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Demand driven material requirements planning or DDMRP is a recent and promising material management method that has been developed and implemented in the practitioner world. Essentially, DDMRP represents a rethinking of the basic MRP logic. By incorporating elements drawn from Lean Systems and the Theory of Constraints and by introducing new features such as dynamic buffers, DDMRP modifies the basic MRP logic so that it is better able to satisfy customer demands in an increasingly demanding, turbulent and dynamic environment. Claims have been made by firms that DDMRP represents a superior planning approach. In this paper, we introduce and explore DDMRP. In addition, we evaluate its effectiveness relative to two other widely accepted approaches – MRP II and Kanban/Lean production – through a series of structured computer simulation experiments. The results strongly indicate that DDMRP does represent a superior approach – one that warrants further academic study.

Keywords: Demand Driven MRP; variability management; MRP; Lean; Kanban

1. Introduction

In 1975, manufacturing planning and control was profoundly changed when Orlicky introduced a systemic approach for material planning – material requirements planning or MRP (Orlicky 1974). MRP enabled firms to improve the quality and effectiveness of their planning and scheduling of dependent demand items. It created more credible schedules and due dates by linking the due-dates of components to the need dates of their parent items. It presented a logic whereby parent demands could be exploded (converted) into the necessary supporting component supply schedules. It identified when orders had to be released to ensure that the materials arrived just when they were needed. It provided managers with a vehicle for evaluating the potential impacts of proposed changes. The result was that MRP helped create an integrated system where changes at any level would result in potential changes at the other levels.

The introduction of MRP along with its various variants (closed loop MRP and MRP II) gave rise to a period of research focused on various aspects of its operation and impact on the firm (e.g. Benton and Whybark 1982; Melnyk and Piper 1981, 1985; Narasimhan and Melnyk 1984; Schmitt, Berry, and Vollmann 1984; Thompson 1983; Whybark and Williams 1976). For the most part, this research has been essentially based on the same logic presented by Orlicky (1974) with some minor changes. While this logic has been updated several times (e.g. Ptak and Smith 2011), the major features of MRP have remained the same: linking the planning and scheduling of dependent demand items to the demand of their parent items, time-phasing of requirements and the use of static safety stocks.

Recently, there has emerged from the practitioner world a fundamental rethinking of the MRP logic – a rethinking that draws on elements of such developments as Lean Systems and the Theory of Constraints (Goldratt and Cox 1992) to improve the overall performance and effectiveness of the MRP logic. In addition, this rethinking has challenged some of the fundamental assumptions of MRP, resulting in the replacement of static safety stock by dynamic buffers. This rethinking has resulted in a new approach – Demand driven MRP (DDMRP) (Ptak and Smith 2016). Evidence emerging from the practitioner world has provided support for the superior performance of this approach (Demand Driven Institute 2017). Companies that have implemented this approach –such as Allergan, British Telecom, Figeac Aero and Michelin – have claimed significant improvements in improving on-time delivery, reducing stock outs and in reducing levels of inventory.

These claims combined with the rethinking of the underlying MRP logic warrant a rigorous review and analysis with the goal of determining whether DDMRP indeed does offer a significant improvement in performance. That is the major objective of this paper – to address the simple research question: Does DDMRP represents a significant improvement in

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planning and scheduling logic? Specifically, this paper reports the results of a comparative study in which DDMRP is compared to two other dominant forms of planning and scheduling: MRP II and Kanban. Using a series of structured computer simulation experiments, the three approaches are implemented and their results evaluated to assess the relative effectiveness of the three approaches. What makes the experiments so interesting is that in some of the experiments, the underlying structure strongly favours the use of Kanban system.

The results, as reported in this paper, strongly support the contention that DDMRP does represent significant improvement in planning and scheduling logic. However, before these results can be presented, it is important to first understand the key features of DDMRP, relative to MRP II and Kanban systems. That is the starting point for this paper.

This article is an extension of an existing research work realised through a thesis (Miclo 2016).

2. MRP, pull systems and DDMRP – an overview

The last decades have seen the development of numerous material management methods. Traditionally, these management methods fall into one of two categories: push or pull (González-R, Framinan, and Pierreval 2011). Push systems release orders from forecasts and firm demand from a set of production plans. In contrast, pull systems manage production from a work-in-process (WIP) level directly linked to final demand (Hopp and Spearman 1996).

2.1 *Push flow fundamentals*

The most famous and widespread material management method in the push category is that of material requirements planning – MRP (Orlicky 1974). Initially, this system was intended to focus on material planning. As such, it suffered from a number of limitations: integration with formal capacity planning and management, lack of integration into the formal manufacturing planning and control system, lack of feedback and integration with the other areas of the firm (e.g. marketing, engineering, finance and human resources). These limitations were addressed to various extents in subsequent modifications to the MRP system – modifications in the form of the closed loop MRP, MRP II (manufacturing resources planning) (Wight 1995) and most recently enterprise resources planning (ERP) and supply chain planning systems (e.g. Olhager 2013; Wilson 2016). Given that MRP has been around since the mid 1970s and MRP II has been with us since the mid 1980s, we will assume that the reader is already familiar with its major features. In this paper, we regard MRP II as a forecasting management system for manufacturing that coordinates the entire production throughout dependent demand: from raw material or components purchasing, to material or human resources within the different plans. MRP II has three main objectives: (i) Guaranteeing resource availability for production and for customer sales; (ii) Minimising inventory; and (iii) Planning and scheduling production and purchasing activities.

2.2 *Pull flow fundamentals*

In contrast to push flow systems, pull flow techniques adapt to real customer demand while controlling the work in process (WIP). This Just-In-Time (JIT) philosophy was developed first in the Toyota Production System after the Second World War and has over time been transformed into Lean Manufacturing and Kanban (Ohno 1988; Sugimori et al. 1977). Its attractiveness and success is indicated by the numerous techniques and procedures that have been developed in support of it (González-R, Framinan, and Pierreval 2011) – techniques such as one-piece flow (Sekine 2005), the constant work in process (Spearman, Woodruff, and Hopp 1990), Demand Flow Technology (Costanza 1996), Critical WIP Loops (Sepehri and Nahavandi 2007), Paired-cell Overlapping Loops of Cards with Authorization (Riezebos 2010) and the Control Of Balance by Card-Based Navigation (Land 2009) – to name a few. These procedures control either the WIP per product[1] or the workload (independently of the products) in a production line. Of these various developments, Kanban and its variants (Extended Kanban system or Generic Kanban system [Lage Junior and Godinho Filho 2010]) are probably the most famous (Thürer, Stevenson, and Protzman 2016; Xanthopoulos, Koulouriotis, and Gasteratos 2017).

Kanban systems associate cards to item's reference and materialise the real requirement and control feedback from the later station (the next activity in the process in general) to its former station in a production system. It manages this flow using four rules (Thürer, Stevenson, and Protzman 2016): (i) The latter station goes to the earlier one to pick up the products it needs, (ii) Earlier station produces items in the quantity indicated by the Kanban card, (iii) No items are made or transported without an associated Kanban and (iv) Always attach a Kanban to the goods container.

2.3 *Push and pull flow evolutions*

Over time, as noted by researchers such as Jodlbauer and Reitner (2012), Milne et al. (2012) and Rossi et al. (2017), both push and pull systems have seen their share of academic improvements and enhancements. In a recent ProQuest search carried out in May 2017, it was noted that in the period from 2000 to 2016, there were an average of 7 refereed articles published in peer-review journals each year – which is a weak amount of articles.

