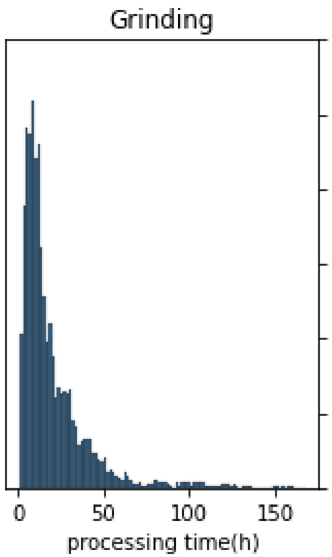
Uncertain processing time

Blades with severe defects could not be repaired

Some blades in a batch are discarded, and substituted with new ones

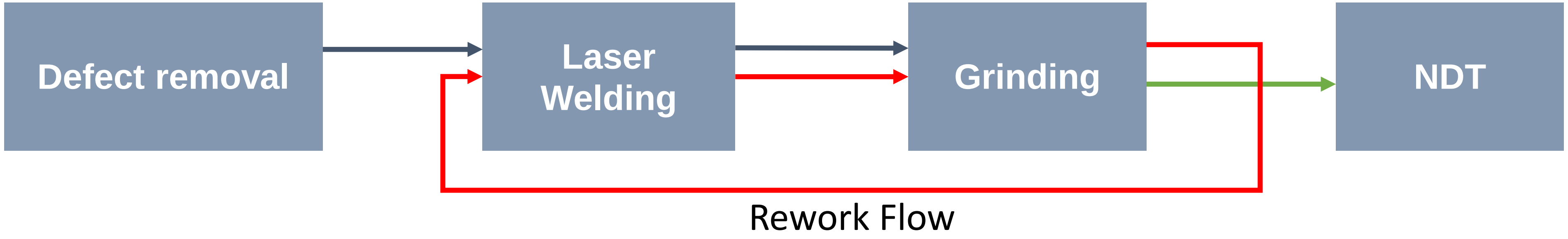
Uncertain number of blades in a repair batch





Grounding on these, the **processing time** of each batch of blades is uncertain, and **cannot** be described by classical distributions

Rework



- For the repair activities laser welding and grinding, blades quite always need to be reworked by repeating these two operations, thus requiring the same resources

- (1,2,1,2) reentrant model, all batches of blades need rework flow

Problem Statement

Laser welding

Grinding

We consider the scheduling of the batches of blades at the **bottleneck resources**, laser welding and grinding phases, for repairing.

2-machine flow shop

The processing times of each batch of blades on the different machines could vary according to the level of damage and number of blades in each batch

General distributed Processing time

All the batches of blades need to be **reworked** by repeating the same sequence of operations

Rework

The objective function of the repair process is to maximize the utilization of the considered resources

Makespan

A robust scheduling approach is needed to mitigate the impact of uncertainty

VaR

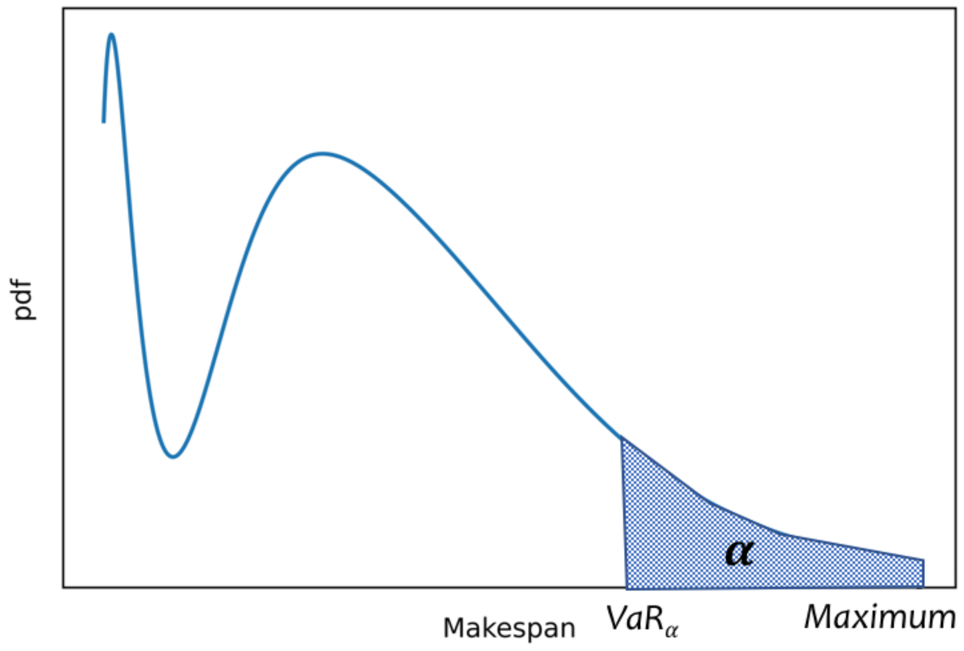
A stochastic 2-machine flow shop scheduling problem with rework

$$F2 \mid (1,2,1,2) - reentrant, \boldsymbol{P}_{ij} \mid VaR(Cmax)$$

Problem Statement – Value-at-Risk

Risk measure is one of popular robust scheduling approach used to determine the value of objective function in order to cover for unexpected uncertainties

1. Estimate the stochastic feature than expected objective function
2. Less conservative than minimax/ minimax regret approach
3. Stem from financial optimization area and popular in scheduling field



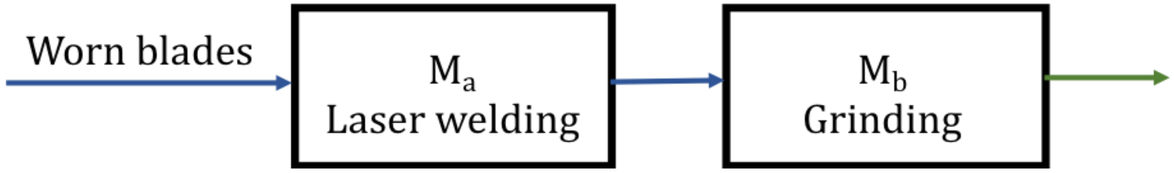
Application Steps:

1. Describe the uncertainties associated to the processing times
2. Derive the distribution of the makespan
3. Evaluate the VaR of the makespan

Managerial Insights:

- VaR value is the maximum makespan we can experience in the best $1-\alpha$ percentage of the scenarios
- The $1-\alpha$ level confidence that the makespan will not excess the VaR value

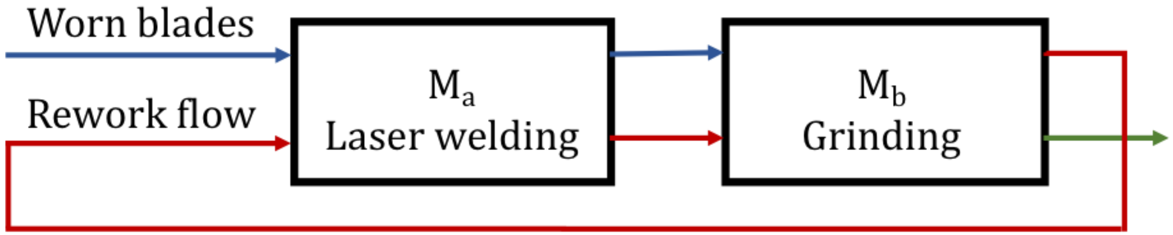
Problem Statement



$$F2/prmu/\ \boldsymbol{p}_{ij}/VaR_{C_{max}}$$

Problem 1

Two-machine permutation flow shop scheduling problem with **stochastic processing times** aiming at minimizing the **value-at-risk** of the makespan



$$F2/reentrant/\ \boldsymbol{p}_{ij}/VaR_{C_{max}}$$

Problem 2

Two-machine **reentrant** flow shop scheduling problem with **stochastic processing times** aiming at minimizing the **value-at-risk** of the makespan

Solution Approach

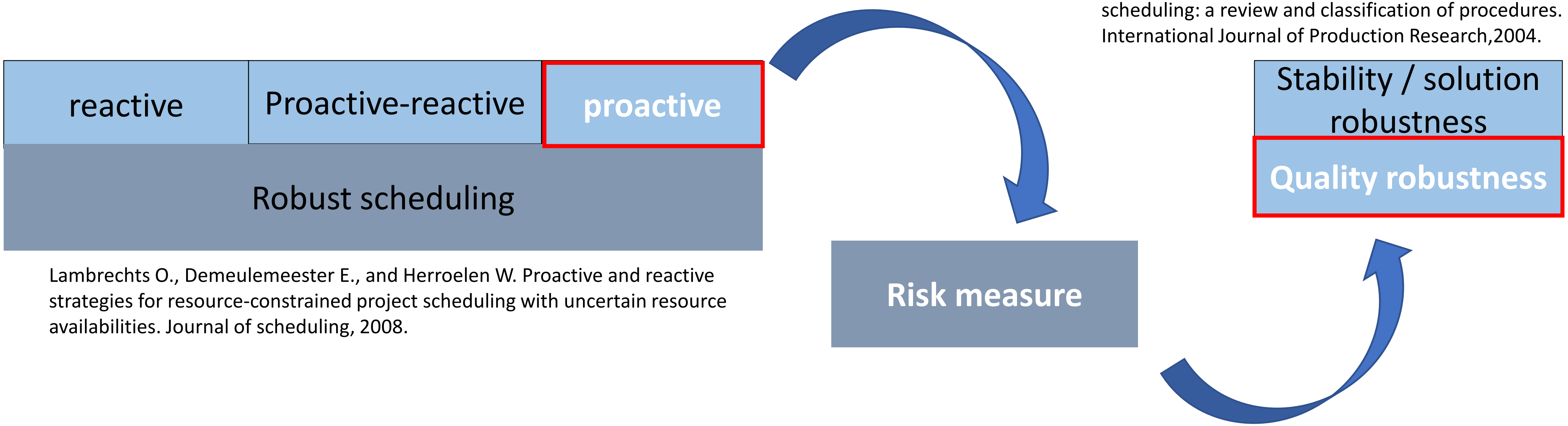
To solve the two-machine (reentrant) flow shop scheduling problem with general distributed processing times, aiming at minimizing the value-at-risk of the makespan:

Phase-type distributions are exploited to fit the general distributed processing times

Markov Activity Network(MAN) is exploited to model the stochastic network

Branch-and-Bound algorithm is developed to find the optimal schedule minimizing the **VaR**, thus mitigate the impact of uncertainty

State of Art



reactive | Proactive-reactive | **proactive**

Robust scheduling

Risk measure

Stability / solution robustness

Quality robustness

Lambrechts O., Demeulemeester E., and Herroelen W. Proactive and reactive strategies for resource-constrained project scheduling with uncertain resource availabilities. Journal of scheduling, 2008.

Herroelen W. and Leus R. Robust and reactive project scheduling: a review and classification of procedures. International Journal of Production Research,2004.

