# The extension and exploitation of the inventory and order based production control system archetype from 1982 to 2015☆

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## ABSTRACT

In 1994, through classic control theory, John, Naim and Towill developed the 'Automatic Pipeline, Inventory and Order-based Production Control System' (APIOBPCS) which extended the original IOBPCS archetype developed by Towill in 1982 — well-recognised as a base framework for a production planning and control system. Due to the prevalence of the two original models in the last three decades in the academic and industrial communities, this paper aims to systematically review how the IOBPCS archetypes have been adopted, exploited and adapted to study the dynamics of individual production planning and control systems and whole supply chains. Using various databases such as Scopus, Web of Science, Google Scholar (113 papers), we found that the IOBPCS archetypes have been studied regarding the a) modification of four inherent policies related to forecasting, inventory, lead-time and pipeline to create a 'family' of models, b) adoption of the IOBPCS 'family' to reduce supply chain dynamics, and in particular bullwhip, c) extension of the IOBPCS family to represent different supply chain scenarios such as order-book based production control and closed-loop processes. Simulation is the most popular method adopted by researchers and the number of works based on discrete time based methods is greater than those utilising continuous time approaches. Most studies are conceptual with limited practical applications described. Future research needs to focus on cost, flexibility and sustainability in the context of supply chain dynamics and, although there are a few existing studies, more analytical approaches are required to gain robust insights into the influence of nonlinear elements on supply chain behaviour. Also, empirical exploitation of the existing models is recommended.

## 1. Introduction

Production planning systems and supply chains are becoming increasingly dynamic under the volatile conditions of the current business environment, triggered by globalisation, the adoption of optimisation management practices (e.g. reducing inventory, decreasing the number of suppliers and outsourcing) and the increasing tendency of mass customization for creating competitive advantage (Amaro et al., 1999). Dynamic characteristics, particularly the bullwhip effect (Lee et al., 1997b), are considered to be the main sources of disruptions in the business world (Christopher and Peck, 2004). The bullwhip effect, for example, refers to a phenomenon in which low variations in demand cause significant changes in upstream production for suppliers, with associated costs such as ramp down and ramp up machines, hiring and firing of staff and excessive inventory levels (Wang and Disney, 2016).

Among the various methods and tools that have been developed to reduce bullwhip effect in the production and control system, Simon (1952)'s control theory with feedback thinking has long been well-recognised. In 1994, through the adoption of a classic control engineering approach, John et al. (1994) developed the Automatic Pipeline, Inventory and Order-based Production Control System (APIOBPCS), which extended the original Inventory and Order-based Production Control System (IOBPCS) archetype (Towill, 1982) by incorporating an automatic work-in-progress (WIP) feedback loop. In this paper, APIOBPCS represents both IOBPCS and APIOBPCS, and the IOBPCS family refers to the two original models and all their variants. These two original models and their variants have been recognised as a framework for a production planning and control system, as they consist of general laws that represent many supply chain contexts, including the famous beer game decision-making heuristic (Sterman, 1989), the order-up-to (OUT) policy (Zhou et al., 2010) as well as various industrial applications (e.g. Coyle, 1977). Therefore, the main purpose of this present work

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☆ In memory of the originator of the IOBPCS family, Prof. Denis R. Towill (1933–2015).
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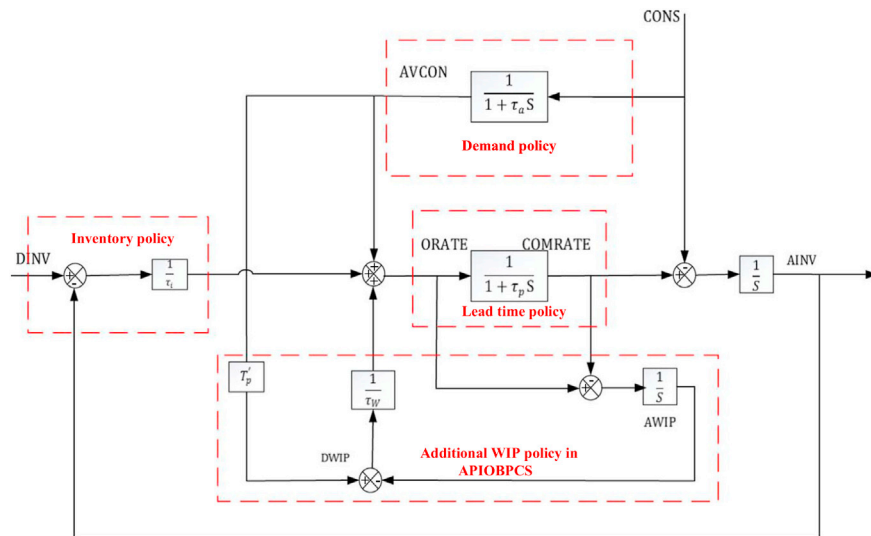  *E-mail address:* NaimMM@cardiff.ac.uk (M.M. Naim).

**Fig. 1.** Block diagram representation of APIOBPCS (including IOBPCS) archetype. Source: original diagram developed by John et al. (1994) and adapted by Sarimveis et al. (2008)

**Table 1**
Notations used in APIOBPCS model.

| Terms | Meaning |
|---|---|
| AINV | Actual inventory |
| AVCON | Average consumption |
| AWIP | Actual WIP |
| DWIP | Desired WIP |
| COMRATE | Completion rate |
| CONS | Consumption rate |
| DINV | Desired inventory |
| ORATE | Order rate placed on pipeline |
| Ta | Time to average consumption |
| Ti | Proportional controller for inventory adjustment |
| Tw | Proportional controller for WIP adjustment |
| Tp | Actual pipeline lead-time |
| Tp' | Estimated pipeline lead-time |
| s | Laplace Operator |

Source: the author.

is to explore how, over three decades, other authors have adopted, exploited and adapted the IOBPCS family to understand supply chain dynamics more completely. Through a systematic review, our paper also explores the methods used to study the IOBPCS family and presents a future research agenda.

The rest of the paper is organised as follows: Section 2 presents an overview of the APIOBPCS ordering model, including four inherent policies and the impact of system parameters on dynamic performance. Section 3 discusses the data collection and data analysis methods. The next two sections present a detailed review of selected papers, followed by a discussion and an agenda for future research. Conclusions, including

the contributions and limitations of this study, are reported in the last section.

## 2. An overview of the APIOBPCS archetype

Towill (1982) developed the IOBPCS framework in a block diagram form to represent a feedback-based production/inventory system, extending the work conducted by Coyle (1977). The model focused on products at an aggregate level. Three system parameters were identified as the fundamental for ideal production/inventory control system design: lead time ($T_p$) for production, a proportional controller ($T_i$) to adjust the inventory discrepancy and a demand smoothing level ($T_a$). John et al. (1994) then incorporated an automated WIP closed loop ($T_w$) into the IOBPCS framework, which led to the APIOBPCS archetype, as shown in Fig. 1 (all nomenclatures is presented in Table 1).

There are two inputs – desired inventory (DINV) and consumption rate (CONS) – which represent the external disturbance, while the order rate placed on the pipeline (ORATE) is a decision variable determined by two feedback proportional controllers ($T_i$ and $T_w$) as well as the averaged feedforward CONS ($T_a$). Thus, the APIOBPCS model can be described as follows: set the order rate as equal to the sum of demand averaged over $T_a$ time units (demand policy), plus the $T_i$ adjustment of inventory discrepancy (inventory policy) and the WIP adjustment of $T_w$ (WIP policy), with due consideration of $T_p$ (Pipeline policy). The APIOBPCS model is essentially equal to the IOBPCS model if $T_w = \infty$, i.e. in the case in which the WIP products are not included.

Therefore, given that $T_p$ the decision makers need to select appropriate values for $T_a, T_w$ and $T_i$, to achieve two conflicting objectives: 1)