In the case of push systems, specifically MRP, there have been attempts to improve its performance and effectiveness by combining it with other elements or techniques. For example, Jodlbauer and Reitner (2012) developed an approach that they called material and capacity requirements planning (MCRP). MCRP integrated capacity planning into MRP. This research tried to improve the performance of a typical MRP system by replacing the static lead times found in such systems with ones that were dynamically calculated based on the capacity utilisations of the resources. More recently, Rossi et al. (2017) developed a capacity-oriented MRP procedure that combines the traditional MRP procedure with an approach based on linear programming. The result is that the system is now able to generate 'more realistic' lead times. These changes can be best described as incremental in nature and ultimately limited. For example, researchers such as Ho and Ireland (2012), Li et al. (2012), Milne et al. (2012) and Sali and Giard (2015) have noted that these various techniques are reaching their limits in terms of their ability to cope with the increasing number of hazards, variances and disruptions that most firms must now deal with.

2.4 *Push and pull flow integration*

To this point, we have treated the push and pull systems as being mutually exclusive. There is evidence from the literature that researchers are exploring the integration of these two approaches. For example, Powell, Bas, and Alfnes (2013) noted that both MRP and lean techniques have strengths for managing material flows and that they should be integrated into a coherent whole. However, this is not an easy undertaking since the use of these two approaches simultaneously leads to conflict. For example, MRP schedules orders in advance of consumption; Lean schedules orders in response to consumption. Consequently, there is a need for innovative solutions that can coherently integrate the best practices of both MRP and Lean.

One potential approach to this integration was proposed by González-R, Framinan, and Pierreval 2011. They indicated that there existed a third category of material management systems that they referred to as a hybrid system. Furthermore, researchers such as Hodgson and Wang (1991a, 1991b), Karmarkar (1986), Villa and Watanabe (1993), and Wang and Xu (1997) have proposed such hybrid push-pull systems. Hybrid push-pull systems can be classified into two categories with a vertical or horizontal push–pull integration (González-R, Framinan, and Pierreval 2011; Olaitan 2016).

A horizontal hybrid push–pull system consists of a succession of pull activities followed by push activities in the process (Cochran and Kaylani 2008). In this case, between pull and push activities, there are semi-finished items (Beamon and Bermudo 2000; Cochran and Kaylani 2008; Olhager and Östlund 1990). These methods use decoupling points by creating independent needs.

A vertical hybrid system has the tactical phase based on a push system and the execution phase dedicated to a pull strategy (Cochran and Kaylani 2008). For example, a MRP II system with sales and operating planning (S&OP) and master production schedule (MPS) finite load smoothing strategies that is combined with a Kanban system at the execution level is an example of a vertical hybrid push-pull system (Flapper, Miltenburg, and Wijngaard 1991). In other approaches, the pull system regulates the workload in the shop and control order execution regardless the system that generate the orders: it can be customers in a Make To Order process but also MRP in a Make To Stock approach (Hopp 2008; Land 2009; Riezebos 2010).

More recently, Ptak and Smith (2011, 2016) have tried to overcome MRP and Lean limitations by designing a hybrid push–pull system that combined both vertical and horizontal approaches. This is called demand driven MRP (DDMRP). It is this system that will serve as the focal point for this study.

2.5 *Demand driven MRP – an overview*

DDMRP is an integral element of a 'demand driven operating model or a manufacturing strategy of dramatic lead-time compression and the alignment of efforts to respond to market demands. This includes careful synchronisation of planning, scheduling and execution with consumption'. (Ptak and Smith 2016). DDMRP refers to the material planning and scheduling component of this system.

DDMRP can be regarded as a hybrid system that takes the best practices from four other systems – MRP, Lean, Six Sigma and the Theory of Constraints (TOC) (Goldratt and Cox 1992). From MRP, DDMRP takes the dependent demand, product explosion and time-phasing; from Lean, it takes the emphasis on waste and variance and the pull flow logic; from Six Sigma, it takes adaptive adjustments possible from outlier variance analysis; and, from TOC, it takes the focus on bottlenecks, acceptance of inventory and the strategic placement of inventory. To better understand the detailed operation of DDMRP, it is recommended that the reader review Ptak and Smith (2016). However, there are certain unique features that differentiate DDMRP from MRP, Lean, Six Sigma and TOC. These DDMRP features are summarised in Table 1.

In reviewing the elements presented in Table 1, it is possible to understand at a very simplistic level the logic driving DDMRP. DDMRP starts with the basic MRP logic. To this logic, DDMRP introduces modifications drawn from TOC and Lean. From TOC, DDMRP introduces the concept of critical items and selective inventory positioning and protection. That is, DDMRP focuses its attention on the critical parts – the strategic parts that are buffered. Just as in the TOC perspective, the focus is to protect and promote flow. This protection is provided through two mechanisms – stock buffers (which are different from safety stock) and lead-time. Furthermore, the stock buffer levels are dynamic – changing in response to various factors. By allowing the stock buffer levels to vary, DDMRP is ensuring that the buffer protection integrity is constant over time. In addition, these buffers play a critical role, based on lessons drawn from Lean – they absorb the effects of variance bidirectionally (i.e. from both supply and demand sides). This, in turn, reduces the level of variance in the execution system, thus helping the schedulers improve the quality of resulting schedules. As previously noted, this is a simplification of the DDMRP logic. For more insights into the intricacies of the logic, the reader is referred to Ptak and Smith (2016).

Like TOC, MRP, Six Sigma and Lean, DDMRP is a development primarily created by practitioners, not academic researchers. It is also a relatively new development – having emerged in the last 10 years. The research team became aware of DDMRP in 2014 due to reports emerging from industry of its impact on performance. Some of the more successful DDMRP implementation results are summarised in Table 2. Several traits attracted the attention of the research team. First were the significant levels of improvement reported. The research team contacted representatives from the various organisations to validate the claimed improvements and found that these improvements were substantiated (in

Table 1. Unique features of DDMRP (Ptak and Smith 2016).

Trait	Explanation	Key decisions/implications
Different categories of parts	This is not ABC analysis. Rather, it is a recognition that parts fall into one of two categories: buffered and non-buffered Buffered parts are strategic parts; parts are strategic for one or more of the following reasons: customer tolerance time, market potential lead time, external variability, inventory leverage, resource protection Non-buffered parts are not strategic parts: e.g. Not sufficient volume, DLT really short (category C in general in a Pareto analysis)	• Which parts are strategic (and why)? • Only buffered items have planned inventory.
Different categories of lead times	Two categories of lead times are introduced. For non-buffered parts, classical production lead times are used (as per traditional MRP logic) Buffered parts have a new lead time – Decoupling Lead Time (DLT) – also known as the Actively-Synchronised Lead time (ASRLT) DLT – defined as the longest, unprotected (unbuffered) lead-time in the BOM	• Non-buffered lead-times – static • Buffered-times – dynamic
Different planning approach	MRP plans by dependence through the BOM. DDMRP daily plans at the positions of independence (buffers) using the net flow equation (on hand + on order – qualified demand) Between the buffers, planning is dependent as in MRP	• Forward order release utilising actual demand and full lead time • Buffers stop system nervousness • Net Flow Equation protects buffer integrity
Dynamic Buffers	The stock buffers associated with strategic parts are allowed to fluctuate to reflect the impact of factors, such as seasonality, volatility of customer demands, load balancing and production ramp-up/ramp-down	• Which buffers are to be allowed to fluctuate? • Why? • What adjustments to make?

Table 2. DDMRP ‘success’ stories (Demand Driven Institute 2017).

