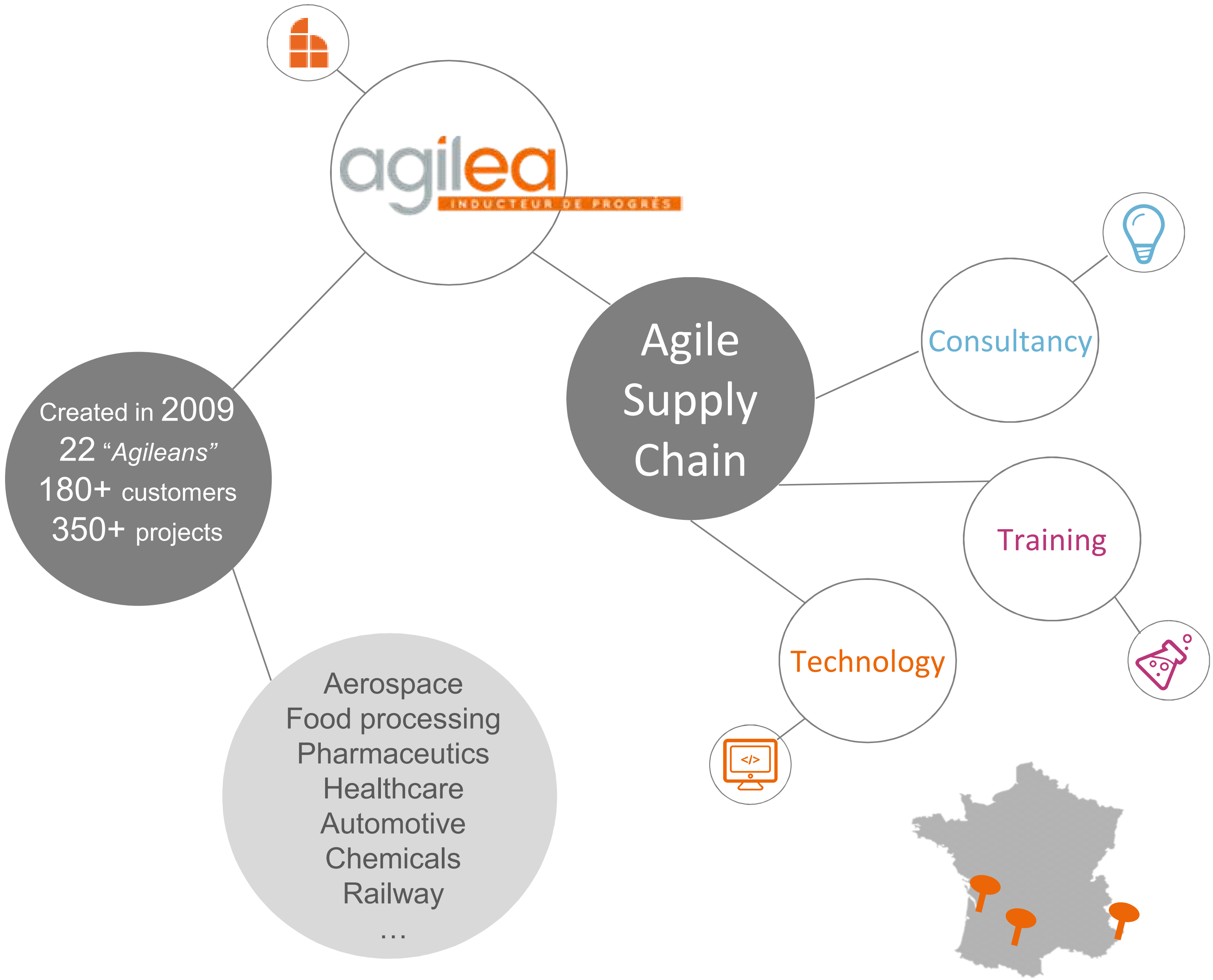
Challenging DDMRP promises and comparison with MRP / Kanban

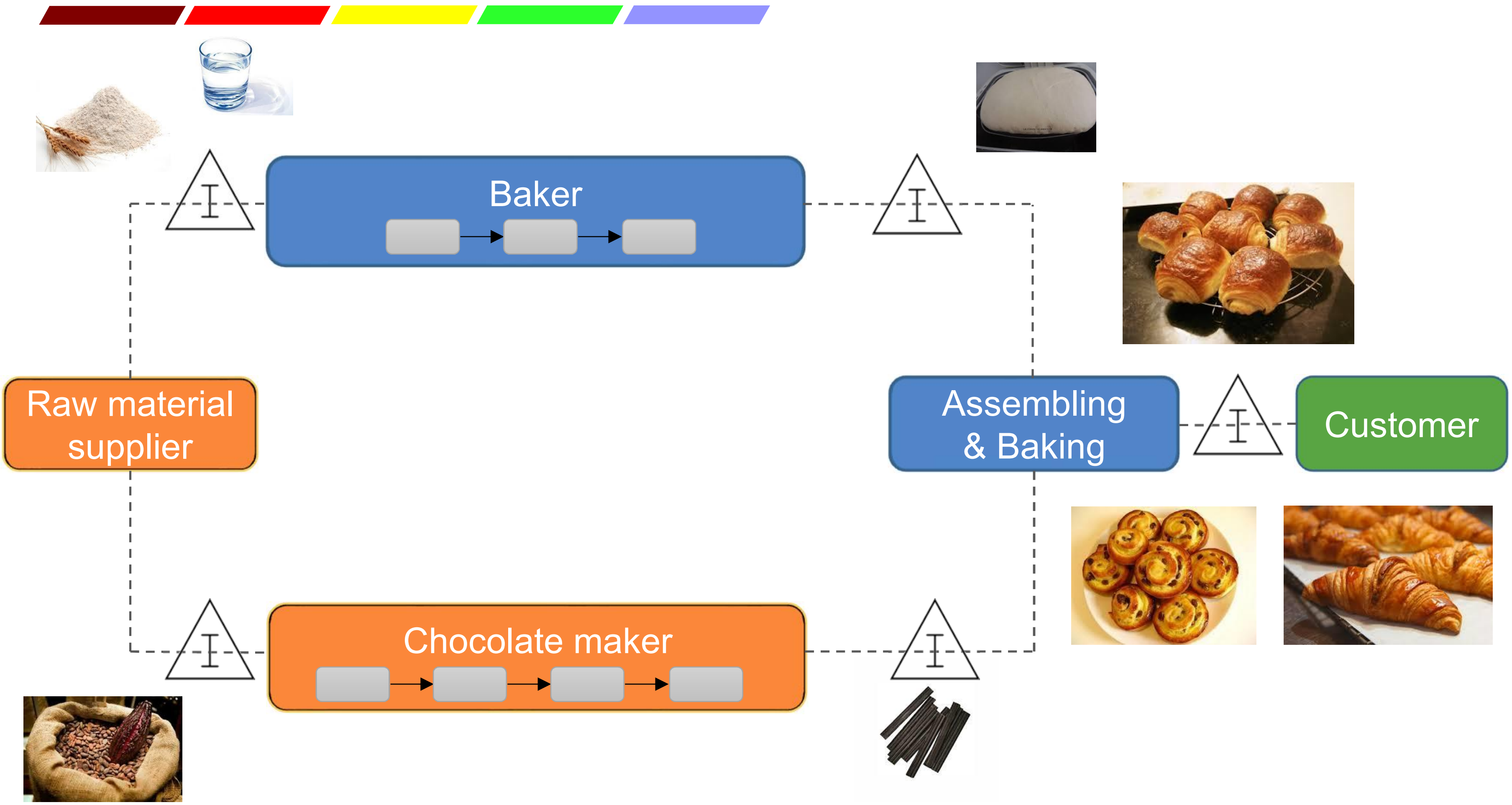
Romain Miclo, AGILEA

PhD work

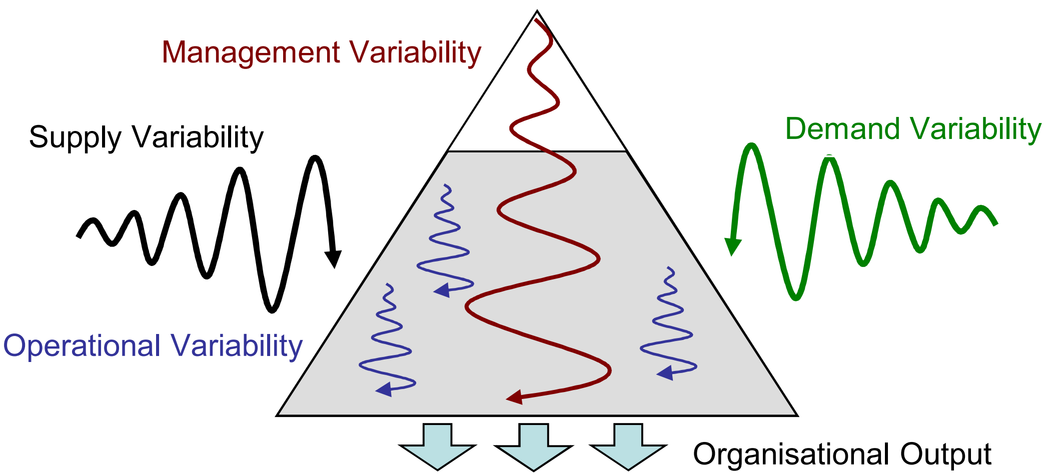
Conference 5-7 July 2017 Lyon, France


agilea
INDUCTEUR DE PROGRÈS
Created in 2009
22 "Agileans"
180+ customers
350+ projects
Aerospace
Food processing
Pharmaceutics
Healthcare
Automotive
Chemicals
Railway
…
Agile Supply Chain
Consultancy
Training
Technology
</>

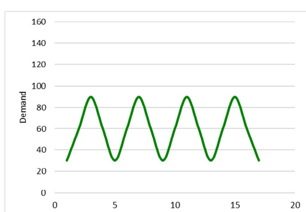
Context

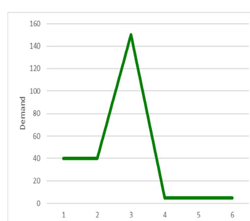

Baker
Raw material supplier
Assembling & Baking
Customer
Chocolate maker

Context



Main variability sources (Ptak and Smith, 2011)





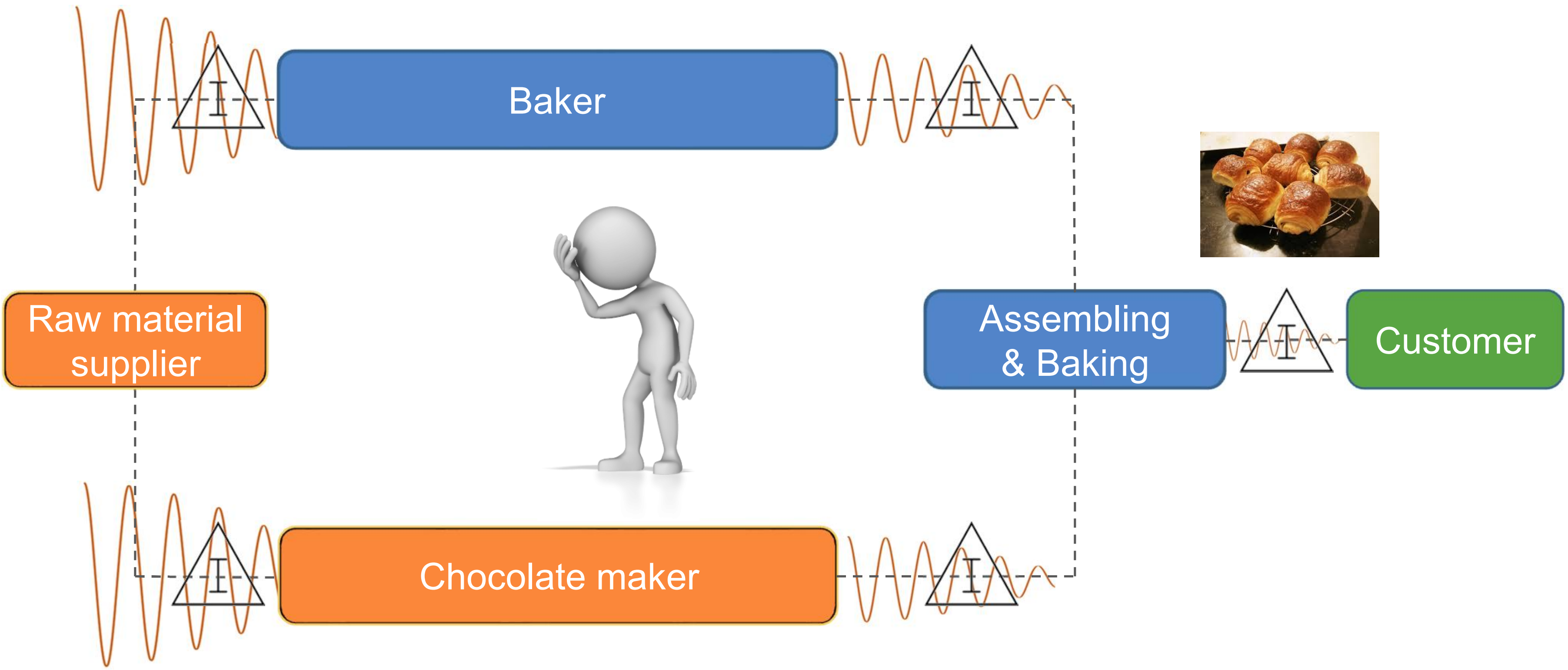
On Time Delivery
(OTD)

Work In Process
(WIP)

⇒ Working Capital
(WC)

Objective: to manage systems to be agile and resilient, satisfy customers and control finances.

Issue



Forrester, Jay W. 'Industry Dynamics'. *Massachusetts, Cambridge*, 1961.

Agenda

1 Context

2 Material management methods

3 Case study – design of experiments

4 Case study – simulation replications

5 Case study – buffer sizing optimisation

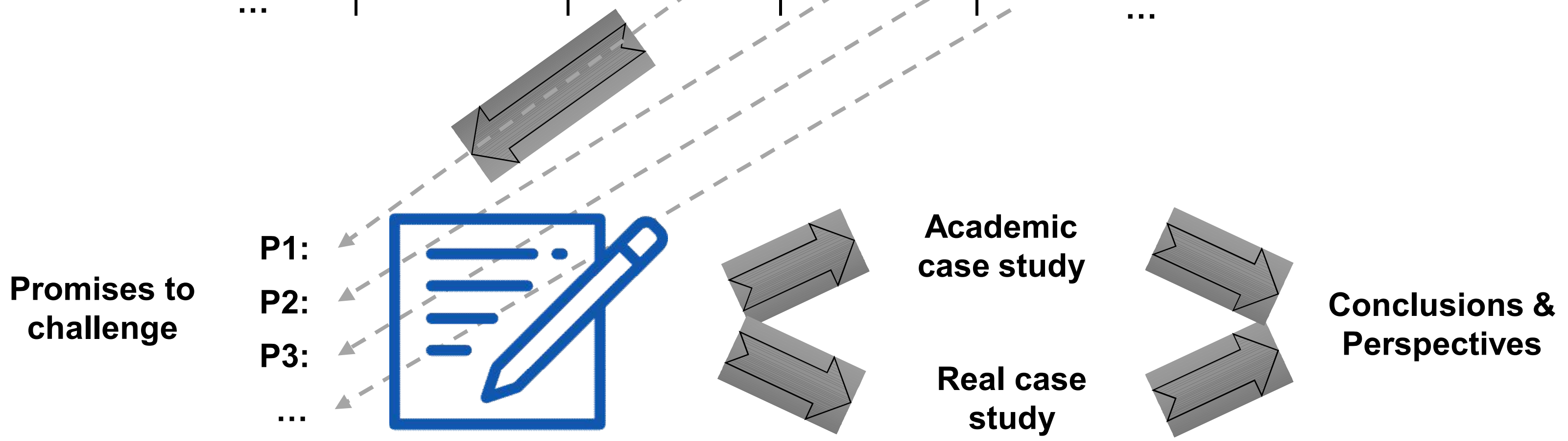
6 Conclusion & Perspectives

Agenda

Our approach

Literature review:

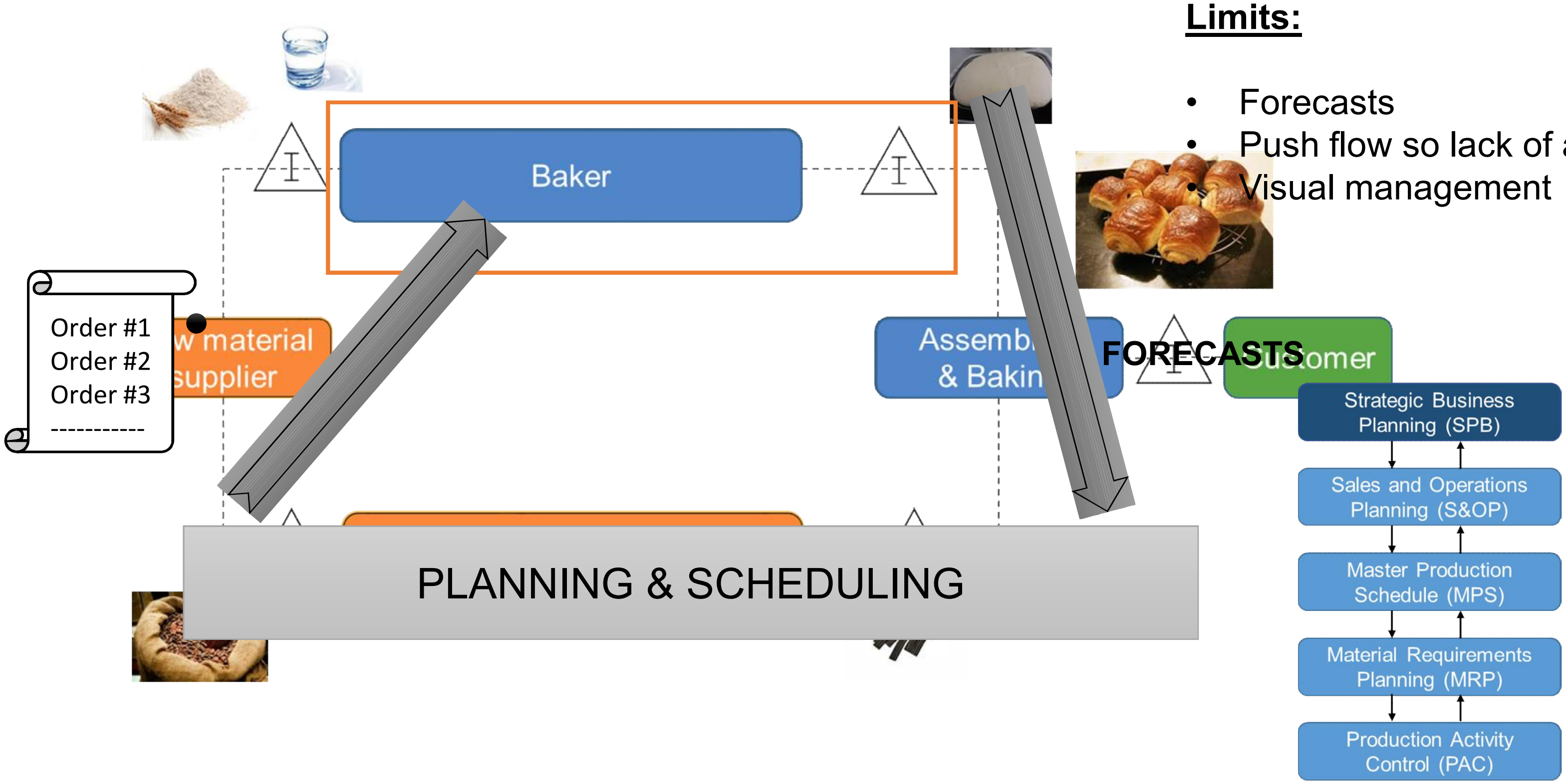
Criteria	MRP II	Kanban	DDMRP	DDMRP comparison
A	---	---	---	+
B				=
C				+
D				+
...				...