**Table 2**
Main IOBPCS family members based on four policies and the target inventory.

| Model | | Target inventory | Demand policy | WIP policy | Inventory policy | Lead time |
|---|---|---|---|---|---|---|
| IOBPCS | Inventory and Order based Production Control System | Fixed | Exponential smoothing | $\frac{1}{\infty}$ | $\frac{1}{T_i}$ | First order lag |
| VIOBPCS | Various Inventory and Order based Production Control System | Multiple of Average market demand | Exponential smoothing | $\frac{1}{\infty}$ | $\frac{1}{T_i}$ | First order lag |
| APIOBPCS | Automatic Pipeline, Inventory and Order based Production Control System | Fixed | Exponential smoothing | $\frac{1}{T_w}$ | $\frac{1}{T_i}$ | First order lag |
| APVIOBPCS | Automatic Pipeline, Various Inventory and Order based Production Control System | Multiple of Average market demand | Exponential smoothing | $\frac{1}{T_w}$ | $\frac{1}{T_i}$ | First order lag |
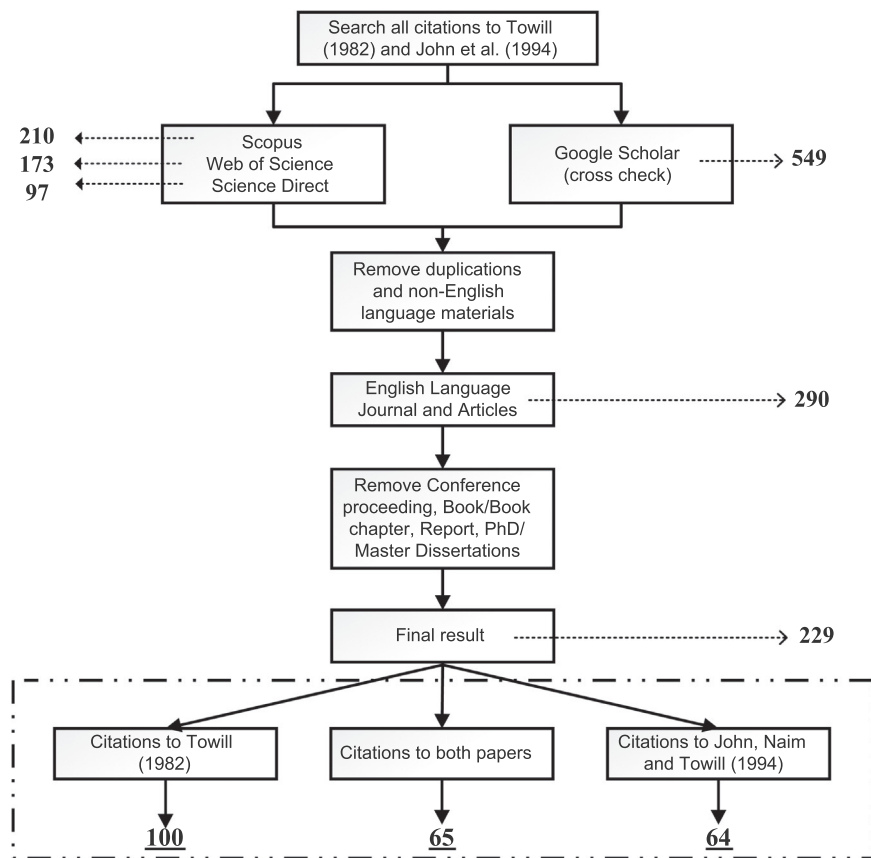
Fig. 2. The data collection process and results. Source: the authors.

rapid inventory recovery and 2) attenuation of the unknown demand fluctuation. The second objective is also called the reduction of the bullwhip effect (Lee et al., 1997b). The APIOBPCS archetype has been modified regarding its four inherent policies in the last three decades, which create a 'family' of models shown in Table 2.

Specifically, the target inventory is either fixed or a multiple of smoothed market demand determined by the demand policy. The method of exponential smoothing is commonly applied in the demand policy in the main IOBPCS family. A proportional controller is utilised for correcting WIP and inventory discrepancies, apart for the IOBPCS/
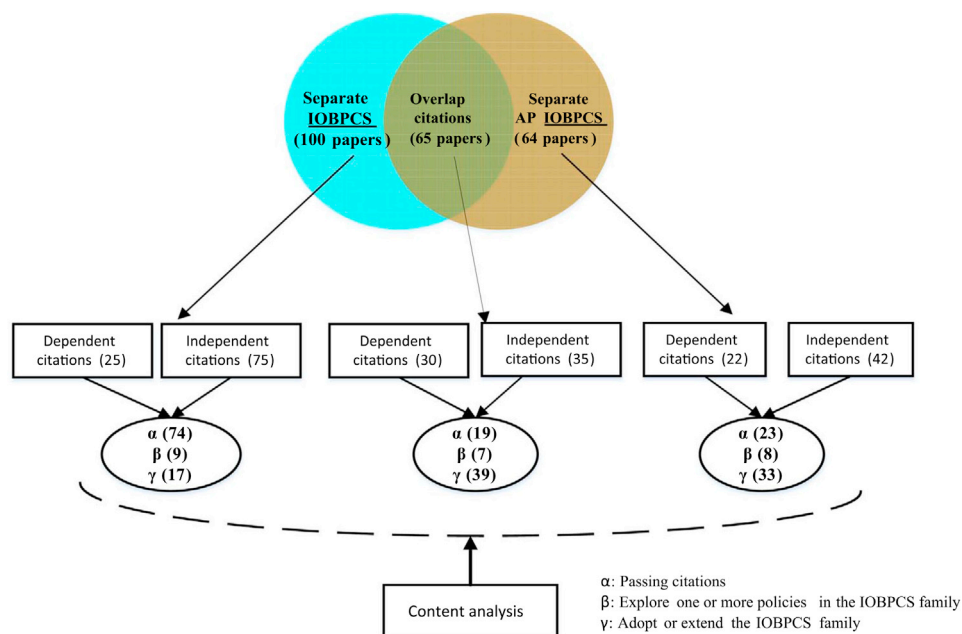


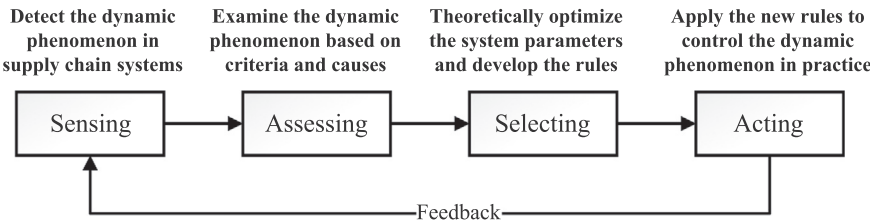Fig. 3. The data analysis process. Source: the authors.

**Fig. 4.** The structure of the γ category papers. Adapted by Robson (2004)

**Table 3**
Descriptive results of the β and γ type papers based on pre-defined categorization.

| Type | Emerging theme | | Total |
|---|---|---|---|
| **β (24)** | *Demand policy* | | 6 |
| | *Lead time/WIP* | | 12 |
| | *Inventory policy* | | 6 |
| **γ (89)** | *Sensing* | Study the dynamic behaviour of the PPC system | 9 |
| | *Assessing* | Stability property | 6 |
| | | Price fluctuation | 3 |
| | | Batching | 3 |
| | *Selecting* | The optimisation of decision parameters in IOBPCS family | 22 |
| | *Acting* | Information management strategy and supply chain collaboration | 23 |
| | | Inventory control model | 12 |
| | *Extension* | Extension of the IOBPCS family | 11 |
| | | | **113** |

Source: the authors.

VIOBPCS archetype that does not consider the WIP products. Finally, the four main IOBPCS archetypes usually adopt a first order lag to model lead time, representing production delay or production unit smoothing level in responding to ORATE change.

## 3. Data collection and analysis

Fig. 2 outlines the data collection process. To search for papers that cited Towill (1982) and John et al. (1994), three electronic databases in the fields of business/management were selected: Scopus, Web of Science and Science Direct. Google Scholar was used to cross-check the citations. Only peer-reviewed academic journals in English were selected to guarantee the quality of the citations. In total, 229 papers were identified; in those papers Towill (1982) was cited 165 times and John et al. (1994) was cited 129 times. Moreover, there were 65 overlapping citations in which both studies were cited. Overall, Towill (1982) was cited more frequently than John et al. (1994) (165 versus 129).

Fig. 3 shows the data analysis process. Specifically, the journal articles were divided into three groups: papers that cited both Towill (1982) and John et al. (1994) were compiled into one group; the two additional groups were comprised of papers in which Towill (1982) or John et al.

(1994) were cited separately (two separate categories in which either the APIOBPCS and IOBPCS model was discussed). This categorization enables an understanding of the development difference between IOBPCS and APIOBPCS, e.g. some authors may adopt APIOBPCS or its variants while others may consider IOBPCS without the WIP products. In each of the three groups of papers, two sub-categories were further specified: independent and dependent citations. Dependent citations were those in which at least one author was a colleague of the original authors, a PhD student, or a member of a research team, while independent citations were cited by individuals who were academically independent of the three original authors. The purpose of this sub-categorization is to understand whether or not the IOBPCS family has received attention from the world-wide academic community rather than self-citations. The result shows that the total number of independent citations was nearly twice that of the dependent citations (152 versus 77), suggesting that the IOBPCS archetype has been recognised in research communities on a global scale.

The content of the reviewed papers was categorised into one of three types: α, β or γ (Naim and Gosling, 2011). The α type papers (116 citations) referred to passing citations that simply cite the two papers in order to increase the quality of the paper's main argument; thus, they will not be reviewed in this present study. A total of 113 papers (24 β type papers and 89 γ type papers) that focus on the application of the IOBPCS family will be reviewed in detail in this paper. The β type category refers to papers that focus on one specific decision policy in the IOBPCS family: demand policy, inventory policy, lead time and pipeline policy. Three large clusters of papers emerge: *Demand policy*; *Lead time/WIP*; *Inventory policy*.

The γ type papers are those that used the complete APIOBPCS model to offer insights into dynamic behaviour or to represent specific supply chain scenarios (extension of the APIOBPCS model). These papers were then sub-categorised based on four main elements of a control engineering system: sensing, assessing, selecting and acting (Fowler, 1999; Robson, 2004) (Fig. 4), due to the analogy between mechanical control systems and a supply chain system (Simon, 1952).