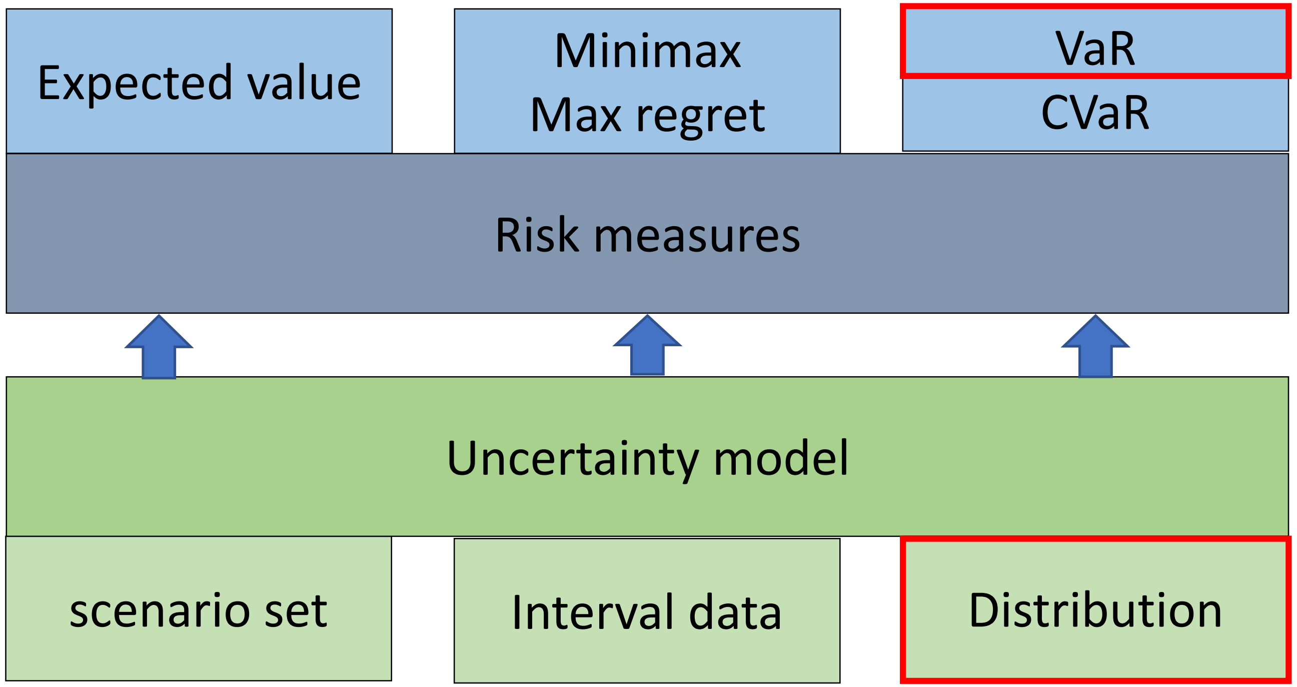
Uncertainties in the remanufacturing plants arise primarily from varying processing times due to the different used phases of manufacturing parts. This thesis focuses on **proactive scheduling**, creating a baseline schedule to pursue the **quality robustness** aiming at minimising the makespan, by exploiting **risk measure.**

State of Art - Stochastic scheduling approaches

MarioLevorato,RosaFigueiredo,andYuriFrota.Exactsolutionsforthetwo-machinerobust flow shop with budgeted uncertainty. European Journal of Operational Research, 2022.

Panos Kouvelis, Richard L Daniels, and George Vairaktarakis. Robust scheduling of a two- machine flow shop with uncertain processing times. IIE Transactions, 2000.

Michel Gourgand, Nathalie Grangeon, and Sylvie Norre. A review of the static stochastic flow-shop scheduling problem. Journal of Decision Systems, 2000.



Expected value

Minimax

Max regret

VaR

CVaR

Risk measures

Uncertainty model

scenario set

Interval data

Distribution

Semih Atakan, Kerem Bülbül, and Nilay Noyan. Minimizing value-at-risk in single-machine scheduling. Annals of Operations Research, 2017.

Learning based approaches: (out of the scope of this thesis, left for future research direction)

- Machine learning, deep learning technologies for scheduling problems
- Reinforcement learning for stochastic scheduling problems

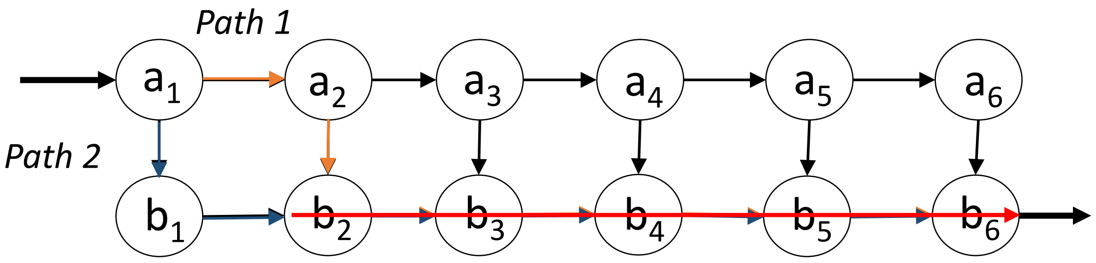
State of Art - Research Gap

1. NO existing contribution addresses **value-at-risk** as the risk measure on the 2–machine (reentrant) flow shop scheduling problem

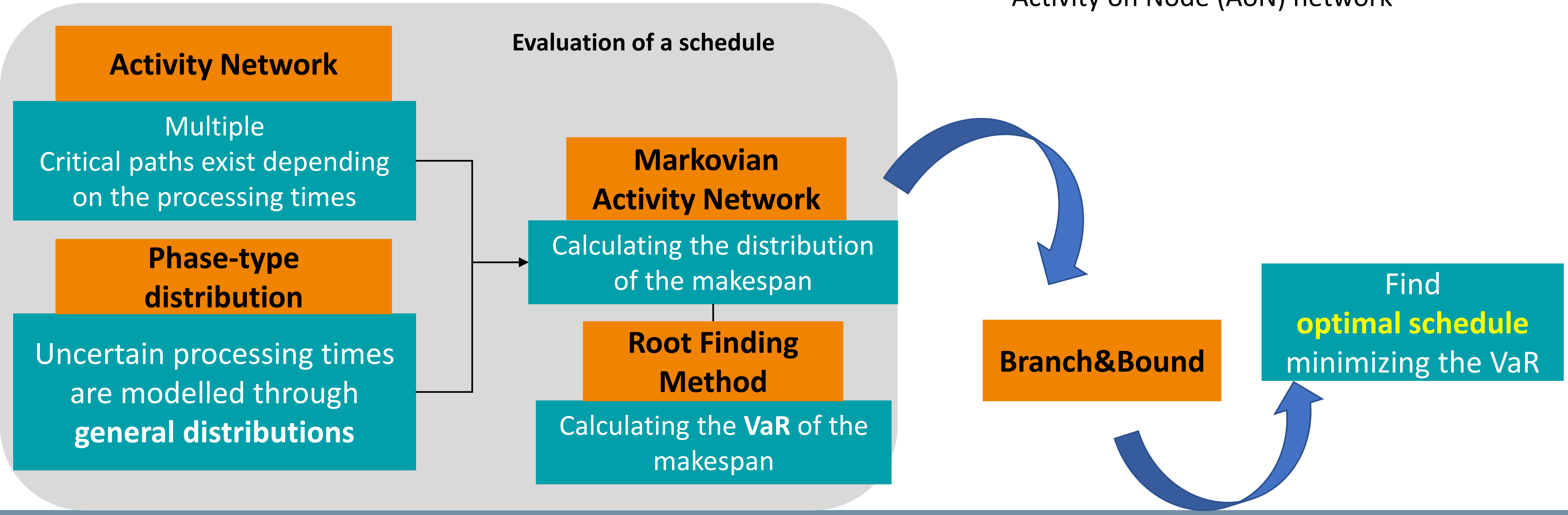
2. The processing time need **general distribution** to fit real distributions in the manufacturing plants

3. Evaluating VaR needs **complete information of distribution** of the makespan grounding on general distributed processing times

Solution Framework



Activity on Node (AoN) network



Evaluation of a schedule

Activity Network

Multiple Critical paths exist depending on the processing times

Phase-type distribution

Uncertain processing times are modelled through **general distributions**

Markovian Activity Network

Calculating the distribution of the makespan

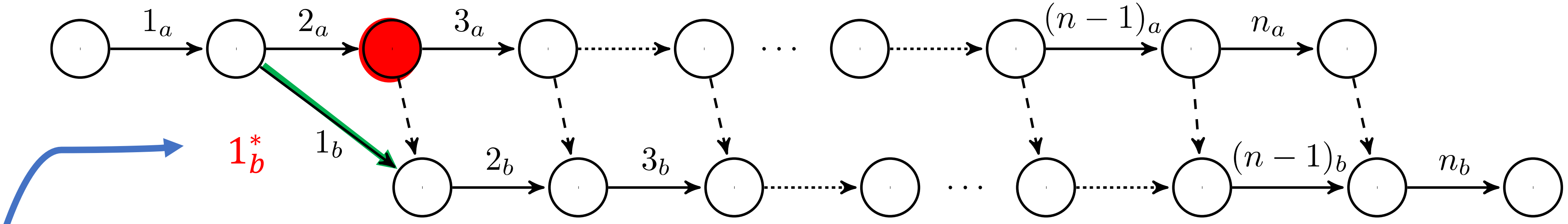
Root Finding Method

Calculating the **VaR** of the makespan

Branch&Bound

Find **optimal schedule** minimizing the VaR

Markovian Activity Network-AoA network



- **Job** index 1,2,…,n, **Machine** index: a,b, Activity on the Arc
- **Nodes** denote the state of the processing
- **Dashed lines** denote the precedence relations

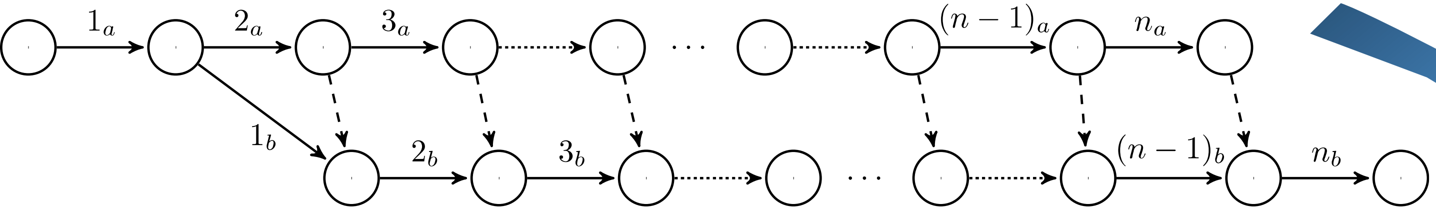
MAN: at a given time *t*, an activity can only be in one of the following states:

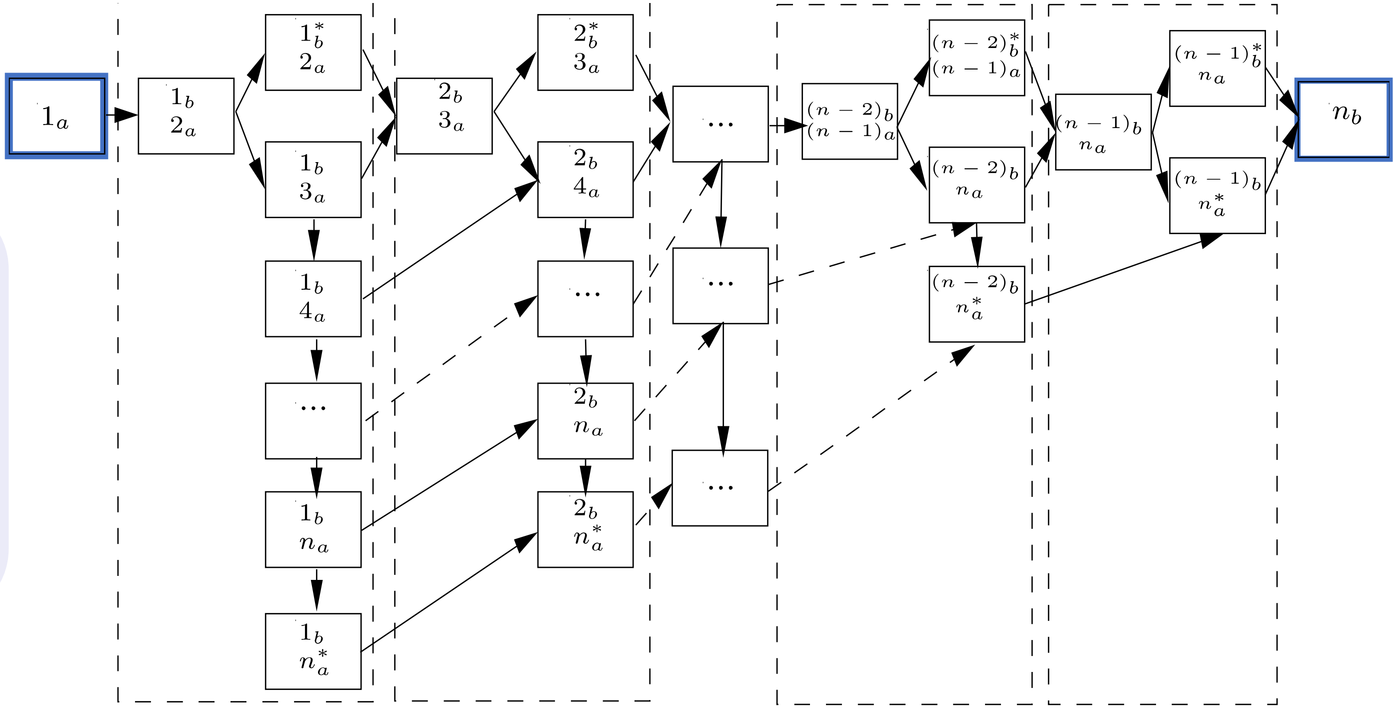
- **active**: it is being executed
- **dormant**: it has been completed but there is an uncompleted activity incident on the same destination node
- **idle**: it is neither active nor dormant

Kulkarni, V. G., & Adlakha, V. G. (1986). Markov and Markov-regenerative PERT networks. *Operations Research*, *34*(5), 769-781.