Company	Information	Reported Benefits
Albea Group	International company with sales of $1.4 billion USD (2016). Supplier of innovative packaging solutions. Began implementation of DDMRP in 2015	Lead time reduced 75% 100% service
a.b.e.® Constructions Chemicals (PTY) LTD	A South African company, part of the global French company – Chryso Group. Provides waterproofing solutions and products from foundations to roof for new construction and remodelling. Began implementation in January 2015.	Backorders as a % of sales have dropped from 16.3 to 2.5% with a 54% inventory reduction, in spite of the fact that sales for many of its products have seen 200–300% growth in annual stock turns.
Michelin	French tyre manufacturer. One of the four largest tyre manufacturers in the world. Known for its innovations in this field (e.g. run flat tyre, radial tyre). Began implementation of DDMRP in late 2016.	Service level from 89.3 to 98.6% in first four months Stock reduction of 10%
IFAM	Spanish based designer and manufacturer of global security solutions in the locksmith market. Began implementation in 2014.	No expedites, no stock outs Inventory reduced 25%
Allergan	A $7 billion + pharmaceutical company (best known for Botox). Began implementation of DDMRP in 2015.	Lead time reduction > 50% Service levels 99+% Inventory reduced >30%
Maquila Internacional de Confeccion (MIC)	Designs, produces and sells children’s garments under licence from companies such as Disney and Mattel. Also supplies direct sales channels for ladies garments. Began implementation in February 2013.	Eliminated outsourcing (was 40%) Lead time 45 days Service levels improved from 60% to >98% Inventory reduced 40% Revenue increased 800% for Christmas Overall revenue doubled
PZ Cussons	Founded in 2002, headquartered in UK Multilingual, multicultural solutions in the following markets: • Consumer goods • Food • Electronics • Industrial products • Pharmaceutical Products include St. Tropez, Imperial Leather, Robb, ZIP, Radiant, Carex (to name a few). Began implementation of DDMRP in September 2012, with system live by March 2013.	25–30% Inventory Reduction Service improvement to 100%
British Telecom	British provider of home broadband equipment, set top boxes and mobile phones. Began implementation in 2015.	32% reduction in Finished Good 43% reduction in excess inventory Availability >99%
Avigilon	Designs and manufactures high-definition surveillance solutions. Began implementation in 2013.	$5 M reduction in backlog with record sales levels 99+% customer service level
Forge USA	Steel forging company based in Houston, TX. Implementation began in 2014.	On time to schedule improved from 50 to 90+% On time to customers improved from 40% to mid 70% Reduced average days late from 30 to <5
Productos Tubulares	Integrated manufacturer of hot finished seamless steel pipes and tubes. Sales $114 million USD (2015). Began implementation in November 2014.	30% reduction in WIP Lead time reduction from 35 to 14 days Revenue increased 60% with 7% less WIP and only 8% increase in finished goods

some cases, the recent results were even more dramatic). Second, the reported lead-time for implementations was also relatively short (often less than one year). It was this combination of reported results and the hybrid logic driving DDMRP that gave rise to this study. Specifically, the research team was interested in determining if DDMRP and the developments that it embodies presented a significant advance in material production planning and scheduling as compared to the alternative, more widely used techniques of MRP II and Kanban/Lean.

3. Research methodology

To address the question posed in the preceding section, this paper draws on a structured experimental design where the data for analysis is generated using discrete event computer simulation. Computer simulation is a technique with a long history in operations management and supply chain management research (e.g. Carvalho et al. 2012; Hollocks 2006; Lee et al. 2002; Manuj and Mentzer 2008; Manuj, Mentzer, and Bowers 2009; Venkateswaran and Son 2004; van der Zee and van der Vorst 2005). For example, it has been used extensively to study job shop scheduling. Discrete event simulation presents researchers many important advantages. As noted by Law (2014), this is a highly flexible approach that can be used for modelling and studying various types of systems such as manufacturing, material, services, health-care, communications or queuing (Schriber, Brunner, and Smith 2012). It has been used to study supply chain disruptions and to propose alternative strategies for dealing with such disruptions (Melnyk, Rodrigues, and Ragatz 2009). It has been used for business process reengineering and for modelling scheduling and planning systems such as MRP and for optimisation (Hollocks 2006). It enables the researcher to have full control over the model and its performance (thus controlling for potential confounding factors such as human intervention). New independent variables can be introduced and the impact of these changes can then be evaluated in terms of how they affect performance. Furthermore, the researcher has full control over the performance measures used and their recording, thus ensuring that there are no missing variables. Finally, a discrete event simulation also can help develop better insight into why the specific results have been generated – thus creating a more complete understanding of changes in the independent variables impact the dependent variables.

The process for addressing the research question consists of four sequential steps. The first is the development of the simulation model (the setting used to generate the data). Next, there is the experimental design, which provides the structure needed to drive the computer simulation model and to identify the independent variables (IVs) of interest. Third, there is the generation of the data. The final stage is data analysis in a way that helps us address the research question. This analysis uses statistical procedures such as ANOVA.

3.1 *Developing the simulation model*

Past research has tried to quantitatively assess material management method behaviours (e.g. Hochreiter 1999; Li 2013; Sarker and Fitzsimmons 1989). The results of these studies have resulted in better WIP and resilience management for pull flow methods compared to push flow material management ones. Li also emphasised the Kanban limit to deal with high demand spikes (Li 2013). Yet, in developing an appropriate simulation model, it is necessary that it represent an acceptable representation of reality. Some of these past studies, especially those dealing with Kanban/Lean, have been criticised for being too simplistic (e.g. Geraghty and Heavey 2006; Hochreiter 1999; Khojasteh and Sato 2015; Koulouriotis, Xanthopoulos, and Tourassis 2010; Sarker and Fitzsimmons 1989). These researchers have noted that these studies have described systems with linear processes, a single product and little or no variability (either in processing times or in demand). Such conditions do not necessarily describe the environments facing most managers and the settings in which systems such as DDMRP, MRP II or Kanban/Lean would be deployed. Consequently, there was a need to develop an alternative setting – one that was more closely aligned with reality. For the purposes of this study, the decision was made to base the discrete event simulation model on the 'Jeu du Kanban©' or Kanban game (Greif, Moisy, and Pesnel 1984) that was developed by the Centre International de la Pédagogie d'Entreprise (CIPE), in France.

3.1.1 *The Kanban game*

The game is based on an actual company that produces and assembles speed reducers. In this game, the company is interested in improving on-time delivery (OTD) and in reducing work-in-process inventories (WIP). The game describes a single workshop that manufactures low power reducers. The workshop consists of five workstations: four machining stations and one assembly station. To assemble a reducer, one oil pan, one gear and one crown are required. In the process, there are two different crowns: one A crown and one B crown, with the A crown machined before the B crown (see Figure 1).

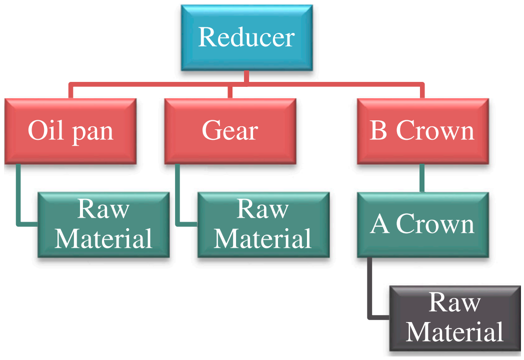

Figure 1. BOM structure for reducers and assembly.

The shop faces demand for six end products and for white A crown – a spare part that is scheduled separately. A simple bill of material (BOM) structure (see Figure 1) is used with every parent only requiring one component. The configuration of the five workstations along with the operating assumptions are summarised in Table 3. The entire simulation is modelled using Witness®, developed by Lanner.

- Mean time between failure (MTBF): a negative exponential distribution NegExp(mean) is used to model real system behaviour. Mean time to repair (MTTR): this time to repair a failure is also assessed with Kanban game data. This time a triangle distribution Triangle(min, mode, max) is used to model real system behaviour.
- Respectively the MTTR and MTBF parameters of each workstation are the following:
- Operation cycle time: for each station, a lot to produce or assemble takes one hour.
- Lot size: in one hour, each station produces or assembles 10 products, except for both crown machining stations with 20 products per hour. Each station has a setting-up time if it produces or assembles another product. Each machine is open five days a week/nine hours per day.
- Human resources are not dealt with: at any time, there are enough employees to have every machine appropriately staffed.
- Transfer operations are considered to be instantaneous.
- Inventory capacities are considered infinite (i.e. there are no space constraints).
- No scrap was produced in the simulation model (scrap rate is not significant in the game and testing was not planned as a parameter in the design of experiments).
- Raw materials are considered infinite (i.e. raw material is always available when needed).
- All the final products have the same selling price: there is no strategy to implement to improve financial throughput (and turnover).