Furthermore, the research methods adopted by all papers were counted and categorised, although some authors adopted multiple
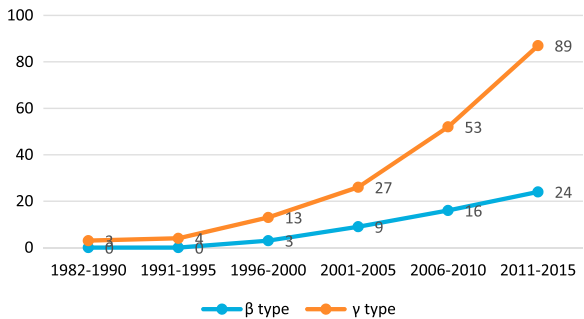


**Fig. 5.** Cumulative citation frequency for β and γ type papers from 1982 to 2015. Source: the authors.
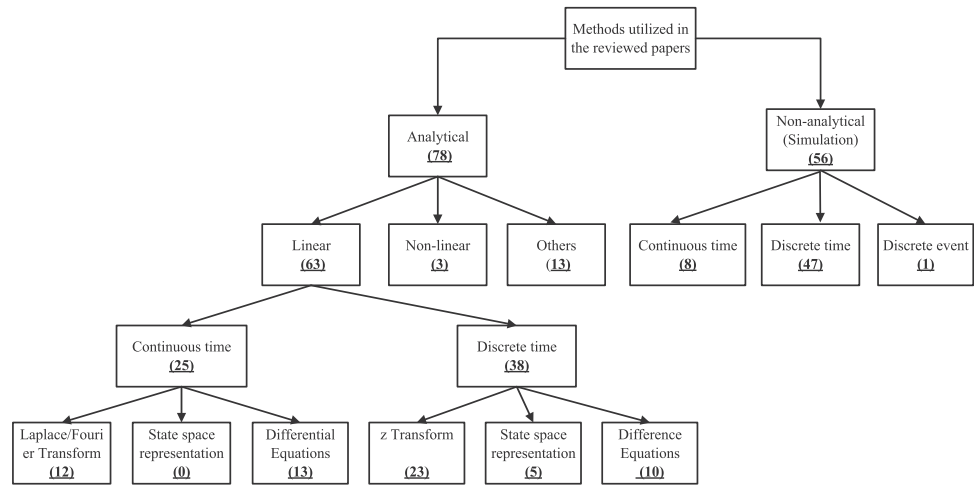
**Fig. 6.** Research methods used in the β and γ papers. Source: the authors. **Other approaches**: Fuzzy approach, MCDM, Taguchi design, genetic algorithm, Åström's method, response surface, Jury inner approach. **Non-linear approaches**: Exact solution, eigenvalue analysis.

**Table 4**
Citation information for the β category papers.

| Emerging theme | Towill (1982) citations | John et al. (1994) citations | Citations to both papers |
|---|---|---|---|
| **Demand policy (6)** | Li et al. (2014) | Xie and Zhou (2012); Campuzano-Bolarín et al. (2013a); Campuzano-Bolarin et al. (2013b) | Dejonckheere et al. (2002, 2003b) |
| **Lead time/WIP policy (12)** | Riddalls and Bennett (2002b); Wilson (2007); Wikner (2003) | Potter and Lalwani (2008); Shukla et al. (2009); Campuzano Bolarín et al. (2009); Spiegler and Naim (2014); Parsanejad et al. (2015a) | Mason-Jones et al. (1997); Towill et al. (1997); Disney and Towill (2005); Aggelogiannaki and Sarimveis (2008) |
| **Inventory policy (6)** | White (1999); Lin et al. (2003); Sourirajan et al. (2008); Chaudhari et al. (2011); Kumar et al. (2013) | Tosetti et al. (2009) | 0 |

research methods. Content analysis was then used to explore the main findings of the selected papers.

## 4. Aggregate results

Table 3 presents the descriptive results of the β and γ type papers. Fig. 5 shows the frequency of each category from 1982 to 2015. A growing body of work is evident for both categories, though category β (24 studies aimed at gaining deeper knowledge about and insights into the demand, lead time, WIP and inventory policies) appears to grow at a steadier pace. For the γ category, less papers focus on *Sensing* (9 citations) and *Assessing* (12 citations) supply chain dynamics. *Selecting* (theoretically optimising the system parameters – 22 citations) and *Acting* (developing relevant rules and applications, e.g. information management strategies – 23 citations, and inventory control models – 12 citations) are the more popular categories. Furthermore, an increasing number of studies have extended the original IOBPCS family into specific supply chain scenarios over the last 10 years (11 citations), such as the Make-to-Order (MTO) supply chains or supply chain systems with constrained production capacity. A detailed review of these works can be found in the following section.

Fig. 5 illustrates the cumulative citation frequency for β and γ papers over the last three decades. More researchers adopt the IOBPCS family as a whole to study supply chain dynamics than those authors who focus on particular policies in the IOBPCS family archetype. Particularly, the number of γ works significantly increased from 2000 to 2015, compared to the 80s and 90s, highlighting the growing interest in the topic.

Fig. 6 presents the distribution of the methods used across the β and γ papers. Simulation (continuous/discrete/discrete event simulation) is the most popular method due to its ability to capture complex dynamic behaviour by recovering a wide range of nonlinear phenomena. The

discrete time based simulation was preferred by researchers, possibly due to the real replenishment rule is dominated by a discrete time ordering policy. Similarly, regarding the analytical-based methods, discrete time domain approaches (38) were given greater consideration than continuous time domain approaches (25), although continuous time-based approaches were adopted in the development of the original APIOBPCS. However, as indicated by Disney et al. (2006a), neither of continuous-based or discrete-based approaches is superior in terms of its usefulness for different purposes and its applicability to different scenarios. A few of the studies considered state space representation approaches, even though it has advantages of observability (observing how the components of the system are responding) and controllability (controlling the value of $T_i$ and $T_W$ to alter the response).

A clear emerging gap is the lack of empirically-based studies aimed at gaining more robust insights into the real-world applications of the IOBPCS family. Conceptual work is still dominant in the papers that examine the IOBPCS family applications in recent years, and most of the authors have studied practical strategies such as VMI in a theoretical way, based on analytical methods.

### 4.1. Review of the β category papers

This section reviews the papers that examined one particular policy based on the IOBPCS archetype, which creates a 'family' of models (shown in Table 2). Table 4 presents the reference of this category to the three citation groups.

#### 4.1.1. Demand policy papers (6 citations)

Demand policy is essentially a forecasting mechanism in the IOBPCS family, which is one of the main sources that induce the bullwhip effect. Dejonckheere et al. (2003) examined the impact of common forecasting

**Table 5**
Citation information for the γ category papers.

| Structure | Emerging theme | Towill (1982) citations | John et al. (1994) citations | Citations for both papers |
|---|---|---|---|---|
| **Sensing** | The dynamic phenomenon of production and planning system **(9 citations)** | Edghill et al. (1988); Ariffin (1992); Edghill and Towill (1990); Parsanejad et al. (2014) | Hodgson and Warburton (2009); Shukla et al. (2012); Shukla and Naim (2015) | Evans et al. (1998); Cannella et al. (2014) |
| **Assessing** | Stability property **(6 citations)** | 0 | Riddalls and Bennett (2002a); Warburton et al. (2004) | Venkateswaran and Son (2007); Sipahi and Delice (2010); Wang et al. (2012); Wei et al. (2013) |
| | Price fluctuation **(3 citations)** | 0 | Campuzano Bolarin et al. (2011) | Naim (2006); Naim et al. (2007) |
| | Batching **(3 citations)** | 0 | 0 | Potter and Disney (2006); Hussain and Drake (2011); Hussain et al. (2012) |
| **Selecting** | The optimisation of decision parameters in IOBPCS family **(22 citations)** | Bonney and Popplewell (1989); Agrell and Wikner (1996); Strozzi et al. (2012); Warburton et al. (2014); Ghane and Tarokh (2012) | Disney and Towill (2003c); Disney et al. (2004b); Disney and Towill (2006); Towill et al. (2007); Warburton and Disney (2007); Venkateswaran and Son (2009); White and Censlive (2015c) | Disney et al. (1997) ;Disney et al. (2000); Warburton (2004); Disney et al. (2006a); Lalwani et al. (2006); Wang et al. (2009); Hussain et al. (2012); Bijulal et al. (2011); White and Censlive (2013); Parsanejad et al. (2015b) |
| **Acting** | Inventory control model **(12 citations)** | Grubbstrom and Wikner (1996); Disney (2007); Towill and Disney (2008); Dominguez et al. (2014); Hassanzadeh et al. (2014) | Disney et al. (2006a); Warburton (2007); Csik et al. (2010); Cannella (2014) | Chen and Disney (2007); Zhou et al. (2010); Hoberg and Thonemann (2015) |
| | Information management strategy and supply chain collaboration **(23 citations)** | Yang and Fan (2014); White and Censlive (2015a) | Mason-Jones and Towill (1997, 1998); Hong-Minh et al. (2000); Disney and Towill (2003a); Disney and Towill (2003b); Disney et al. (2004a); Lin et al. (2010); Yang et al. (2011); Hosoda and Disney (2012); Li et al. (2013); Xie and Ma (2014) | Disney and Towill (2002b); Disney and Towill (2002a); Disney et al. (2003); Dejonckheere et al. (2004); Cannella and Ciancimino (2010); Cannella et al. (2011); Ciancimino et al. (2012); Cannella et al. (2014); Cannella et al. (2015); Han and Wang (2015) |
| **Extension** | Extension of IOBPCS family **(11 citations)** | Wikner (2005) | Cannella et al. (2008); Hoberg et al. (2007); Spiegler et al. (2012); Turrisi et al. (2013) | Tang and Naim (2004); Wikner et al. (2007); Zhou and Disney (2006); Zhou et al. (2006); Hussain et al. (2015); White and Censlive (2015b) |

Source: the authors.

mechanisms, including exponential smoothing, moving average and demand signal processing, on the Amplitude Ratio (AR) through the ORATE/CONS transfer function in a single discrete time system based on the OUT policy (a special case of the APIOBPCS ordering rule). They concluded that the bullwhip effect is generated for all forecasting methods in this context. However, the AR is less than 1 for some frequencies with a moving average approach in which the plot follows a sinusoidal shape. Moreover, the AR increases proportionally to the demand single processing mechanism.

