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An empirical comparison of MRPII and Demand-Driven MRP

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Abstract: The Demand-Driven MRP (DDMRP) is a method for managing flows in manufacturing and distribution that is supposed to manage uncertainties better than traditional Manufacturing Resources Planning (MRP) using some principles of pull approaches. In this paper, a case-study is investigated in order to objectively and quantitatively compare these two systems. A Discrete-Event Simulation (DES) approach is used to evaluate impacts on system behaviors regarding both methods. Results show insights on the interests of DDMRP.

Keywords: Production control, JIT Manufacturing, flexible manufacturing.

1. INTRODUCTION

Satisfying customers and making margins are companies' main purpose. In order to achieve these goals, they must find a compromise between various objectives; on time delivering, reducing lead-times and thus Work In Process (WIP), reducing costs of goods sales.

To manage physical or economical flows lots of methods are known. Manufacturing Resource Planning (MRPII) is the most widespread, Wallace (1984). Pull flow policies (production depends on the real consumption, real demand) are also widespread. Another recent and promising method is Demand-Driven Material Requirements Planning (DDMRP), Ptak et al. (2011). "DDMRP is a multi-echelon demand and supply planning and execution methodology." It is developing since 2000 and is already set up in some companies in the United States. Furthermore it generates an increasing interest of industrial managers and researchers. Its main originalities are in the strategic DDMRP buffer positioning, dimensioning and execution replenishment policies so that the different sources of variability (from supply, operational, demand and management) can be managed. Therefore, DDMRP is said to combine best practices of MRPII, Wallace (1984), Lean, Ohno (1987), Theory Of Constraints (TOC), Goldratt (1990), Distribution Resource Planning, Martin (1985), 6 sigma, Deming (1993) and with some innovations. But there is no scientific comparison to objectively demonstrate differences between managing flows with DDMRP or MRPII and other pulling methods such as Kanban, Ohno (1982) or ConWIP, Spearman (1990).

This paper focuses on the comparison of DDMRP with the classical MRPII, analysing scenarios on a famous academic case study. A literature review is used to identify potential DDMRP contributions that are discussed on the case study.

2. LITERATURE REVIEW

2.1 Manufacturing Resource Planning (MRPII)

Manufacturing Resource Planning (MRPII) is the most widespread planning method in the world. MRP and then MRPII were developed in the 1970s. It requires demand forecasts and plans all the manufacturing activities: it is a push flow method. MRPII is "a method for the effective planning of all resources of a manufacturing company. Ideally it addresses operational planning in units, financial planning in dollars, and has a simulation capability to answer what-if questions. It is made up of a variety of processes, each linked together: business planning, production planning (sales and operations planning), master production scheduling, Material Requirements Planning (MRP), Orlicky (1975) , capacity requirements planning, and the execution support systems for capacity and material. […] Manufacturing Resource Planning is a direct outgrowth and extension of closed-loop MRP", Apics Dictionnary (2008).

The general market behaviour has evolved in the last 30 years generating more instabilities of the demand, of the supplies and of internal processes. These variabilities result in creating more difficulties to establish accurate forecasts, generating nervousness in MRP behaviour what is a bullwhip effect source, Lee et al. (1992).

2.2 Pull flow management policies

Pull methods aim to directly manage production from the real demand in order to reduce variability created by planning and decrease WIP in the process only with "what is needed". One of the well-known methods was created in the Toyota Production System: Kanban, Ohno (1982). Kanban is a just-in-time manufacturing process in which operators are informed of buffers consumption (usually throughout Kanban cards) and replenish their buffers according to inventory priorities and real time machines availability. Kanban has been declined in various versions, Lage Junior et al. (2010).

ConWIP (Constant Work In Process) is another pull flow management method developed in the Theory of Constraints,

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Spearman (1990). This method constrains the level of WIP in a process. It has also been declined in various versions, Prakash et al. (2014). The comparison between Kanban, ConWIP and a “classical“ push flow method is shown in figure 1 below.

Both push flow methods (MRPII) or pull flow methods (such as Kanban and ConWIP) have their advantages, their lacks and hypothesis need to be set up.