Markovian Activity Network-CTMC

AoA network with all the processing times are stochastic variables





- Automatically generation of all the possible states
- The first state is 1_a
- The last state is n_b
- From the initiation of first state until the absorbing state, i.e., completion of n_b, is the **makespan** of the network (stochastic)
- A continuous time Markov chain (CTMC)

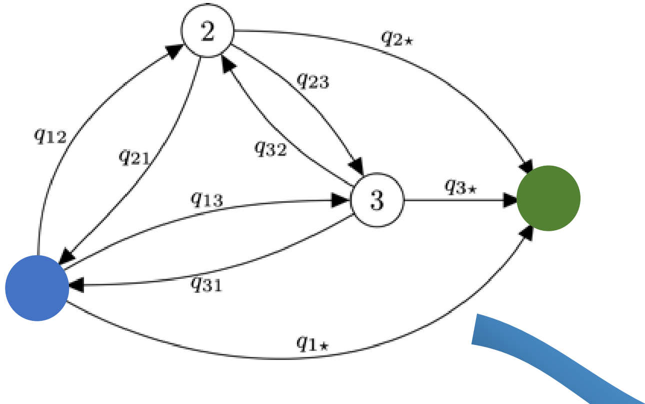
Kulkarni, V. G., & Adlakha, V. G. (1986). Markov and Markov-regenerative PERT networks. *Operations Research*, *34*(5), 769-781.

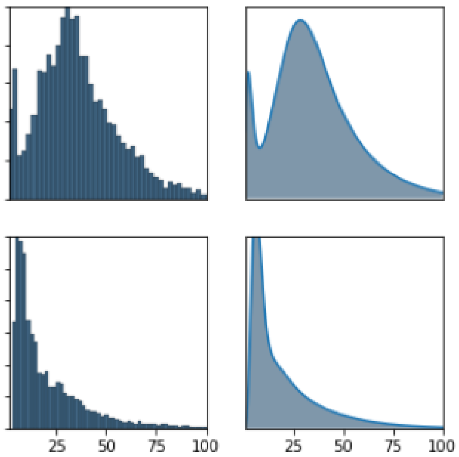
Markovian Activity Network(Phase-type)

All the processing times are stochastic variables

- ▪Fit the general distribution with multi-peak/heavy tail
- ▪Could be incorporated into MAN(only for exponential version in Kulkani)

Example of a PH distribution





PH fitting result example

Phase-type distributions

- ▪Convolution or mixture of exponential distributions
- ▪Theoretically fit any kind of distributions
- ▪Represented by a initial vector β and matrix T
- ▪Could be incorporated into MAN

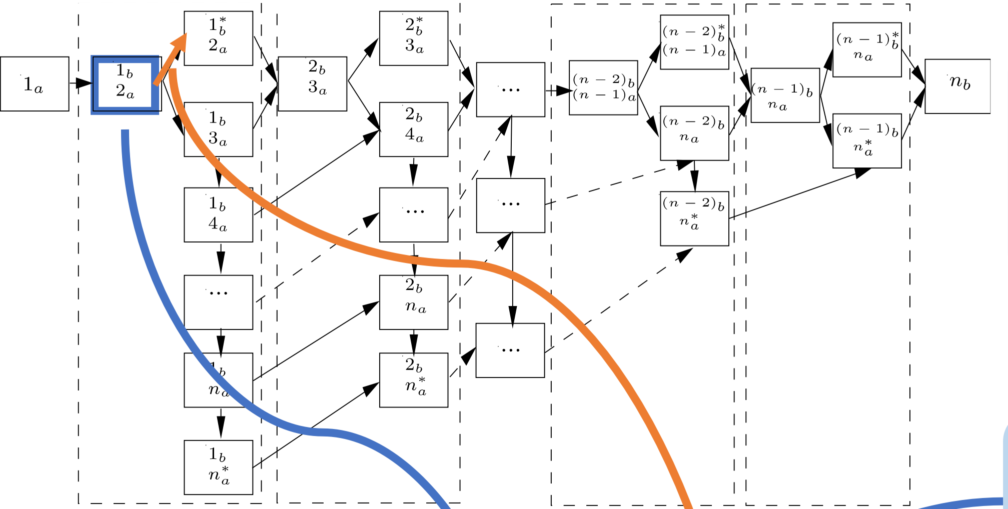
$$\beta = [\,0.5 \quad 0 \quad 0.5\,]$$

$$T = \begin{bmatrix} -2.4 & 0.91 & 0.74 \\ 1.3 & -2.5 & 1.2 \\ 0 & 0.85 & -0.85 \end{bmatrix}$$

PH example

Angius, A., Horváth, A., & Urgo, M. (2021). A kronecker algebra formulation for markov activity networks with phase-type distributions. *Mathematics*, *9*(12), 1404.

Markovian Activity Network(Kronecker Operation)



The CTMC can be used to derive the infinitesimal generator matrix for **exponential distributed** processing times, while for **phase-type distributed** processing times, **Kronecker operations** are needed to derive the infinitesimal generator matrix

Representation of **state condition**:

- Kronecker sum all **running** activities
- Diagonal block matrix in CTMC infinitesimal matrix

$$D(\boldsymbol{s}) = \bigoplus_{\boldsymbol{s_u}=R} T_u$$

Example:

- state $(1_b, 2_a)$: $T_{1_b} \oplus T_{2_a}$
- state $(1_b, 2_a)$ to state $(1_b^*, 2_a)$: $t_{1_b} \otimes I_{2_a}$

Representation of **transition between states**:

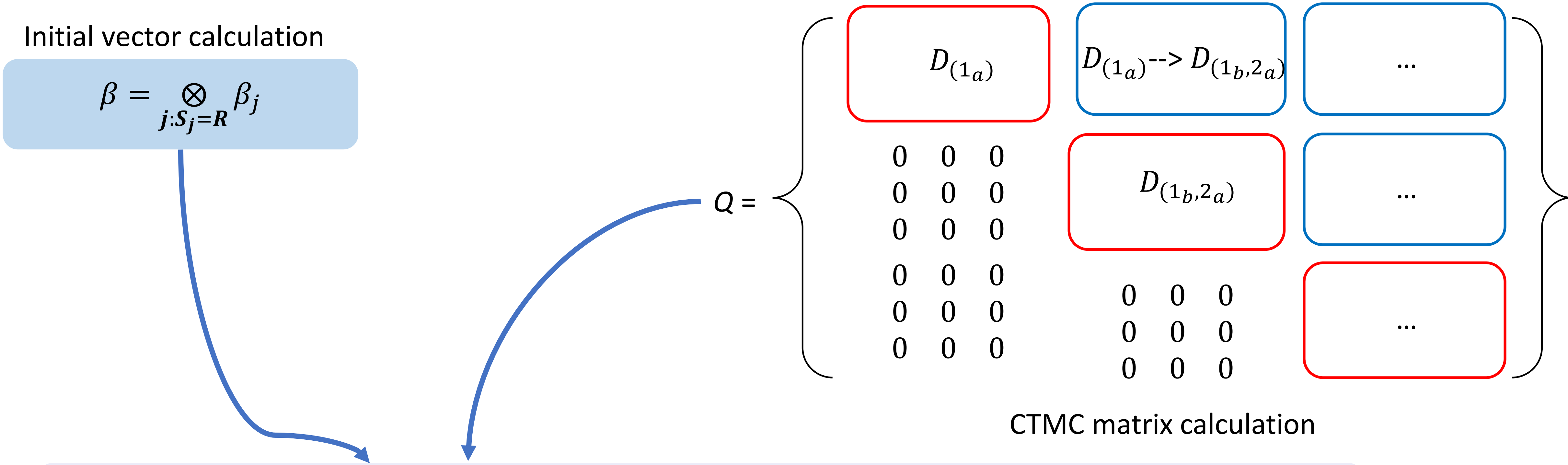
- Kronecker product based on state transition
- Non-diagonal block matrix in CTMC infinitesimal matrix

$$\otimes S_v\,, \quad S_v = \begin{cases} t_v, R-C \\ \beta_v, P-R \\ I_v, R-R \end{cases}$$

R:running	P: pending, waiting for its predecessors to complete and be allowed to start	C: complete	derived from MAN assumption: active/dormant/idle
T: Matrix of PH distribution	β :initial vector of PH distribution	$t = -T\mathbb{I}$	I : identity matrix

Angius, A., Horváth, A., & Urgo, M. (2021). A kronecker algebra formulation for markov activity networks with phase-type distributions. *Mathematics*, *9*(12), 1404.

Markovian Activity Network(2-m flow shop)



Initial vector calculation

$$\beta = \bigotimes_{j:S_j=R} \beta_j$$

$$Q = \left\{ \begin{array}{ccc} D_{(1_a)} & D_{(1_a)} \text{-->} D_{(1_b,2_a)} & \dots \\ \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} & D_{(1_b,2_a)} & \dots \\ \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} & \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} & \dots \end{array} \right\}$$

CTMC matrix calculation

$F(t) = 1 - \beta * e^{t*Q}\mathbf{1}$ Exponential of matrix, Computation intensive

$VaR_\alpha = \inf\{t |\ F(t) \leq 1 - \alpha\}$ Root finding operation with multiple expm operations

α is the pre-specified risk level

Numerical approach to calculate the exponential of matrix and Root Finding

Multiple approaches exist to calculate the exponential of matrix operation and root finding to calculate the VaR of distribution. We select some of them to identify the best performing ones with extensive experiments.

- Exponential of matrix operation $F(t) = 1 - \beta * e^{t*Q}\mathbf{1}$
  - Eigen decomposition/Jordan canonical form, *exact*
  - CAM method, *approximate* approach
  - Krylov method, *approximate* approach

Burgelmanand J, Vanhoucke M.Computingprojectmakespandistributions:Markovian pert networks revisited. Computers & Operations Research, 2019.

Higham NJ. The scaling and squaring method for the matrix exponential revisited. SIAM Journal on Matrix Analysis and Applications, 2005.

Al-Mohy A and Higham NJ. Computing the action of the matrix exponential, with an application to exponential integrators. SIAM Journal on Scientific Computing, 2011.

- Root finding approach $VaR_\alpha = \inf\{t|\ F(t) \leq 1 - \alpha\}$
  - Bisection
  - False position method
  - Illinois method
  - Boost, Bracket and solve method

McNamee, John M., and Victor Pan. *Numerical Methods for Roots of Polynomials-Part II*. Newnes, 2013.

Boost. Boost C++ Libraries. http://www.boost.org/, 2020.