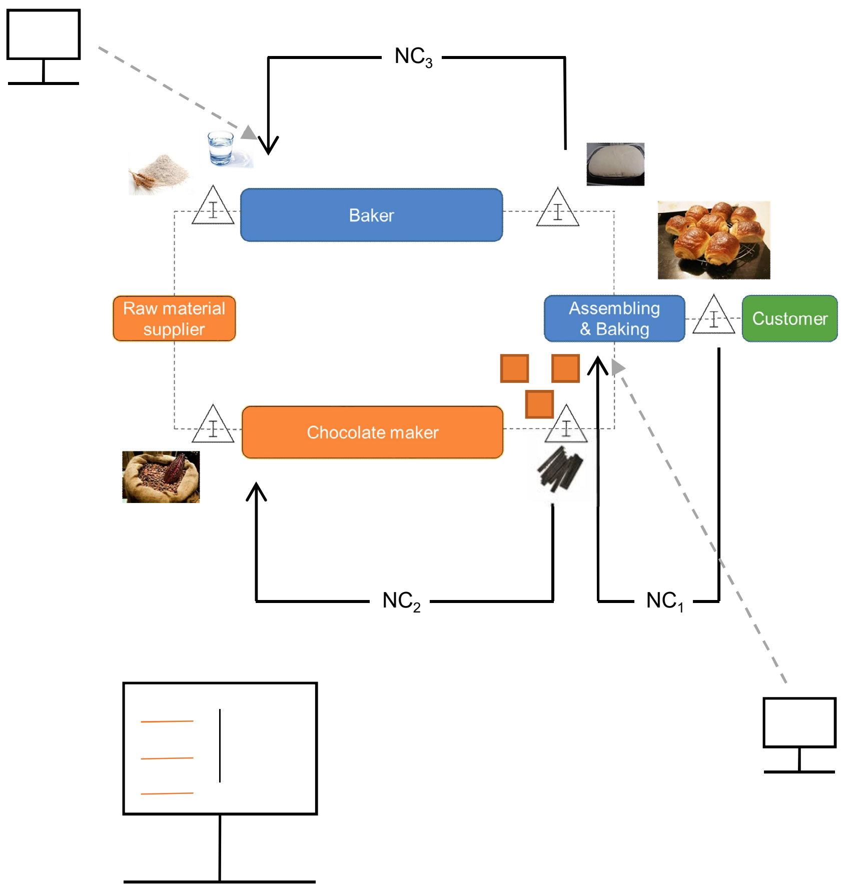
Manufacturing Resources Planning (MRP II)

Limits:

- Forecasts
- Push flow so lack of agility
- Visual management

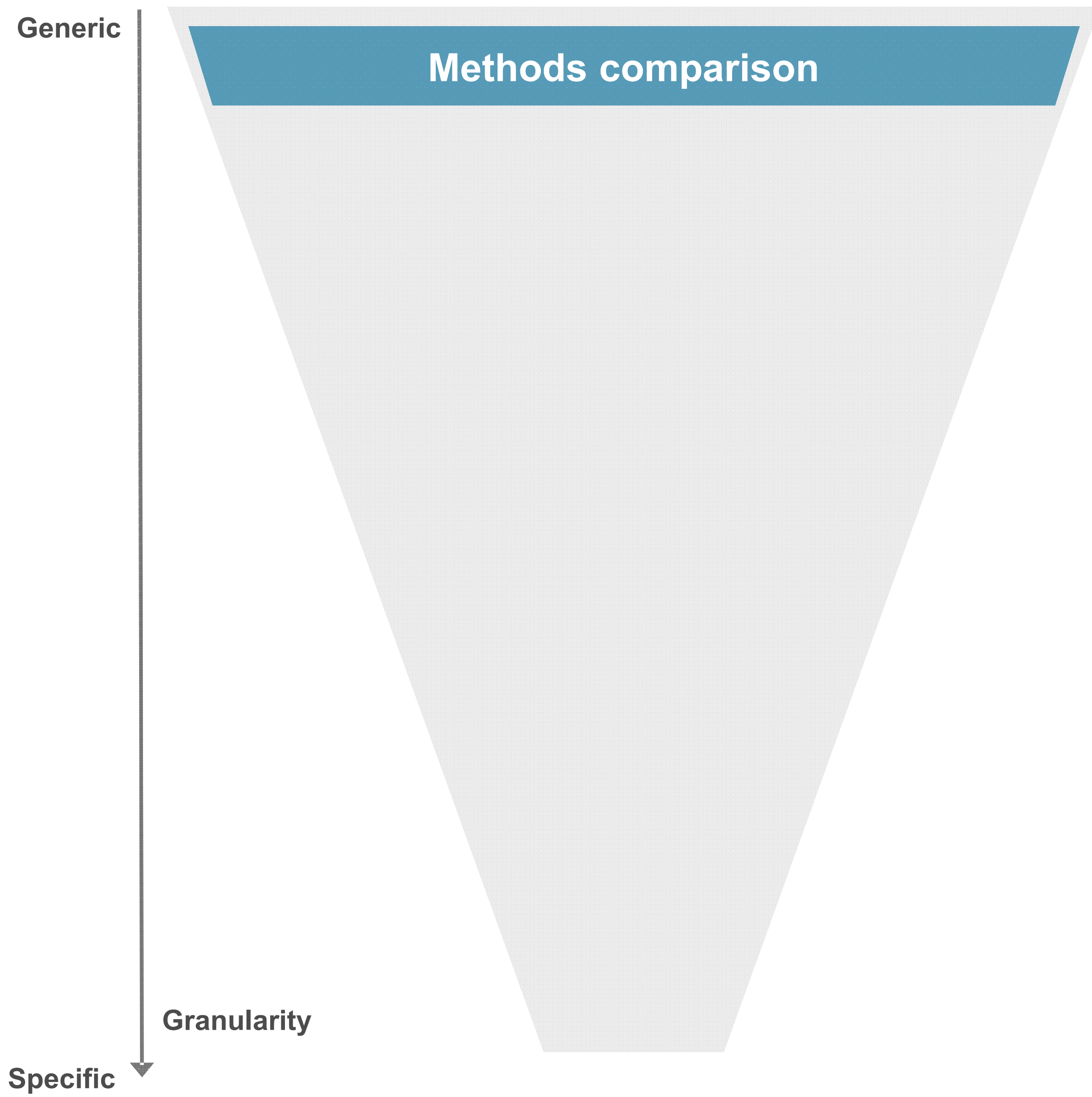


Specific Kanban



Limits:

- Demand spikes
- Seasonality


Generic
Methods comparison
Granularity
Specific

Literature review

Demand Driven MRP:

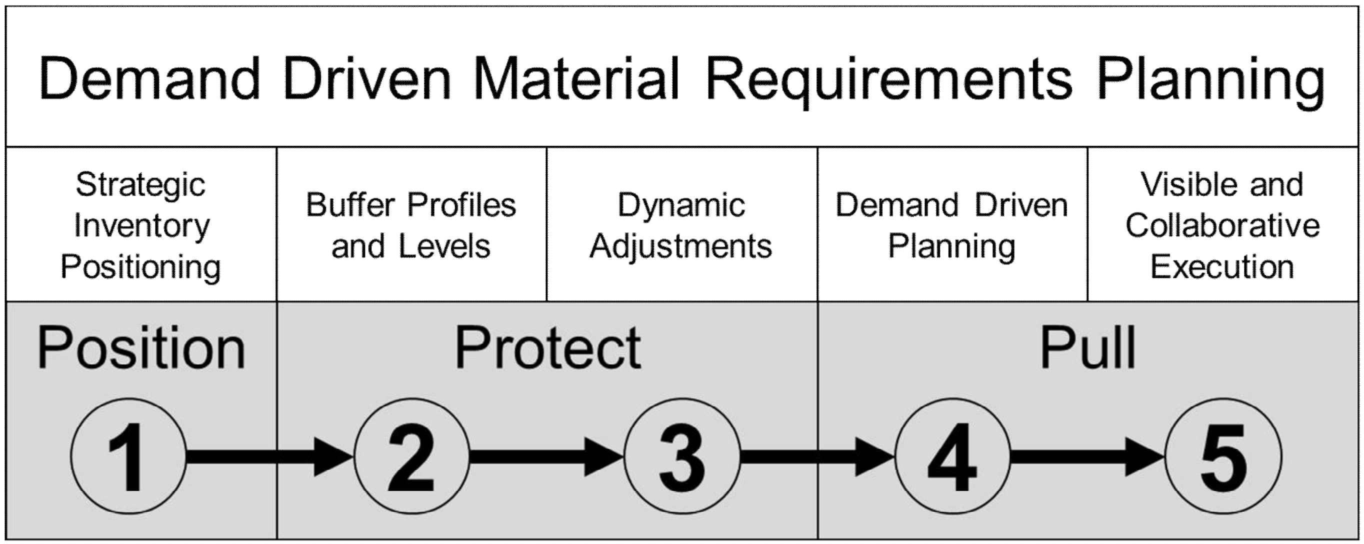
- Ptak, Carol, and Chad Smith. *Orlicky's Material Requirements Planning 3/E*. McGraw Hill Professional, 2011.
- Ptak, Carol, and Chad Smith. *Demand Driven Material Requirements Planning (DDMRP)*. Industrial Press, Inc., 2016.

- **Nearly no work from a scientific point of view**

  - Rim, Suk-Chul, Jingjing Jiang, and Chan Ju Lee. 'Strategic Inventory Positioning for MTO Manufacturing Using ASR Lead Time'. In *Logistics Operations, Supply Chain Management and Sustainability, 2014*.
  - Ihme, Mathias, and Roy Stratton. 'Evaluating Demand Driven MRP: A Case Based Simulated Study', 2015.
  - Jiang, Jingjing, and Suk-Chul Rim. 'Strategic Inventory Positioning in BOM with Multiple Parents Using ASR Lead Time'. *Mathematical Problems in Engineering* 2016

$\Rightarrow$ **Hence the research work interests and the thesis title:**
Challenging the Demand Driven MRP Promises

The 5 DDMRP components



Ptak, Carol, and Chad Smith. *Demand Driven Material Requirements Planning (DDMRP)*. Industrial Press, Inc., 2016.

Demand Driven INSTITUTE

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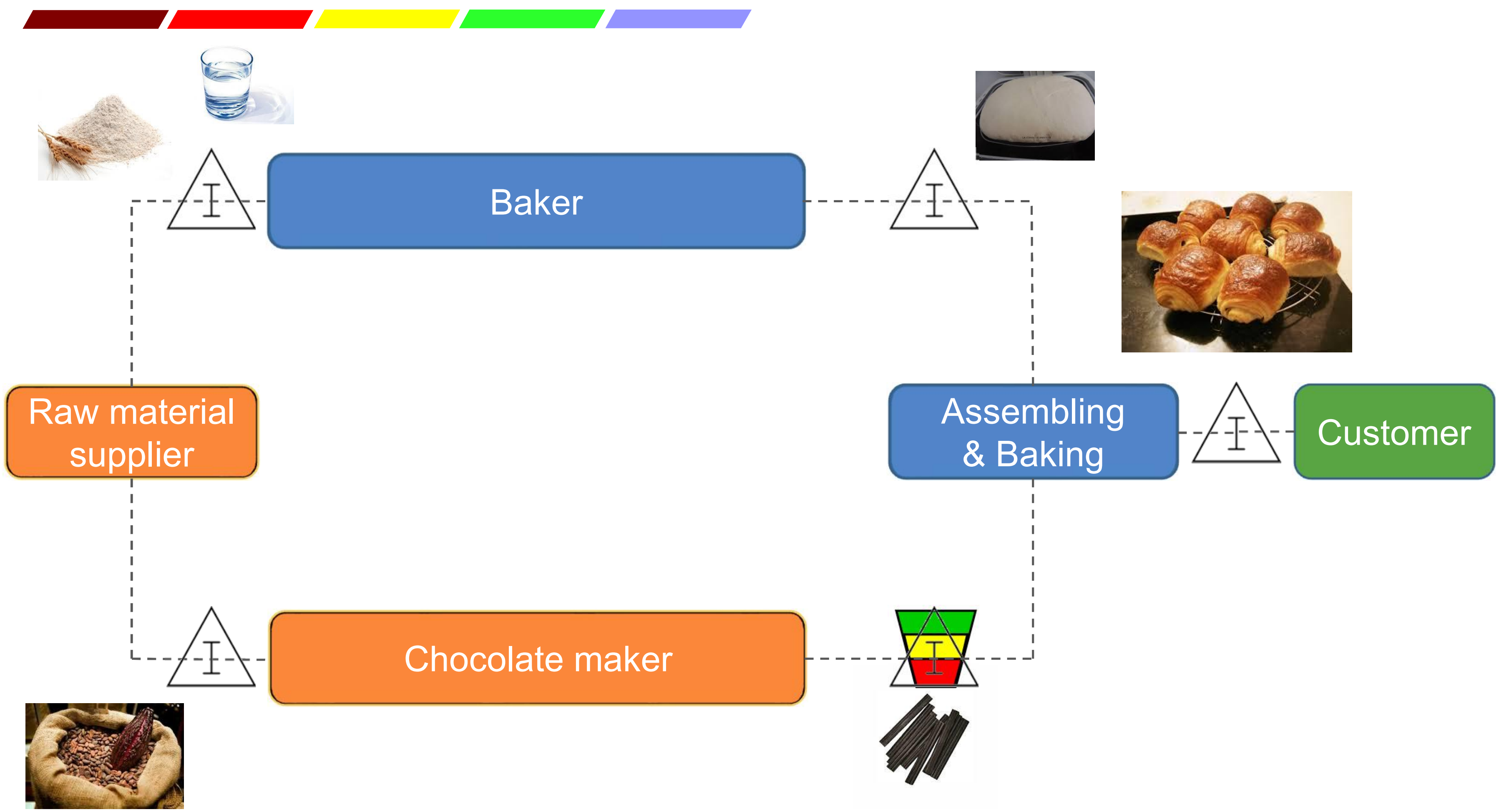
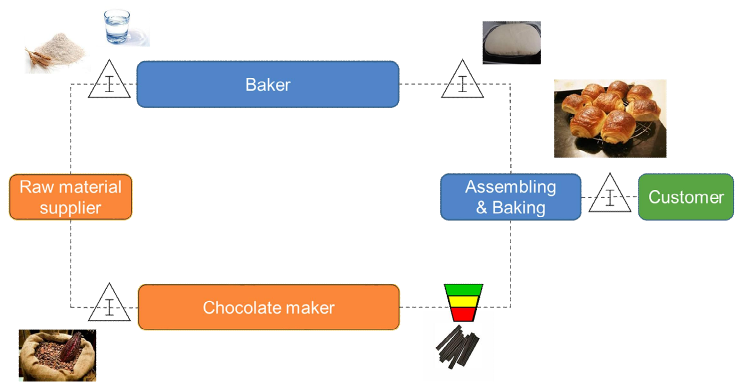
DDMRP Description



DDMRP Description

4

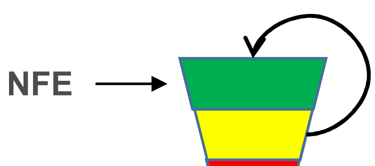


Planning

Net Flow Equation (NFE)

= On hand + Supply Orders – (Day Demand + Spike in Lead Time)

Stock position (On hand + Supply Orders – Day Demand)



- Supply order #1 Qty : x

Chen, Fangruo, and Yu-Sheng Zheng. ‘Evaluating Echelon Stock (R, nQ) Policies in Serial Production / Inventory Systems with Stochastic Demand’. *Management Science* 40, no. 10 (1994).