The operation of the model is straightforward. At the start of every day, a production schedule is generated consisting of the amount of end items demanded by the customer (six reducers and the spare part). The amount ordered is drawn from a Beta distribution. The amount of variance in the demand is treated as an independent variable (as will discussed later in this paper). Performance is based on 12 measures (the dependent variables): overall average on-time-delivery (Average OTD), on-time-delivery by end item (Reducer 1 to 6 and White Crown OTD), average work-in-process (Average WIP), standard deviation of the work-in-progress (Standard Deviation WIP), average orders late (Average orders late) and maximum orders late (Maximum orders late).

Table 3. Initial configuration and operating conditions of the workshop.

Machines	Oil pan machining	Gear machining	Crown machining phase A	Crown machining phase B	Assembling
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)
MTBF (hr)	NegExp (17.80)	NegExp (11.6)	NegExp (9.70)	NegExp (15.19)	NegExp (21.25)

The Kanban game was selected because it embodied a more realistic treatment of an actual manufacturing system – one in which DDMRP or MRP II or Kanban/Lean would be used. It is a system with a broader and more varied mix of products, multi-level bills of material, significant set-up time considerations, different demand scenarios, a combination of manufacturing and assembly operations and the scheduling of both end items and spare parts.

3.1.2 *Simulation practices*

System Initialisation: While several methods have been proposed for determining warm-up period (Law and Kelton 1991), the easiest and most straightforward approach is to run a preliminary simulation of the system, preferably with at least three to five replications (Law and McComas 1991), and use a graphical method to observe at what time the system reaches statistical stability. Indeed, the visual inspection of time-series of key output statistics, for instance, hourly throughput or average utilisation of a resource, is one of the best method (score of 20 according to 5 criteria: Simplicity, Ease of implementation, Accuracy, Assumptions, Parameter estimation) studied in (Robinson 2014). The length of the warm-up is the point at which the time-series appears to randomly vary around a constant mean. This approach is simple, conservative and usually satisfactory. For our case study, the warm-up period is six months.

Common Random Numbers (CRN): CRNs is a popular and useful variance reduction technique widely used in discrete event computer simulations, when the goal of the research is to compare and evaluate two or more alternative configurations or systems (Law 2014; Law and Kelton 1991). In this study, 40 different CRNs are used so that the first run for every cell (where the design is described in the following section) uses the same set of random number seeds. Consistent with analysis practice, in the subsequent ANOVA analysis, the CRNs are treated as blocking factors.

Run length: For each replication, the recommended length of the simulation run for a steady-state simulation is dependent upon the interval between the least frequently occurring even. It is usually a good idea to run the simulation enough times to let every type of event (including rare ones) happen at least a few times if not several hundred. The more time periods over which model is run, the more confident we are as researchers that the results represent a steady-state behaviour. For the simulated system, the length of each run was 12 months, which represents at least 41 breakdown occurrences for a machine (this event is the rarest one in the simulation).

3.1.3 *A comment on the Kanban game*

Before leaving this discussion of the simulation vehicle, it is important to observe that this test environment can be viewed as somewhat challenging for system such as DDMRP and MRP II. This environment was not designed to stand in the way of Kanban/Lean since the game was realised to teach how to apply Lean tools and principles. Initially, we would expect strong performance from Kanban/Lean.

3.2 *The experimental design*

The experimental design consists of two factors: type of planning system (at three levels) and demand variability (at two levels). For the first factor, *planmeth*, the three levels consist of DDMRP, Kanban/Lean and MRP II. The second factor, *demvar*, consists of two levels: low and high. Given the 40 runs per cell (as previously noted), this resulted in a full factorial design consisting of 240 runs (3 × 2 × 40). These runs formed the basis of the subsequent analysis.

3.2.1 *Detailed discussion of how planmeth was operationalised*

3.2.1.1. *DDMRP. Position of the Buffers*: Regarding DDMRP implementation, the first step deals with buffer positioning. The buffer must be positioned where it compresses lead times and reduces variability. A ROI analysis must validate this first step. As far as the case study is concerned, the different questions are which type of products must be buffered. Firstly, due to the Make-To-Stock (MTS) environment (cf. the real customer demand is only known on the day of the order), the six reducers must be buffered. This assumption also concerns white A crowns (spare parts). Seven products out of 16 must already be buffered with stocks. The different scenarios for assessing the impacts of buffering products were realised: if all components are buffered, it dramatically decreases decoupling lead time (DLT) for reducers; however, it may cost in terms of inventory.

The best theoretical buffer positioning scenario is with 14 products out of 16 are buffered, which is all the products except for green and red A crowns (Miclo et al. 2016). With all 16 products buffered, WIP would increase.

Buffer Sizing: For the initial value (without variability), the DLT, LT factors and variability factors have been chosen and were detailed (Miclo et al. 2016) accordingly to DDMRP Theory:

- *DLT:* the initial DLT values are equivalent to those calculated from the buffer positioning step.
- *Lead Time (LT) factors*: as mentioned before, the assembling, oil pan machining and gear machining steps are potential bottlenecks. All these products have close DLTs. In addition, DLT for the B crown (LT for A crown added to LT for B crown) is also close to other products DLT. This is why the initial LT factor is the same for all products and is set at 50%. Green and red base LT factors initially have equivalent percentages.
- *Variability factor*: all products must manage sources of variability (especially with this high demand level scenario). It is difficult to assess system behaviour and whether variability is lower or higher for final products or components. Therefore, variability factors are also initially set at 50% for the 14 products.

For more information about the details of how DDMRP was modelled, the reader is advised to contact the paper's corresponding author.

3.2.1.2 *Kanban/Lean.* Central to this final planning system is load/capacity management. Consequently, a schedule was developed in terms of the number of Kanban cards needed. The objective was to try to repeat this schedule and to have an adaptive system when there was controlled variability. From this schedule, the theoretical number of Kanban cards has been assessed. This number is calculated with the following formula (Sugimori et al. 1977):

$$y = \frac{D \times (T\omega + Tp) \times (1 + \alpha)}{a}$$

where, y – Number of Kanban cards; D – Demand per unit time; $T\omega$ – Waiting time of Kanban; Tp = Processing time; α = Policy variable (equivalent to a safety zone); a –Container capacity.

For the following, L is described as the maximum waiting time of Kanban and processing time:

$$L = T\omega + Tp$$

To get the initial Kanban number (y), the following strategy has been applied: there is demand each day with several set-up operations possible for assembling (with six reducers). The system must be able to be flexible but also to be able to produce several lots from the same product if there is enough capacity (especially for assembling, gear and oil pan machining). The implemented L value depends on the number of times a product is produced (once a week for some and twice a week for others). Furthermore, the schedule is a 'perfect schedule' if demand is well distributed. Therefore, a safety factor (α) is initially defined (and rounded up) to have y for all the products. As detailed, the Kanban implementation is an iterative method, so the cards would (and will) be changed after being compared to system behaviour.

The notion of a red indicator was also introduced. The red indicator represents a product production emergency and is calculated with a Kanban transfer time equivalent to zero. This assumption is representative of reality with more and more companies that use RFID technology or barcodes to reach this objective (electronic Kanban) and improve their processes with real-time location systems (Micilo et al. 2015).

This red value is in the 'Red indicator' line: a product becomes an emergency when there is only this amount of available space for this product on the Kanban table. Furthermore, the 'Green indicator' for each product represents the amount of Kanban cards to produce in a row at a minimum. The objective is to limit the set-up operation number, especially when there are several emergencies (to avoid changing the product each time one lot size has been produced). This parameter can be compared to the DDMRP green zone which can be the minimum quantity for a supply order. Regarding Kanban execution, there are only two ways of changing the product machined (or assembled): when there is an emergency (a red indicator is reached), the current product is not in an emergency zone.