Grounding on extensive tests and comparison, **Krylov expm approach** and,
Boost **Bracket and solve method** were proved to be the most promising approaches

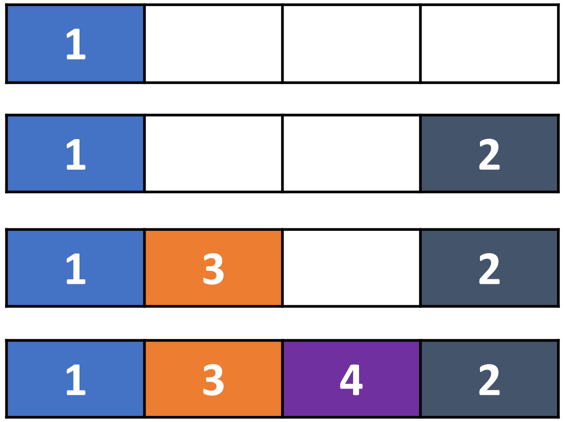
Branch-and-Bound

Grounding on the estimation of schedule solutions, we developed branch and bound algorithms to find the optimal schedule

- Branching scheme
- Search Strategy
- Initial solution
- Bounds (leaf nodes and partial nodes)
- Dominance rule

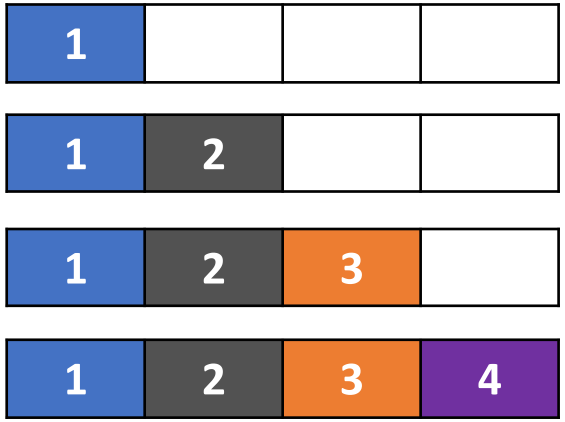
Branch-and-Bound | Branching scheme

Two simple branching schemes are exploited



SCHEDULE

Alternative branching scheme
Best performing one for the **non-rework** version
balance the two machines



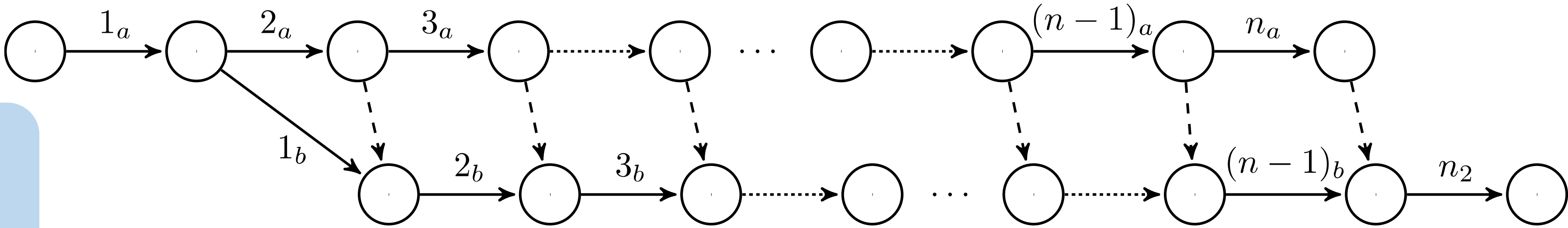
SCHEDULE

Forward branching scheme
Applicable for rework version, straight-forward

For both the branching schemes, a **depth first exploration strategy** is exploited, this provide the capability of finding feasible solutions as soon as possible to be used for pruning

Branch-and-Bound | Evaluation of leaf nodes

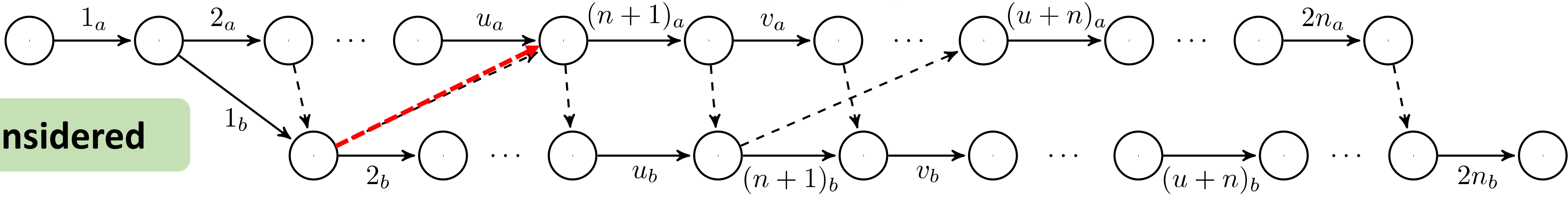
For the estimation of leaf nodes, proposed AoA network and MAN can be exploited directly



AoA network without considering rework

When rework is considered

Precedence relation between job *1* and job *n+1*



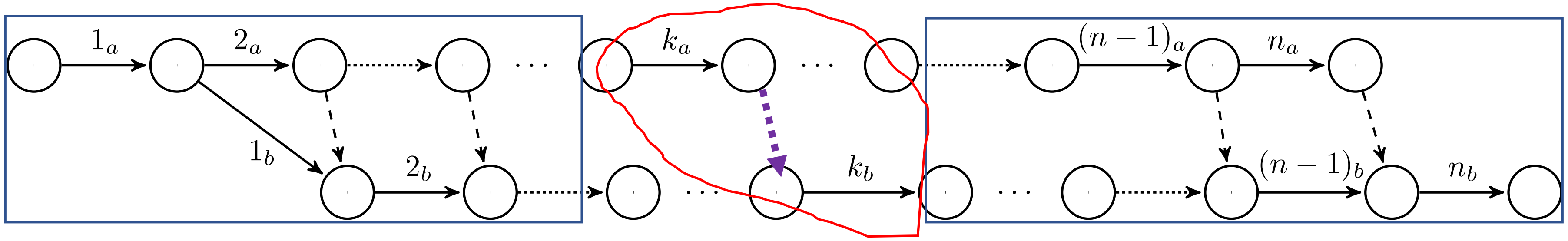
- Rework activities are modelled as additional jobs
- Rework constraints apply:
  - Rework job should be scheduled after the processing of the job, e.g., 1_b $(n+1)_a$
  - Rework jobs cannot be processed earlier than 2 jobs after the corresponding original job (unless remaining jobs < 2)

Branch-and-Bound | Evaluation of non-leaf nodes

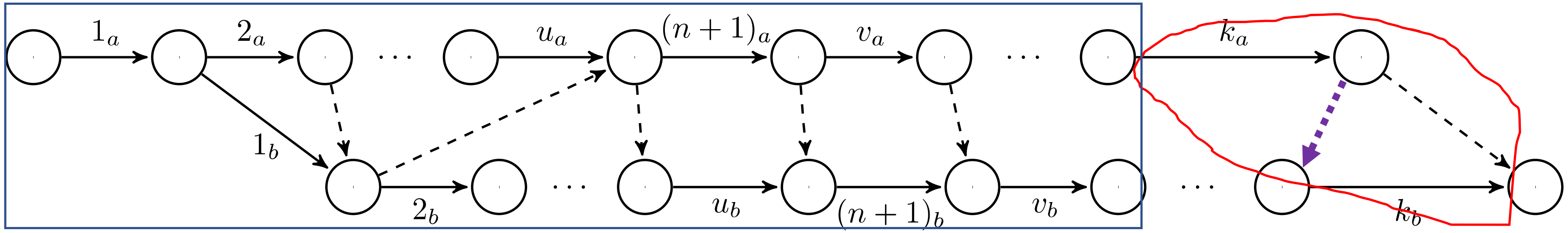
In the considering branching tree, non-leaf node, represent the partial schedule with a subset of scheduled jobs N, and the remaining subset N’ with jobs not yet scheduled

Assigned jobs

Unassigned jobs



Under alternative branching scheme

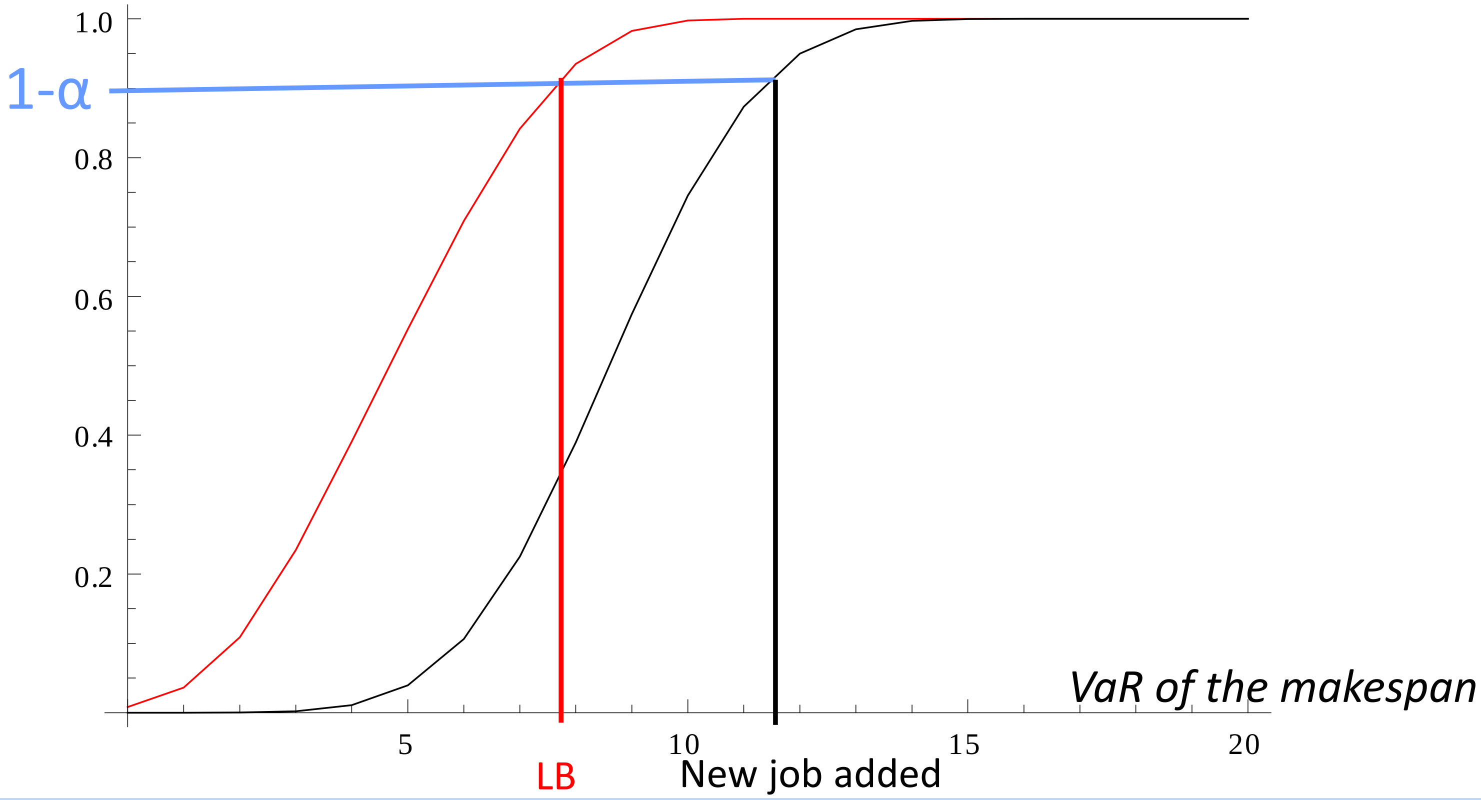


Under forward branching scheme

- **Precedence constraints** among operations for un-sequenced jobs are **relaxed**
- CTMC generation scheme can be used for the new AoA to estimate the VaR

Branch-and-Bound | Definition of lower bound

- VaR of the Makespan is a regular objective function: a new job is added, the VaR will increase



- The proposed lower bound will guide the search in the branch process of the algorithm to cut the branches without possibility finding optimal schedule

Pinedo, M. L. (2012). *Scheduling* (Vol. 29). New York: Springer.

Branch-and-Bound |Definition of an Initial solution

To set the initial upper bound for the branch tree, an initial solution schedule is generated by a **heuristic rule:**

Arranging all the jobs according to the **decreasing order** of $\boldsymbol{E(J_a) - E(J_b)}$

E(J_a) and E(J_b) are the expected value of the processing times of job j on machine *a* and *b*.

Note:

- This is the optimal schedule for 2-machine permutation flow shop with **exponential** processing time[1]
- For reentrant problem, if the resulting schedule is in conflict with the constraints affecting the sequencing of rework jobs, they are shifted towards the right until the conflicts are eliminated.

The result schedule will be set as the **initial** solution schedule, with the corresponding VaR as the initial incumbent solution.

Baker, K.R. and Trietsch, D., 2011. Three heuristic procedures for the stochastic, two-machine flow shop problem. Journal of Scheduling, 14(5), pp.445-454.

Branch-and-Bound | Dominance rule

Dominance rules are used to eliminate sub-problems that are dominated by other sub-problems in the search tree, meaning that they cannot contain a better solution than one that has already been found.

Job *j'* should precede job *j* in order to minimise the value-at-risk of the makespan

$$if\ j'_a \leq_{lr}\ j_a\ and\ j'_b \geq_{lr}\ j_b$$

lr: likelihood ratio

Note: This rule can only be applied when the first machine is never idle (the without rework version problem), while in the reentrant version problem, the first machine may be idle to wait for the completion of a first-pass job

By applying dominance rules at each step of the search process, the algorithm is able to quickly prune large portions of the search space, focusing its efforts on the most promising sub-problems. This allows the algorithm to efficiently explore the space of potential solutions.

Chang, C. S., & Yao, D. D. (1993). Rearrangement, majorization and stochastic scheduling. *Mathematics of Operations Research*, *18*(3), 658-684.