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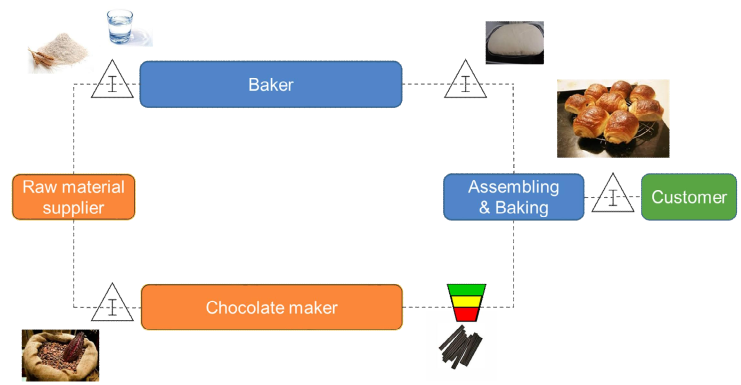
DDMRP Description

4

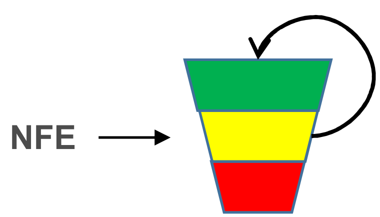


Planning

Net Flow Equation (NFE)

= On hand + Supply Orders – (Day Demand + Spike in Lead Time)

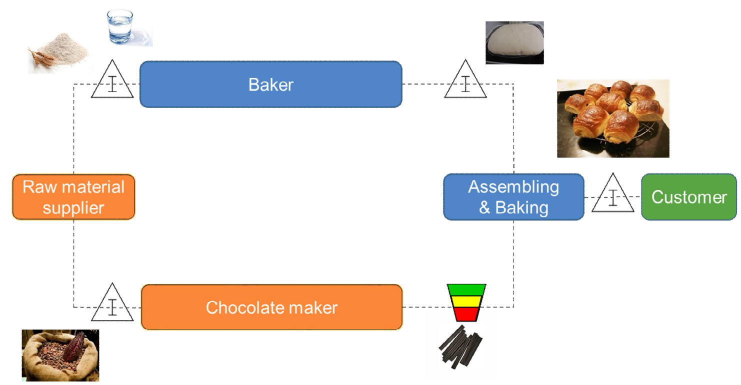
Stock position



- Supply order #1 Qty : x

DDMRP Description

4

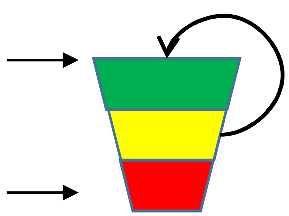


Planning

Net Flow Equation (NFE)

= On hand + Supply Orders – (Day Demand + Spike in Lead Time)

Stock position

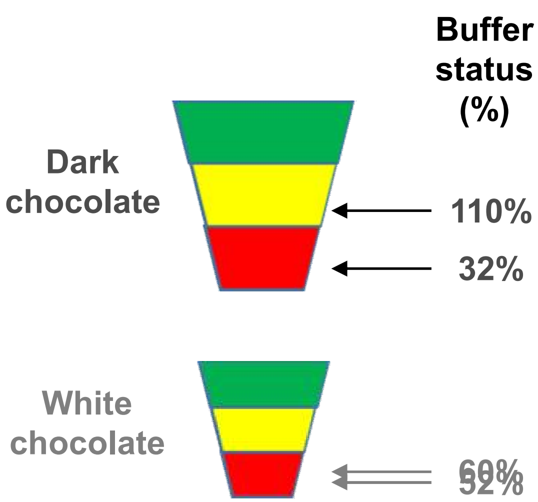


- Supply order #1	Qty : x
- Supply order #2	Qty : y (y>x)
- Supply order #...	Qty : …

DDMRP Description

5 Execution:

Buffer status = On hand inventory / Buffer Red Zone



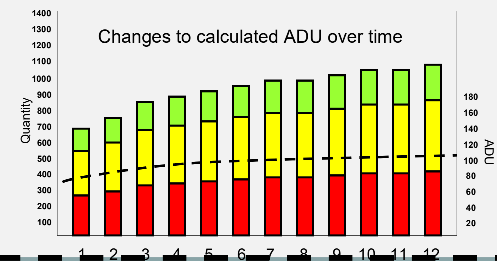
~~- Supply order #1~~	~~Dark chocolate~~	~~Qty : x~~
- Supply order #2	Dark chocolate	Qty : y
- Supply order #3	White chocolate	Qty : z

DDMRP Description

Buffer Level Adjustment (3)

Recalculated Adjustments

Buffer levels flex as Average Daily Usage is updated.



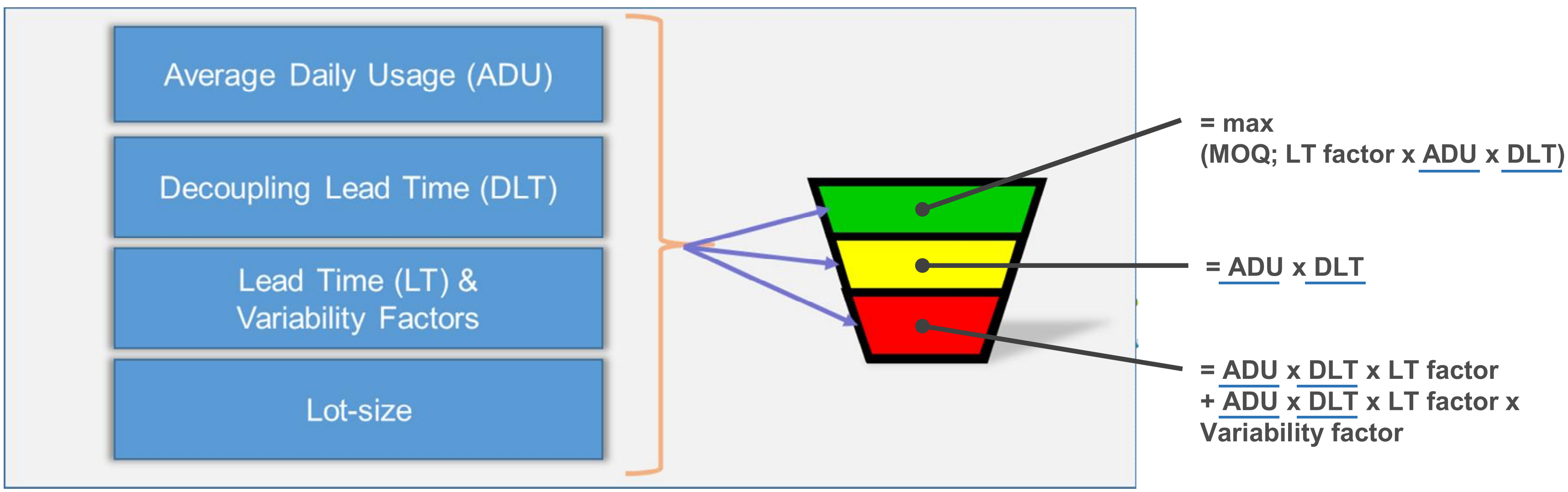
Planned Adjustments

Buffers are intentionally flexed up in anticipation of planned uplifts or seasons and then flexed down.

Ptak, Carol, and Chad Smith. *Demand Driven Material Requirements Planning (DDMRP)*. Industrial Press, Inc., 2016.

DDMRP Description

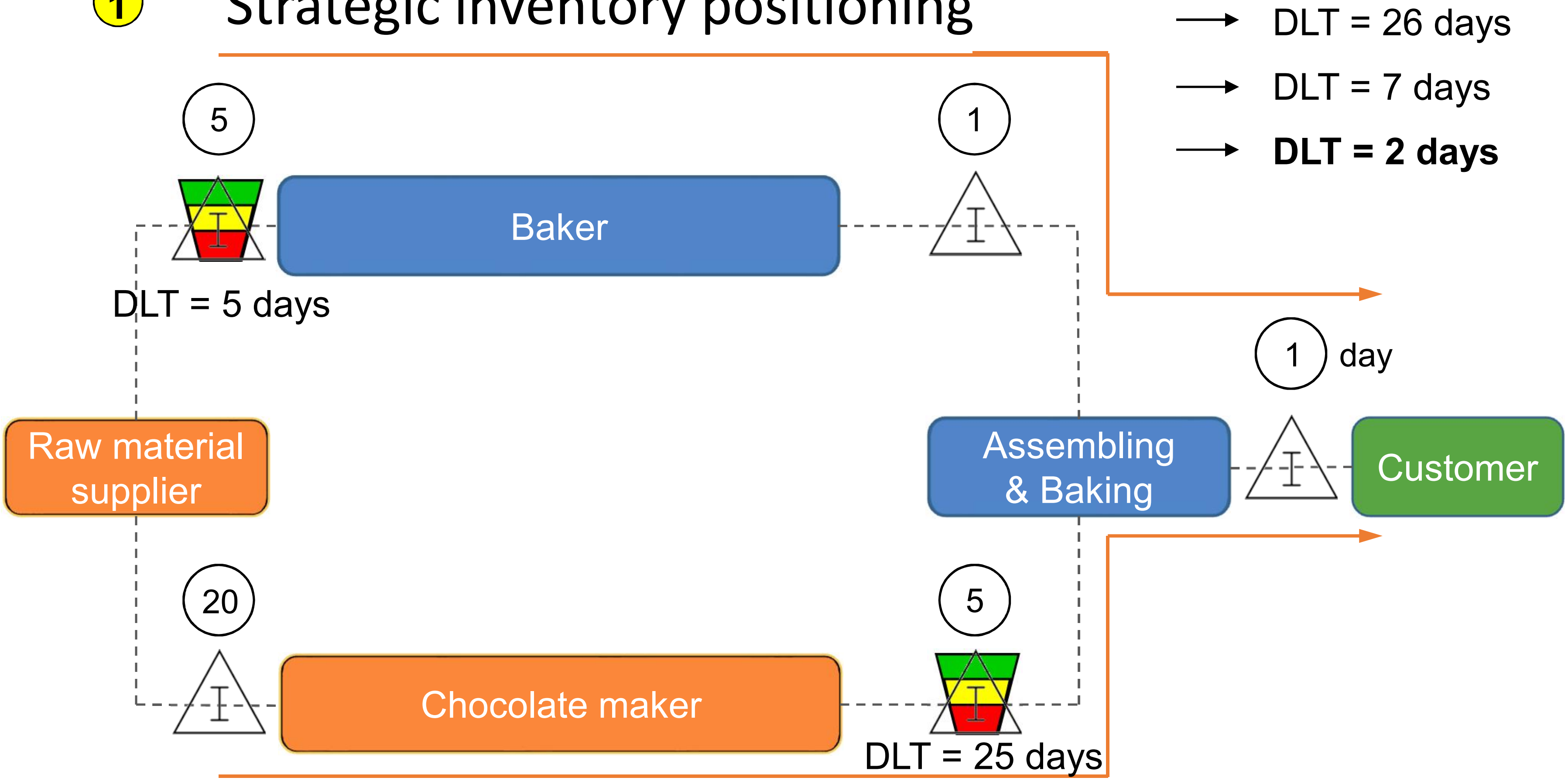
2 Buffer level setting



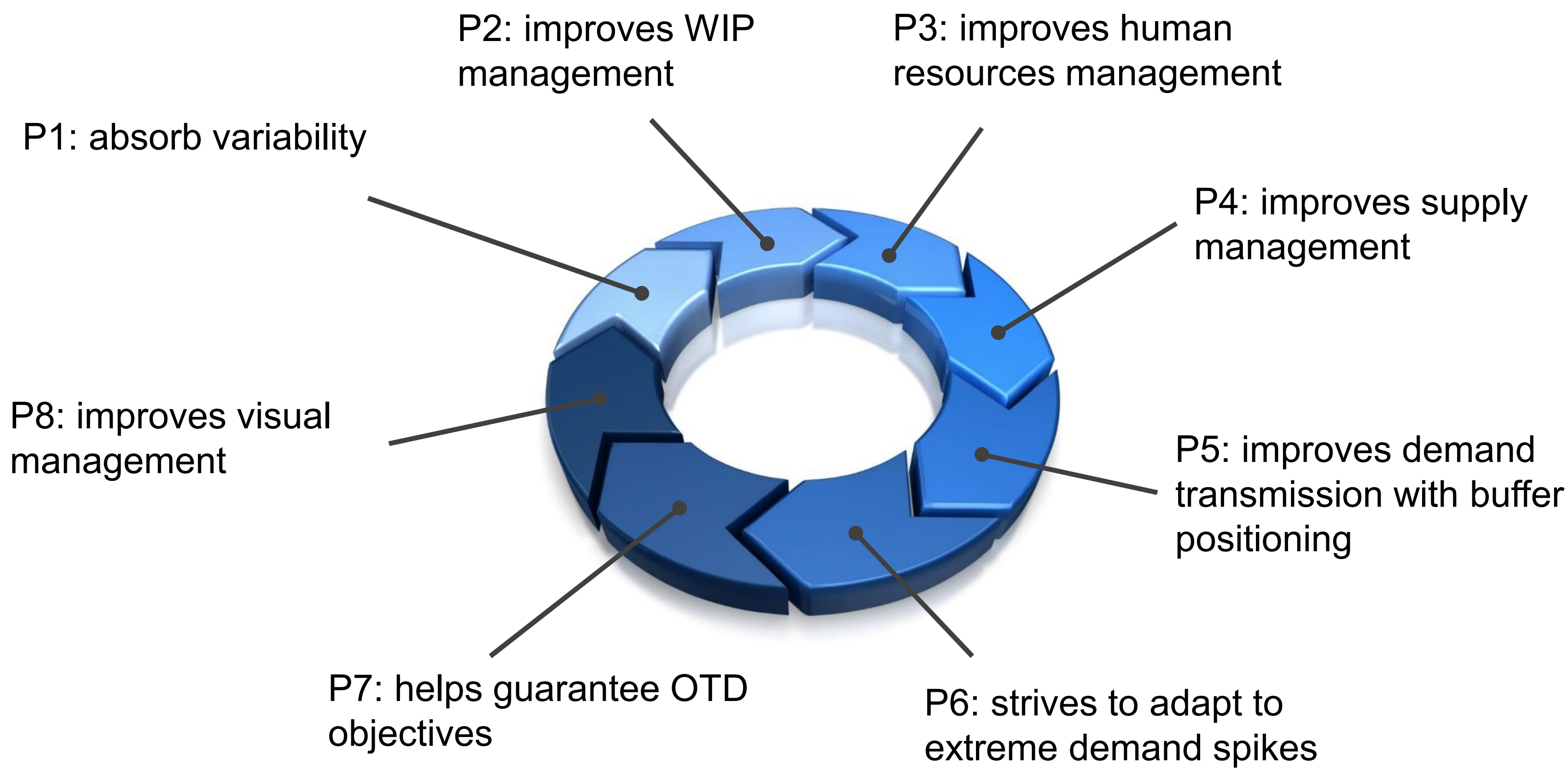
Ptak, Carol, and Chad Smith. *Demand Driven Material Requirements Planning (DDMRP)*. Industrial Press, Inc., 2016.