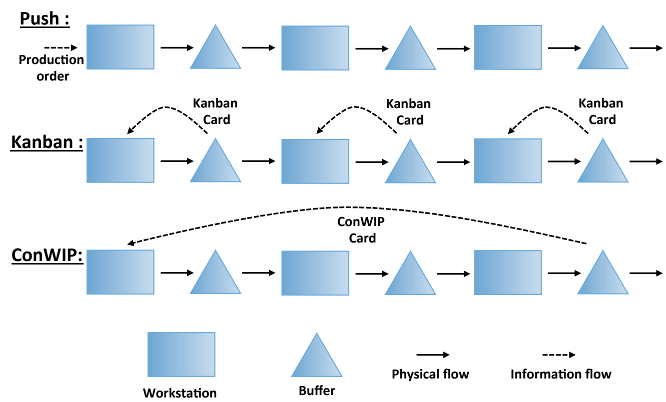

Fig. 1: Kanban and ConWIP vs. push system

2.3 C. Demand-Driven Materials Requirements Planning (DDMRP)

DDMRP is a “multi-echelon materials and inventory planning and execution solution.“, Ptak et al. (2011), Smith et al. (2013). It is implemented in 5 steps as shown in Fig. 2.

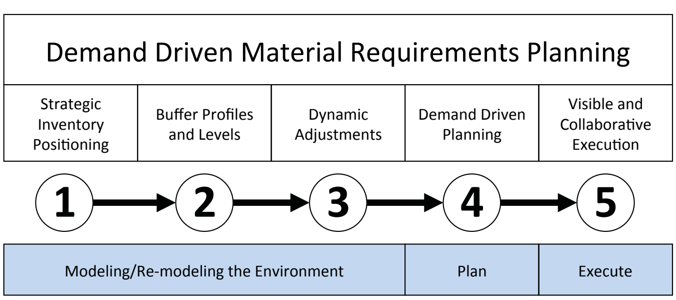

Fig. 2: 5 steps to implement DDMRP, Ptak et al. (2011)

The first step deals with “Strategic Inventory Positioning“. It evaluates from a financial point of view if there are benefits to position or not a buffer on an article of a Bill Of Materials. This step is the most strategic and original. Succeeding in positioning DDMRP buffers will help a lot to correctly implement the method. Then, the DDMRP principle is to pull replenishments between strategic buffers; but to deduce and push plan orders for unbuffered articles. Buffers are supposed to control the dispersion of variability (supply, operational, demand and management) in the manufacturing system.

As soon as the buffers are positioned it is possible to define the “buffer profiles and levels“. A buffer is replenished according to its “Available Stock Equation” (ASE) that is the inventory position minus qualified spikes. Qualified spikes refer to huge demand orders whose production have to be anticipated of some production lead-time and thus made on demand. This available stock equation (ASE) is compared to 3 buffer alert levels: red (the safety stock), yellow (the mean in-process replenishment quantity) and green (the replenishment size). These zones will visually help to decide on buffer replenishments: anytime the ASE enters the yellow zone a replenishment order is put to reach the green zone upper level. In execution context, stock buffer is also decomposed in three zones (red, yellow and green), but different, so that orders can be prioritized and scheduled according to the alert.

In DDMRP, the design of buffer levels (for planning and execution) is made dynamically according to formulas (1). Average Daily Usage (ADU) is the result of demand forecasting. ASRLT is an original concept of DDMRP. It is the longest unprotected sequence (considering a sum of lead times) in the bill of material of a buffered article. As buffers are supposed to control variability, unprotected sequences are considered between buffered articles. As for MRPII, the choice of the lead time value remains a critical point of DDMRP.