Implementation

- Phase-type distributions are modeled using the **BuTools** library **:** a rich toolbox for Markovian performance evaluation

  Horváth G.and Telek M. Butools 2: a rich toolbox for markovian performance evaluation. In VALUETOOLS, 2016.

- Matrix related operations are performed by means of the **Eigen library:** a high-level C++ library of template headers for linear algebra, matrix and vector operations

  Guennebaud G, Jacob B, et al. Eigen v3. http://eigen.tuxfamily.org, 2010.

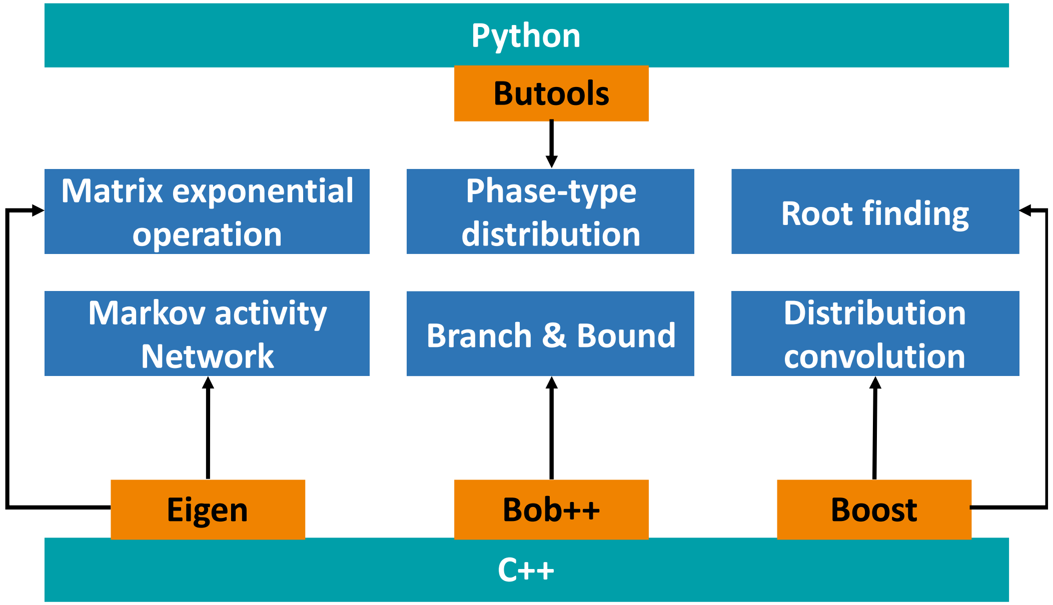
- The Branch-and-Bound algorithm is implemented with the support of the **Bob++** library: a framework for solving optimization problems with branch-and-bound methods

  A Djerrah, Le Cun B., V-D Cung, and Roucairol C. Bob++: Framework for solving optimization problems with branch-and-bound methods. 2006 IEEE

- Root finding approach is implemented with **Boost** Bracket-and-solve package

  Boost. Boost C++ Libraries. http://www.boost.org/, 2020

- The whole algorithm is coded in **C++**, and the experiments are run on a Windows 7 workstation with a 2.6 GHz processor and 64 GB of RAM



EXPERIMENTS ON
TWO-MACHINE FLOW SHOP SCHEDULING PROBLEM

Experiments – Generation of testing instances

The proposed algorithm is tested on randomly generated instances

1. Generation of scheduling instances
2. Generation of the distributions

Note: This is randomly generated due to existing flow shop instances(e.g., Taillard dataset) are large (>30 jobs) and deterministic

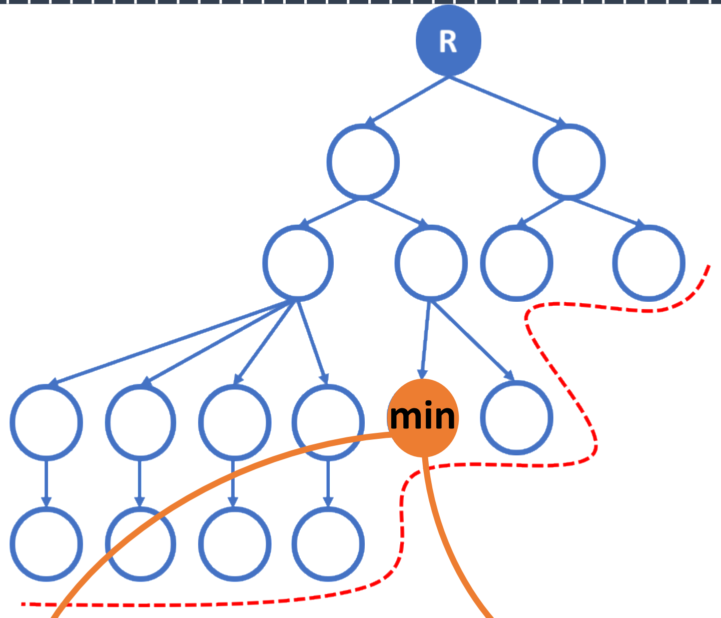
- Two machine flow shop with n = 10, 20, 30 and 50 jobs
- Processing time of each job on each machine follows a **general phase-type** distribution, with **mean value** randomly sampled from [0,20],[30,50] and [60,80] and **number of phases** randomly sampled between [1, 4]
- Risk level (1, 5, 10 and 20%) --> 99, 95, 90 and 80% quantiles
- 20 instances for each combination of risk level and number of jobs
- 320 instances in total

Experiments – Computational Results

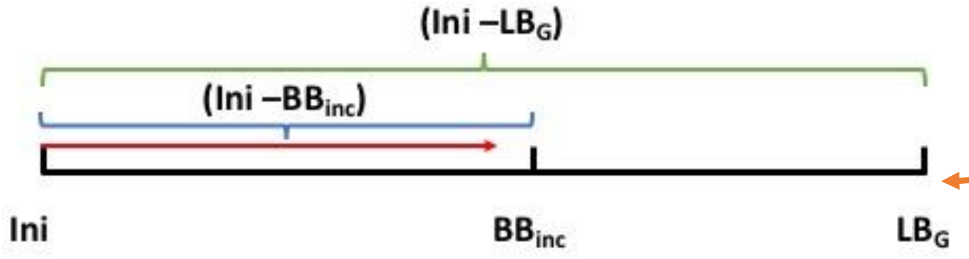
For the experiments, a time limit of 3600s is set

# jobs	Solution time(seconds)		
	min	max	mean
10	3.1	346.6	118.4
20	28.4	3600	1254
All	3.1	3600	1029

36.7% of the 20 jobs cannot be solved to optimal



Branching tree when the time limit is reached



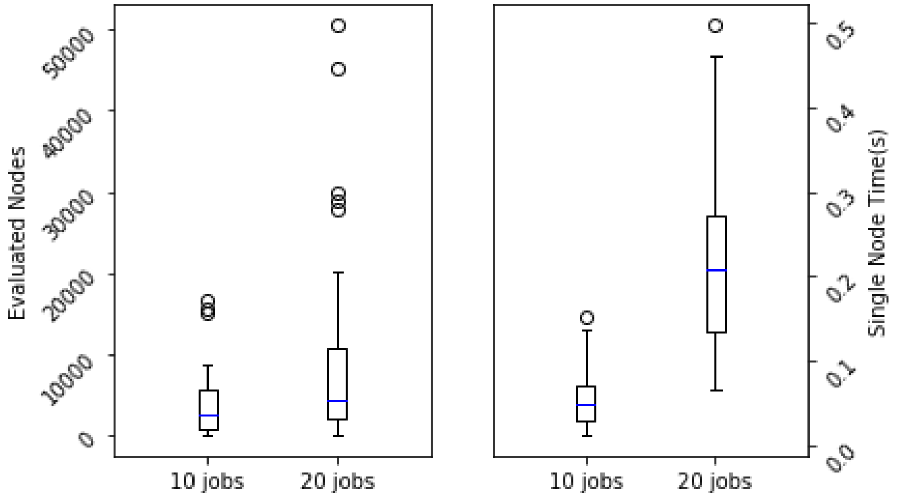
GAP: $\dfrac{(Ini - BB_{inc})}{(Ini - LB_G)}$

# jobs	min	max	mean
30	22.1	87.6	46.3
50	19.6	78.2	45.4

Experiments – analysis of significant factors

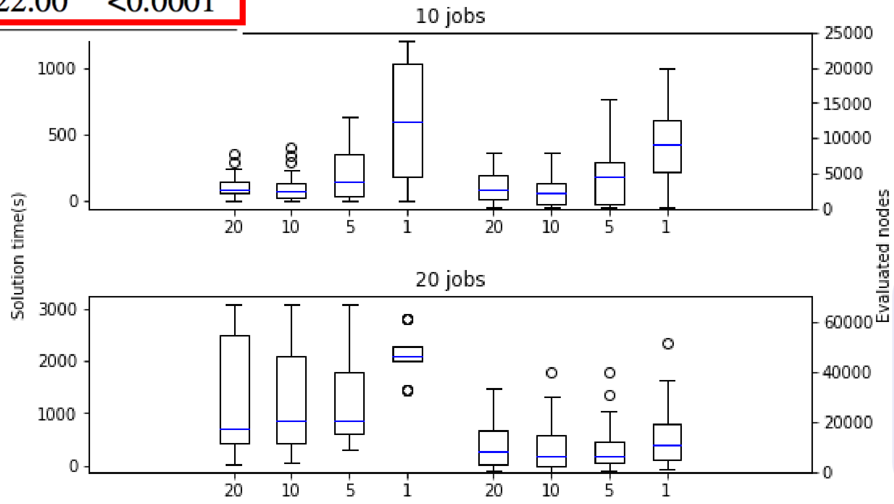
Statistical analysis to identify the significant factors in the algorithm

Mood's Median Test	DF	χ^2	p-value
solution time *vs* number of jobs	1	59.64	<0.0001
solution time *vs* risk level	3	4.77	0.19
evaluated nodes *vs* number of jobs	1	0.34	0.56
evaluated nodes *vs* risk level	3	11.09	0.011
evaluation time per node *vs* number of jobs	1	65.01	<0.0001
evaluation time per node *vs* risk level	3	1.98	0.58
solution time *vs* risk level (10-job instances)	3	19.60	<0.0001
evaluated nodes *vs* risk level (10-job instances)	3	22.00	<0.0001



Larger number of jobs:
1. larger branching tree
2. Larger CTMC state space

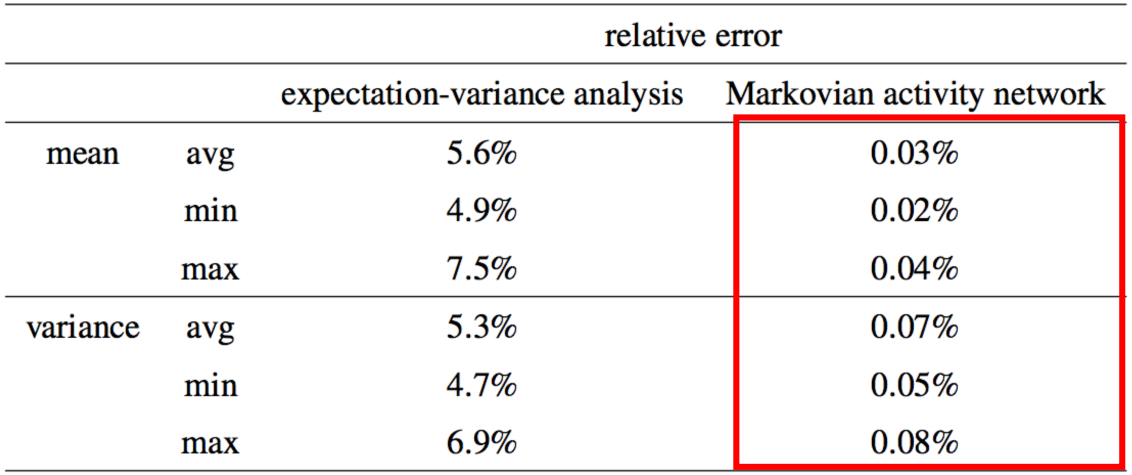
Significant factor:
1. Number of jobs
2. Risk level on 10 jobs, due to the fact that the experiments on 20 jobs is not complete



Smaller risk level
1. Quantile close to 1, curve is flat
2. More similar nodes hard to prune