DDMRP Description

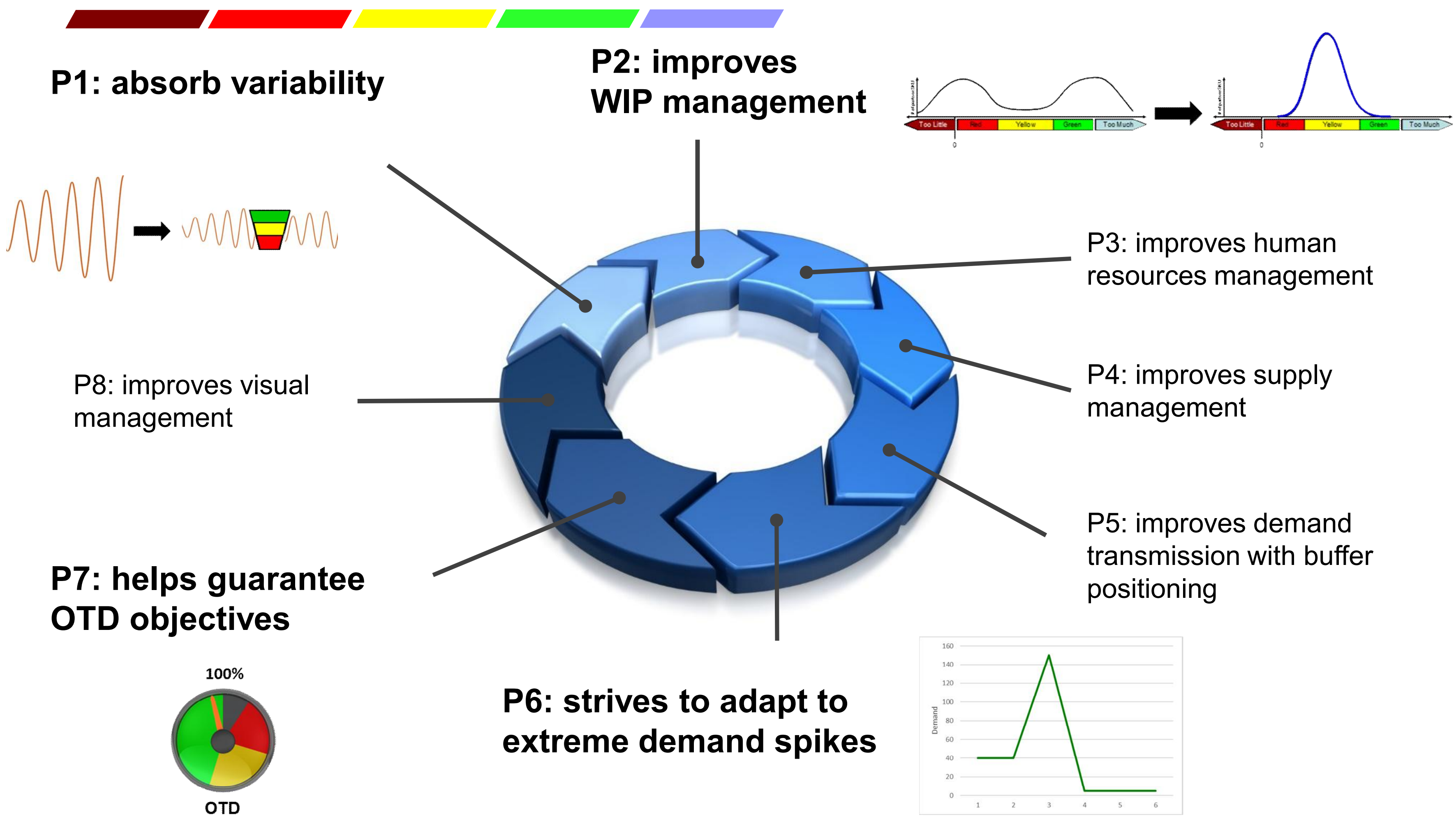
1 Strategic inventory positioning

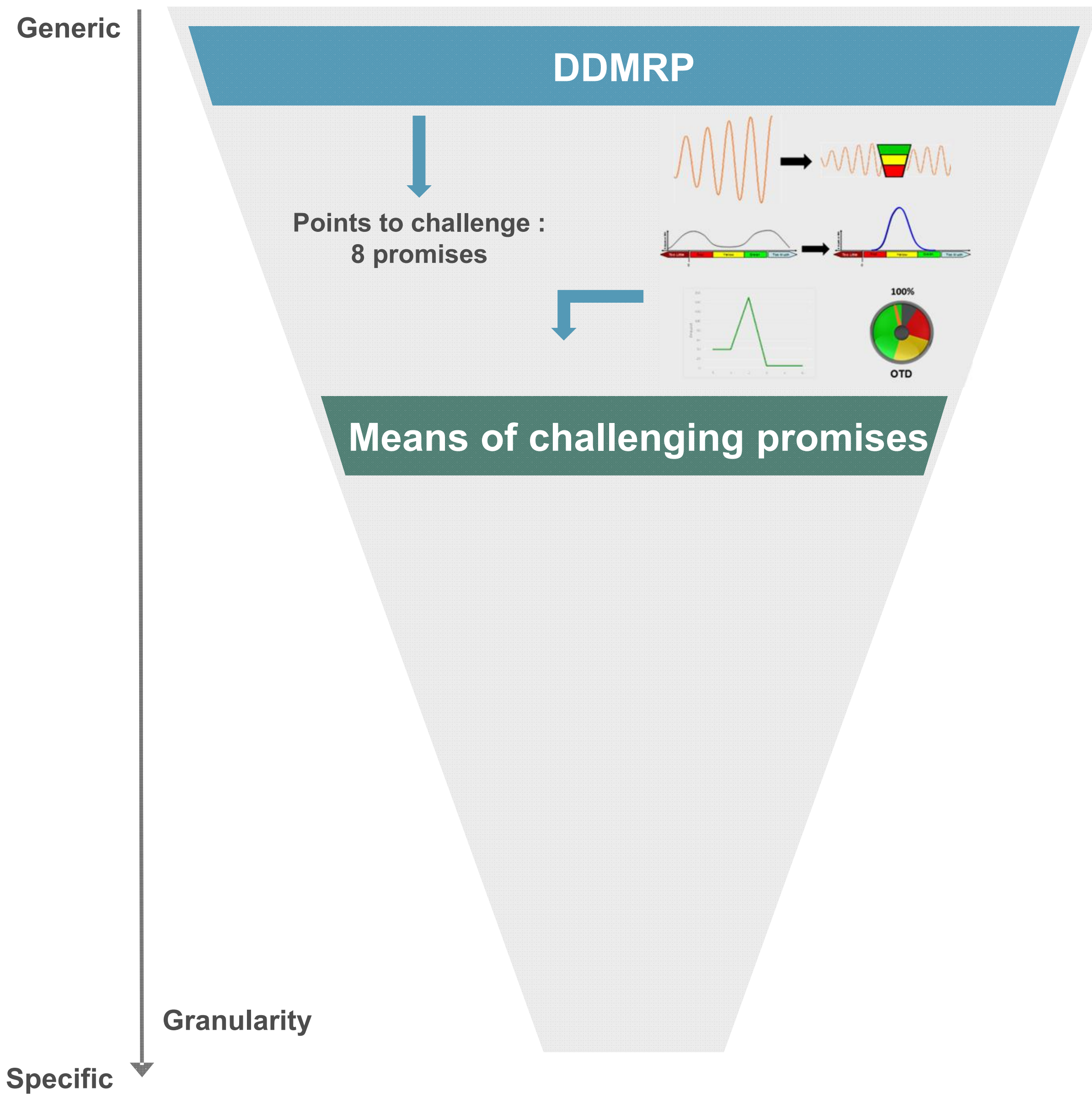


DDMRP Promise to challenge

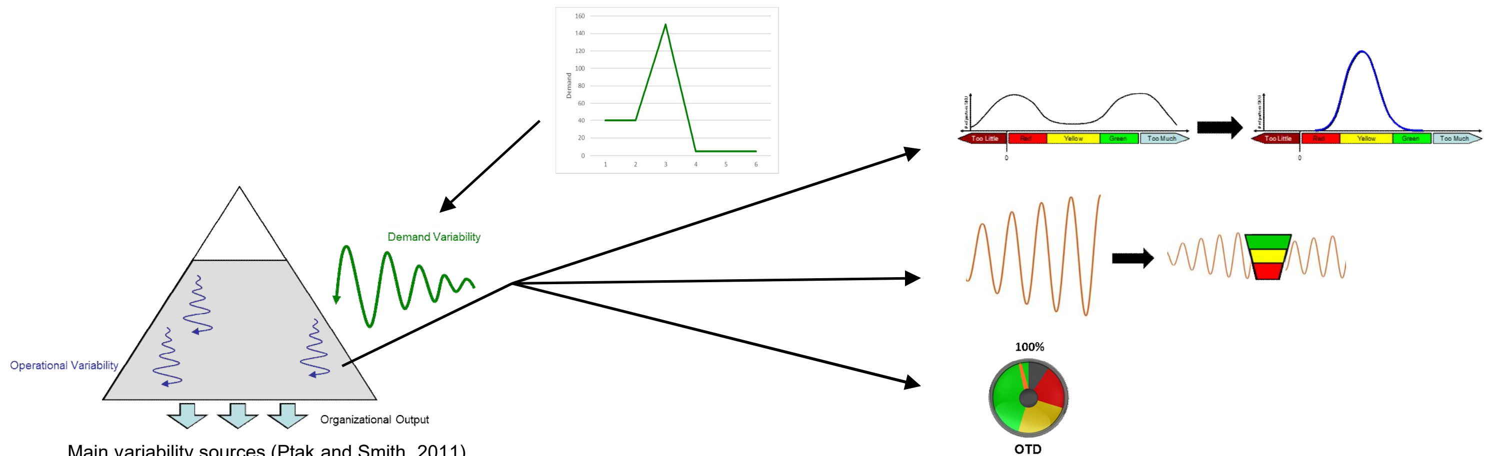


4 main promises challenged




Generic
DDMRP
Points to challenge :
8 promises
100%
OTD
Means of challenging promises
Granularity
Specific

Our approach



Main variability sources (Ptak and Smith, 2011)

OTD
WC

Experimental Design → **Model system** → **Performance analysis**

Experimental Design

- Initial scenario
- Operational variability
- Seasonality
- Demand profiles (spikes and troughs)

Model system

- MRP II
- Kanban
- DDMRP

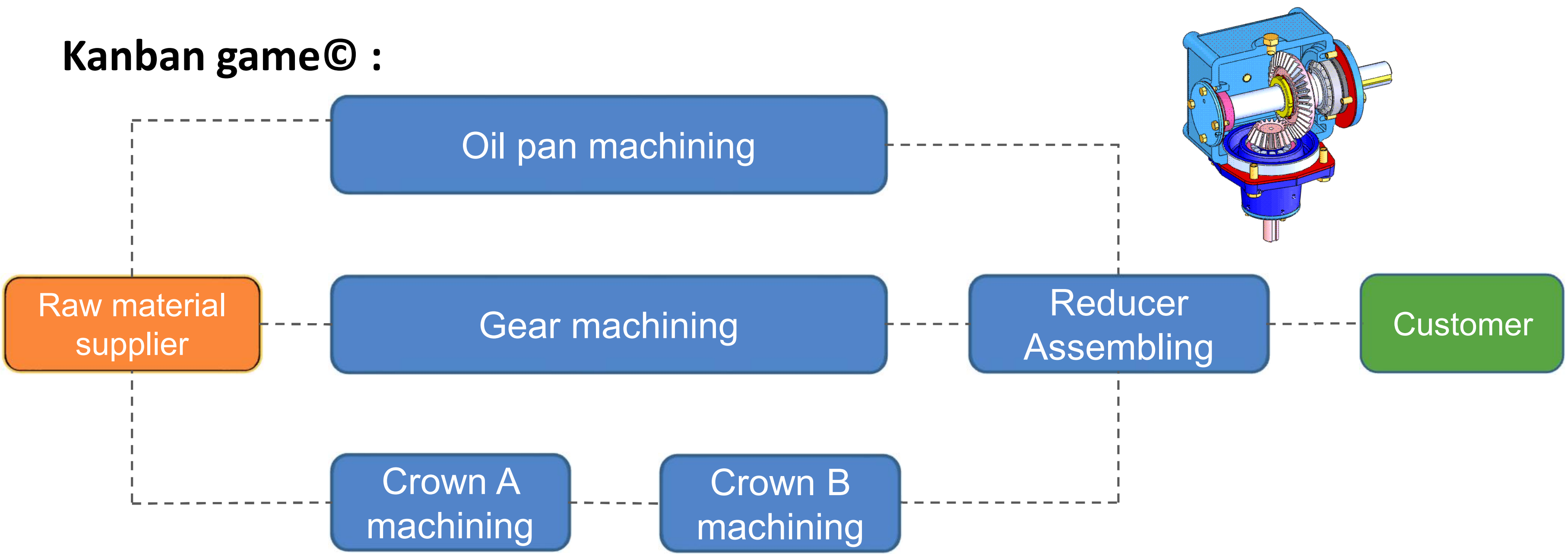
Performance analysis

- Parameter changes

Agenda

Academic case study

Kanban game© :



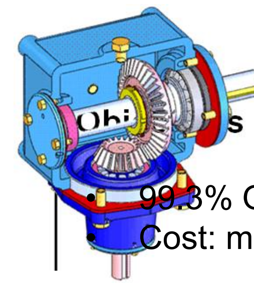
Representative case reality:

- Assembling operation (3 BOM levels)
- 16 references (6 finished products)
- 4 machining operations
- Machine breakdowns

Limits:

- One activity for each routing
- Significant setting up times
- Operation cycle time similar for each activity

Academic case study



- 99.3% OTD
- Cost: minimizing WC

Oil pan machining

Raw material supplier — Gear machining — Reducer Assembling — Customer

Crown A machining — Crown B machining

	MRPII	Kanban	DDMRP
Methods:	• S&OP • MPS • MRP • Scheduling *Fixed order*		• Buffer positioning ✓ • Buffer sizing ✓ • Dynamic adjustment ✓ • DDMRP planning ✓ • Execution with buffer status ✓
Possible levers:	• Safety stocks • S&OP maximum	• Kanban number • Red indicator • Green indicator	• Lead time factor (red and green) • Variability factor • DLT

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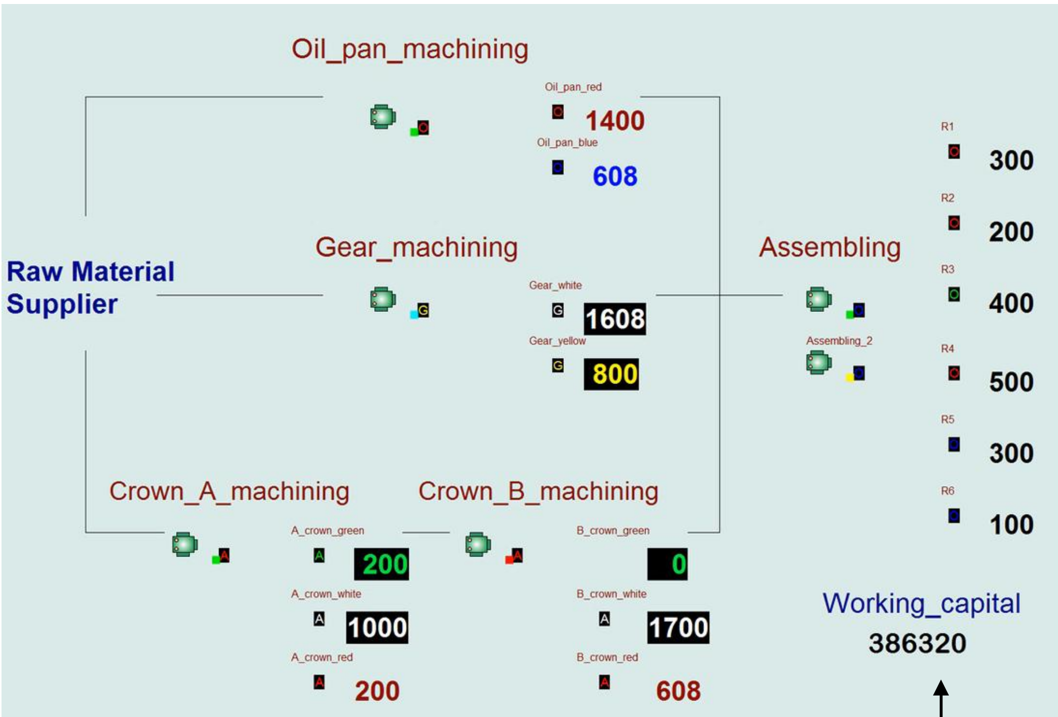
Simulation model



Detailed Output : — Initialise statistics

		R1			R2		
4	Period	Orders	Deliveries	*Missing*	Orders	Deliveries	*Missing*
5	Init			*0*			*0*
6	0	200	200	*0*	0		*0*
7	1	100	100	*0*	0		*0*
8	2	0		*0*	0		*0*
9	3	200	200	*0*	100	100	*0*
10	4	200	200	*0*	0		*0*
11	1	100	100	*0*	0		*0*
12	2	200	200	*0*	0		*0*
13	3	0		*0*	0		*0*
14	4	100	100	*0*	0		*0*
15	5	200	200	*0*	0		*0*
16	1	100		*100*	100		*100*
17	2	200		*300*	100		*200*
18	3	0		*300*	0		*200*
19	4	100		*400*	0		*200*
20	5	200		*600*	0		*200*
21	1	200		*800*	0		*200*
22	2	100		*900*	0		*200*
23	3	0		*900*	0		*200*
24	4	200		*1100*	100		*300*
25	5	200		*1300*	0		*300*
26	1	100		*1400*	0		*300*
27	2	200		*1600*	0		*300*
28	3	0		*1600*	0		*300*
29	4	100		*1700*	0		*300*
30	5	200		*1900*	0		*300*
31	1	100		*2000*	100		*400*

Witness® simulation model

- 5 minutes for 1 year
- 6 months warm up
- 6 months statistics

Working Capital (WC)

Excel® spreadsheet for delivery orders

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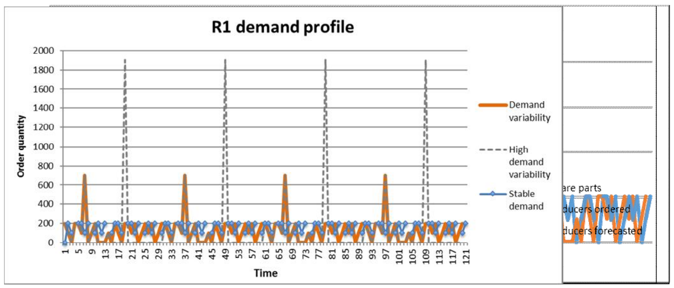
Design of experiments



	MRP				DDMRP				Kanban			
	WC (%)	OTD (%)	Safety Stock		WC (%)	OTD (%)	Buffer Zone		WC (%)	OTD (%)	Kanban Number	
			Red	Comp			Red	Comp			Red	Comp
1 - Initial state (stable demand)	**100%**	**99.3%**	100%	100%	**101%**	**100%**	100%	100%	**100%**	**100%**	100%	100%
2 - External variability	**125%**	**99.5%**	**145%**	107%	**105%**	**99.8%**	105%	87%	**111%**	**99.8%**	116%	102%
3 - Seasonality	**138%**	**99.8%**	**175%**	116%	**116%**	**99.4%**	111%	102%	**121%**	**99.4%**	98%	81%
4 - External variability sharply increased with 5 days of frozen demand	**197%**	**94.5%**	**180%**	**141%**	**158%**	**99.8%**	**126%**	90%	**134%**	**95.4%**	**139%**	111%

R. Miclo, F. Fontanili, M. Lauras, J. Lamothe et B. Milian 2016. "An empirical study of Demand-Driven MRP"
6th International Conference on Information Systems, Logistics and Supply Chain (ILS Conference)

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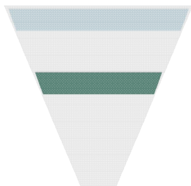
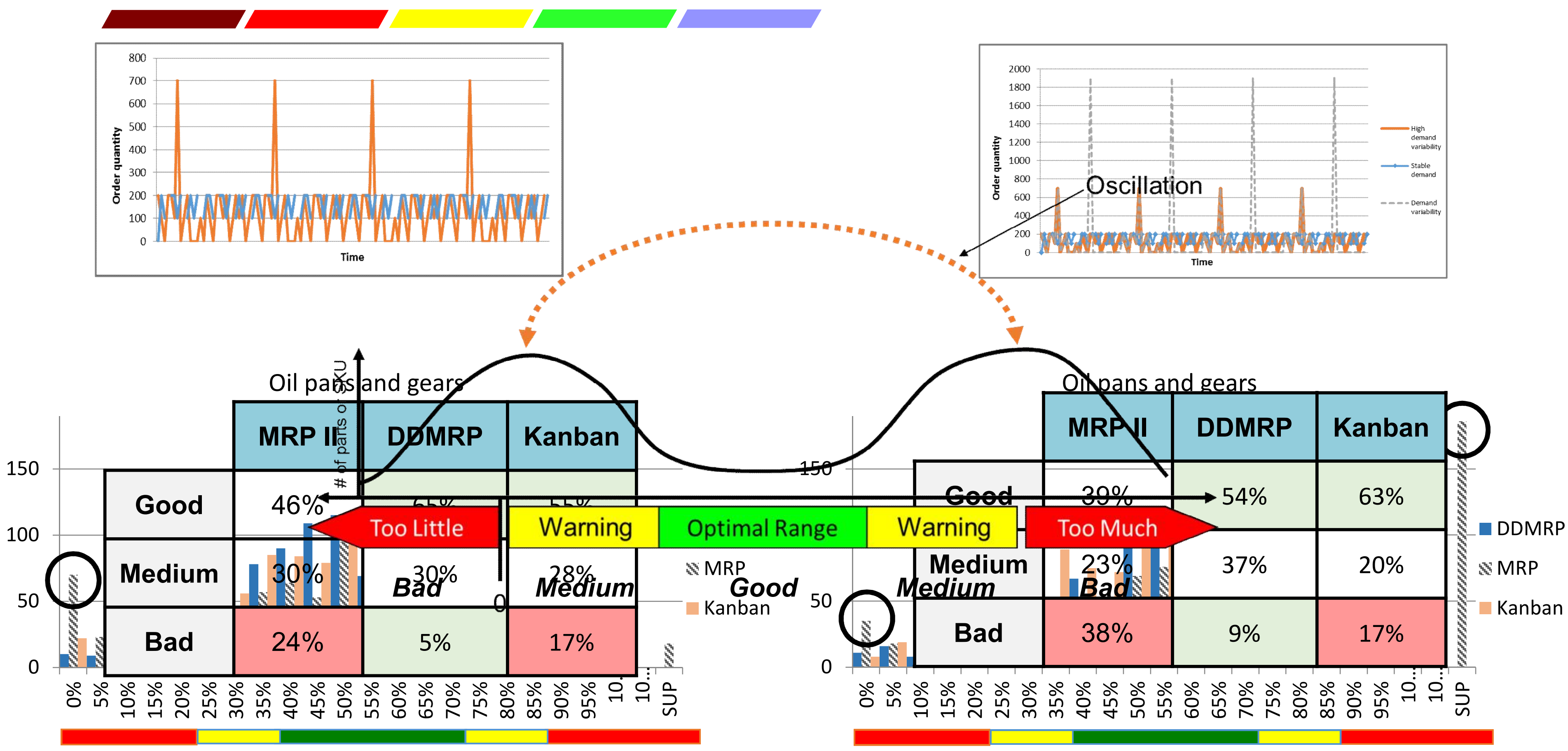


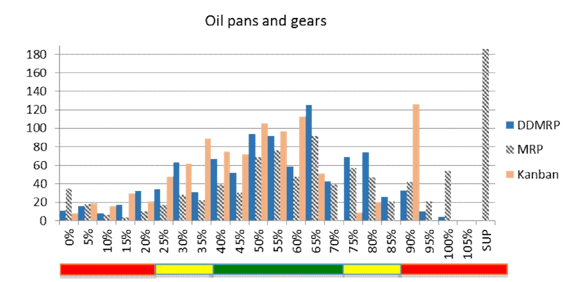
Inventory distribution



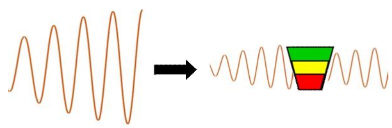
R. Miclo, F. Fontanili, M. Lauras, J. Lamothe et B. Milian 2016. "An empirical comparison of MRP II and Demand-Driven MRP" *8th IFAC on Manufacturing Modelling, Management & Control (MIM conference)*