When the production of the product changes, a prioritisation is made. The most highly prioritised product (prod.) is the one with the highest ratio:

$$\text{Ratio (prod.)} = \text{Kanban cards available on the table (prod.)/total amount of Kanban cards (prod.)}$$

3.2.1.3 *MRP II.* MRP II has been implemented from S&OP to the scheduling step. About S&OP, its objective is 'only' to decide which quantity of all reducers can be produced in a month (from the reducer family point of view). The Master Production Schedule (MPS) plans the assembling orders for each reducer (from R1 to R6) up to a maximum quantity of 390: this is equivalent to a week without breakdowns and one set-up for each product for assembling, oil pan machining and gear machining. The MPS is based on the average forecasted demand. Furthermore, it considers possible backlogs at the end of the month to plan for this backlog and future demand for the next month (with a 390 maximum). If the maximum threshold is reached, the orders are planned by product priority (compared with the current on-hand level).

From this MPS, a weekly MRP is calculated with the BOM to satisfy assembly consumption. MRP is realised for oil pans, gears and both crowns. MRP also considers potential backlogs to plan for them in the future. Whether for MRP or MPS, a safety stock is initially calculated for each product in order to protect against forecast errors (short-term demand changes) and will be adjusted for the different scenarios.

The final step deals with scheduling these production and assembly orders. An initial schedule was defined to meet customer demands from initial on-hand. This schedule was realised to use different components to assemble the reducers (e.g. assembly orders requiring red oil pans were not all planned in a row). A sequence was also defined for the components to limit the set-up operations. This appropriate sequence will be repeated however the quantity of each order will be modified each time MPS or MRP is calculated.

What is more, in MRP II implementation, if an order is not completed when the MRP or MPS calculation is realised, the next period will continue with this order. However, the quantity of this order (or others that were already planned) can be adjusted.

To conclude, the three methods' implementations are coded consistent with the experimental design. The main characteristics of the three methods are detailed in Table 4 below, inspired from (Krajewski et al. 1987).

3.3 *Data generation*

Central to the generation of the data were two factors: the planning method and the level of demand variability. In the previous section, we addressed the planning method; in this section, we will address the demand variability. Two scenarios have been simulated with *low* and *high* variability demand. In theory, low demand variability is the environment where MRP II and Kanban must be efficient. Therefore, the three methods should have satisfactory results that are close to each other. To analyse the ability of the three methods to deal with uncertainty, a high variability demand scenario was introduced.

For these two scenarios, the demand facing the simulation system was generated from a Beta distribution. This distribution was selected because of its ability to simulate actual demand variability. The demand is given by the formula demand = k_1 * Round(k_2 * Beta(a,b)/k_1), where k_1 is a factor allowing to discretize the continuous values in k_1 increments from 0 to k_2: [0; k_1; 2 * k_1; 3 * k_1; …; k_2].

In the Kanban Game, k_1 is equal to 10 for components R1 to R6 and is equal to 20 for the Crowns_A. The factor k_2 corresponds to a value close to the maximum level of the demand. Finally, a (alpha) and b (beta) are the intrinsic parameters of the Beta distribution corresponding to the shape and the scale. The demand parameters for each component respectively for the low or high variability scenario are in Table 5.

Table 4. Main MRPII, Kanban and DDMRP characteristics.

Characteristics	MRP II	Kanban	DDMRP
Tactical view[a]	S&OP defined once with maximum S&OP value.	Card dimensioning following (SUGIMORI et al. 1977) equation	Buffer positioned and sized (Ptak and Smith 2016)
Type of orders	Production order released	Circular movement of Kanban cards	Supply order generated
Order generation	MPS monthly calculated for reducers MRP weekly realised for components	Kanban cards indicate replenishment need	Daily Net Flow Equation
Execution priority	Scheduling following forecasts and backlogs	Red indicator or ratio(prod.)	Buffer status
Forward visibility	5 days end products firmed demand for MPS	5 days end products firmed demand not used	5 days end products firmed demand for spikes detection

[a]Realised one time for each demand variability level because forecast variations are the same for MRP II and average real demand are the same for Kanban and DDMRP (not the need to resize safety stocks for MRP II, Kanban cards and DDMRP buffers during the simulation year of each replication).

Table 5. Demand parameters for each component (with low or high variability).

Type of demand variability	Product	Parameters
Low	R1	10 * Round (20 * Beta (1.6, 1)/10, 0)
Low	R2	10 * Round (12 * Beta (1, 3)/10, 0)
Low	R3	10 * Round (20 * Beta (1.1, 0.9)/10, 0)
Low	R4	10 * Round (40 * Beta (1, 1.2)/10, 0)
Low	R5	10 * Round (22 * Beta (1.3, 2)/10, 0)
Low	R6	10 * Round (23 * Beta (0.3, 0.5)/10, 0)
Low	White A Crowns	20 * Round (55 * Beta (0.2,0.3)/20, 0)
High	R1	10 * Round (190 * Beta (0.1, 1.5)/10, 0)
High	R2	10 * Round (35 * Beta (0.1, 1.5)/10, 0)
High	R3	10 * Round (150 * Beta (0.12, 1.5)/10, 0)
High	R4	10 * Round (270 * Beta (0.1, 1.5)/10, 0)
High	R5	10 * Round (110 * Beta (0.12, 1.5)/10, 0)
High	R6	10 * Round (120 * Beta (0.12, 1.5)/10, 0)
High	White A Crowns	20 * Round (105 * Beta (1.5, 5)/20, 0)

3.4 *Method of analysis*

Statistically, the results were analysed using a univariate full factorial ANOVA, where there were three main effects (planmeth, demvar and rep (which represented the CRNs used at $n = 40$)) and one two-way interaction effect (planmeth*demvar). The independent variable, rep, was treated as a blocking factor, which meant that it was only evaluated as a main effect (to determine if the results were influenced by the specific random number stream). After running each ANOVA, a pairwise comparison was then executed on the planning method (planmeth) to determine if there were significant differences in performance between the planning methods and to identify potential families (a family consists of two or three planning methods where there was no significant difference in performance between the methods). All statistical analyses were done using STATA 14 (StataCorp 2015).

4. Analysis and results

The results of the 240 simulation runs are summarised in Table 6. These results point to some initial interesting findings. First, DDMRP appears to dominate the other two methods irrespective of the level of demand variability. For the cases of low demand variability, this finding is surprising because this environment is the one most conducive to a system such as Kanban/Lean. Second, in general, overall MRP II is least effective in terms of performance. Third, when demand variability increases, the performance of all three methods is adversely affected. However, again, DDMRP is least influenced. Kanban has nevertheless slightly less WIP on average that DDMRP (with high demand variability): the reason is that DDMRP reaches to anticipate demand and deliver customer (better OTD). These are initially promising results. To really explore and test the impact of the various factors on performance, we must look at the ANOVA results.

For all ANOVA test, significant is set at 0.05 level. As can be seen from this Table, the performance of the system is significantly influenced by the planning method (for all 12 dependent variables), the level of demand variability (except in the case of White Crowns OTD) and the interaction between planning method and demand variability. CRNs generally have no impact on performance (except for Reducer 1 OTD and average WIP).