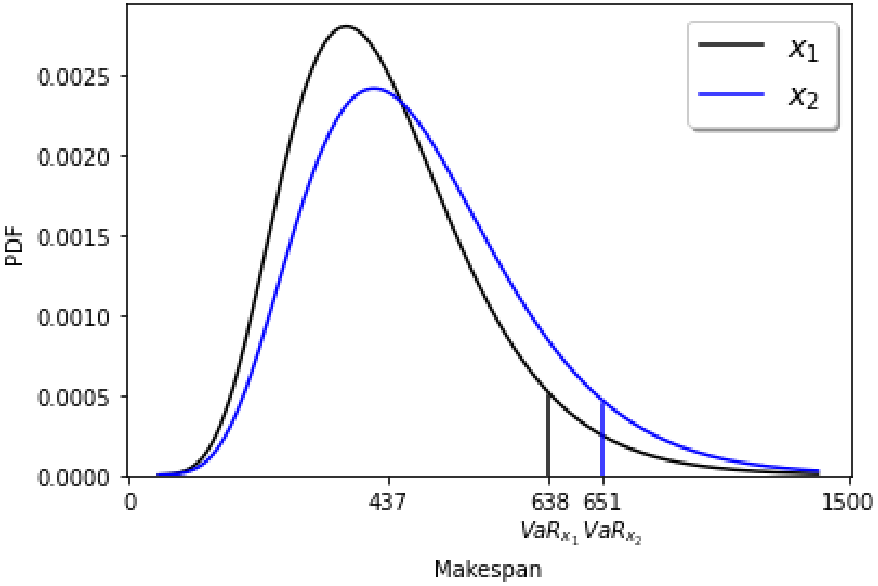
Experiments | Comparison with expected-variance approach

- Mixture normal distribution to fit the **general distribution** **YES**
- **Exact estimation** of makespan distribution considering dependent critical paths **NO**



		relative error	
		expectation-variance analysis	Markovian activity network
mean	avg	5.6%	0.03%
	min	4.9%	0.02%
	max	7.5%	0.04%
variance	avg	5.3%	0.07%
	min	4.7%	0.05%
	max	6.9%	0.08%

Comparison with Monte Carlo simulation



VaR *vs* Expectation-Variance

- Two schedules with similar expectation + variance, one of them is dominating the other one on VaR
- VaR provides the capability of considering the **right tail** of the distribution of the makespan, with the aim of mitigating the impact of worst cases

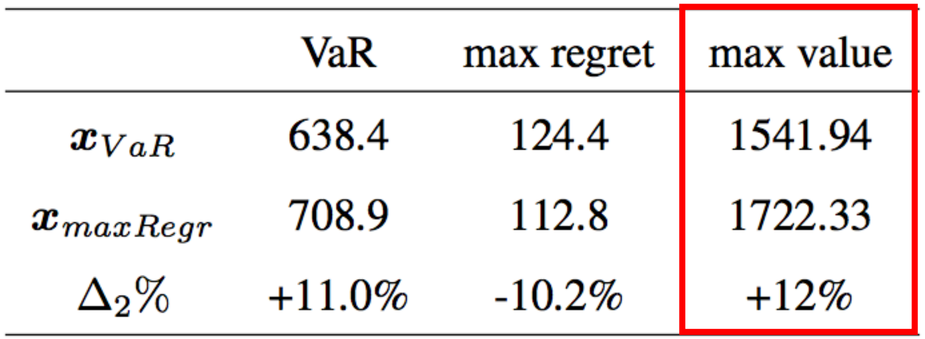
Sarin, S. C., Nagarajan, B., & Liao, L. (2010). Stochastic scheduling: expectation-variance analysis of a schedule. Cambridge university press.

Experiments | Comparison with minimax regret approach

max regret: largest possible difference between the **chosen schedule** and the **best schedule** could get.

The probability for two schedules to incur in a **maximum** value of the makespan:

$$P\left(max_{VaR} > max_{maxReg}\right) \approx 0$$



	VaR	max regret	max value
$\boldsymbol{x}_{VaR}$	638.4	124.4	1541.94
$\boldsymbol{x}_{maxRegr}$	708.9	112.8	1722.33
$\Delta_2\%$	+11.0%	-10.2%	+12%

Performance of schedules on a random instance

With the aim of balancing the risk associated with **extreme scenarios**, the VaR approach is able to provide a reasonable and less cautious solution

Panos Kouvelis, Richard L Daniels, and George Vairaktarakis. Robust scheduling of a two-machine flow shop with uncertain processing times. IIE Transactions, 32(5):421–432, 2000.

EXPERIMENTS ON
TWO-MACHINE *REENTRANT*
FLOW SHOP SCHEDULING PROBLEM

Experiments – Generation of testing instances

- Two sets of test instances have been generated, i.e., **small** and **medium** instances.
  - Small instances set, n = 5, 6 and 8 jobs with 2n = 10, 12 and 16 jobs
  - Medium instance set has sizes n = 10, 15 and 20, with 2n = 20, 30 and 40 jobs

- The processing times are modelled with phase-type distributions generated using the BuTools library, the value of the mean is randomly sampled from [0, 20], [30, 50] and [60, 80]. The number of phases is randomly chosen between [1, 4].

- Multiple experiments have been carried out considering different risk levels α (5%, 10% and 20%).

- A set of 20 test instances has been generated, for each combination of the number of jobs n and risk level α, for a total of 420 instances.

Experiments – B&B Results

# jobs	Solution time (sceconds)		
	min	max	mean
5 (10)	0.7	15.9	5.7
6 (12)	2.6	241.4	81.9
8 (16)	582.8	3600	2638.5
All	0.7	3600	906.8
12.3% of the 8(16) jobs cannot be solved to optimal			

Exact solution of B&B for **small** instances

Within the time limit, the B&B can solve up to 8(16) jobs instances

For the experiments, a time limit of 3600s is set

The B&B incumbent solution when the time limit is reached, can improve the initial solution in a good way

$$\Delta\% = \frac{S_{ini} - BB_{inc}}{BB_{inc}} * 100$$

#job	B&B		
	min	max	mean
10(20)	4.5	18.3	9.1
15(30)	4.9	8.3	6.1
20(40)	1.6	5.2	3.7
25(50)	1.1	6.1	2.6

Performance of **me** tion to optimality

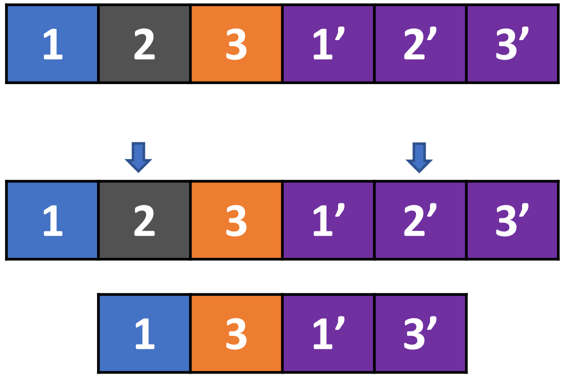
Heuristic algorithms - IG

The proposed branch-and-bound algorithm cannot get the optimal solution for medium size instance, heuristic approaches are proposed together with the MAN estimation of the schedules.

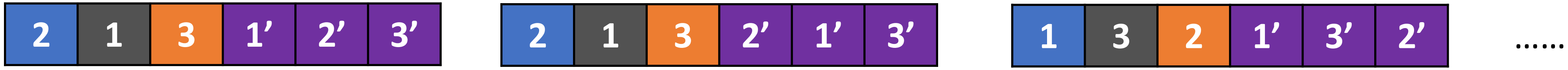
Iterated Greedy is a local search heuristic algorithm

1. Initial full schedule

2. Random chosen one job and its rework job and take them out



3. Iterated insert and keep the best performed schedule



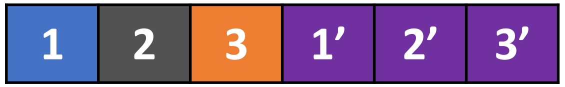
4. Until no improvement **or** the number of iterations is reached

Rubén Ruiz and Thomas Stützle. A simple and effective iterated greedy algorithm for the permutation flowshop scheduling problem. European journal of operational research, 2007

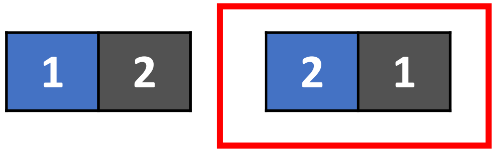
Heuristic algorithms - NEH

NEH is a efficient constructive heuristic for flow shop scheduling problem

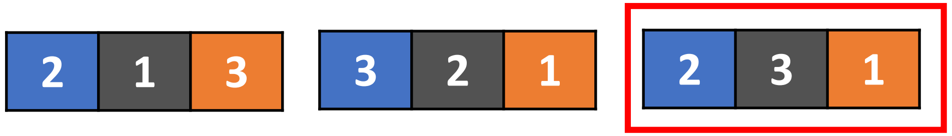
1. Initial schedule



2. Take first two, calculate LB value with MAN, keep smaller one



3. Choose the 3rd job from initial schedule, insert into all possible positions



4. Until all jobs are assigned

… …

Nawaz, M., Enscore, E. E. Jr. and Ham, I. 1983. A heuristic algorithm for the m-machine, n-job flow-shop sequencing problem. *Omega*,

Experiments – Heuristic approaches

$$\Delta\% = \frac{S_{ini} - Output}{Output} * 100$$

#job	IG			NEH			B&B		
	min	max	mean	min	max	mean	min	max	mean
10	1.1	155	7.1	0.3	6.9	2.1	4.5	18.3	9.1
15	0.0	15.5	6.6	0	13.8	3.5	4.9	8.3	6.1
20	0.0	15	7.6	1.7	7.5	4.8	1.6	5.2	3.7
25	1.7	19.6	8.1	3.2	13.9	7.6	1.1	6.1	2.6

Performance of larger instances from initial solution to optimality

IG heuristic performs good on the medium sized instances, and dominate NEH heuristic

Experiments – Comparison with minimax approach/ expected value approach

2 random instances, 5-job, 8–job are chosen

- three optimal schedule for each instance, (VaR, minimax, deterministic expected value)
- 1000 random scenarios for each instance
- Calculate Makespan under 1000 scenaros in 3 schedules

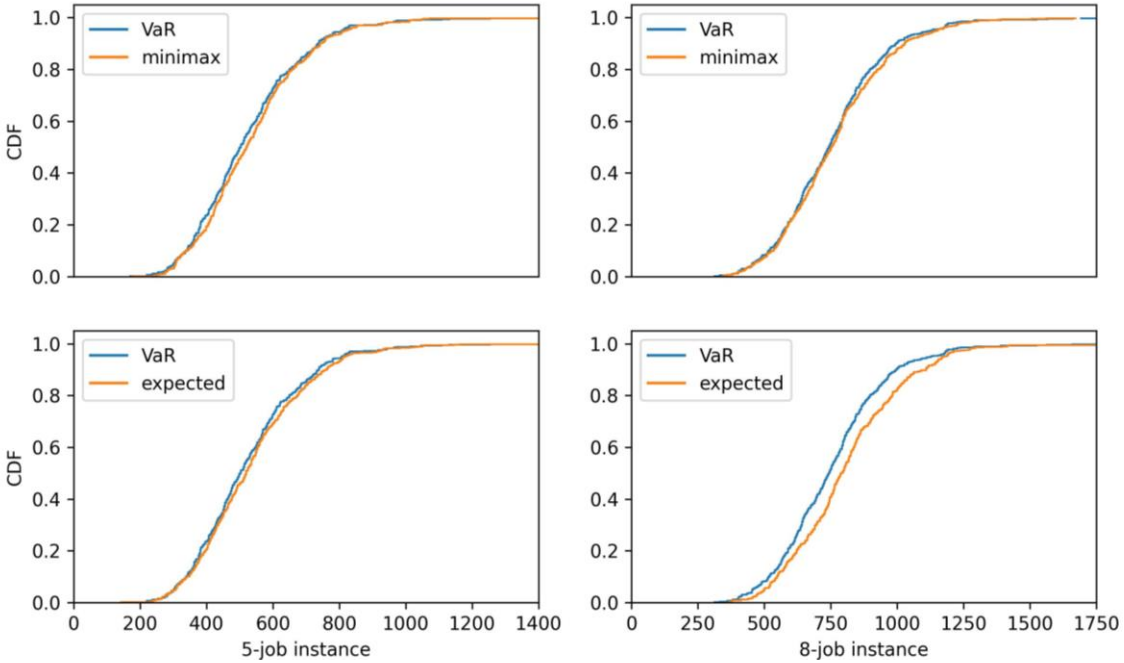
	VaR	Expected value	minimax
ins1	633/1000	213/1000	154/1000
ins2	511/1000	172/1000	317/1000

The number of best scenarios under this approach

VaR approach better

	Minimax (%)			Expected value (%)		
	mean	min	max	mean	min	max
ins1	4.1	-29.5	33.2	3.9	-31.1	36.8
ins2	1.5	-25.2	37.1	7.2	-25.9	31.5

Makespan differences, VaR smaller on average and protect extreme scenarios



CDF of the makespan obtained with different alternative approaches, over the 1000 sampled scenarios.