Dejonckheere et al. (2002) studied high order (linear and quadratic) exponential smoothing techniques based on a continuous time version of the APIOBPCS archetype. A zero steady-state drift in AVCON can be achieved for the ramp and parabolic input CONS by adopting higher order models. However, this resulted in a greater bullwhip effect at the expense of the moving higher order models with the same $T_a$ value. System performance, such as inventory and production adaptation costs, can only be improved by choosing the appropriate $T_a$ value, thus limiting the applicability. It is important to note that the more complex Damped Trend forecasting method was tested by Li et al. (2014) to explore the bullwhip generating behaviour within the context of the OUT ordering policy.

Xie and Zhou (2012) modelled uncertain demand as a symmetrical triangle fuzzy number to study the dynamic behaviour of a single production-inventory system based on APIOBPCS. Using a simulation, they confirmed that the bullwhip effect can be reduced at the expense of fuzzy demand forecasting, which has become sharper. However, this study did not consider other conflicting performance metrics, such as the fill rate, thus limiting the insight of the fuzzy approach applications. Campuzano-Bolarín et al. (2013a) and Campuzano-Bolarín et al. (2013b) addressed this gap and extended the single echelon to a dyadic and three-echelon supply chain context based on the APIOBPCS ordering policy.

It can be seen that a forecast-driven supply chain is commonly found in a Make-to-Stock (MTS) system, which offers products with high standardisation/low customisation and a relatively long life cycle. The selected studies agree that supply chain dynamics, such as the bullwhip effect, are generated in such a context because of the forecasting error in each supply chain echelon, although specific forecasting approaches/system parameters can be implemented to reduce those dynamics in specific circumstances.

*4.1.2. Lead time and WIP policy (12 citations)*
The lead time/WIP policy in the IOBPCS family was investigated based on two aspects: lead time representation/estimation and the study of transport/shipment behaviour within the context of supply chain dynamics.

WIP information plays a significant role in enhancing production-inventory system performance (Parsanejad et al., 2015a). An important assumption in the APIOBPCS archetype is the full visibility of the lead time used in the WIP closed feedback loop to eliminate inventory drift over a long period of time, which occurs when the ordering policy requires an estimated lead time before generating the orders. Inventory drift refers to the permanent discrepancy between the targeted inventory level and the actual inventory level after a step change in demand, which directly influences the customer service level (CSL). However, such an assumption is often not realistic in a multi-products plant with great lead time variations and other uncertainties, such as the lack of raw material (Towill et al., 1997). Several attempts have been made to accurately and timely estimate the lead time to achieve a zero inventory offset based on the IOBPCS family, including the incorporation of a nonlinear feedback control loop to continuously monitor the lead time (Towill et al., 1997), the utilization of the previous estimated $T_p'$ as a current WIP signal and adding it into the AVIOBPCS ordering policy (Disney and Towill, 2005), the development of an adaptive control methodology to identify the online lead time (Aggelogiannaki and Sarimveis, 2008) and the adoption of a proportional-integral (PI) control principle (Sarimveis et al., 2008).

For lead time representation, a first order lag is commonly adopted to model the smoothed lead time in the IOBPCS family in order to represent

**Table 6**
An overview of the main information management strategies.

| Information management strategy/Supply chain collaboration | Details |
| --- | --- |
| **Electronic point of sale (EPoS)** | Share market data across supply chain players (Mason-Jones, 1999; Dejonckheere et al. 2003) |
| **Vender-managed inventory (VIM)** | Vendors/suppliers take responsibility for manging the stock levels of their customers (Magee, 1958; Disney and Towill, 2003a) |
| **E-shopping** | Create a direct information and material flow between manufacturers and end customers (Disney et al. 2004a) |
| **Emergency trans-shipments** | Allow the emergent transport route to bypass an echelon in the supply chain (Hong-Minh et al.2000) |
| **Elimination** | Distributor is removed from the supply chain (Wikner et al. 1991) |
| **Information exchange** | The retailer and supplier order independently, and exchange demand information and action plans (Dejonckheere et al. 2004) |
| **Supply chain synchronisation** | The supplier takes charge of the customer's inventory replenishment at the operational level and uses this visibility in planning its own supply operations (Ciancimino et al. 2012) |

either the 'level' or the 'rate' of production completion (Wikner, 2003). However, its gradual tail-off (the result of smoothing) is unrealistic due to the reality of a constant production rate with an abrupt ending, which is different from the machine level perspective (Riddalls and Bennett 2002a). Riddalls and Bennett (2002b) demonstrated the qualitative difference between a first order lag delay and a pure delay in modelling the dynamic supply chain based on the APIOBPCS model. Using a differential equation, they adopted the concept of a pure delay to design a heuristic feedback ordering that could adaptively respond to the external disturbance.

The literature also addressed the topic of transport/shipment behaviour in the supply chain dynamics context. Specifically, Potter and Lalwani (2008) simulated the APIOBPCS model to investigate the impact of demand amplification on transport performance in a single production-distribution system under different capacity constraints. They indicated that the increasing level of demand amplification damages the transport performance. However, when the vehicle capacity is less than the average demand, the transport performance is improved, resulting in an increase in demand amplification. This is because the increased variability is attenuated by the existence of the 'spare' capacities. Campuzano Bolarín et al. (2009) confirmed that the negative impact of transport disruption resulted in lead time variability.

Wilson (2007) studied the influence of transport disruption on the dynamic behaviour that occurred between two echelons in a five-echelon supply chain. A traditional supply chain and a vendor managed inventory (VMI) supply chain were used to compare the performance differences



**Fig. 7.** Accumulative Citations for γ type papers from 1982 to 2015. Source: the authors.

through a simulation. The result showed that the VMI-APIOBPCS had less of an effect on transport disruption than a traditional supply chain, and a serious inventory fluctuation happened in the warehouse and Tier 1 suppliers in traditional supply chain structure. Shukla et al. (2009) focused on the bullwhip effect that demand single processing had on downstream shipment behaviour (the backlash effect). Using the system dynamic method and Fourier Transform (FT), they found that the shipment amplifications were greater than the peak orders for all the echelons of a four-tier supply chain. Spiegler and Naim (2014) proposed a strategy for reducing this phenomenon by introducing transport capacity constraints at the expense of increasing backlog and inventory costs.

Material/information delay is one of the fundamental reasons for dynamic generation (Forrester, 1958); consequently, accurately monitoring lead time and WIP information is crucial for improving dynamic performance. A number of contributions were found in this area of study. However, it should be acknowledged that it is difficult to manage lead time/WIP information due to its variability. For example, a significant management effort is needed to continuously monitor and identify online lead time, and Disney and Towill's (2005) approach should be fine-turned due to the simultaneous existence of actual and estimated lead time parameters. Furthermore, even though a PI controller can be used to eliminate inventory drift, its long time span might only fit specific types of products with an extended life cycle.

*4.1.3. Inventory policy (6 citations)*

Inventory policy refers to the inventory control principles, which consist of the proportional (P), Integral (I) and Derivative (D) approaches. Sourirajan et al. (2008) examined the impact of P, PI and PD on the bullwhip effect under different forecasting conditions in a single-echelon supply chain. Using z-transform, they found that the P controller is good for a high forecasting error situation, the PI controller strategy works well in a scenario in which the forecasting bias is higher than the forecasting error and the PD ordering principle delivers excellent performance in the context of moderate forecasting errors. Lin et al. (2003) investigated the value of the PI controller in damping the bullwhip effect using the z-transform technique. Similarly, Kumar et al. (2013) simulated a five-echelon supply chain and found bullwhip effect is lessened when the PI and the P controller principles are used. White (1999) tested a more sophisticated PID controller and found that an 80% reduction in the stock level could be achieved at the expense of increasing the bullwhip effect and destabilising the system. The same findings were confirmed by Chaudhari et al. (2011) though a simulation.