Plan Adjustment Factors (PAF) are percentages used to raise or lower ADU. They enable to model and smooth big seasonal variabilities, promotions, and can be considered as the result of a Rough Cut Capacity Planning. Variability factor is used to protect from uncertainty: it is a part of the red zone and represents the safety stock. Lead-time factor is different for long lead-time or short lead-time products: when the ASRLT is long the lead-time factor is small (in order to often produce long-lead time products with a small order quantity).

$$
\begin{aligned}
&\text{GreenZone} = \text{Max}(\text{YellowZone}.\ \text{LTFactor};\ \text{LotSize}) \quad (1)\\
&\text{YellowZone} = \text{ADU}.\ \text{ASRLT}\ .\ \text{PAF}\\
&\text{RedZone} = \text{YellowZone}.\ \text{LTFactor}.\ (1+\text{VariabilityFactor})\\
&\text{TopOfRed} = \text{RedZone}\ ;\\
&\text{TopOfYellow} = \text{TopOfRed} + \text{YellowZone}\\
&\text{TopOfGreen} = \text{TopOfYellow} + \text{GreenZone}.
\end{aligned}
$$

Finally, when DDMRP zones are defined, planners and operators can visually decide on quantity to replenish (in plan view) and orders to prioritize (in execution view).

3 AN EMPIRICAL STUDY

3.1 Approach

The case study comes from the “Centre International de la Pédagogie d’Entreprise“ (CIPE) Kanban serious game, CIPE website. This case study has been used to teach numerous professional and students differences between MRP and Kanban. All the input data is available, with multi-references, components, subassembly parts and an assembling activity.

The dynamic adaptation properties of DDMRP are promising. Nevertheless, we still lack of some empirical or theoretical studies in order to validate them. In order to address this issue, we use Discrete-Event Simulation (DES) as a tool enabling to get predictive results, evaluate impact of parameter changes. Lanner Witness® is the DES software used here. In the DES software, in order to compare differences from each flow management policy, the management part (simulator) will be separated from the operational part (emulator). The DES operational model (emulator part) will therefore be the same for various flow management policies evaluation. The simulator part being in charge of sending required signals for the emulation part.

Main Key Performance Indicators (KPI) that will permit to decide which method to choose are: On-Time Delivery (OTD) and Working Capital (WC, valuation of Work in Process and stocks). Secondary indicators enabling also to decide are: WIP level, load production means and system nervousness.

In order to get an interesting benchmark, different scenarios will be analysed. For each scenario, a DDMRP simulation will be compared to a MRPII one.

3.2 Case study data

The case study deals with a company that produces reducers composed of three parts: one oil pan, one gear and one crown. Each of these components needs one machining step except for crowns which need two (A crown and then B crown). An oil pan can be red or blue, a gear white or yellow and a crown white, green or red. 6 different reducers and one spare part (A crown white) are sold (table 1). Products are made to stock. Demand occurs every morning.

Table 1. Products sold with respective BOM

R1	Oil_pan_red	Gear_yellow	B_crown_white
R2	Oil_pan_red	Gear_yellow	B_crown_green
R3	Oil_pan_red	Gear_yellow	B_crown_red
R4	Oil_pan_red	Gear_white	B_crown_white
R5	Oil_pan_blue	Gear_white	B_crown_green
R6	Oil_pan_blue	Gear_white	B_crown_red
Spare parts	/	/	A_crown_white

Table 2. Machine input parameters

Machines	Oil pan machining	Gear machining	Crown machining phase A	Crown machining phase B	Assem-bling
Cycle Time (hr)	1	1	1	1	1
Lot size	100	100	200	200	100
Setting-up time (hr)	3	3	2	4	1
MTBF (hr)	NegExp(17.80)	NegExp(11.6)	NegExp(9.70)	NegExp(15.19)	NegExp(21.25)
MTTR (hr)	Triangle(1.1,2.2,4.4)	Triangle(0.86,1.73,3.46	Triangle(0.48,0.96,1.92)	Triangle(0.4,0.8,1.6)	Triangle(0.8,1.6,3.2)

There are 5 machines (table 2) which have a cycle time of 1 hour each. The production lot size is 100 parts in 1 hour except for both crowns machining with 200 parts per hour. Mean-Time Between Failure (MTBF) is modeled with a negative exponential distribution law and Mean-Time To Repair with a triangle distribution law. There are also fixed set-up times per machine for each change of reference. Depending on failures and demand, the bottleneck can move from Assembly, to Oil Pan or to Gear machine.