The makespan values of the alternative approach **stochastically larger** than those of the VaR approach, indicating first-order stochastic dominance.

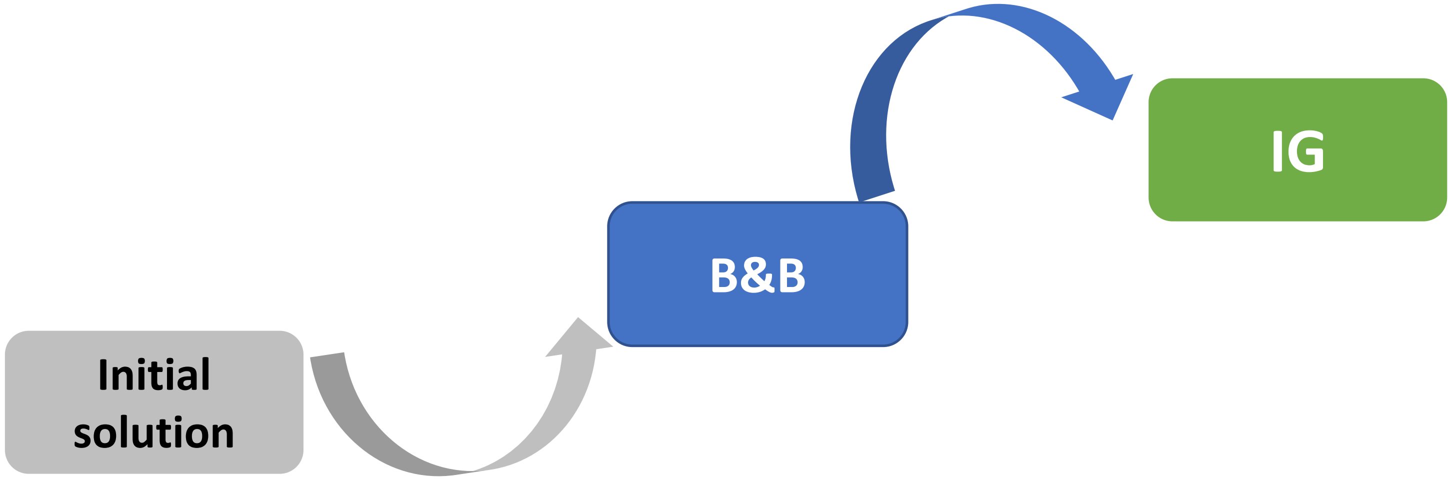
Levorato M, Figueiredo R,and Frota Y.Exact solutions for the two-machine robust flow shop with budgeted uncertainty. European Journal of Operational Research, 2022.

Integrated approach (B&B + IG)

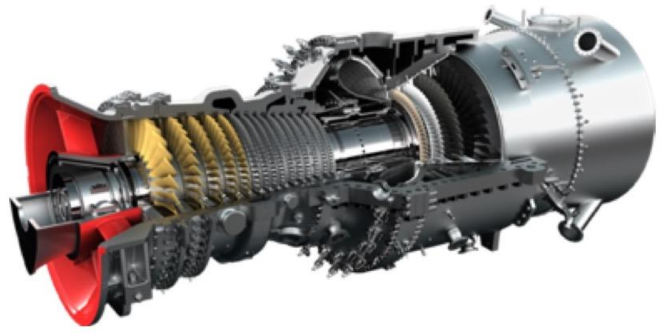
Grounding on the analysis on the experiments, an integrated approach could be exploited to solve the larger instances

1. Grounding on the initial solution, apply the **B&B** algorithm, set a time limit, collect the **incumbent** solution

2. Take the **incumbent** solution as input, apply **IG**, until the stop criteria is respected



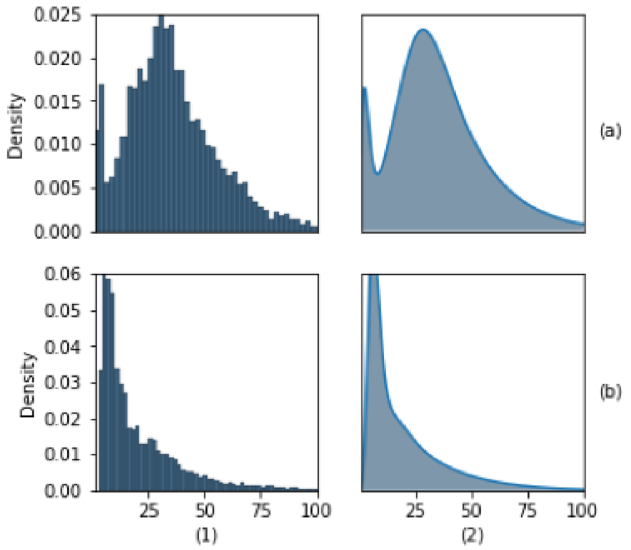
Case Study – 2 machine flow shop with rework



AE 94.3A gas turbine

Turbine blade

Ansaldo Energy remanufacturing parts



Historical data of processing time distribution, and the phase-type fitted ones within 10-15 phases

- **Ansaldo Energia S.p.A.** is an Italian power engineering company, based in Genoa, Italy.
- Production lines: **gas turbines**, steam turbines and generators.
- The gas turbines models manufactured are named: AE64.3A, AE94.2, AE94.2K, **AE94.3A**.
- Ansaldo Energia also provides service for their products worldwide: maintenance, **remanufacturing**
- Three months secondments was planned, cancelled due to Covid pandemic

Case Study – stochastic 2-machine flow shop with rework

- Integrated approach
- 2 turbines instance, i.e., 12 batches of blades, i.e., 12 jobs (24 in total including rework job)
- Historical data from remanufacturing department of Ansaldo Energy

Improvement from initial schedule solution				
jobs	Risk	min	max	mean
6	20%	0	11.6	5.7
	10%	1.7	13.5	5.5
	5%	1.6	8.5	5.1
12	20%	1.6	14.1	7
	10%	1.5	12.9	7.2
	5%	0	15.2	8.4

Computation time(seconds)				
jobs	Risk	min	max	mean
6	20%	14	497	155
	10%	209	707	459
	5%	115	338	221
12	20%	2396	3600	3299
	10%	2316	3600	3202
	5%	2404	3600	3173

Conculsion

1. This dissertation studied the scheduling of **remanufacturing activities** of gas turbine blades with huge processing time uncertainties
2. The risk measure based scheduling approach (**VaR**) can pursue the trade-off between expected value and extreme scenarios, compensate for weaknesses of alternative robust scheduling approach
3. **Phase-type distributions** are used to fit real general distributions in the remanufacturing activities
4. The non-independent property among various critical paths is addressed by exploiting **MAN** approach, which is a promising exact approach to estimate the distribution of the makespan

4. The proposed approach can solve small sized instances to optimility (<= 20 jobs), and the incumbent solution/heuristic can also provide a good solution for medium sized instances
5. The efficency of the proposed approach is demonstrated on random generated instances and real industrial applications

1. The future may focus on **acceleration of computation,** e.g., efficient branching scheme, theoretical dominance rule, **various scheduling problem**, e.g., m-machine scheduling, **other objectives** (lateness, tardiness).

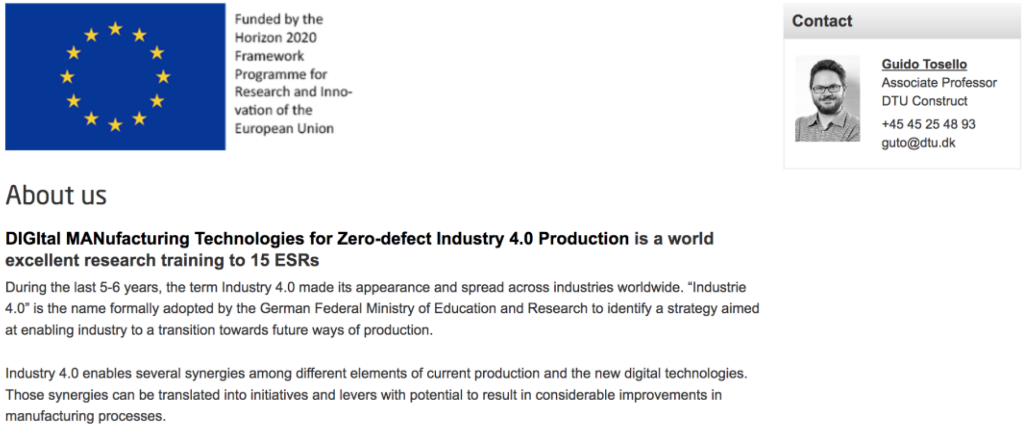
Research project

- **DIGIMAN 4.0** (Digital Manufacturing Technologies for Zero-defect Industry 4.0 Production)
- Marie Skłodowska-Curie Actions, Horizon 2020

Project Coordinator:
Prof. Guido Tosello, Mechanical Engineering, DTU, Denmark

15 PhDs

- Politecnico di Milano (ITALY)
- University of Pisa (ITALY)
- Technical University of Denmark (DENMARK)
- Karlsruhe Institute of Technology (GERMANY)
- University of Zaragoza (SPAIN)
- Tekniker (SPAIN)



Funded by the Horizon 2020 Framework Programme for Research and Innovation of the European Union

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About us

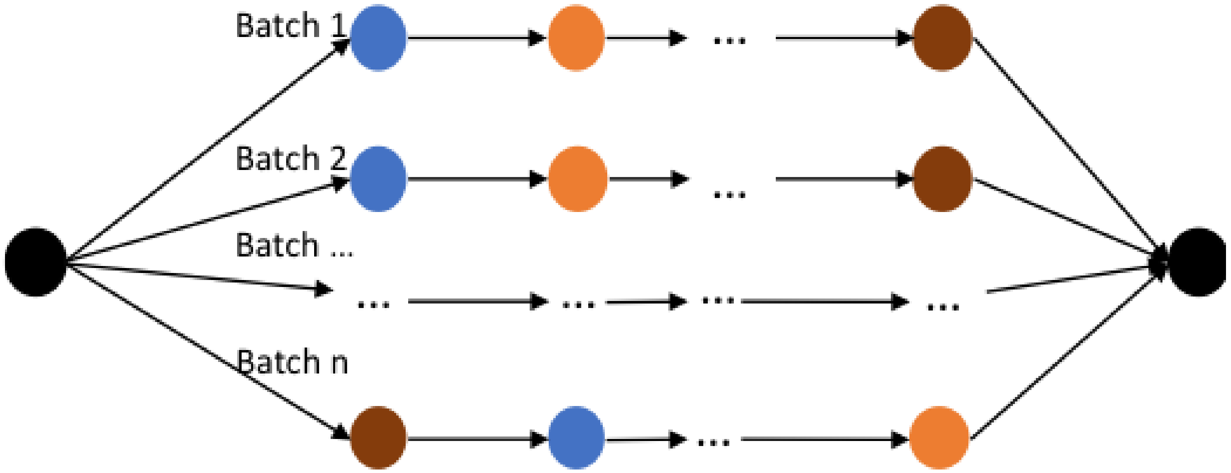
DIGItal MANufacturing Technologies for Zero-defect Industry 4.0 Production is a world excellent research training to 15 ESRs

During the last 5-6 years, the term Industry 4.0 made its appearance and spread across industries worldwide. "Industrie 4.0" is the name formally adopted by the German Federal Ministry of Education and Research to identify a strategy aimed at enabling industry to a transition towards future ways of production.