So far, the results tell us that the selection of the planning method is important and that the planning method's effectiveness is influenced by the level of demand variability. While these results are important, they do not help us to address the research question driving this study – does DDMRP represent a significant improvement in planning approaches? To answer this question, we turn to pairwise comparisons. That is, for every ANOVA, the pairwise comparison test compares on pairwise basis the difference in means and assesses whether this difference is significant. These results are reported for all 12 dependent variables in Appendix 1. In reviewing these results, a word of caution regarding interpreting the findings. For example, for the first dependent variable, Average OTD, we find that the first contrast between Kanban and DDMRP is negative and significant. This means (1) that the mean Average OTD for DDMRP was higher than that generated by Kanban; and, (2) this difference was significant. If this contrast had been positive, it would have indicated that Kanban performed better than DDMRP. Had the contrasts been insignificant, then this would have indicated that we had identified a family – a group of results where there is no real difference in means. In

Table 6. Summarised results.

	Experimental conditions					
DependentVariables	DDMRP Low Var	Kanban Low Var	MRP II Low Var	DDMRP High Var	Kanban High Var	MRP II High Var
Average OTD (%)	99.74	99.61	89.41	96.06	85.28	84.08
Reducer 1 OTD (%)	99.95	100.00	90.78	91.68	71.10	92.53
Reducer 2 OTD (%)	100.00	99.90	98.49	100.00	99.86	90.53
Reducer 3 OTD (%)	99.42	99.67	85.29	87.56	78.25	64.76
Reducer 4 OTD (%)	99.78	99.40	81.90	97.57	64.94	89.96
Reducer 5 OTD (%)	99.75	99.97	89.60	99.92	93.99	71.40
Reducer 6 OTD (%)	99.39	99.74	81.59	95.73	89.23	82.68
White Crown OTD (%)	99.92	98.56	98.19	99.95	99.62	96.66
Average WIP (units)	66.44	78.43	85.59	87.48	84.92	119.66
Standard Deviation WIP	39.58	48.9	59.86	53.00	43.06	113.46
Average orders late (units)	.40	.72	2.72	1.47	1.79	6.25
Maximum orders late (units)	.63	.75	8.68	2.68	4.05	17.4
# Observations	40	40	40	40	40	40

reviewing the pairwise comparisons for all 12 dependent variables, we find that DDMRP is always the best performer. Simply put, it dominates. However, to simplify this analysis, we have recast the pairwise comparisons in series of ranks. This is done in Table 7. For this analysis, the best performer is assigned rank 1, the worse rank 3. When there is a tie (indicating a family), the ranks are combined and divided by then number in the time. So, if both DDMRP and Kanban/Lean were tied as best, they would be given a rank of 1.5 ((1 + 2)/2). The overall average ranks for each of the three planning procedures are presented in the final row.

The summarised rank analysis presented in Table 7 emphasises the dominance of DDMRP. For six of the 12 dependent variables, DDMRP is significantly better than either Kanban/Lean or MRP II; for the remaining six, DDMRP is tied with Kanban/Lean. In nearly all cases (except for reducers 1 and 4 OTD), MRP II performed the worst.

We can now address the research question posed in this paper: Does DDMRP represents a significant improvement in planning approaches? For the set of conditions evaluated in this study, the results provide evidence of improved results. However, we now have to look at DDMRP from a broader perspective – that is done in the next section.

5. Discussion and directions for future research

In many ways, the results of this initial study are surprising. Given the results reported in industry, the research team was interested in determining whether the reported results were unique to the firms or whether they were really due to

Table 7. Pairwise comparisons summarised.

Dependent Variable	DDMRP	Kanban	MRP II
Average OTD	1.00	2.00	3.00
Average WIP	1.00	2.00	3.00
Standard Deviation WIP	1.50	1.50	3.00
Average orders late	1.50	1.50	3.00
Maximum orders late	1.50	1.50	3.00
Reducer 1 OTD	1.00	3.00	2.00
Reducer 2 OTD	1.50	1.50	3.00
Reducer 3 OTD	1.50	1.50	3.00
Reducer 4 OTD	1.00	3.00	2.00
Reducer 5 OTD	1.50	1.50	3.00
Reducer 6 OTD	1.00	2.00	3.00
White Crown OTD	1.00	2.00	3.00
AVERAGE RANK	1.25	1.92	2.83

the presence of DDMRP. Also, the research team expected that DDMRP and Kanban/Lean should be appropriately equivalent when faced by low demand variability. After all, such variability combined with the structure of the simulated test environment should be conducive to the performance of Kanban/Lean. Yet, the team was surprised by how dominant DDMRP was. In other words, there is something there.

After considering the results in the light of the logic employed by DDMRP, these results became more intuitive. What DDMRP was doing was to blend and integrate various aspects of MRP, Lean, Six Sigma and TOC into one unified planning system – one that was able to tap into the strengths offered by these various procedures. By drawing on the best practices of these various approaches, DDMRP was able to deal with the challenges facing it more effectively. That is, buffers were used to absorb variances and allow the effective scheduling of production to the floor. Also, because the buffers were dynamic, they were allowed to change in response to factors such as increasing levels of demand variability (thus allowing a constant level of protection) without causing or exacerbating nervousness. Finally, there was selective use of buffers – not all areas needed buffering. This meant that buffers were applied where needed and eliminated where not needed.

However, this study should not be viewed as an unconditional acceptance of DDMRP. To achieve such a position, DDMRP needs to be studied in greater detail. It needs to be evaluated under alternative test environments and alternative test conditions (e.g. increasing the level of processing variance experienced on the shop floor or delivery variance from our suppliers). Furthermore, DDMRP embodies a series of features taken from other materials management methods (as previously summarised in Table 1). It would be useful to understand how these features affect performance – whether they are as main effects or through their interaction with the other features. Finally, as noted by Ptak and Smith (2016), DDMRP is only one part of a broader approach (Demand Driven Adaptive Enterprise) to improving planning, scheduling and overall management – an approach that includes elements such as performance measurement and adaptive S&OP. These elements (and their impact) and other questions we leave for future research to explore.

6. Concluding comments

The Operations and Supply Chain Management fields are becoming more turbulent and dynamic. Consequently, there is a need to develop and evaluate alternative systems and approaches that can help firms and their management better deal with the challenging demands of this new environment. In this study, we have focused one such new alternative approach – DDMRP. We have presented this approach in broad terms; we have compared it to the alternative approaches – approaches such as Kanban/Lean and MRP II. We have evaluated it in a test environment that, at first glance, should favour Kanban/Lean and found that it outperforms the alternatives. Our conclusion – there is something noticeable and worthwhile in DDMRP.

In some ways, DDMRP is exciting since it represents the first major rethinking of the MRP logic and approach since Orlicky (1974) first introduced its logic. It is an integrative approach that draws on the best features of accepted approaches such as TOC, MRP, Six Sigma and Lean. Consequently, conceptually and from a results perspective, DDMRP is exciting since it appears to work. However, we recognise that our study is not conclusive. Rather, we hope that other researchers will further explore this new development to assess its limits (if any) and to better understand how the various aspects of its logic and approach influence performance. It may very well be that DDMRP does represent the next step in the evolution to planning and scheduling excellence – a path that began with MRP and has evolved through the introduction of Lean, Six Sigma and TOC.

Disclosure statement

No potential conflict of interest was reported by the authors.

Note

1. Product: “Any good or service produced for sale, barter, or internal use.” (APICS dictionary, 15th edition, 2016).

References

Beamon, B. M., and J. M. Bermudo. 2000. “A Hybrid Push/Pull Control Algorithm for Multi-stage, Multi-line Production Systems.” *Production Planning & Control* 11: 349–356.

Benton, W. C., and D. C. Whybark. 1982. “Material Requirements Planning (MRP) and Purchase Discounts.” *Journal of Operations Management.* 2 (2): 137–143.

Carvalho, H., A. P. Barroso, V. H. Machado, S. Azevedo, and V. Cruz-Machado. 2012. “Supply Chain Redesign for Resilience Using Simulation.” *Computers and Industrial Engineering* 62 (1): 329–341.

Cochran, J. K., and H. A. Kaylani. 2008. “Optimal Design of a Hybrid Push/Pull Serial Manufacturing System with Multiple Part Types.” *International Journal of Production Research* 46: 949–965.