For the 16 references (6 reducers, 2 oil pans, 2 gears and 6 crowns), an initial state (initial on-hand inventory), forecasts and variations of these forecasts (for a week) must be managed. Production costs enable to evaluate WC in the simulation model, Maskell et al. (2004). Selling prices are also given and enable to evaluate gross sales. Input data is given as example in table 3 for 8 of the 16 parts (only yellow gear is not sold).

Table 3. Article input parameters

Parts	R1	R2	R3	R4	R5	R6	A crown white	Yellow gear
Initial state	500	100	100	600	200	100	1000	700
Forecasts	700	75	550	900	400	350	1100	
Variations	100	75	150	150	200	150	400	
Production costs (€)	100	100	100	100	100	100	9	25
Selling price (€)	150	150	150	150	150	150	30	

Table 4. The 6 weeks demand orders

Week	Period	R1	R2	R3	R4	R5	R6	A crown white
1	1	200		100	200			
	2	100		200	300			500
	3				100	200	100	500
	4	200	100	100	200	100		
	5	200		100	200	100	200	400
2	6	100		200	400			
	7	200		200	400	100		
	8				100	200	200	400
	9	100		200		100	100	
	10	200		100	200	100	200	400
3	11	100	100	200	300			600
	12	200	100	100	400			
	13				100	200	200	400
	14	100		200		100		
	15	200			200	100	100	400
4	16	200		100	200			
	17	100		200	300			500
	18				100	200	100	500
	19	200	100	100	200	100		
	20	200		100	200	100	200	400
5	21	100		200	400			
	22	200		200	400	100		
	23				100	200	200	400
	24	100		200		100	100	
	25	200		100	200	100	200	400
6	26	100	100	200	300			600
	27	200	100	100	400			
	28				100	200	200	400
	29	100		200		100		
	30	200			200	100	100	400

Table 5. sequencing for one week

Oil pan machining		Gear machining		Crown A machining		Crown B machining		Assembling	
Part	Qty	Part	Qty	Part	Qty	Part	Qty	Part	Qty
Oil_pan_blue	600	Gear_white	1100	A_crown_red	600	B_crown_red	800	R3	600
Oil_pan_red	2500	Gear_yellow	1500	A_crown_green	800	B_crown_green	800	R2	100
Oil_pan_blue	400	Gear_white	900	A_crown_red	600	B_crown_white	1800	R5	400
				A_crown_white	3200	B_crown_red	400	R4	1000
								R1	700
								R6	500

Table 3 gives forecast data for one week with a hypothesis of a stable demand trend over the weeks. 6 weeks of demand orders are given (table 4). Undelivered articles are delivered as soon as possible.

3.3 MRPII and DDMRP Implementation

In the case study, the system has enough capacity (in theory) but has a consequent general load. The goal is first to deliver customers on time and then to minimise the WIP amount (and therefore the WC.

With MRPII, a choice must be made to define an amount of reducers to produce (Sales and Operations Planning). At the Master Production Scheduling level the production is divided into the 6 reducers by keeping the same total amount of reducers. Then the MRP can compute for each reference the production orders. A final step is realised each week to get the sequencing. Table 5 shows the final sequencing for one week (it will be repeated all along the simulations, but the orders quantity depend on the MRP computation).

As regards DDMRP, with all the input data the "Strategic inventory positioning" can be done. Let refer to Miclo et al. (2015) for the implementation of this phase for the present case study. Table 6 shows the selected configuration according to the DDMRP methodology: all the components have to be buffered except some of the A Crown (Green and red). For each product, ASRLT is computed considering the number of cycles, of setups it is possible to do in a week in order to have the weekly load under the weekly capacity. The variability factors will be adjusted considering various sources of uncertainty.

From an execution point of view, when there are two orders to sequence, the priority is given to the reference with the lowest percentage of its stock compared to the Red plus Green buffer zone (mean stock). Therefore, the production sequence can dynamically change in DDMRP.