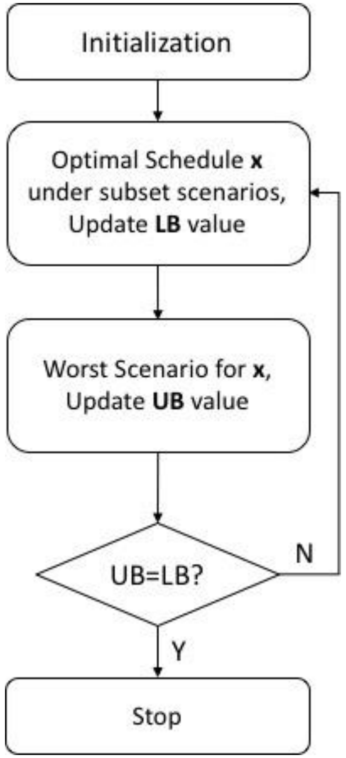
Industry 4.0 enables several synergies among different elements of current production and the new digital technologies. Those synergies can be translated into initiatives and levers with potential to result in considerable improvements in manufacturing processes.

Industrial Case - RCPSP

To satisfy the requirement of the company, a minimax regret robust scheduling approach is exploited on the whole process



Note: same color, same resource


Initialization

Optimal Schedule **x** under subset scenarios, Update **LB** value

Worst Scenario for **x**, Update **UB** value

UB=LB?

N

Y

Stop

The **maximum regret** of a schedule can always be attained at an extreme scenario, only upper and lower bound of interval processing time need to be considered.

Mixed integer programming approach

Artigues, C., Leus, R., & Talla Nobibon, F. (2013). Robust optimization for resource-constrained project scheduling with uncertain activity durations. *Flexible Services and Manufacturing Journal*, *25*, 175-205.

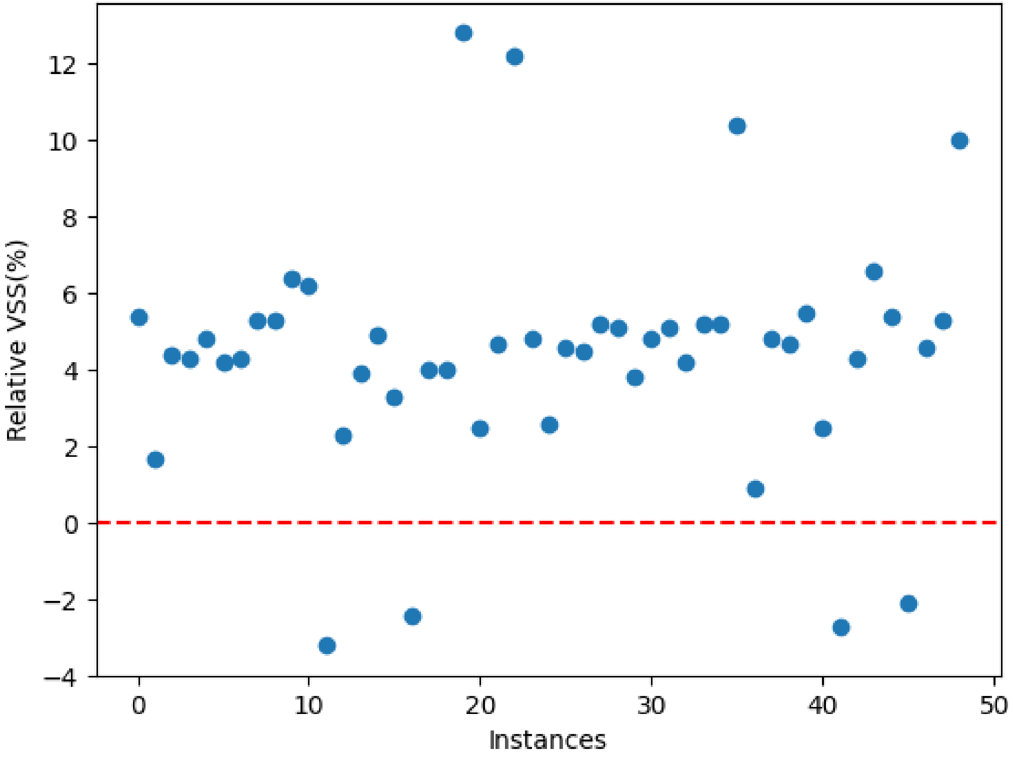
Industrial Case - Comparison with expected value approach

Evaluation of the effectiveness of robust scheduling approach

$$VSS = \frac{1}{|S|}\sum_{s} EVS_s - RVS_s$$

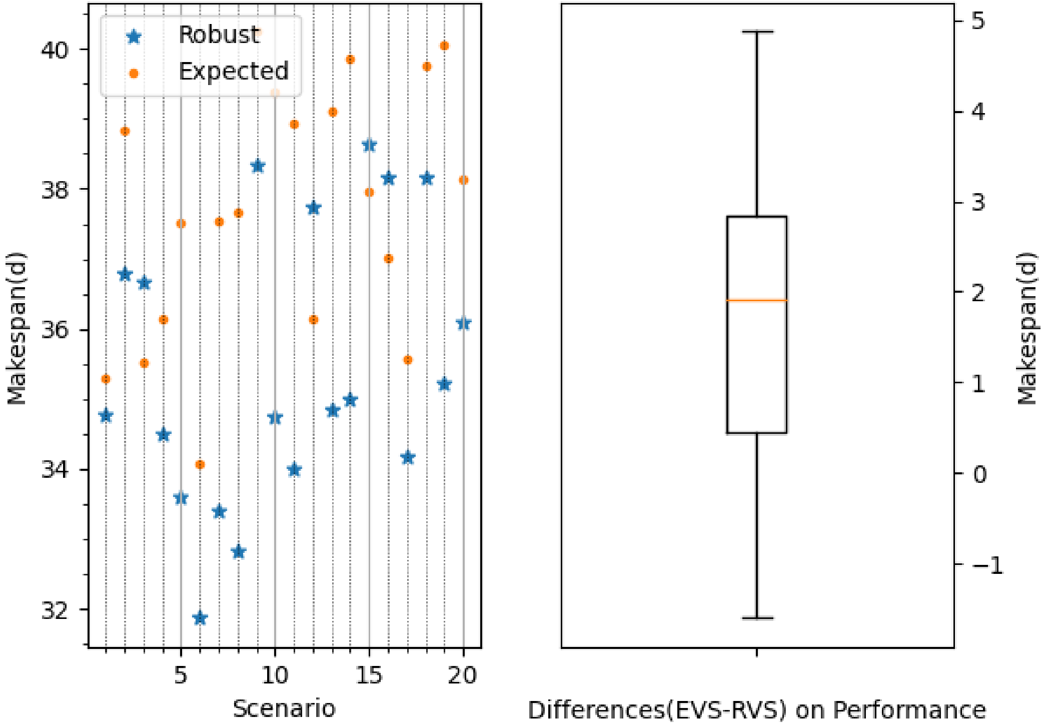
EVS: result from expected value approach

RVS: result from robust scheduling approach



Relative value of VSS

Most of them **>0**, i.e., robust approach is better than expected value approach

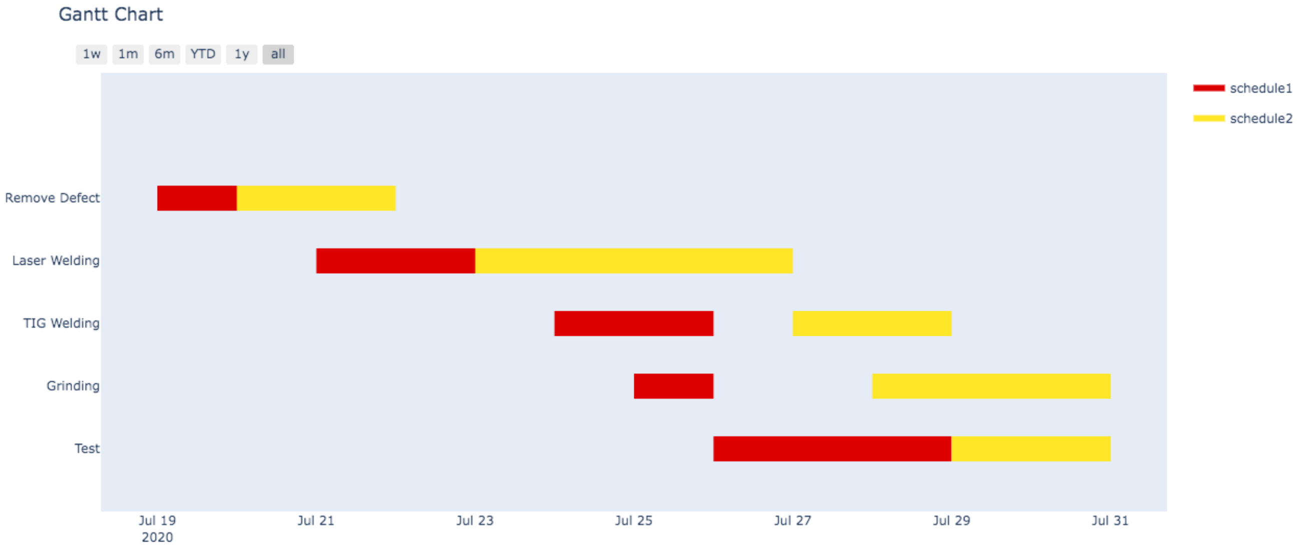


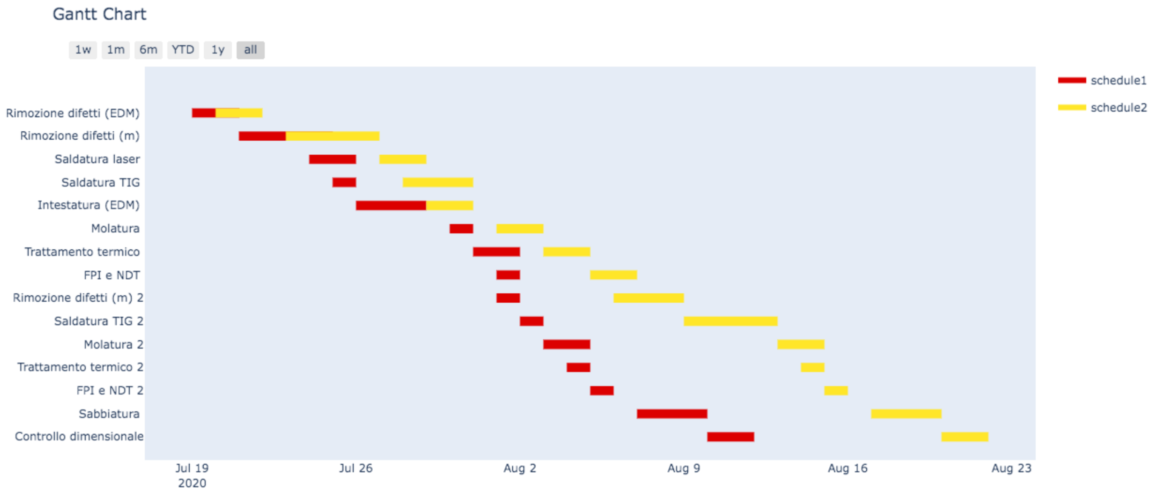
Random choosen 20 scenarios for one instance,

Mosth of the makespan from robust approach is smaller than expected value approach

Industrial Case - Software

A robust scheduling software was delivered to the remanufacturing department of Ansaldo Energia





Gantt chart interfaces of robust scheduling software

Publications & Conferences

1. Lei Liu and Marcello Urgo. A branch-and-bound approach to minimise the value-at-risk of the makespan in a stochastic two-machine flow shop, **International Journal of Production Research 2023**
2. Lei Liu and Marcello Urgo. Robust scheduling of a remanufacturing process for the repair of turbine blades, **CIRP Annals - Manufacturing Technology 2023**
3. Lei Liu and Marcello Urgo. Robust scheduling in a two-machine re-entrant ow shop to minimise the value-at-risk of the makespan: a branch-and-bound and heuristic algorithms based on Markovian Activity Networks and phase-type distribution, **Annals of Operations Research** (Second-round review, revised version submitted in May 2023)

4. Lei Liu and Marcello Urgo. Scheduling remanufacturing activities for the repair of turbine blades: an approximate branch and bound approach to minimize a risk measure. Selected Topics in Manufacturing: AITeM Young Researcher Award 2021.
5. Lei Liu and Marcello Urgo. A robust scheduling framework for re-manufacturing activities of turbine blades. Applied Sciences 2022.

1. 04/2022, Ghent, Belgium, 18th International workshop on Project Management and Scheduling (**PMS**)
   - Finalist of Best Student Award
2. 01/2022, Milano, Italy, XV **AITeM** Conference (Italian Association of Manufacturing Technology),
   - Finalist of Young Researcher Award
3. 07/2021, Athens, Greece, 31st European Conference on Operational Research(**EURO**)