Costanza, J. R., 1996. The Quantum Leap in Speed-to-market. Denver, CO: Jc-IT Institute of Technology

Demand Driven Institute. 2017. *Case Studies*. http://www.demanddriveninstitute.com/case-studies.

Flapper, S. D. P., G. J. Miltenburg, and J. Wijngaard. 1991. “Embedding JIT into MRP.” *International Journal of Production Research* 29: 329–341.

Geraghty, J., and C. Heavey. 2006. “A Review and Comparison of Hybrid and Pull-type Production Control Strategies.” *Stochastic Modeling of Manufacturing Systems* 307–329.

Goldratt, E. M., and J. Cox. 1992. *The Goal: A Process of Ongoing Improvement*. Great Barrington, MA: North River Press.

González-R, P. L., J. M. Framinan, and H. Pierreval. 2011. “Token-based Pull Production Control Systems: An Introductory Overview.” *Journal of Intelligent Manufacturing* 23: 5–22.

Greif, M., C. Moisy, and E. Pesnel. 1984. *Guide Du Kanban*. CIPE.

Ho, C., and T. C. Ireland. 2012. “Mitigating Forecast Errors by Lot-sizing Rules in ERP-Controlled Manufacturing Systems.” *International Journal of Production Research* 50: 3080–3094.

Hochreiter, T. A. 1999. “A Comparative Simulation Study of Kanban, CONWIP, and MRP Manufacturing Control Systems in a Flow Shop.” M.Sc. Dissertation, University of Florida.

Hodgson, T. J., and D. Wang. 1991a. “Optimal Hybrid Push/Pull Control Strategies for a Parallel Multistage System: Part I.” *International Journal of Production Research* 29: 1279–1287.

Hodgson, T. J., and D. Wang. 1991b. “Optimal Hybrid Push/Pull Control Strategies for a Parallel Multistage System: Part II.” *International Journal of Production Research* 29: 1453–1460.

Hollocks, B. W. 2006. “Forty Years of Discrete-event Simulation – A Personal Reflection.” *Journal of the Operational Research Society* 57: 1383–1399.

Hopp, W. 2008. ML: Factory Physics. 3rd ed. New York: McGraw-Hill.

Hopp, W., and M. Spearman. 1996. *Factory Physics: Foundations of Factory Management*. Chicago, IL: InvinIMcGraw Hill.

Jodlbauer, Herbert, and Sonja Reitner. 2012. “Material and Capacity Requirements Planning with Dynamic Lead times.” *International Journal of Production Research* 50 (16): 4477–4492.

Karmarkar, U. 1986. *Push, Pull and Hybrid Control Schemes*. Rochester, NY: Graduate School of Management, University of Rochester.

Khojasteh, Y., and R. Sato. 2015. “Selection of a Pull Production Control System in Multi-stage Production Processes.” *International Journal of Production Research* 53: 4363–4379.

Koulouriotis, D. E., A. S. Xanthopoulos, and V. D. Tourassis. 2010. “Simulation Optimisation of Pull Control Policies for Serial Manufacturing Lines and Assembly Manufacturing Systems Using Genetic Algorithms.” *International Journal of Production Research* 48 (10): 2887–2912.

Krajewski, L. J., B. E. King, L. P. Ritzman, and D. S. Wong. 1987. “Kanban, MRP, and Shaping the Manufacturing Environment.” *Management Science* 33 (1): 39–57.

Lage Junior, M., and M. Godinho Filho. 2010. “Variations of the Kanban System: Literature Review and Classification.” *International Journal of Production Economics* 125 (1): 13–21.

Land, M. J. 2009. “Cobacabana (Control of Balance by Card-based Navigation): A Card-based System for Job Shop Control.” *International Journal of Production Economics* 117 (1): 97–103.

Law, A. 2014. *Simulation Modeling and Analysis*. 5th ed. Dubuque: McGraw-Hill Education.

Law, A. M., and W. D. Kelton. 1991. *Simulation Modeling and Analysis*. New York: McGraw-Hill.

Law, A. M., and M. G. McComas. 1991. Secrets of Successful Simulation Studies. In *Proceedings of the 23rd Conference on Winter Simulation, IEEE Computer Society*, 21–27. Washington, DC.

Lee, Y. H., M. K. Cho, S. J. Kim, and Y. B. Kim. 2002. “Supply Chain Simulation with Discrete–Continuous Combined Modeling.” *Computers and Industrial Engineering* 43 (1–2): 375–392.

Li, Z. 2013. *Design and Analysis of Robust Kanban System in an Uncertain Environment*. Karlsruhe: KIT Scientific Publishing.

Li, X., R. Sawhney, E. J. Arendt, and K. Ramasamy. 2012. “A Comparative Analysis of Management Accounting Systems’ Impact on Lean Implementation.” *International Journal of Technology Management* 57: 33–48.

Manuj, I., and J. T. Mentzer. 2008. “Global Supply Chain Risk Management.” *Journal of Business Logistics* 29 (1): 133–155.

Manuj, I., J. T. Mentzer, and M. R. Bowers. 2009. “Improving the Rigor of Discrete-event Simulation in Logistics and Supply Chain Research.” *International Journal of Physical Distribution and Logistics Management* 39 (3): 172–201.

Melnyk, S. A., and C. J. Piper. 1981. “Implementation of Material Requirements Planning: Safety Lead times.” *International Journal of Operations and Production Management.* 2 (1): 52–61.

Melnyk, S. A., and C. J. Piper. 1985. “Leadtime Errors in MRP: The Lot Sizing Effect.” *International Journal of Production Research* 23 (2): 253–264.

Melnyk, S. A., A. Rodrigues, and G. L. Ragatz. 2009. “Using Simulation to Investigate Supply Chain Disruptions.” In *Supply Chain Risk, International Series in Operations Research & Management Science*, 103–122. New York: Springer.

Micilo, R., F. Fontanili, G. Marques, P. Bomert, and M. Lauras. 2015. “RTLS-based Process Mining: Towards an Automatic Process Diagnosis in Healthcare.” *IEEE International Conference on Automation Science and Engineering (CASE)*, 1397–1402. Gothenburg: IEEE.

Miclo, Romain. 2016. “Challenging the ‘Demand Driven MRP’ Promises’: A Discrete Event Simulation Approach”. PhD thesis, *Ecole Des Mines D’Albi-Carmaux*. https://tel.archives-ouvertes.fr/tel-01673811/document.

Miclo, R., F. Fontanili, M. Lauras, J. Lamothe, and B. Milian. 2016. “An Empirical Comparison of MRPII and Demand-driven MRP.” *IFAC-Pap., 8th IFAC Conference on Manufacturing Modelling, Management and Control MIM*, 49: 1725–1730. Troyes.

Milne, R. J., C.-T. Wang, C.-K. A. Yen, and K. Fordyce. 2012. “Optimized Material Requirements Planning for Semiconductor Manufacturing.” *Journal of the Operational Research Society* 63: 1566–1577.

Narasimhan, R., and S. A. Melnyk. 1984. “Assessing the Transient Impact of Lot Sizing Rules following MRP Implementation.” *International Journal of Production Research* 22 (5): 759–772.

Ohno, T. 1988. *Toyota Production System: Beyond Large-scale Production*. Boca Raton, FL: CRC Press.

Olaitan, O. A. 2016. *A Framework for Creating Production and Inventory Control Strategies (Doctoral)*. Dublin: Advanced Processing Technology Research Centre (APTRC), Dublin City University.

Olhager, J. 2013. “Evolution of Operations Planning and Control: From Production to Supply Chains.” *International Journal of Production Research* 51: 6836–6843.

Olhager, J., and B. Östlund. 1990. “An Integrated Push–Pull Manufacturing Strategy.” *European Journal of Operational Research* 45: 135–142.

Orlicky, J. A. 1974. *Material Requirements Planning: The New Way of Life in Production and Inventory Management*. New York: McGraw-Hill.