Table 6. Buffering cost analysis for products sold, gears and oil pans

		R1	R2	R3	R4	R5	R6	A white crown	Yellow gear	White gear	Red oil pan	Blue oil pan	B white crown	B green crown	B red crown	A green crown	A red crown
	Forecasts	700	75	550	900	400	350	1100									
	ADU	140	15	110	180	80	70	**540**	265	330	445	150	320	95	180		
	Changes per week	1	1	1	1	1	1	2,67	0,84	0,84	0,98	0,98	1,93	1,93	1,93	2,67	2,67
	ASRLT (in days)	5,0	5,0	5,0	5,0	5,0	5,0	1,9	5,9	5,9	5,1	5,1	2,6	4,5	4,5	1,9	1,9
	Lead Time factor Green	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%		
	Variability Factor	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%		
	Lead Time factor Red	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%		
	Yellow	700	75	550	900	400	350	1011	1574	1960	2282	769	830	424	804		
	Green	350	100	275	450	200	175	505	787	980	1141	385	415	212	402		
	Red Up	350	38	275	450	200	175	505	787	980	1141	385	415	212	402		
	Red Bottom	175	19	138	225	100	88	253	394	490	571	192	208	106	201		
Planning	**Top Of Red**	600	100	500	700	300	300	800	1200	1500	1800	600	700	400	700		
	Top Of Yellow	1300	200	1100	1600	700	700	1900	2800	3500	4100	1400	1600	900	1600		
	Top Of Green	1700	300	1400	2100	900	900	2500	3600	4500	5300	1800	2100	1200	2100		
623 668 €	**Average inventory (€)**	77500	15000	63750	92500	40000	38750	9475	39839	49752	130378	43577	9076	5061	9010		

3.4 Experiment Plan

As far as the initial research statement are concerned, considering the contribution of DDMRP when compared to MRP, the bibliography (§2.3) enables to formulate the following hypothesis:

(H1) DDMRP has better performances when considering internal, external or seasonal variabilities,

(H2) DDMRP counteracts variability within the buffer management,

(H3) DDMRP reduces risks on spike demand using an anticipation mechanism in the ASE calculation,

(H4) DDMRP maintains buffers in less risky zones.

In order to test these hypothesis, various scenarios have been implemented as defined in Table 7.

Table 7. Simulation scenarios

Sc#	Scenario	Parameters
Sc1	Initial scenario	Kanban serious game with stable weekly demand profile
Sc2	Sc1 + Internal variability	Triangular laws (+/- 50%) on operations lead times and set-up.
Sc3	Sc1 + Demand spike	Spike = 8*forecasted demand
Sc4	Sc1 + Internal variability + spikes	Sc2 and Sc3 parameters
Sc5	Sc3 + Demand visibility	Demand is known 1 week (assembly Lead time) before
Sc6	Sc3 + Seasonal demand	Each product has a seasonal demand profile (PAF) but total load per month is stable.
Sc7	Sc6 + Demand visibility	Demand is known 1 week (assembly lead time) before.

For each scenario the simulation protocol is the following:

- Each simulation repeats 8 cycles of 6 weeks of demand. The simulation horizon is thus of 48 weeks. Scenarios that require hazard (triangular laws) are replicated 5 times.
- The first 4 cycles (24 weeks) were necessary as warm up in order to stabilize the system. So the last 24 weeks are considered for the assessment of any scenario.
- The management policy (MRP or DDMRP) is adjusted so that the system has at least 99,3% of OTD and minimise the Working Capital (WC = cost of {WIP + stocks}). This assessment of WC using a DES is based on a methodology proposed by Maskell et al. (2004).
- In order to assess hypothesis H2 to H4, the stability of inventories and the nervousness of the supplies are analysed.

This protocol aims at approximating the behaviour of a decision maker that tries to reach a desired operating point: low working capital but high on-time delivery rate. This operating point induces that the bottleneck is saturated. So, the system is very sensible to small changes of parameters that can make the system under-capacited and diverge in term of backorders. Consequently the adjustment is sometime hard to obtain.

4. EXPERIMENT RESULTS

Table 8 exposes the assessment of the simulation for each scenario considering both MRP and DDMRP management policies with both OTD and WC indicators that are measured. WC is presented in % of the WC for the reference scenario (WC for Sc1 with the MRP policy is base 100).