Overall, there is an increasing tendency for investigating the impact of lead time/WIP on the dynamics (12 citations), while less studies are found to focus on forecasting in dynamic induction (6 citations). For the inventory control policy (6 citations), it should be noted that the PID control principle has not received much attention from the academic community due to its overlapping role with integral adjustment and the forecasting component, as well as the increased tuning effort of combining all three principles in an ordering system (Sarimveis et al., 2008).

*4.2. Review of the γ category papers*

Table 5 provides the references for this category according to the three citation groups.

*4.2.1. Sensing*

*4.2.1.1. The dynamic nature of a production and planning system (9 citations).* Due to the ability of the IOBPCS family to represent a real production and planning system, extensive studies attempted to detect various dynamic behaviours of such a system based on the IOBPCS family.

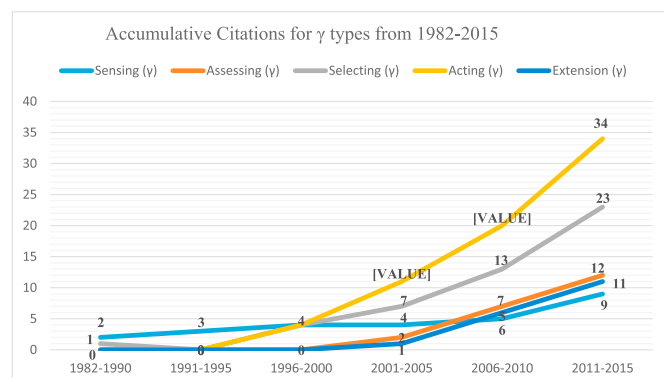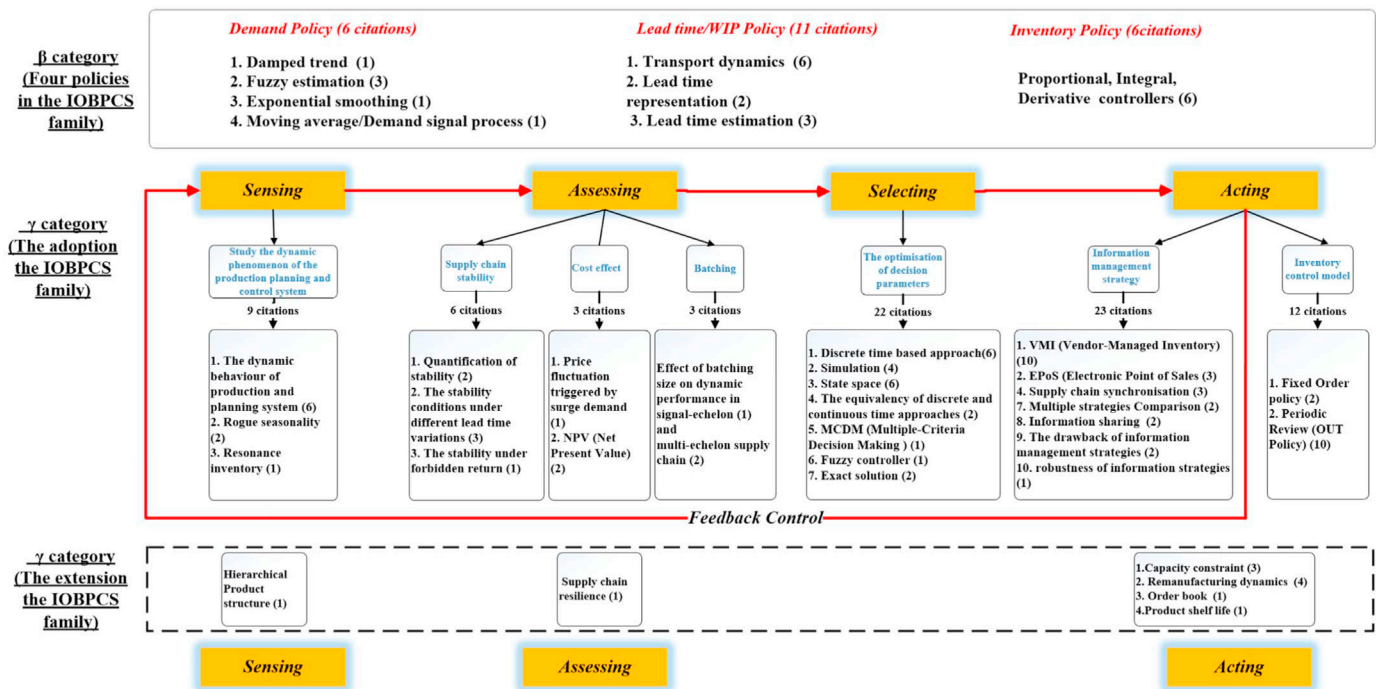Edghill et al. (1988) tested the dynamic behaviour of a production

**Fig. 8.** Synthesis of literature review findings. Source: the authors.

system (similar to the APIOBPCS) based on a case study conducted within an industrial project. They observed the demand amplification under such a production-distribution system, and they highlighted the benefit of understanding the dynamic characteristics of models for a manufacturing system design. Ariffin (1992) examined the inventory recovery ability of the IOBPCS model through step demand input. The simulation result revealed that the production inventory system is inherently dynamic and complex, and better control of the system performance can be realised. Cannella et al. (2014) examined the situation of an extremely volatile market based on the APIOBPCS ordering policy. Using a simulation, their result suggests that a smoothing policy improves the operational performance (bullwhip, inventory level and customer service level [CSL]) at the expense of slightly decreasing CSL.

Evans et al. (1998) applied the structured methodology in a logistics control system in the Master Production Scheduler known as the 'To Make' model, which is conceptualised by continuous time A$^2$PIOBPCS (time-varying version of APIOBPCS with the utilization of pipeline information) including a non-linear adaptive loop for more accurate lead time estimation (Towill et al., 1997). A simulation was conducted to analyse the dynamic performance based on step, frequency and sawtooth demand patterns. Two findings were highlighted: 1) the inclusion of WIP controller improves the CSL while maintaining a stable inventory condition and 2) accurate representation of lead time has a significant influence on the system dynamic behaviour.

Edghill and Towill (1990) investigated the difference between IOBPCS and VIOBPCS (variable target) using frequency response methods such as bode plots. They claimed that IOBPCS has a lower Amplitude ratio (AR) and a larger phase shift than VIOBPCS, which gives credence to the managerial insight that adopting IOBPCS can result in a low production capacity requirement and high CSL at the expense of slow system response in comparison to VIOBPCS, which is a similar to the finding in a study conducted by Parsanejad et al. (2014).

Shukla et al. (2012) assessed several time-series transformation techniques, i.e. Fourier transform (FT), autocorrelation function (ACF), cross correction function (CCF), autoregressive model (ARM) and discrete wavelet transform (DWT) for rogue seasonality detection based on the APIOBPCS archetype. Rogue seasonality is characterised as a cyclic pattern in the order/inventory variable or other variables first

identified by Forrester (1961) that damage cost efficiency and effectiveness due to the unnecessary ramp and down cycles of the production and inventory levels. They concluded that FT is effective for detecting rogue seasonality, while DWT and ARM are less effective methods. Shukla and Naim (2015) then validated the signature and index identified by Shukla et al. (2012) through the lens of control theory. They confirmed the robustness and validity of the index as an indicator for rogue seasonality.

The phenomenon of resonance inventory was also investigated. Resonance inventory is the unwanted inventory behaviour (i.e. a transient surge) for upstream players of a supply chain even if the retailer has a reasonable ordering rule. Hodgson and Warburton (2009) revealed the possible reasons for resonance inventory by solving a differential equation exactly in an OUT policy context. They confirmed that the reason for resonant inventory behaviour, as others may suspect, is the independent ordering decision in each echelon of a supply chain frequently reflected in the industry.

Other methods/strategies, e.g. System Dynamics (Forrester, 1958, 1961) and the beer game model (Sterman, 1989), which are used to detect dynamic phenomenon of production control systems, were compared. The advantage of control engineering methods based on the IOBPCS family lies in its analytical power to understand the reason/-causes behind the phenomenon, even though this type of linear-based simplified model needs some unrealistic assumptions, such as free return and infinite capacity. Future research is needed to develop more advanced non-linear methods to capture more realistic supply chain systems without sacrificing analytical capability.

### 4.2.2. Assessing

#### 4.2.2.1. Stability property (6 citations).
A number of studies assessed the dynamic nature based on criteria/main sources of supply chain dynamics, which are further categorised as the stability property, price fluctuation and batching sources.

Stability is a fundamental property of a supply chain system. From the linear system perspective, the system is stable if the trajectory will eventually return to an equilibrium point irrelevant to the initial

condition, while an infinity trajectory is present if the system is unstable (Wang et al., 2012). A system has critical stability when it is located at the edge of the stability boundary that is only mathematically available, and when the system oscillations are regular and infinite for that situation.

Riddalls and Bennett (2002a) first quantified the stability of a supply chain based on APIOBPCS in a production-inventory system. They adopted the pure delay and moving average forecasting approaches in APIOBPCS to quantify the maximum lead time in the absolute stable condition via a Smith predictor and the Bellman and Cooke's theorem. Unfortunately, their stability function result was not fully correct. Warburton et al. (2004) derived a more precise stability criteria using the Lambert W function and Nyquist Stability criteria. Their result is guaranteed to be correct by simulation verification. Furthermore, they adopted the second order Padé approximation to gain an understanding of general stability in a continuous time domain.