Promises overview

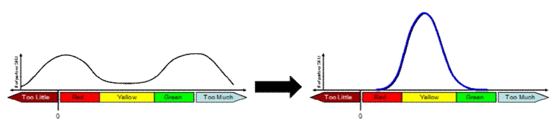
	MRP		DDMRP		Kanban	
	WC (%)	OTD (%)	WC (%)	OTD (%)	WC (%)	OTD (%)
1 - Initial state (stable demand)	100%	99.3%	101%	100%	100%	100%
3 - External variability	125%	99.5%	105%	99.8%	111%	99.8%
4 - Seasonality	138%	99.8%	116%	99.4%	121%	99.4%
5' - External variability sharply increased with 5 days of frozen demand - V2 Kanban	197%	94.5%	158%	99.8%	134%	95.4%



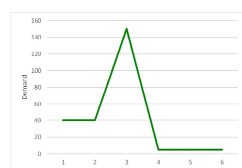
P1:



P2:

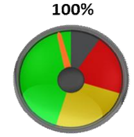


P6:



P7:

100%



OTD

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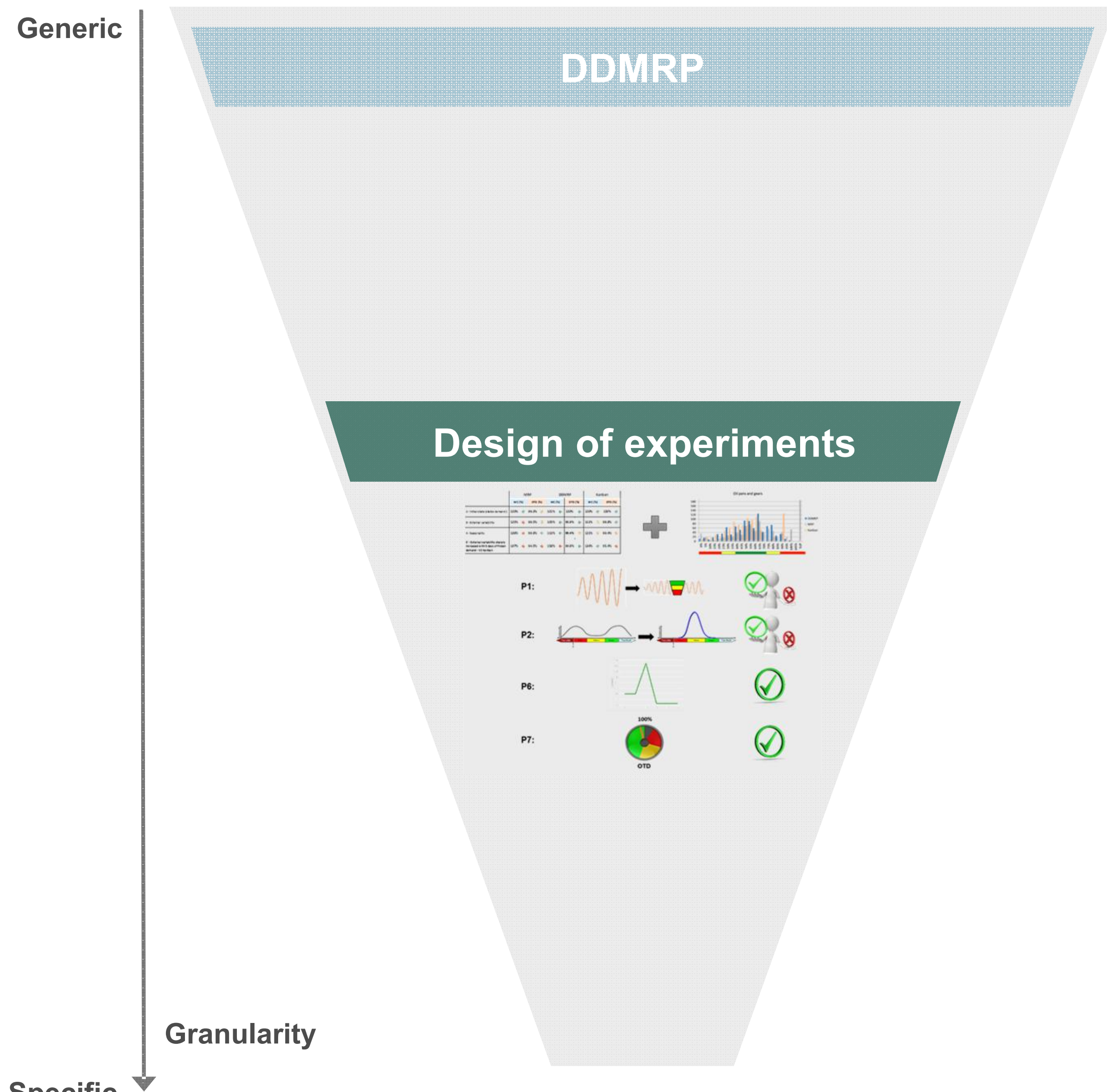
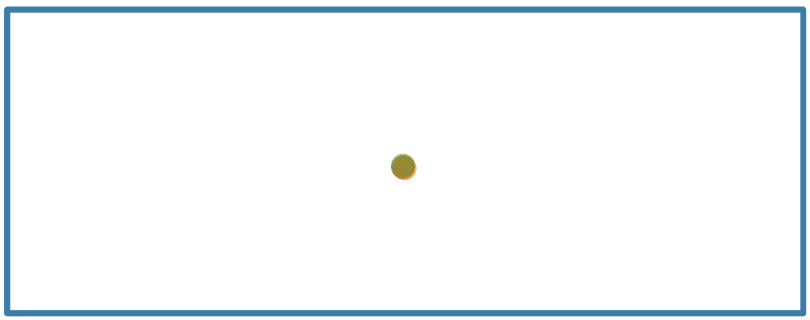

Generic
DDMRP
Design of experiments
P1:
P2:
P6:
P7:
100%
OTD
Granularity
Specific

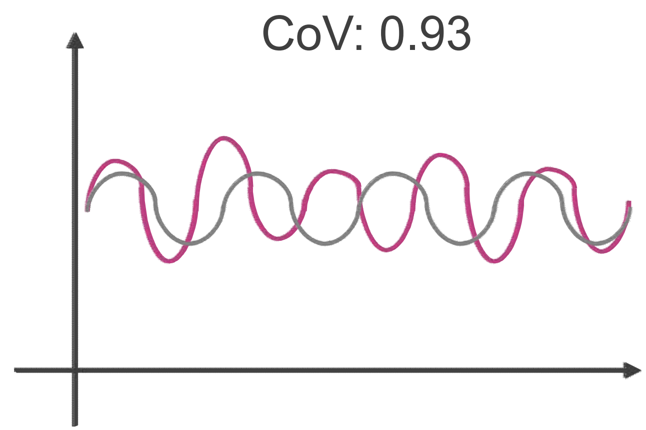
Agenda

Comparison method

DDMRP MRP II Kanban

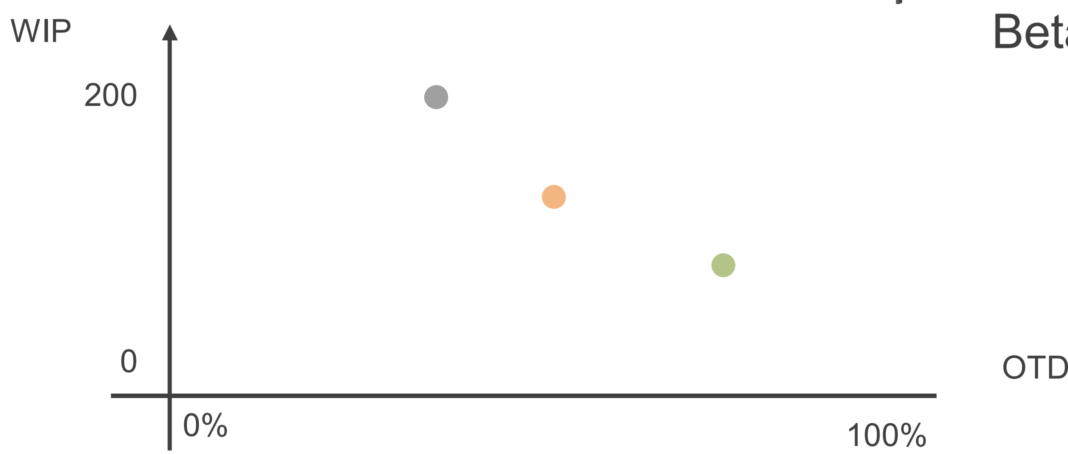


Demand variability:

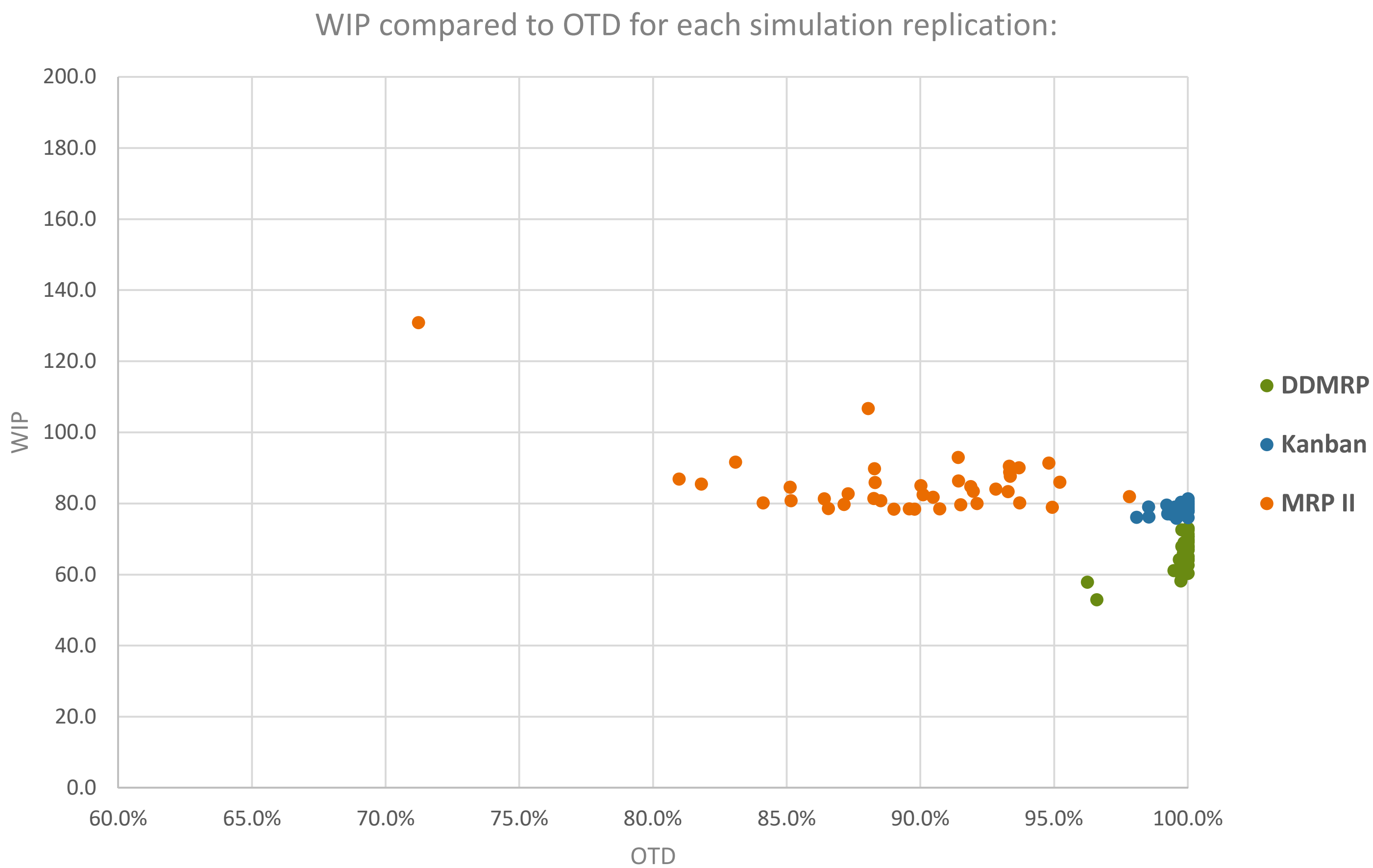


Beta Distribution law

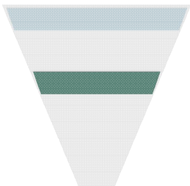
Results:



Results with low variability



And if demand variability was higher?



High variability

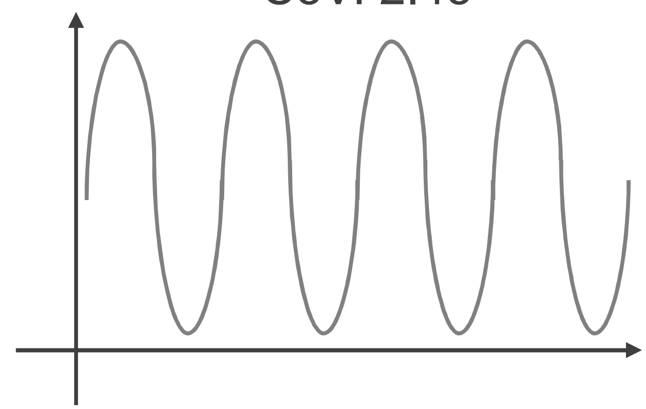
DDMRP

MRP II

Kanban

Demand variability:

CoV: 2.45



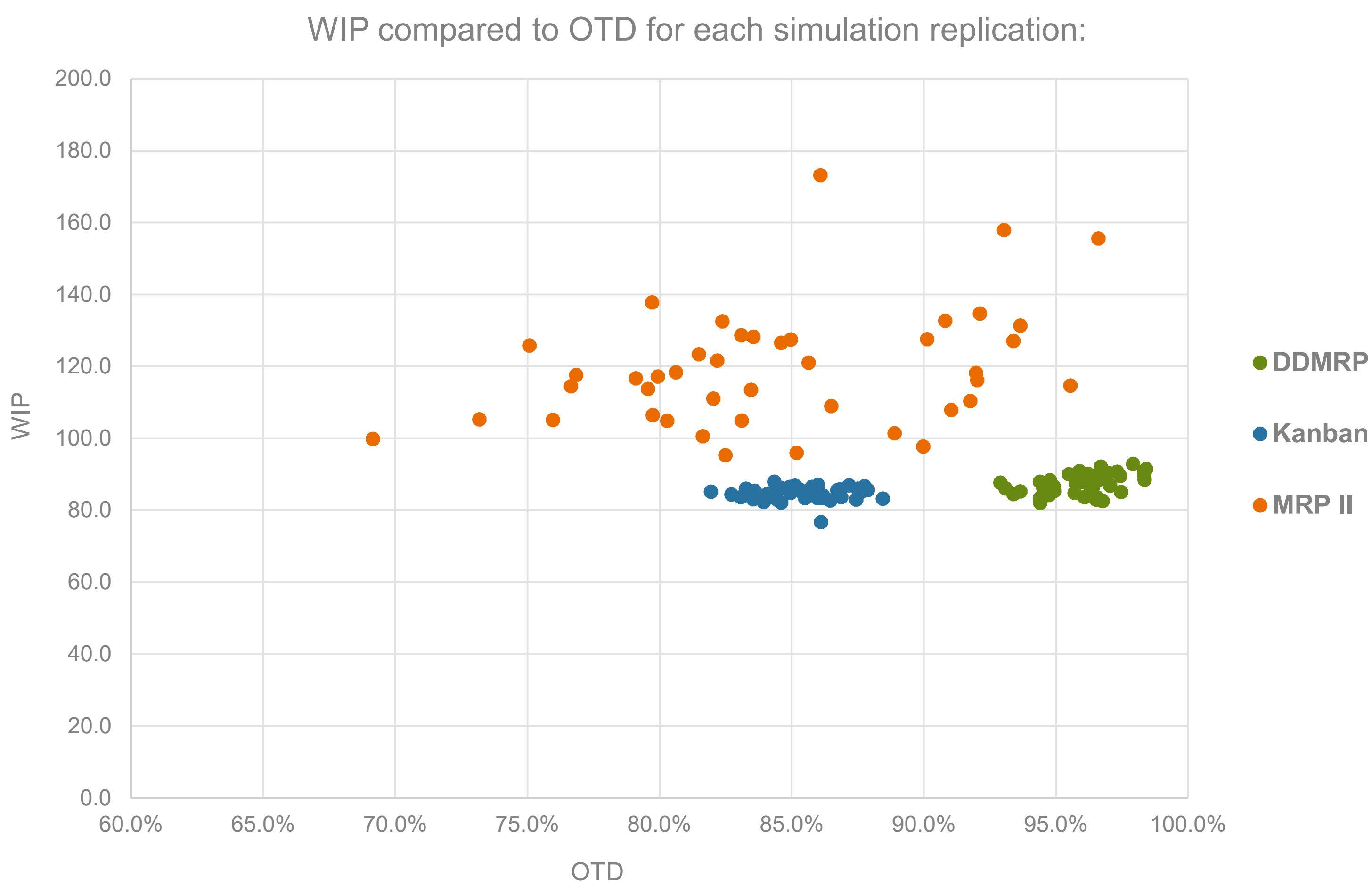
Beta Distribution law

Results:

WIP

OTD

Results with high variability



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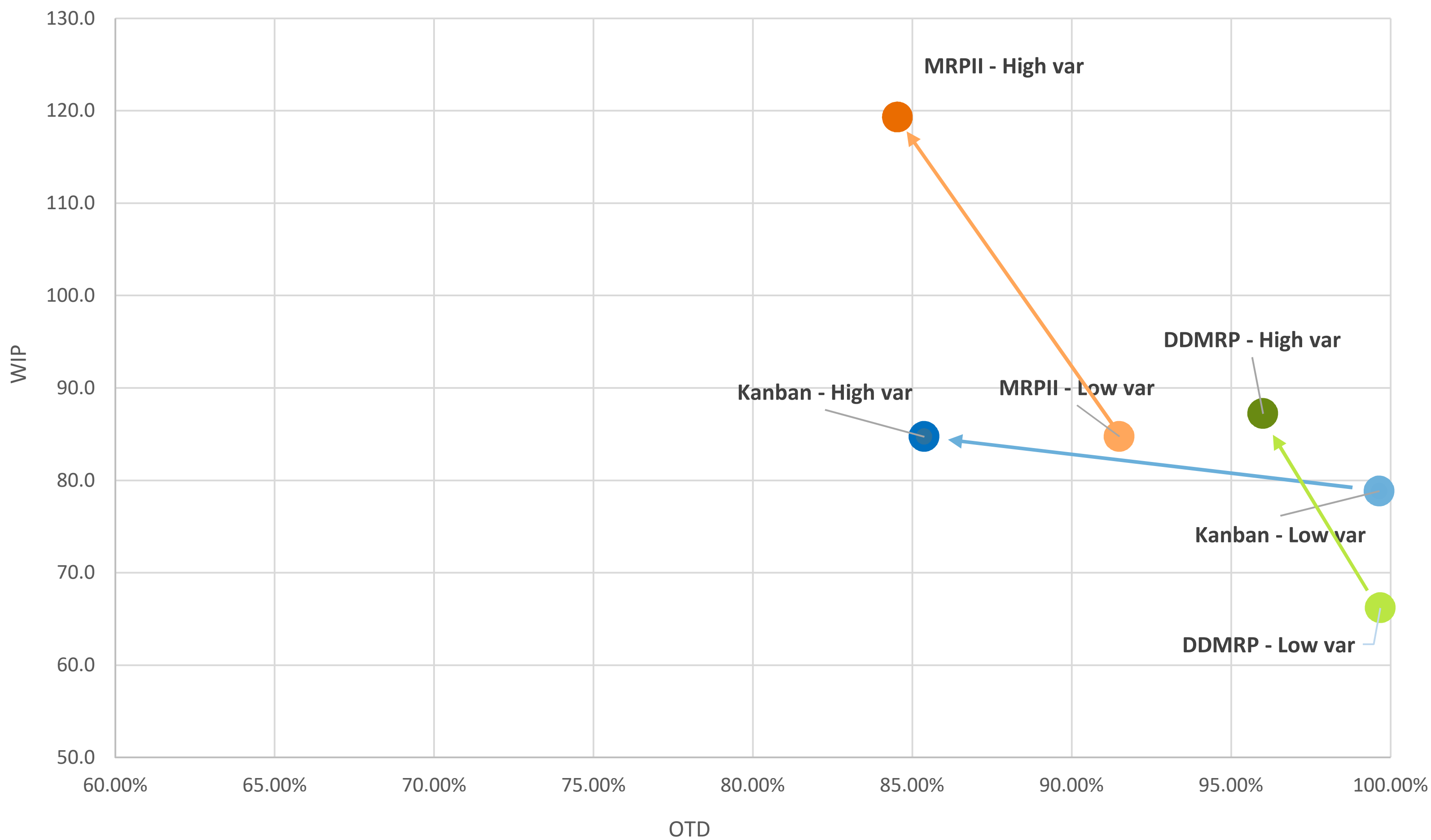
Conclusion