It can be seen that the objective OTD can be satisfied in nearly all the situations (except Sc6 for DDMRP). But, DDMRP requires less WC what means less WIP and stocks: in general 10% less. Moreover, analysing at the policy adjustment, DDMRP appears to be impressively stable when facing variabilities: the same adjustment satisfies Sc2 to Sc7 while safety stocks need to be adapted for MRP.

Comparing scenarios Sc3 and Sc4, it can be noticed that summing internal and external (spike) variabilities does not change anything for both policies. Indeed, safety stocks (for MRP) and Variability Factor (that generates the safety zone for DDMRP) can be used for both types of variabilities. Consequently DDMRP appears to be more efficient and more stable: this validates hypothesis H1.

Table 8. Scenarios assesment

Sc#	Policy	OTD %	WC %	Policy adjustments
Sc1	MRPII	99,3	Base 100	Safety Stock = 2000
Sc1	DDMRP	100	101	LT Factor Green= 80%, Variability Factor = 30 %
Sc2	MRPII	99,9	122	Safety Stock = 2600
Sc2	DDMRP	100	109	LT Factor Green = 80%, Variability factor = 50%
Sc3	MRPII	99,5	125	Safety Stock = 2900
Sc3	DDMRP	99,9	111	LT Factor Green = 80%, Variability factor = 50%
Sc4	MRPII	99,8	125	Safety Stock = 2900
Sc4	DDMRP	99,6	116	LT Factor Green = 80%, Variability factor = 50%
Sc5	MRPII	99,5	118	Safety Stock = 2300
Sc5	DDMRP	99,8	113	LT Factor Red&Green= 80%, Variability factor = 50%
Sc6	MRPII	99,8	139	Safety Stock = 3500
Sc6	DDMRP	98,8	117	LT Factor Green= 80%, variability Factor = 50% Lot Size = 200
Sc7	MRPII	99,3	137	Safety Stock = 2900
Sc7	DDMRP	99,3	119	LT Factor Green = 80%, Variability factor = 50%

Compared to Sc3, Sc5 considers that demand can be known 1 week before. The impact for MRPII is that the MRP calculus can be done considering real demand for the first week and forecasts for the rest of the planning horizon. The consequence is that products are assembled on order and safety stocks are reduced. This is also verified when comparing Sc6 and Sc7.

In DDMRP, the consequence is that spike demand orders are considered in the computation of the "Available Stock Equation" (ASE) 1 week before their real demand and thus generate replenishment orders anticipated of 1 week (the assembly lead time). Consequently, only the spike demand orders are assembled on demand. Nevertheless, we could not take advantage of this process for reducing some of the DDMRP parameters. Therefore the only effect was a small increase of final inventories. That seems to invalidate hypothesis H3.

Now, it can be noticed that in Sc6, DDMRP does not succeed in satisfying the objective OTD. Analysing at this specific simulation, it appears that some spikes happen at moments of high seasonal demand. In such cases, one demand order can exceed the TopOfGreen Level (see equation (1)) what means that the shop cannot have enough final inventory to serve the demand. This does not happen for DDMRP in Sc7, because spikes are anticipated. Consequently, hypothesis H3 can be validated: the spike anticipation is useful for huge demand orders that cannot be replenished with a pull mechanism. Such orders require to be made on demand or at least forecasted.