Several authors investigated the relationship between stability property and lead time. Venkateswaran and Son (2007) examined stability under different information update frequencies (i.e. sampling intervals) using z-transform techniques and Jury's stability test in a single manufacturing system. Two main findings were revealed: 1) a high information frequency update is needed for large discrepancy adjustment values in APIOBPCS and 2) stable DE-APIOBPCS is dependent on the sampling interval.

Sipahi and Delice (2010) considered the chain stability property under three different delays: decision making, production and transport delay structured on the APIOBPCS continuous time domain. They developed a stability map with respect to different delays to support management decision making, since desirable inventory behaviour can be visualised by combining three delays on the map. However, the adoption of linear assumption could limit their research findings, since a real supply chain is constrained by several variables that cannot be reflected in the linear equations.

The stability condition for arbitrary lead time was analysed in discrete time APIOBPCS by adopting a differential equation and a state space approach (Wei et al., 2013). A stable region independent of lead time was developed, which can determine the precise stable region with the increase of lead time. Thus, the stability gap in an arbitrary lead time region was addressed, and this approach can be easily applied to other IOBPCS families.

Wang et al. (2012) investigated a constrained nonlinear production and inventory system (forbidden return) under 1 and 2 periods of actual and perceived transport delay based on the APIOBPCS model. Via a linear model, eigenvalue analysis and simulation, all of the complex non-linear dynamic behaviours in the system were analysed. The authors indicated that system stability and CSL are significantly dependent on an accurate estimation of lead time, and a careful system design is needed to avoid the periodicity and chaos present in the simulation result. However, this study was limited to the context of a single-valued, piecewise linear supply chain system, while a more complex context, such as multi-valued discrete nonlinearity (output is determined by history of input) needs to be considered.

It can be seen that a majority of the studies focused on stability under various lead time scenarios, and its behaviour can be visualised based on linear assumptions with the help of relevant linear techniques. However, complex phenomenon (e.g. chaos behaviour) will be present if nonlinearity is introduced, and its associated managerial decisions may be different from the linear-based systems. To address this issue and further increase the relevance of these studies to practice, future research must investigate more advanced non-linear theories.

*4.2.2.2. Price fluctuation (3 citations). Price fluctuation* is one of the main factors that induce the bullwhip effect ( *Lee et al. 1997b)*. If the price policy used at a retailer site (e.g. the purchase discount between wholesalers and retailers, full stock for holiday promotion) delivers the wrong demand/forecasting information to upstream wholesales and

manufacturers in the supply chain this can lead to large order and inventory variability. Campuzano Bolarin et al. (2011) investigated how the price fluctuation factors triggered by a staggered step demand influenced the ordering distortion in a four-level supply chain based on an APIOBPCS ordering policy. Their result confirmed the previous seminal work (Lee et al., 1997a) that price fluctuation generates the bullwhip effect. However, their study does not offer analytical insight for improvements, e.g. how to reduce the bullwhip effect under the staggered step demand.

Cost effect on supply chain dynamics was also explored from the net present value (NPV) perspective. NPV refers to the discounted future value that results from the interest rate. However, the traditional NPV calculation does not recover the dynamic behaviour, and Naim (2006) addressed this gap by introducing $NPV_V$, which represents the variance of $NPV$ triggered by inherent system dynamic factors (e.g. bullwhip, inventory variance). Using a simulation, Naim (2006) examined the impact of $NPV_V$ on three supply chain models (traditional, electronic point of sale (EPoS) and VMI) based on the APIOBPCS model. The result indicated that EPoS yields the lowest dynamic costs, while the rankings for VMI and a traditional supply chain were dependent on production costs and inventory variation costs. $NPV_V$ was further tested in an MTO and MTS manufacturing system (Naim et al., 2007).

Although price fluctuation plays an essential role in bullwhip induction and it is understood from other dimensions, such as game theory (Özelkan and Çakanyildirim, 2009) and the Economic Order Quantity (EOQ) model (Sodihi and Tang 2014), few studies have investigated price fluctuation using control theory by adopting the IOBPCS family in order to answer 'what' questions (e.g. what is the possible consequence of price fluctuation in a dynamic supply chain system?) and 'how' questions (e.g. how to decide the relevant policies to mitigate such an effect?). This is a gap that future research should aim to fill.

*4.2.2.3. Batching effect (3 citations).* Order batching is another main source of the bullwhip effect (Burbidge, 1981). There are two main types of batching: time-based (periodic) batching and order quantities batching (Potter and Disney, 2006). The former refers to a replenishment frequency that is lower than the frequency of the goods that are actually received, while the latter results from the EOQ or other constrains (e.g. vehicles, packages).

Potter and Disney (2006) examined the batch size effect on order variance in a simple production control system. Based on a simulation study investigating the impact that various batch sizes had on the bullwhip effect under a deterministic and stochastic demand scenario, the authors found that the bullwhip effect can be minimised when the batch size is equal to or less than demand with a multiple relationship in both demand structures. However, this approach might only be applicable to a simple supply chain structure, such as one that does not consider a forecasting approach. Hussain and Drake (2011) and Hussain et al. (2012) addressed that gap by exploring the bullwhip effect and the batching size in a multi-echelon supply chain model based on APIOBPCS.

Few of the studies in the literature assessed the main sources of supply chain dynamics based on the IOBPCS family; in fact, only 6 studies focus on batching and price fluctuation and no studies considered the sources of shortage gaming (Lee et al., 1997b). Furthermore, the stability property was examined in many contexts, such as arbitrary lead time and different information delays. However, most studies concentrated on a single production-distribution environment, which limits the applicability of their findings to dynamic and complex supply chain systems.

*4.2.3. Selecting4.2.3.1. The optimisation of decision parameters in the IOBPCS family (23 citations)*

After the dynamic phenomenon is assessed based on relevant criteria and primary sources, a theoretical optimisation of the decision parameters (*Ti, Tw* and *Ta*) in the IOBPCS family is needed, which can be categorised as the linear based approach (control theoretic techniques) and the nonlinear based mechanisms (simulation, exact solution, etc.).

Using the linear, time invariant, infinite dimensional assumption (LTI), Bonney and Popplewell (1989) studied the applicability of the

discrete-time z-transform technique based on the IOBPCS ordering policy. They claimed that the z-transform technique was applicable for: a) adopting a new forecasting approach; b) using MRP, c) improving the quality of the data and d) reducing lead times.

Several other authors also considered the z-transform technique. Disney and Towill (2003c) measured the bullwhip effect in a discrete ordering system context based on the DE-APIOBPCS model, i.e. they set $T_i = T_w$, which was first proposed by Deziel and Eilon (1967), in which the bullwhip is equal to '*the sum of the square of the discrete of the system impulse response*' (Disney and Towill, 2003c, p.161). Two findings were indicated: 1) it is possible to set a proportion of error for the inventory and pipeline policy rather than fully correcting them in each replenishment cycle and 2) increasing the age of the forecasts improves the system dynamics. Disney and Towill (2006) further discussed the DE-APIOBPCS by revealing the relationship between $T_i$, $T_p$ and $T_a$. Based on a simulation cross-check, the user guidance is developed as: $T_i = T_w = (T_p + 1)$ and $T_a = 2(T_p + 1)$. Furthermore, Disney et al. (2004b) developed two forms of the objective functions. The first objective function is the so-called 'golden ratio' used to identify the optimal gain in the WIP and inventory feedback loop, and the second objective function enables visualisation of the entire range of possible solutions for different weightings.

Bijulal et al. (2011) added a safety stock component in APVIOBPCS, and they considered cost and CSL performance in the production control system under independent and identically distributed (i.i.d) demand. They adopted a discrete time domain approach and used a simulation, and the result showed the new model achieved high CSL (above 50%). In addition, the average cost for desired CSL could be reduced by properly tuning the system parameters. Similar findings were reported by Parsanejad et al. (2015b).

Venkateswaran and Son (2009) optimised a three-echelon hierarchical supply chain by using discrete event simulation (DES) and non-linear optimisation techniques. The robustness (stability) as well as control parameters are analysed and the results indicated that the performance and robustness of supply chain plans can be improved via concurrent consideration of performance and stability.

A discrete time system has also been studied based on a state space model. This model has the advantage of controllability and observability (Lalwani et al., 2006) as well as the possibility of representing a multi-echelon supply chain system (White and Censlive, 2015c). By transforming the z-transfer function into a control canonical form, Franklin et al. (1998) simplified the analysis of the IOBPCS family and they obtained a state space model that only contained z (delay operator $z^{-1}$). In particular, they focused on APVIOBPCS (variable inventory target), and they developed its state space representation. It is not surprising that the state space is fully controllable and observable due to the nature of the discrete time transfer function (only including the controllable and observable parts of the system).

White and Censlive (2013) addressed the fact that Lalwani et al.'s (2006) model did not capture various production delays (only one-time unit delay is investigated). They derived the controllable and observable state space model using an exponential smoothing delay without losing generality. The state space approach was also adopted by Strozzi et al. (2012), who explored the divergence of a logistic chain model within the OUT policy.