WIP distribution vs On Time Delivery:



Conclusion

DDMRP	Kanban	MRP II
➢ Very reliable performances ➢ Satisfactory for On Time Delivery and WIP	➢ With pull flow vision, able to absorb some variability and guarantee good performance ➢ Significantly breaks when variability raises (equivalent average OTD as MRP II)	➢ Unstable AND unsatisfying performances ➢ More true as variability is increasing

Agenda

1 Context

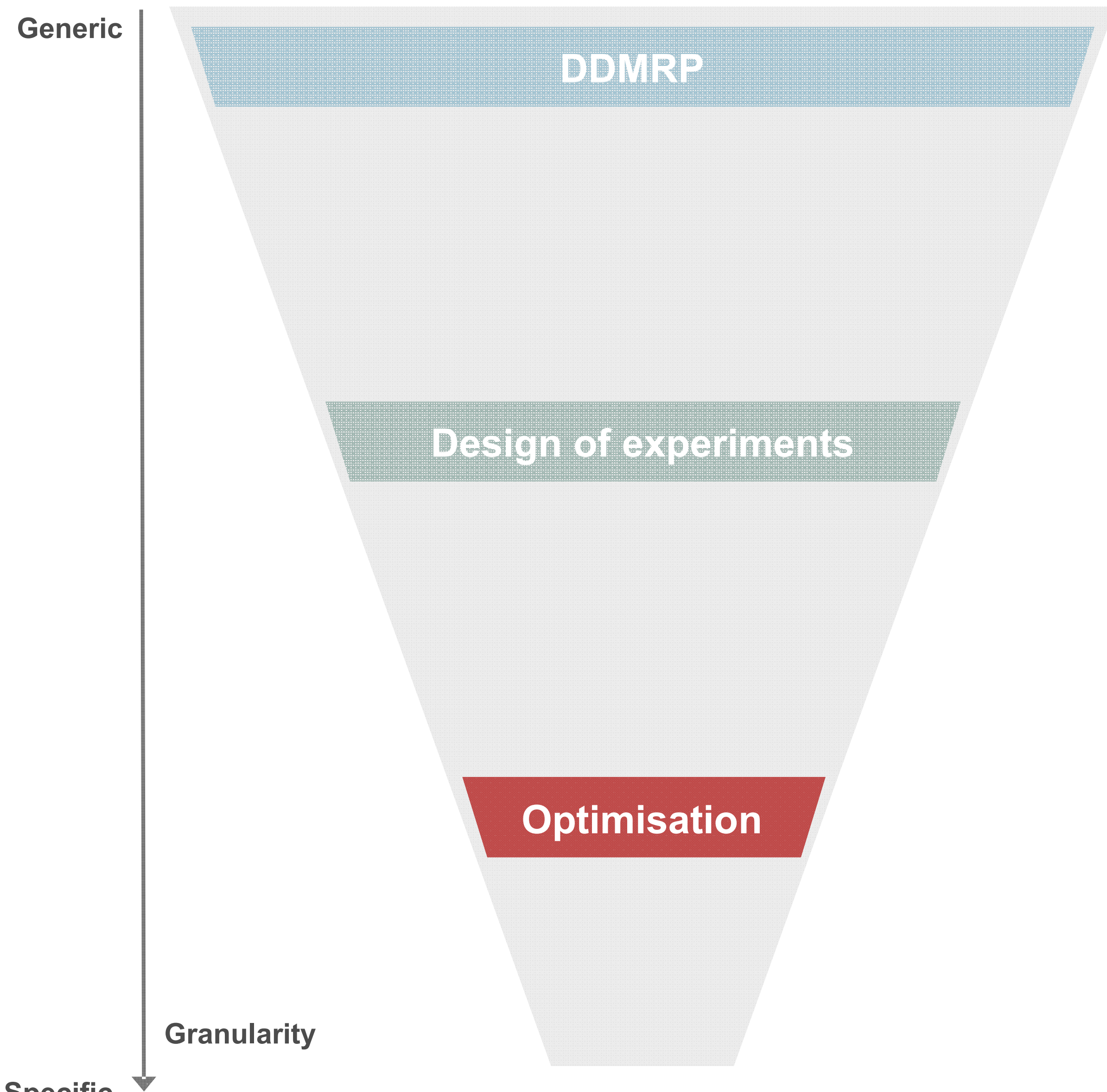
2 Material management methods

3 Case study – design of experiments

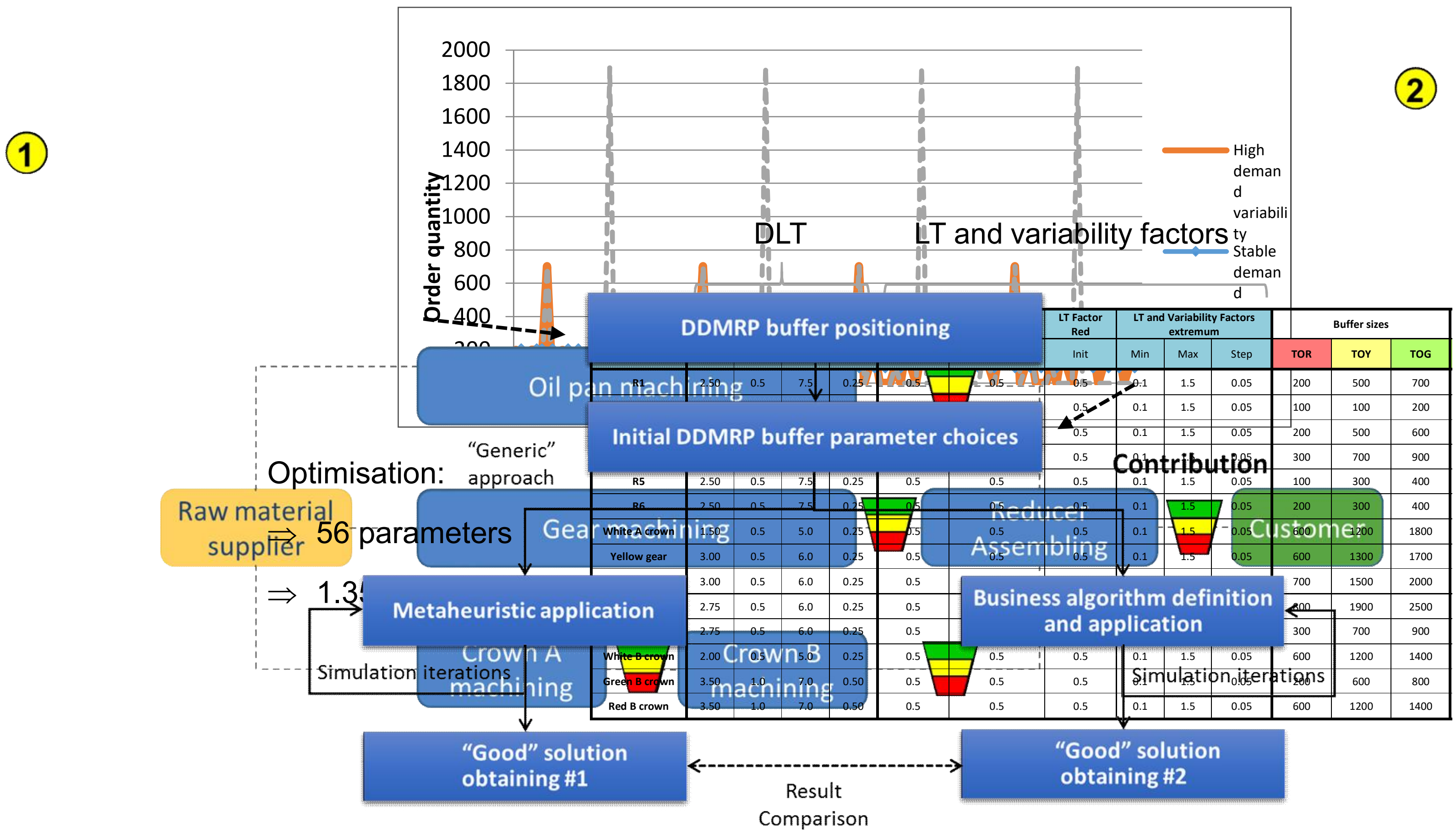
4 Case study – simulation replications

5 **Case study – buffer sizing optimisation**

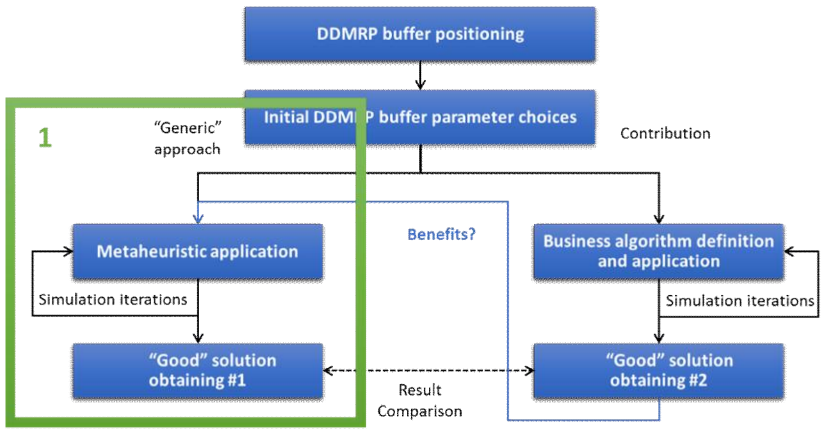
6 Conclusion & Perspectives


Generic
DDMRP
Design of experiments
Optimisation
Granularity
Specific

Our approach



Simulated annealing application



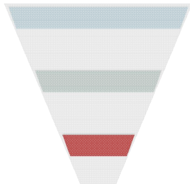
Simulated Annealing algorithm:

- **in order to try to rapidly find a good solution**
- **with a goal programming objective function**

Parameters

- Initial temperature: 100
- Cooling rate: 0.91
- Cooling step: 25

$$Objective\ function = Min\,\{\underbrace{WC}_{\text{Minimising WC}} + \underbrace{Max(0\,;\ 100{,}000{,}000\ \times\ [0.993 - OTD])}_{\text{Reaching OTD objective}}\}$$

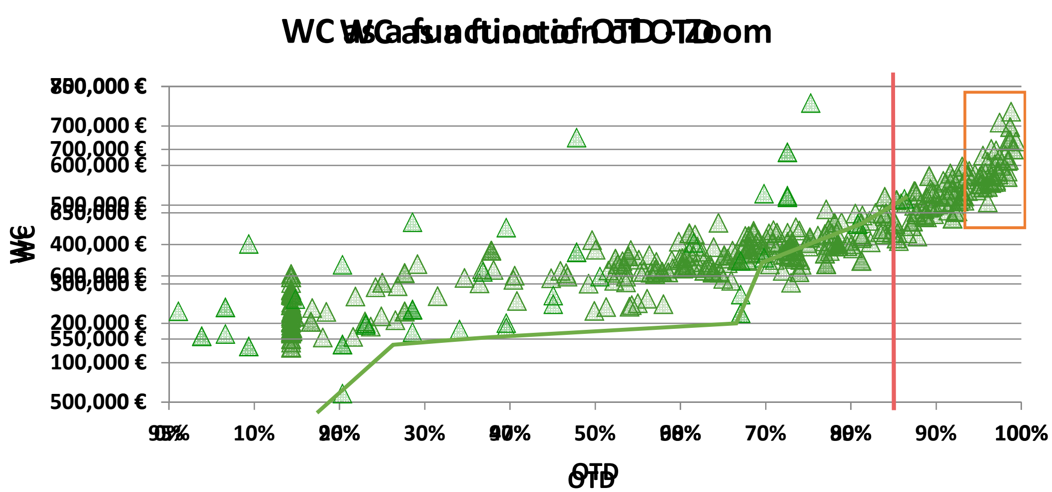


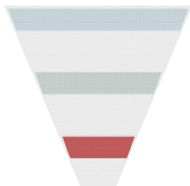
Simulated annealing results

Scenario number	559
Scenarios with OTD < 50%	421 (75.3%)
Scenarios with OTD > 99.3%	1 (0.2%)
Scenarios with WC > 1m€	0 (0.0%)
Scenarios with WC <1m€ and OTD > 99.3%	1 (0.2%)

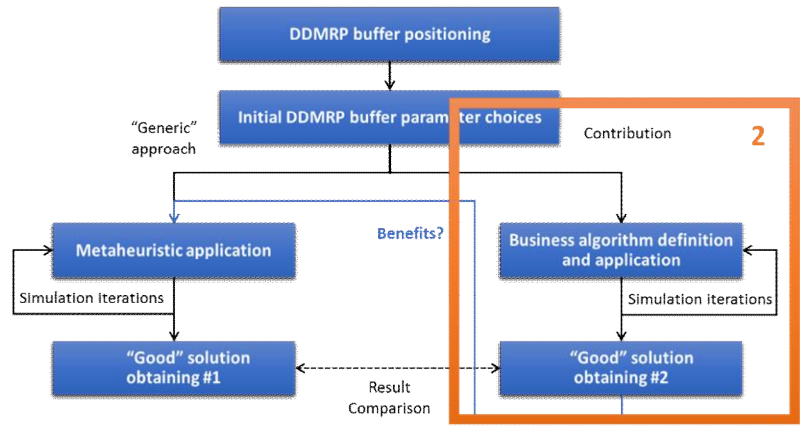
→ Difficult to find a good solution

Optimisation duration:
48 hours





Business algorithm definition



Business algorithm sliced into 4 blocks:

- **3 first to reach OTD objective**
- **4th to minimise WC**

Business algorithm: OTD objective

Block #1:

Goal:

- **Sizing reducers green zones (LT factor)**

```
While OTD < 99,3%  "This part goal is to achieve OTD objective"
// Block 1
    If in the second semester nb_delay > 6 AND counter ≠ 3 AND counter_2 ≠ 4
        For all reducers
            Initial_green_zone (ref)=Green_zone (ref)
            If nb_delay(ref) >=2
                Reducer (ref)=1
                Green_zone (ref)=green_zone (ref)+100

                Counter = counter +1
                Counter_2 = counter_2 + 1
            End If
        Next reducer
        SIMULATE()
        Iteration = iteration + 1
```

Block #2:

Goal:

- **Sizing the whole reducer buffers (DLT)**

```
// Block  2
    Else If counter=3 and nb_delay > 6
        If OTD (iteration) > OTD (iteration-1)
            // Block  2.1
            For all reducers
                If reducer (ref)=1
                    Green_zone (ref)=green_zone (ref)-100
                    DLT (ref) = DLT (ref) + 0.5 day
                End If
            Next reducer
            SIMULATE()
            Iteration = iteration + 1
        Else
            // Block 2.2
            For all reducers
                If reducer (ref) = 1
                    Green_zone (ref) = initial_green_zone (ref)
                    DLT (ref) = DLT (ref) + 0.5 day
                End If
            Next reducer
            SIMULATE()
            Iteration = iteration + 1
            Counter = 0
        End If
```

If not →

Block #3:

Goal:

- **Sizing components buffers (which reached zero inventory in the simulation)**

```
//Block 3
    Else If counter_2 = 4 and nb_delay > 6
        For all components
            DLT (ref) = DLT (ref) + 0.5 day
            Counter_2=0
        Next component
        SIMULATE()
        Iteration = iteration + 1
    End If
End While
```

```
// Block 4
While OTD > 99,3% "This part goal is to reduce WC when OTD objective is reached"
    For all references
        If min_WIP (ref) > 0
            DLT (ref) = DLT (ref) – 0.5 day
        End If
    Next reference
    SIMULATE()
    Iteration = iteration + 1
End While
```

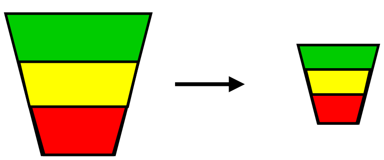
Business algorithm: WC objective and results

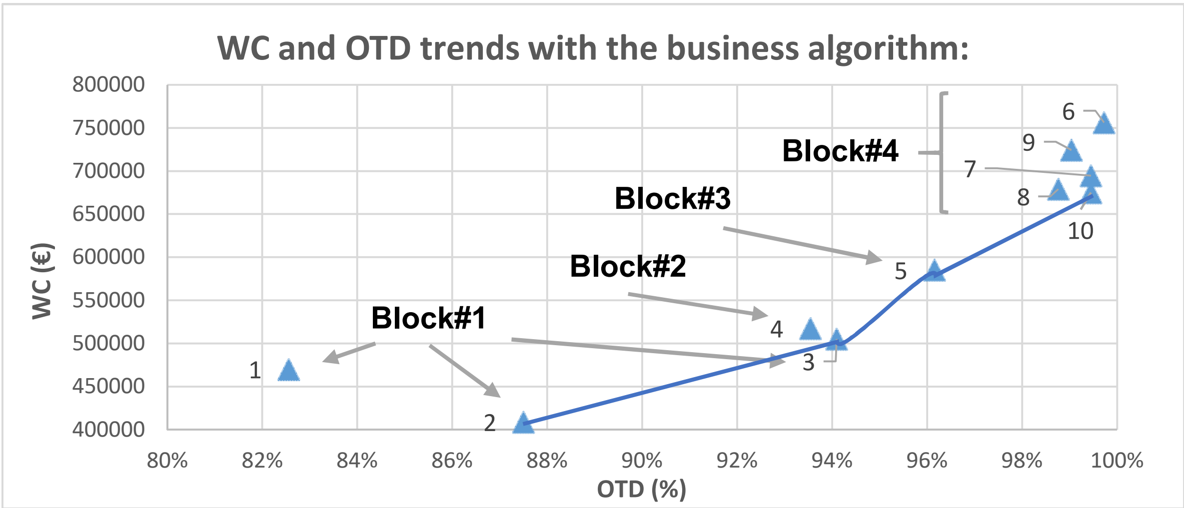
Block #4:

Goal:

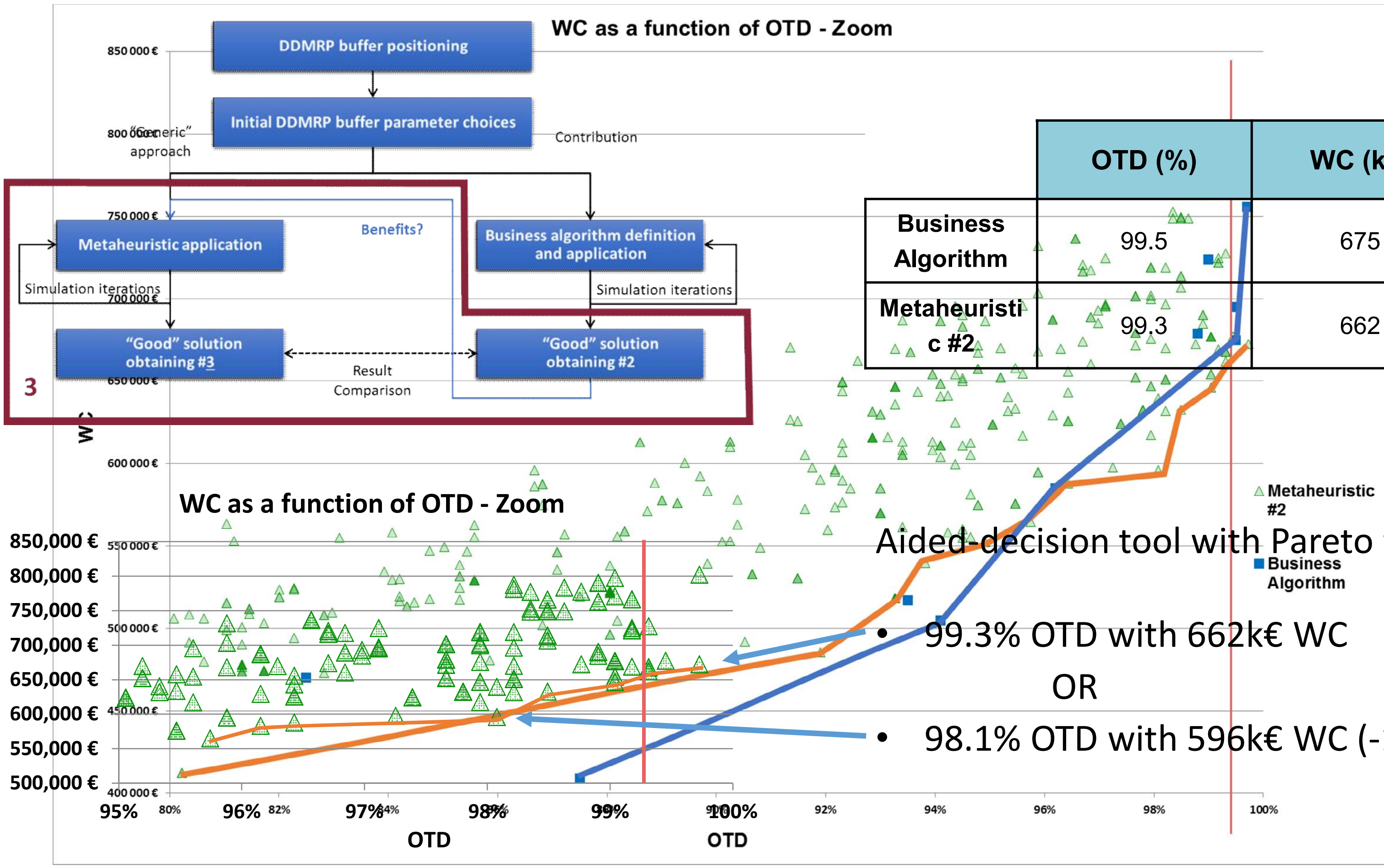
- As soon as OTD objective is reached: minimise WC
- DLT reduction for all references that never reached zero inventory

Simulation: 1 hour
For the 10 iterations





Simulated annealing #2



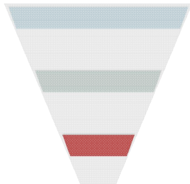
	OTD (%)	WC (k€)
Business Algorithm	99.5	675
Metaheuristic #2	99.3	662

Aided-decision tool with Pareto front:

- 99.3% OTD with 662k€ WC

OR

- 98.1% OTD with 596k€ WC (-10%)



Optimisation overview

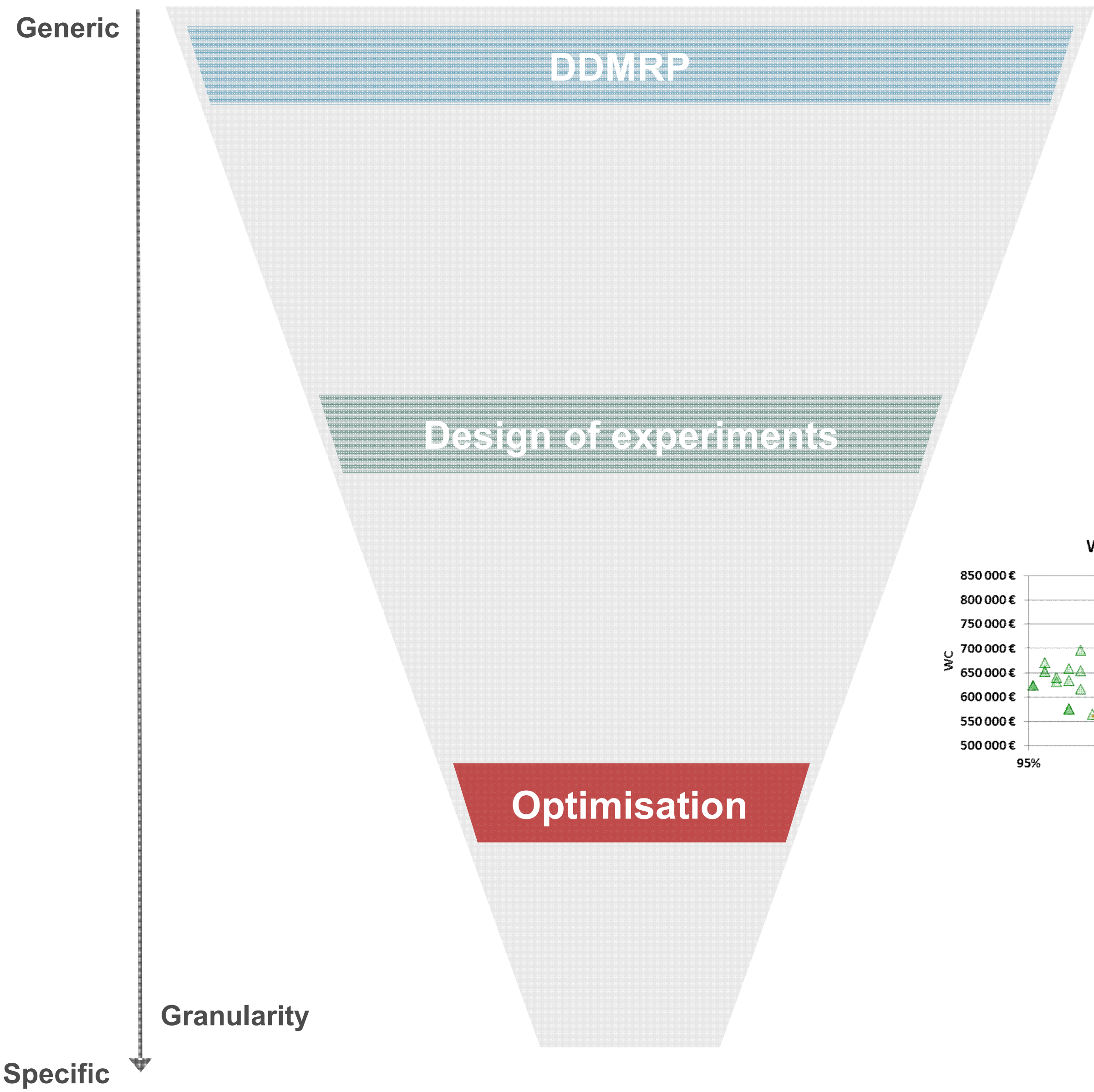
DDMRP buffer sizing:

- **indeed a critical subject**

Discrete Event Simulation helps to choose appropriate parameters:

- **Simulated annealing approach** 
- **The business algorithm proposed** 

With fewer iterations


Generic
DDMRP
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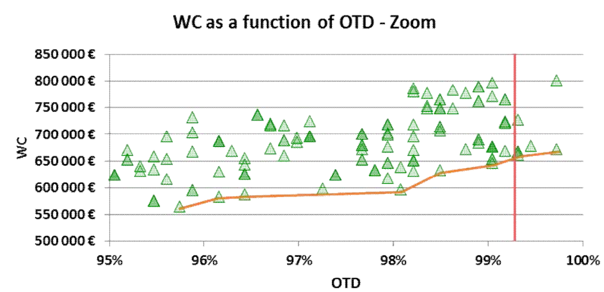
WC as a function of OTD - Zoom
850 000 €
800 000 €
750 000 €
700 000 €
650 000 €
600 000 €
550 000 €
500 000 €
WC
95%
96%
97%
98%
99%
100%
OTD


Business algorithm

Agenda

1 Context

2 Material management methods

3 Case study – design of experiments

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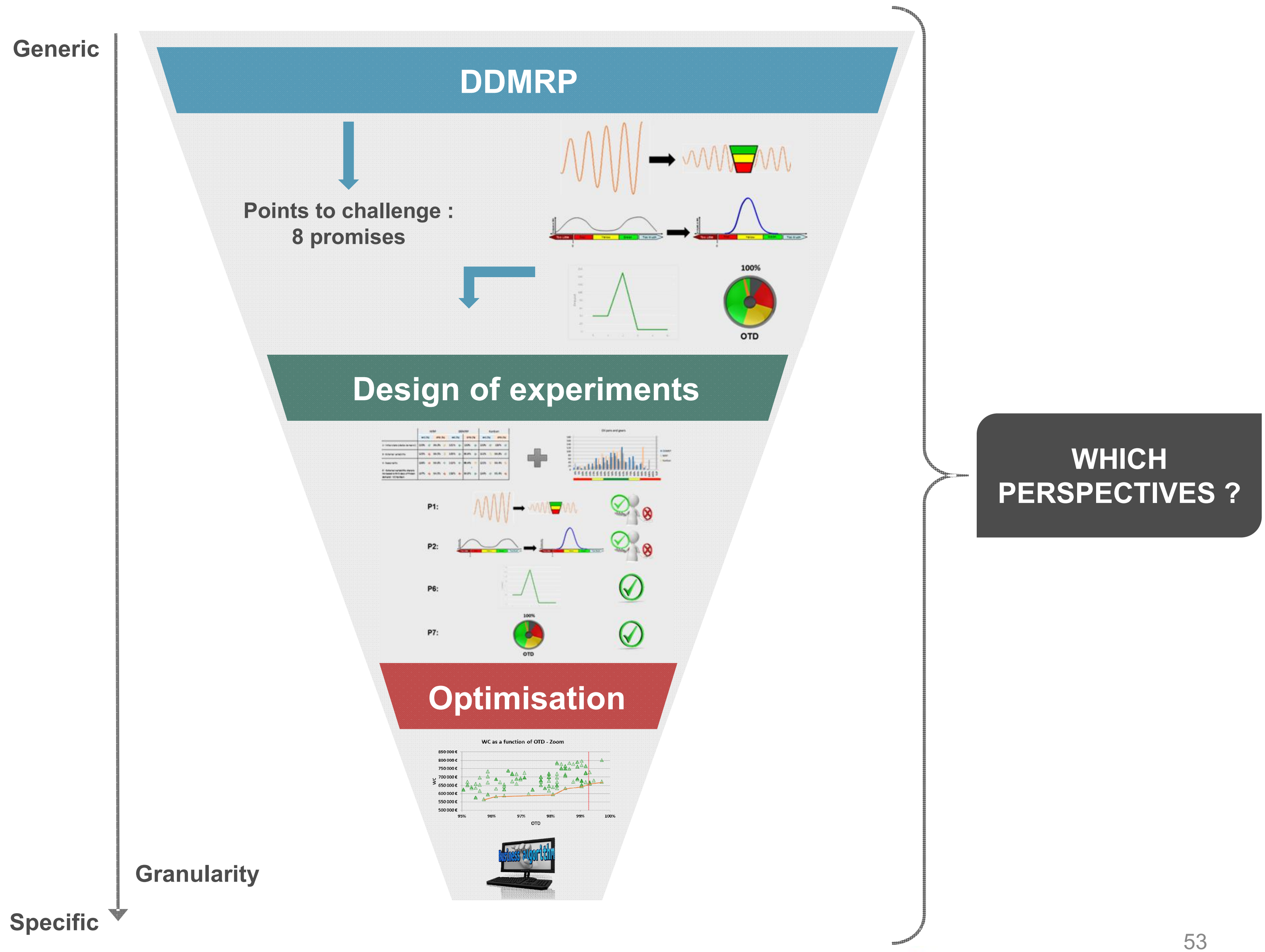
5 Case study – buffer sizing optimisation

6 Conclusion & Perspectives

Demand Driven World
transforming push and promote into position and pull

agilea
INDUCTEUR DE PROGRÈS



Generic
DDMRP
Points to challenge :
8 promises
100%
OTD
Design of experiments
P1:
P2:
P6:
P7:
Optimisation
WC as a function of OTD - Zoom
Granularity
Specific
WHICH PERSPECTIVES ?

Common Laboratory: AGIRE

AGIRE: AGIle and Resilient Enterprise

IMT Mines Albi-Carmaux
École Mines-Télécom

ARMINES

agilea CONSEIL

- An industrial transposition tool from research world to industrial one
- From 2017 to 2021
- 5 full-time equivalent: PhD students / research engineer / professors…
- Budget: 2M€

Common Laboratory: AGIRE

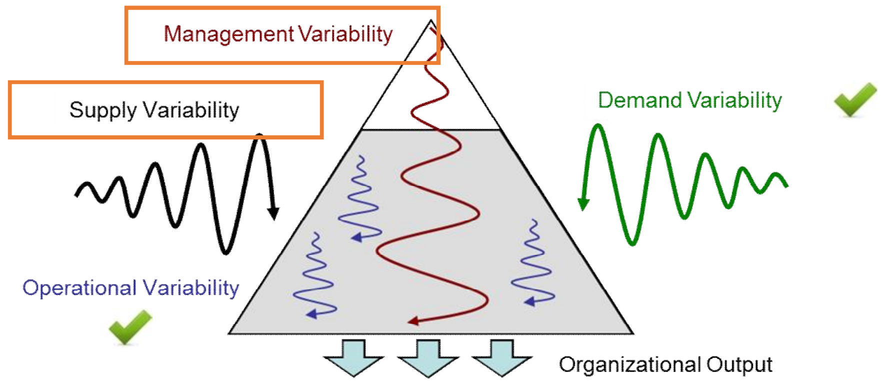
- Work with Polytechnique Montréal / Michigan state university / University of Amsterdam
- DDMRP with its perspectives:
  - Semi-aided tool for positioning buffer
  - Semi-aided tool for sizing strategic buffers
  - Challenge time and capacity buffers
  - DDMRP resilience (compared to other methods)
  - …


Thank you

Industrial:

- > Next steps (DDMRP interest)
- >  : real interest to semi-automatically position and size DDMRP strategic buffers.
- > : generalisation and applicability for different sector activity
- > Generic DDMRP simulation modules : Dynamism

Short term:



> Sensitivity analysis : DDMRP breaking points

> Design of experiments and/or Optimisation with a "non-theoretical compliant" buffer positioning

> Case study limits to investigate

Future research works

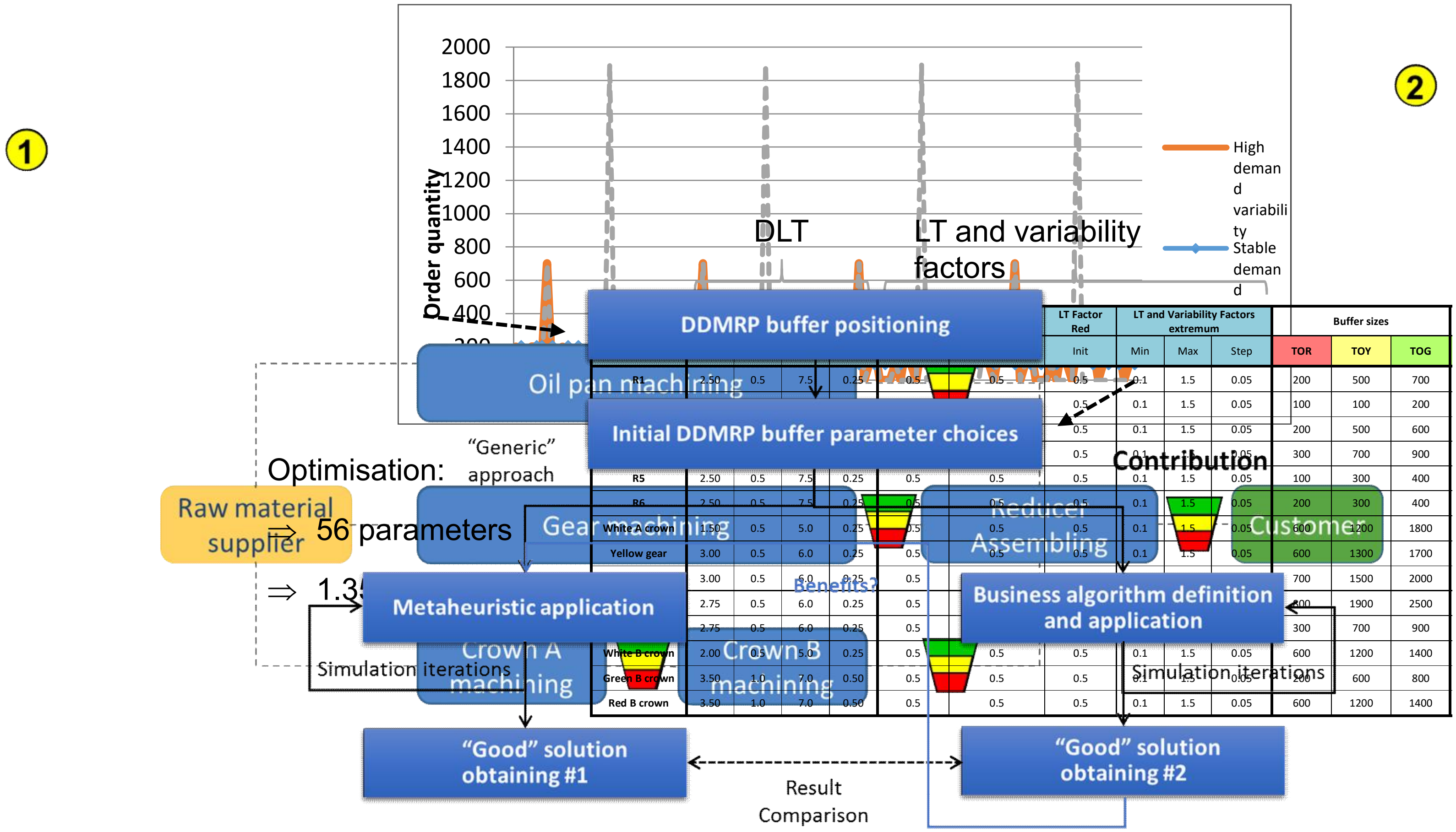
Long term:

> Decision-aided tool to semi-automatically:
- position DDMRP buffers
- size DDMRP buffers

> DDMRP investigations with a distribution scope

> DDMRP resilience compared to a significant crisis

> Another PhD work next year on this topic (AGILEA in collaboration with Mines Albi).