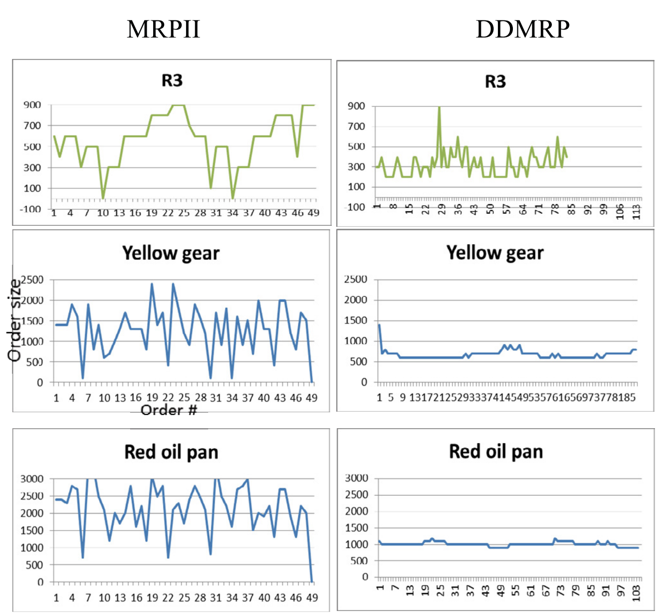

Fig. 3: Size of Replenishment orders for Sc7

Figure 3 plots the size of replenishment orders for three references for Sc7 and both MRPII and DDMRP. Similar behaviours have been noticed in all the scenarios and for all the references. Replenishment orders appear to be much smaller for DDMRP that for MRPII. Moreover, orders have big size variability in MRPII. While in DDMRP, size of the orders has a small variability for finished products (it is due to the spike demands), but nearly no variability for components. Conversely MRPII generated one order per week, while DDMRP generates much more orders. Nevertheless, this increase in the number of orders does not generate a so big increase in the number of setups for the machines and was regulated by the DDMRP execution priorities. Hence, it can effectively be conclude that buffers are regulating the system variability: H2 is validated.

The stock level of reducers (finished products) and components were read twice a day during a simulation. Figure 4 plots the distribution probability of the stock level for MRPII and DDMRP in scenario Sc7. Similar plots were obtained in other scenarios. It can be seen that for MRPII the distribution is quite flat: the probability is high to have over stocks at some moments and lack of stocks at other moments. Nevertheless, the distribution is not bimodal as suggested by Ptak et al. (2011). On the contrary in DDMRP the plot is much more centered: the stock more rarely enters the dangerous zones. Consequently hypothesis H4 can be validated.

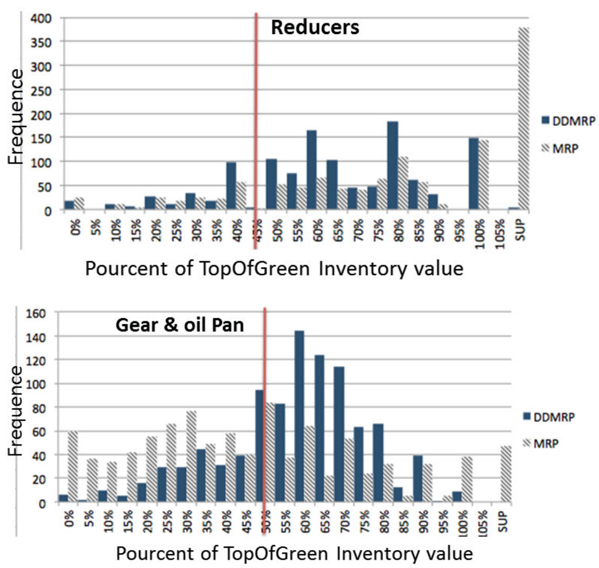

Fig. 4: Frequencies of some stock level for Sc7

5. CONCLUSION

This paper developed a comparative study of Demand Driven MRP to the classical MRPII on a use case using Discrete Event Simulation (DES). Several sources of variabilities have been combined: internal (instability of operating times and setups), external (spike demand and seasonality of demand). Nevertheless, DDMRP appear to dominate MRPII in all the scenarios as it enables to reach the same level of OTD with less WC (10% less in general), and less nervousness.

Such results show that DDMRP develops properties that are recognized to pull flow management policies. But the were obtained while demand was not stable at all. Indeed, DDMRP continuously adapts the buffer level to the demand trend changes but appeared to be sensible to huge unforecasted demand. Nevertheless, a spike management process is proposed with DDMRP that proves it is efficient if huge demand can be anticipated. Therefore, DDMRP appears to be pull oriented for normal demand and push oriented for spikes.

Two kinds of perspective appear as evidence. The first consists in testing DDMRP in other environments in particular some industrial complex situations with a huge product variety and important variability sources. The second consists in comparing DDMRP to pull flow management policies such as some adaptations of Kanban and ConWIP systems.

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