Although continuous time approaches were adopted by the two original papers by Towill (1982) and John et al. (1994), the discrete linear system has received more attention, which is consistent with the fact that a real replenishment system is often monitored in a periotic way (Vassian, 1955). However, neither of these systems is superior for application in different real scenarios (Disney et al., 2006b), e.g. examining the stability property through continuous time approaches while adopting a discrete time system for the stochastic response (Warburton and Disney 2007).

The optimisation process of decision parameters in the IOBPCS family

was also investigated using multi-criteria decision making (MCDM) (Agrell and Wikner, 1996). Agrell and Wikner (1996) claimed that MCMD is beneficial for ensuring the transparency of the optimisation process in both continuous and discrete time systems. Hussain et al. (2012) provided additional details about the impact that the system parameters ($T_i$, $T_w$ and $T_a$) had on system dynamic performance, including their interactions in an information-sharing-based multi-echelon supply chain. Using simulation and adopting the Taguchi design for their experiments, they identified two strong interactions: 1) information sharing and a smoothed level of forecasting mechanism and 2) interactions between the system parameters ($T_i$ and $T_w$; $T_w$ and $T_a$; $T_i$ and $T_a$).

In terms of non-linear approaches, simulation is a popular choice that researchers have adopted to represent a more realistic complex supply chain system. Disney et al. (1997) optimised the APIOBPCS model based on performance metrics, including: 1) inventory recovery time, 2) the ability to filter out unwanted demand frequency and 3) the robustness of the production's response to changes in lead time and lead time distribution. By introducing a step input, they showed that demand adjustment $T_a$ should be twice as high as the production delay, pipeline adjustment $T_w$ should be slightly greater than the triple production lead time, and inventory correction $T_i$ should be slightly less than the production lag. Disney et al. (2000) added two extra performance metrics, including WIP robustness (which examines the robustness of the pipeline policy in responding to different lead times) and selectivity (how the system accesses the robustness of a design to change the system parameters). They demonstrated the importance of fully understanding the trade-off between inventory level and factory order in improving system performance.

By utilising the Lambert W function, Warburton (2004) developed an exact solution for a surge demand pattern based on the APIOBPCS policy. A complex Lambert W function in an exponential was derived to explain the sensitive relationship between production delay and inventory oscillation. The analytical solution demonstrated that proper selection of the system parameters is necessary in order to improve system performance based on three criteria: the time to recover the inventory drift, the WIP adjustment and demand smoothing. Warburton et al. (2014) also utilised an exact solution for the OUT policy under an arbitrary, time-variant and non-linear demand pattern. They derived the exact form of the estimated demand and the target WIP, and they limited the model to the pre-shape function (the initial boundary condition to the delay differential equation), which showed the inventory behaviour in a complex demand environment without losing high accuracy.

Fuzzy controller was also considered for optimising the tuning parameters ($T_a$, $T_i$ and $T_w$). Ghane and Tarokh (2012) analysed a bi-objective supply chain (adopting APVIOBPCS) based on a fuzzy controller. Their result suggested that Fuzzy logic is applicable to and adaptable for non-linear approximation.

Based on this literature review, it can be concluded that a simplified linear system has the ability to show the system structures and provide rich managerial insight for the relationship between decision policies and performance metrics. However, such approaches are often criticised as being unrealistic for a real production and planning system (e.g. free return, infinite capacity). Thus, a simulation may be an alternative that researchers can use to represent complex non-linear elements; however, a simulation is, essentially, a trail-and-error process and it cannot provide analytical improvement. Other more advanced methods, such as exact solutions, were considered by several authors (e.g. Warburton, 2004; Warburton et al., 2014), but these solutions need to be more fully developed in the future.

*4.2.4. Acting4.2.4.1. Inventory control model (12 citations)*

The final step is controlling the dynamic property based on different actions in various supply chain scenarios. Two emerging topics were found in the literature review: the inventory control model and information management/supply chain collaboration.

There are two basic inventory replenishment rules in a real

production planning and control system: the continuous time rule and the discrete time ordering rule (fixed order or periodic re-ordering systems) (Rao, 2003). Fixed order means that the same quantity of products is ordered at varying time intervals, and the number of products that are ordered must reach an OUT level pre-determined by decision makers in the periodic reordering system. It should be highlight that the OUT policy is essentially the APIOBPCS archetype when $T_i=T_w=1$. This literature review found many studies that focused on the OUT policy due to its prevalence in a wide range of industries.

Disney et al. (2006a) investigated order and inventory variance and customer service level (CSL) in a generalised OUT policy based on different demand process, including independent and identically distributed (i.i.d.), weakly stationary auto regressive (AR), moving average (MA) and auto regressive moving average (ARMA) demand processes. Based on z-transform analysis, a win-win strategy that reduces the inventory level while maintaining an adequate CSL can be realised by carefully tuning the system parameters, although a slight increase in the safety stock to cover some instances of the ARMA demand pattern needs to be considered.

Disney (2007) investigated a generalised OUT policy by incorporating a net stock proportional controller and a WIP proportional controller to examine the reduction of the bullwhip effect in a single echelon of a supply chain. He suggested using the innovative Jury Inner approach to directly conduct a stability test that is difficult, if not impossible, using the traditional transfer function technique in radicals for a high order system. Towill and Disney (2008) illustrated how the OUT policy can be used to control supply chain risks that result from the bullwhip effect. Using experimental simulation, they emphasised the importance of up-to-data delivery lead time information sharing as well as data adaptability to reduce relevant supply chain risks in an OUT policy.

Warburton (2007) studied the OUT policy under a ramp demand pattern. He solved the continuous-time inventory and ordering equations, and revealed that such ordering policy allows the inventory to continuously return to the desired level under the critically stable solution. Another significant finding is that the ordering policy is independent of the ramp demand slope, even with the inclusion of noise in the demand; thus, it is highly applicable in practice. Csik et al. (2010) also used the OUT policy to solve the exact inventory balance delay differential equations, which offers an understanding choice of the parameter values needed to reduce bullwhip effect.

Chen and Disney (2007) studied a more representative demand pattern, stochastic ARMA (1,1 with conditional expectation forecasting using z-transform and the normal distribution probability density function). They added the proportional controller to the OUT policy to exploit the piece-wise linear ordering cost and linear inventory cost pre-defined by the authors. They indicated that this type of ordering structure outperformed the original myopic OUT policy when considering the convex ordering cost. The OUT policy was also examined based on the smoothed ordering policy and information sharing/supply chain collaboration (Dominguez et al., 2014; Cannella, 2014; Hassanzadeh et al., 2014) in a multi-echelon supply chain structure. Both papers highlighted the benefit of combining a smoothed ordering policy and information sharing in OUT in order to improve system performance. However, customer demand is limited in the i.i.d. assumption, which cannot represent a real demand pattern.

Grubbstrom and Wikner (1996) explored the fixed order policy by examining the system's dynamic response to the inventory trigger control policy. In such a system, the stock is replenished in batches when the inventory level exceeds or falls below a trigger level. Using difference and differential equations, the common sawtooth inventory pattern can be reproduced. Hoberg and Thonemann (2015) used the linear control method to study the fixed order policy; they optimised the system parameters based on performance metrics, including order variability, cost and responsiveness. Furthermore, Zhou et al. (2010) highlighted the capability and compatibility of the IOBPCS family for managing SKU inventory.

In conclusion, the OUT policy was extensively assessed through different representative demand patterns, due to its popularity in many industries. It was found that the IOBPCS family is capable of representing the OUT policy, and researchers highlighted the fact that smoothed control of the OUT policy with careful selection of system parameters enables significant system performance improvement.4.2.4.2. Information management and supply chain collaboration strategies (23 citations)

Many studies considered the impact of information management strategies on reducing supply chain dynamics. Two sub-categories were further developed: 1) the specific information management strategy and 2) the general information sharing strategy. Table 6 provides an overview of primary specific information management strategies examined in the reviewed studies.

Regarding the EPoS strategy, Mason-Jones and Towill (1997, 1998) conducted a simulation to explore the value of EPoS in a supply chain dynamic in a four-level supply chain structure based on the APIOBPCS ordering model. They suggested that the demand amplification can be decreased with improved system response speed by sharing market sales information across each player. They also extended the original 'material decoupling point' to the 'information decoupling point' and highlighted a number of benefits that could result if the information decoupling point moved to upstream, i.e. sharing the EPoS across the entire supply chain.

A number of researchers also examined the VMI from the supply chain dynamics perspective. The VMI strategy refers to the context from which the manufacturer manages customer's (e.g. distributor's) stock. This was first discussed by Magee (1958), and it became popular with the development of information technology (Disney and Towill, 2003a). Based on the IOBPCS ordering family, the VMI strategy has been extensively studied, including the reduction of the bullwhip effect (Disney and Towill, 2003a, 2003b), its characteristics of robustness and stability (Disney and Towill, 2002a; Lin et al., 2010), the optimisation of the VMI model (Disney and Towill, 2002b; Xie and Ma, 2014), the incorporation of a third party logistics provider (Li et al., 2013), the nonlinear effect on system performance (Han and Wang, 2015) and the labour supply flow (White and Censlive, 2015a). It should be noted that linear control approaches are the main choice in the studies cited above, which offer guidance for improving system performance, such as optimisation of the system parameters and the trade-off between different performance metrics. Simulation was often adopted to cross-check these analytical results. These researchers agreed that VMI was able to reduce dynamic behaviour, including the bullwhip and rogue effects in supply chains, thereby improving system performance.