1
2
DLT
LT and variability factors
High demand variability
Stable demand
Order quantity
DDMRP buffer positioning
Initial DDMRP buffer parameter choices
Optimisation: 56 parameters
⇒ 1.35
"Generic" approach
Raw material supplier
Oil pan machining
Gear machining
Crown A machining
Crown B machining
Reducer Assembling
Customer
Contribution
Benefits?
Metaheuristic application
Simulation iterations
Business algorithm definition and application
Simulation iterations
"Good" solution obtaining #1
"Good" solution obtaining #2
Result Comparison
LT Factor Red
LT and Variability Factors extremum
Buffer sizes
Init
Min
Max
Step
TOR
TOY
TOG

1 Context

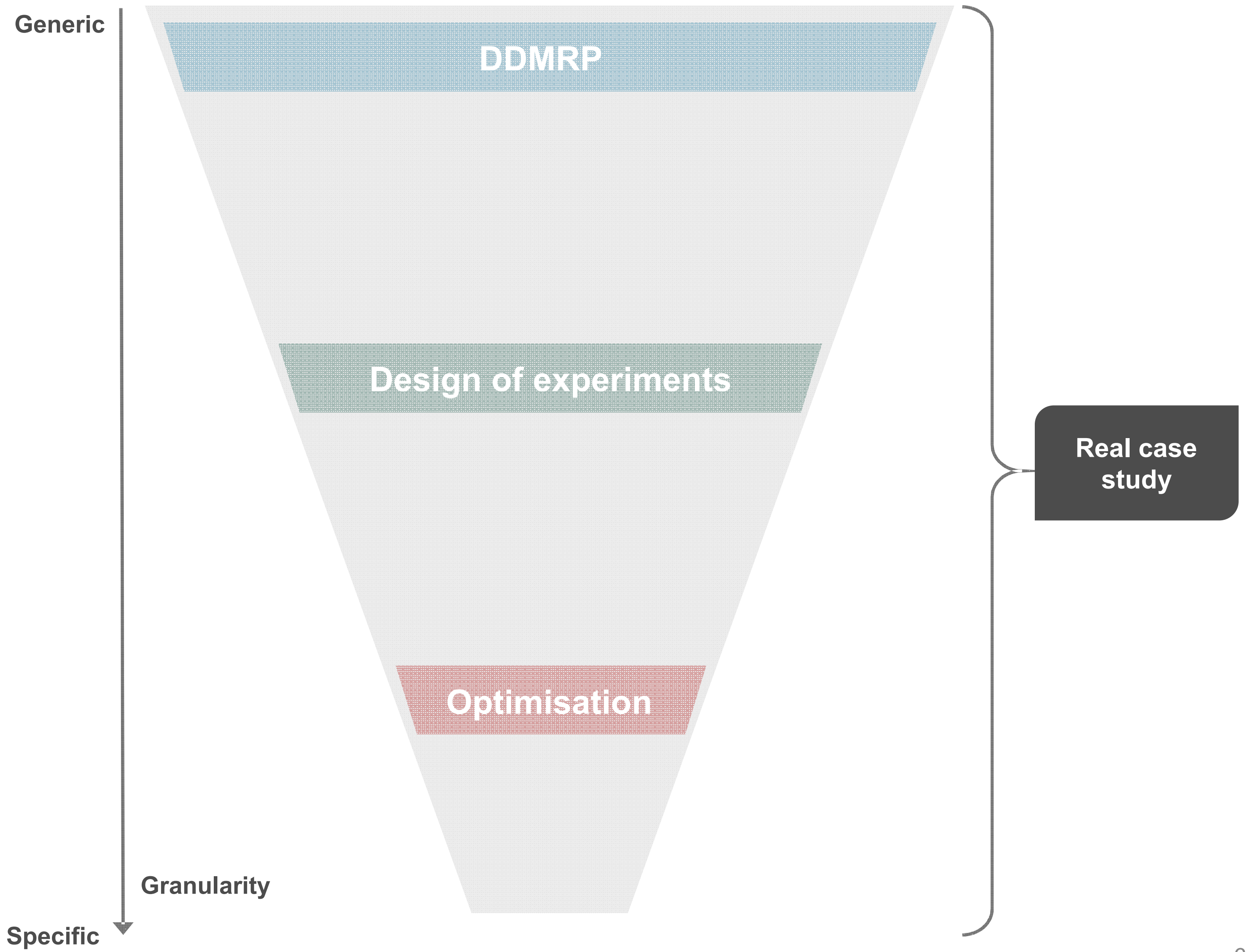
2 Material management methods

3 Academic case study – part #1

4 Academic case study – part #2

5 Real case study

6 Conclusion & Perspectives



Demand Driven World

transforming push and promote into position and pull

agilea INDUCTEUR DE PROGRÈS

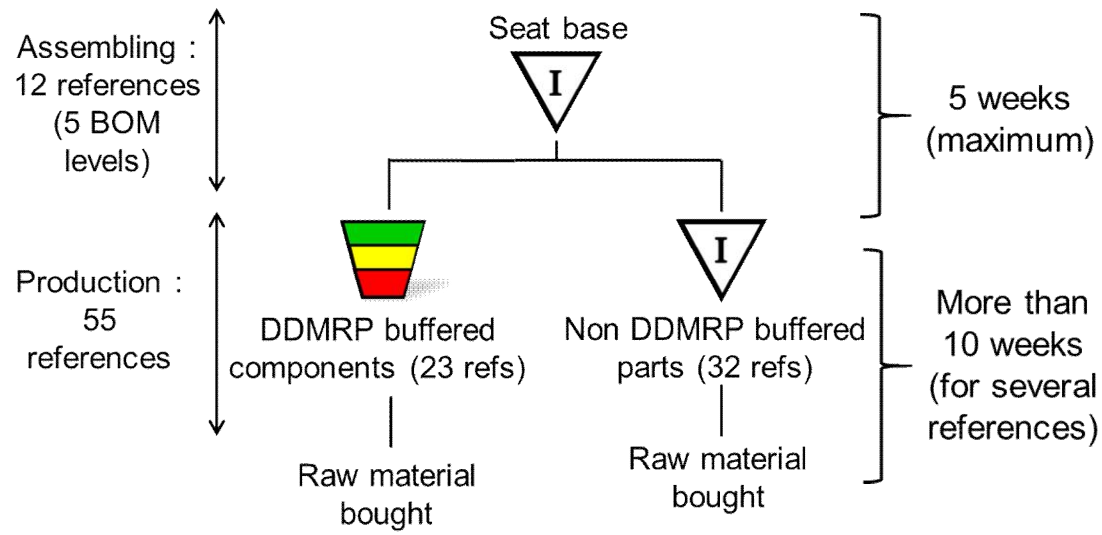
DDMRP implementation to a French company in Saintes :

- JV Group

- Finished or subassembly products for aeronautical, railway, nuclear and leisure.

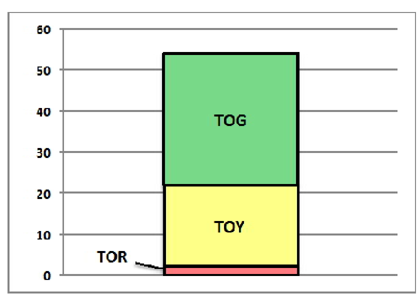
DDMRP implementation to a French company in Saintes : JV Group

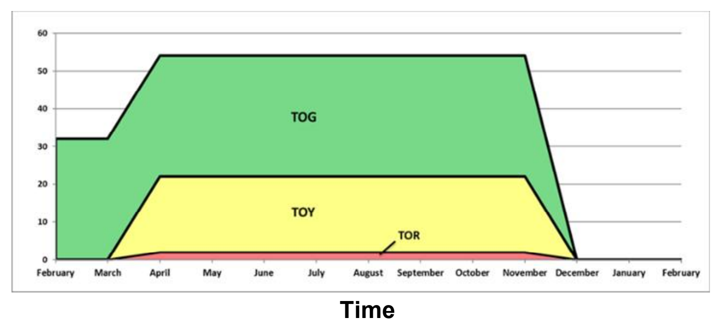
> **Buffer positioning** 1

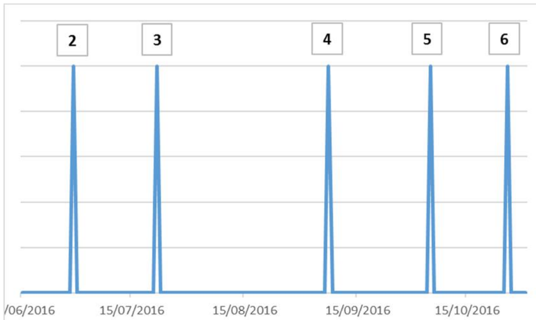


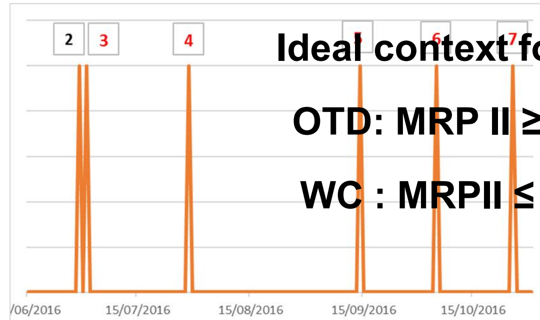
- **Up to 15 activities for components**
- **Subcontracting operations**
- **Different operating cycle times**

> **Buffer sizing and dynamically adjusted** 2 & 3









Ideal context for MRP II:

OTD: MRP II ≥ DDMRP

WC : MRPII ≤ DDMRP

Delivery date variability

SEAT BASE → **MRP** / **DDMRP**

Other products → **MRP Production orders**

FLOW SIMULATION → **Performance analysis**

- **OTD**
- **WC**

Demand variability results

Delivery date variability: 3 weeks in advance

MRP II Delivery date	On time ?
05/29/2016	✘
06/18/2016	✔
07/05/2016	✘
07/19/2016	✔
08/25/2016	✔
10/04/2016	✔
10/16/2016	✔
12/19/2016	✔
01/16/2017	✔
02/16/2017	✔

OTD (%)	80
Average seat base WC (€)	99,000

DDMRP Delivery date	On time ?
05/12/2016	✔
06/19/2016	✔
06/28/2016	✔
07/19/2016	✔
08/31/2016	✔
10/04/2016	✔
10/10/2016	✔
12/19/2016	✔
01/16/2017	✔
02/16/2017	✔

OTD (%)	100
Average seat base WC (€)	97,000

Limit of DDMRP variability absorption

Demand variability: <u>3 weeks</u>		Demand variability: <u>4 weeks</u>		Demand variability: <u>5 weeks</u>	
Delivery date	**On time ?**	**Delivery date**	**On time ?**	**Delivery date**	**On time ?**
05/12/2016	✓	05/12/2016	✓	05/12/2016	✓
06/19/2016	✓	06/18/2016	✓	06/18/2016	✓
06/28/2016	✓	06/26/2016	✓	06/26/2016	✓
07/19/2016	✓	07/17/2016	✓	07/03/2016	✓
08/31/2016	✓	09/01/2016	✓	09/04/2016	✗
10/04/2016	✓	09/28/2016	✗	09/25/2016	✗
10/10/2016	✓	10/04/2016	✓	09/29/2016	✓
12/01/2016	✓	11/21/2016	✓	11/14/2016	✓
01/02/2017	✓	12/19/2016	✓	12/12/2016	✓
01/26/2017	✓	01/19/2017	✓	01/12/2017	✓

LESSONS

- **100% OTD with 3 weeks delay**
- It is the limit delay that DDMRP can theoritically absorb.

DDMRP implementation in JV Group:

OTD: DDMRP > MRP II

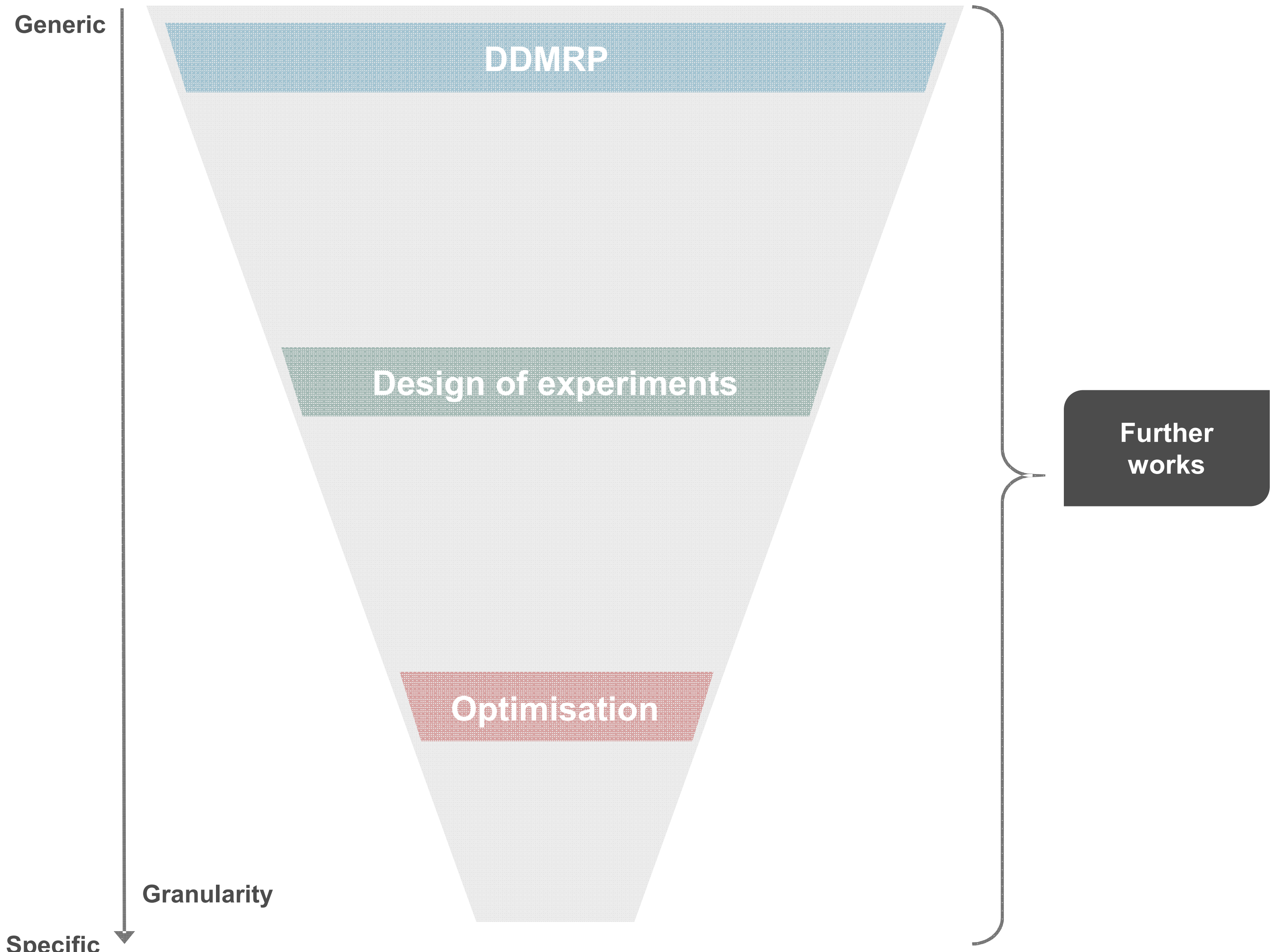
WC: DDMRP <=> MRP II

In reality:

> From the 5th plane, 5 weeks demand in advance.
  - DDMRP manages to deliver customer with an emergency execution.

> JV Group wants to implement DDMRP on other products and other sites.

DDMRP


Generic
DDMRP
Design of experiments
Optimisation
Granularity
Specific
Further works

Conferences

- **Romain Miclo, Matthieu Lauras, Franck Fontanili, Jacques Lamothe, Philippe Bornert, Guillaume Revenu** 2014. Enhancing Collaborations by Assessing the Expected Financial Benefits of Improvement Projects *Enterprise Interoperability VI Proceedings of the I-ESA Conferences , 2014* **, Volume 7, pp 189-200**
- **Romain Miclo, Matthieu Lauras, Franck Fontanili, Jacques Lamothe, Philippe Bornert, Guillaume Revenu** 2014. Working-Capital Improvement through Value Stream Mapping Costing and Discrete-Event Simulation *Proceedings of the 5th International Conference on Information Systems, Logistics and Supply Chain CONNECTING WORLDS ILS 2014 - Breda (Netherlands), August 24-27*
- **Romain Miclo, Franck Fontanili, Philippe Bornert et Pascal Foliot** 2014. Working Capital Reduction in a Complex System through Discrete-Event Simulation *Winter Simulation Conference*
- **Miclo, R., F. Fontanili, G. Marquès, P. Bomert, and M. Lauras**. 'RTLS-Based Process Mining: Towards an Automatic Process Diagnosis in Healthcare'. In *2015 IEEE International Conference on Automation Science and Engineering (CASE)*, 1397–1402, 2015.
- **F. Fontanili, E. Lamine, M. Lauras, R. Miclo et H. Pingaud** 2016. Une démarche outillée à base de RTLS, Process Mining et simulation pour le diagnostic organisationnel des parcours patients en établissement hospitalier. *11è Conférence Francophone d'Optimisation et Simulation - MOSIM 16*