Powell, D. J., I. Bas, and E. Alfnes. 2013. “Integrating Lean and MRP: A Taxonomy of the Literature.” *IFIP International Conference on Advances in Production Management Systems. Sustainable Production and Service Supply Chains*, 485–492. State College, PA.

Ptak, C., and C. Smith. 2011. *Orlicky’s Material Requirements Planning 3/E*. New York: McGraw Hill Professional.

Ptak, C., and C. Smith. 2016. *Demand Driven Material Requirements Planning (DDMRP)*. Norwalk, CT: Industrial Press.

Riezebos, J. 2010. “Design of POLCA Material Control Systems.” *International Journal of Production Research* 48: 1455–1477.

Robinson, S. 2014. *Simulation: The Practice of Model Development and Use*. 2nd ed. New York: Palgrave MacMillan.

Rossi, Tommaso, Rossella Pozzi, Margherita Pero, and Roberto Cigolini. 2017. “Improving Production Planning through Finite-capacity MRP.” *International Journal of Production Research* 55 (2): 377–391.

Sali, M., and V. Giard. 2015. “Monitoring the Production of a Supply Chain with a Revisited MRP Approach.” *Production Planning & Control* 26 (10): 769–785.

Sarker, B. R., and J. A. Fitzsimmons. 1989. “The Performance of Push and Pull Systems: A Simulation and Comparative Study.” *International Journal of Production Research* 27 (10): 1715–1731.

Schmitt, T. G., W. L. Berry, and T. E. Vollmann. 1984. “An Analysis of Capacity Planning Procedures for a Material Requirements Planning System.” *Decision Sciences* 15 (4): 522.

Schriber, T. J., D. T. Brunner, and J. S. Smith. 2012. “How Discrete-event Simulation Software Works and Why It Matters.” *Winter Simulation Conference (WSC) Proceedings* 1–15. Berlin.

Sekine, K. 2005. *One-piece Flow: Cell Design for Transforming the Production Process*. New York: Productivity Press.

Sepehri, M. M., and N. Nahavandi. 2007. “Critical WIP Loops: A Mechanism for Material Flow Control in Flow Lines.” *International Journal of Production Research* 45 (12): 2759–2773.

Spearman, M. L., D. L. Woodruff, and W. J. Hopp. 1990. “CONWIP: A Pull Alternative to Kanban.” *International Journal of Production Research* 28 (5): 879–894.

StataCorp. 2015. *Stata Statistical Software: Release 14*. College Station, TX: StataCorp LP.

Sugimori, Y., K. Kusunoki, F. Cho, and S. Uchikawa. 1977. “Toyota Production System and Kanban System Materialization of Just-in-time and Respect-for-Human System.” *International Journal of Production Research* 15 (6): 553–564.

Thompson, K. 1983. “MRP II in the Repetitive Manufacturing Environment.” *Production and Inventory Management* 24 (4): 1–14.

Thürer, M., M. Stevenson, and C. W. Protzman. 2016. “Card-based Production Control: A Review of the Control Mechanisms Underpinning Kanban, ConWIP, POLCA and COBACABANA Systems.” *Production Planning and Control* 27 (14): 1143–1157.

Venkateswaran, J., and Y. J. Son. 2004. “Impact of Modelling Approximations in Supply Chain Analysis – An Experimental Study.” *International Journal of Production Research* 42 (15): 2971–2992.

Villa, A., and T. Watanabe. 1993. “Production Management: Beyond the Dichotomy between ‘Push’ and ‘Pull’.” *Computer Integrated Manufacturing Systems* 6 (1): 53–63.

Wang, D., and C.-G. Xu. 1997. “Hybrid Push Pull Production Control Strategy Simulation and its Applications.” *Production Planning & Control* 8 (2): 142–151.

Whybark, D. C., and J. Gregg Williams. 1976. “Material Requirements Planning under Uncertainty.” *Decision Sciences* 7 (4): 595–606.

Wight, O. 1995. *Manufacturing Resource Planning: MRP II: Unlocking America’s Productivity Potential*. New York: John Wiley.

Wilson, J. M. 2016. “The Origin of Material Requirements Planning in Frederick W. Taylor’s Planning Office.” *International Journal of Production Research* 54 (5): 1535–1553.

Xanthopoulos, A. S., D. E. Koulouriotis, and A. Gasteratos. 2017. “Adaptive Card-based Production Control Policies.” *Computers & Industrial Engineering* 103: 131–144.
van der Zee, D. J., and J. G. A. J. van der Vorst. 2005. “A Modeling Framework for Supply Chain Simulation: Opportunities for Improved Decision Making.” *Decision Sciences* 36 (1): 65–95.

Appendix 1. Pairwise comparison by independent variable

				Bonferroni	
Independent variable	Planning method comparison	Contrast	Standard error	t	$p > \|t\|$
Average OTD	Kanban vs. DDMRP	−0.055	0.005	−10.30	0.000
	MRP II vs. DDMRP	−0.111	0.005	−21.08	0.000
	MRP II vs. Kanban	−0.057	0.005	−10.77	0.000
Reducer 1 OTD	Kanban vs. DDMRP	−0.103	0.008	−12.49	0.000
	MRP II vs. DDMRP	−0.042	0.008	−5.06	0.000
	MRP II vs. Kanban	+0.061	0.008	7.43	0.000
Reducer 2 OTD	Kanban vs. DDMRP	−0.001	0.007	−0.16	1.000
	MRP II vs. DDMRP	−0.055	0.007	−7.55	0.000
	MRP II vs. Kanban	−0.054	0.007	−7.38	0.000
Reducer 3 OTD	Kanban vs. DDMRP	−0.045	0.020	−2.22	0.084
	MRP II vs. DDMRP	−0.185	0.020	−9.03	0.000
	MRP II vs. Kanban	−0.139	0.020	−6.82	0.000
Reducer 4 OTD	Kanban vs. DDMRP	−0.165	0.013	−13.19	0.000
	MRP II vs. DDMRP	−0.127	0.013	−10.18	0.000
	MRP II vs. Kanban	0.038	0.013	3.00	0.009
Reducer 5 OTD	Kanban vs. DDMRP	−0.029	0.017	−1.63	0.312
	MRP II vs. DDMRP	−0.193	0.017	−11.07	0.000
	MRP II vs. Kanban	−0.165	0.017	−9.44	0.000
Reducer 6 OTD	Kanban vs. DDMRP	−0.031	0.010	−3.06	0.000
	MRP II vs. DDMRP	−0.154	0.010	−15.33	0.000
	MRP II vs. Kanban	−0.124	0.010	−12.27	0.000
White Crown OTD	Kanban vs. DDMRP	−0.008	0.003	−2.81	0.016
	MRP II vs. DDMRP	−0.025	0.003	−8.38	0.000
	MRP II vs. Kanban	−0.017	0.003	−5.57	0.000
Average WIP	Kanban vs. DDMRP	4.720	1.234	3.82	0.001
	MRP II vs. DDMRP	25.662	1.234	20.79	0.000
	MRP II vs. Kanban	20.942	1.234	16.96	0.000
Standard DeviationWIP	Kanban vs. DDMRP	−4.669	3.357	−1.39	0.498
	MRP II vs. DDMRP	49.367	3.357	12.02	0.000
	MRP II vs. Kanban	45.036	3.357	13.41	0.000
Average Orders Late OLT	Kanban vs. DDMRP	0.322	0.174	1.85	0.199
	MRP II vs. DDMRP	3.548	0.174	20.35	0.000
	MRP II vs. Kanban	3.226	0.174	18.50	0.000
Maximum Orders Late OLT	Kanban vs. DDMRP	0.750	0.517	1.45	0.445
	MRP II vs. DDMRP	11.388	0.517	22.04	0.000
	MRP II vs. Kanban	10.638	0.517	20.59	0.000