Hong-Minh et al. (2000) studied the dynamic effect of an emergency transport-shipment strategy and compared it with three other strategies: 1) EPoS, 2) Excel and 3) elimination, in a four-echelon supply chain based on APIOBPCS. Using a simulation, the result showed that Excel appears to be the poorest strategy, while the elimination strategy performed the best; however, excellent dynamic performance was achieved when the elimination, EPoS and emergency transport-shipment strategies were combined.

General information exchange strategies, such as information sharing (IS), collaborative planning, forecasting and replenishment (CPFR) and supply chain synchronisation (SCS), were explored in the context of a dynamic environment. For example, Yang and Fan (2014) compared traditional, IS and CPFR strategies for managing operation and disruption demand risks, Dejonckheere et al. (2004) and Cannella et al. (2011) investigated IS and a smoothed ordering policy in an OUT context, Cannella and Ciancimino (2010) and Ciancimino et al. (2012) examined the value of smoothed replenishment and the impact of SCS on reducing supply chain dynamics and Cannella et al. (2015) explored the impact of a coordinated, decentralised supply chain system on CSL. These studies agreed that information sharing strategies are able to reduce the bullwhip effect, and two common findings emerged: 1) the more information sharing, the better the overall system performance and 2) the bullwhip effect is reduced in smoothing replenishment settings at the expense of slightly damaging CSL.

While most of the researchers mentioned above advocated that information sharing based strategies can improve the dynamic behaviour of supply chain systems, Disney et al. (2004a) suggested that information sharing and communication technology (ICT) could create a complex environment that is more difficult for decision making. Five types of supply chains were explored (traditional, reduced, EPoS, VMI and e-shopping) using the z-transform technique and the beer game model. The analytical z-transform techniques showed that the bullwhip effect is reduced when strategies, such as EPoS or elimination, are adopted in the supply chain. However, the beer game model indicated that ICT increased the complicity level of human decision-making by adding too much information and complicated calculations, leading to poor management and high inventory costs. Similarly, Hosoda and Disney (2012) presented an ordering strategy they called Controlling Dynamic Strategy (CDS), and they compared it with the information technology enabled time lag elimination strategy (TES) based on an OUT policy in a single-echelon supply chain. Using a differential equation and numerical analysis, they claimed that TES should be considered if the inventory cost is a major concern in the supply chain, while CDS is an appropriate strategy if the production cost dominates the production-inventory system.

Yang et al. (2011) examined the robustness of various information management strategies to cope with uncertainty (e.g. demand, lead time and production rate) based on APIOBPCS. Performance metrics, including inventory costs and CSL were adopted. Utilising simulation and the Taguchi method, they suggested that e-shopping is the most robust strategy among all the information management strategies, while VMI is the worse in an uncertain environment.

As noted, many papers examined the benefit of using information management strategies to reduce supply chain dynamics based on the IOBPCS family. However, topics, such as the negative side of information management strategies, multi-products with stochastic demand patterns context and the impact of sharing imprecise information, are largely ignored in the literature. Furthermore, most studies adopted linear-based simplified approaches to recover the underlying relationship between information management strategies and supply chain dynamics, which is difficult to represent in a real complex supply chain environment. Future research should also consider more complex and advanced nonlinear methods.

### 4.3. The extension of the IOBPCS family (11 citations)

Since the APIOBPCS archetype is a very general law used to represent a real supply chain system, many of the reviewed articles examined extensions of its applications in different supply chain contexts.

The first extension is the remanufacturing supply chain. Remanufacturing production is very attractive for academic research and real-life business practice due to its significant cost saving and sustainability benefits (Zhou et al., 2006). Several papers attempted to study the dynamic behaviour of a remanufacturing production system based on the IOBPCS family, including the investigation of its general dynamic behaviours through differential equations (Turrisi et al., 2013) and the incorporation of 'push' (Tang and Naim, 2004) and 'pull' (Zhou et al., 2006; Zhou and Disney, 2006) inventory control policies. The 'push' system refers to a remanufacturing production loop without a feedback control in which the returned items are 'pushed' to the remanufacturing activities and end up in the servable stock, while the 'pull' system is represented by a Kanban policy (Just-in-Time principle) and a serviceable inventory system is adopted to include both manufacturing and remanufacturing products, i.e. a reverse product is assumed to be as good as a new product. This type of serviceable inventory influences the manufacturing and remanufacturing process so that the modelling remanufacturing loop is viewed as the return yield.

The studies included in this category argue that a dynamic performance (e.g. bullwhip, responsiveness) of the remanufacturing system is better than a normal production system without considering the reverse process. The level of information sharing also plays a crucial role in improving dynamic behaviour. However, these papers only examined a single production-distribution system and a simple customer demand pattern input under linear assumptions. Future research should focus on more complex supply chains under realistic assumptions, such as a multi-tier, multi-structure systems.

The IOBPCS family was also extended to the MTO system by adding the order book process (order backlog as the time buffer) and by developing a variable order-book-based production control system (VOBBPCS) (Wikner et al., 2007). Based on simulation and continuous time approaches, the new model with a feedback loop has the capability of handling volume and lead time flexibility by tuning $T_a$ and $T_{ob}$ (time to adjust the order book to the target value), making it much more relevant to the practice.

The understanding of supply chain resilience based on the IOBPCS family is another extension topic (Spiegler et al., 2012). Using the control engineering term, resilience includes the rising time (recovery), the setting time (response) and the time between the peak and steady-state point (readiness) of the system response to the external disturbance, in which ITAE (Integral Time Absolute Error) can be used as a performance metric. Using continuous time based approaches and simulation, Spiegler et al. (2012) concluded that supply chain dynamics affect resilience due to delay and information feedback, and the trade-off between production on-cost/robustness and supply chain resilience has to be considered.

The IOBPCS family was also extended to the non-linear context to represent a more realistic supply chain system, including the capacity constrained supply chain under different inventory control models (i.e. decentralised and centralised, the periodic and continuous replenishment rule) Cannella et al. (2008), different information sharing strategies (Hoberg et al., 2007) and the effect of capacity constraints and safety stock on the backlog bullwhip in a two-tier supply chain (Hussain et al., 2015). It should be noted that these studies indicated that an important relationship exists between a capacity constrained system and dynamic behaviour, but little analytical insight was provided about how to improve that relationship, which leaves practitioners questioning how to design their supply chain control systems.

While most studies analyse the dynamic behaviour of production-inventory/supply chain systems based on the IOBPCS family from the aggregate level perspective, few study focus on the complex relations of materials and capacities. Wikner (2005) addresses this gap by analysing the dynamic behaviour of a hierarchical production structure represented by three models (Base Stock, Kanban and Material Requirements Planning). Using simplification approach and Laplace transform, the author concluded that the extended model based on Axsäter (1976) (similar to the IOBPCS archetype) has the capability to represent the dynamic of a number of different system management principles.

Finally, APIOBPCS and APVIOBPCS were adopted to explore the effect of shelf life on supply chain dynamics (White and Censlive, 2015b). Oscillatory behaviour was found in two models for responding to a step demand triggered by the interaction between the bullwhip and shelf life effects. Furthermore, White and Censlive (2015b) compared the performance of two models and suggested that APVIOBPCS performed better for reducing the bullwhip effect through a discard feedback controller, and an even greater reduction can be achieved if an information sharing strategy, such as VMI or electronic data transfer (EDT), is implemented into the model.

To conclude, the original IOBPCS/APIOBPCS model in a one-echelon forecast-driven manufacturing context was extended to various environments (e.g. MTO, remanufacturing) under a complex system structure (e.g. non-linear system, the concept of resilience). This highlights the generalisability of the original IOBPCS family in understanding supply chain dynamics, and rich managerial insight can be offered through analytical methods. However, such an extension is still in its early stage as most of the findings presented in the reviewed papers are conceptual.

This limitation can be overcome by additional empirical studies using contextual-based methodologies (such as case studies) as well as through the exploration of advanced mathematical tools (such as non-linear methods).

Overall, the trend highlights that researchers appear to have switched their interests from the early stage of sensing/assessing supply chain dynamics to the stage of controlling dynamic properties (selecting and acting) (Fig. 7). Particularly, various information management strategies have been extensively examined (23 citations), possibly due to the increase in Information and Communication Technology (ICT) adoption and economy globalisation over the last decade. In addition, researchers have noted the equivalence of the OUT policy and APIOBPCS (set $T_i=T_w=1$) due to its popularity in the industry (12 citations).

## 5. Conclusions and future research agenda

The main purpose of our paper was to explore how two models (IOBPCS and APIOBPCS), well recognised as base frameworks for production planning and control systems, have been adopted, exploited and adapted in the academic literature. A synthesis of the findings is presented in Fig. 8. Out of the 229 selected papers, 116 (α category) simply cited the two original studies (Towill, 1982; John et al., 1994) in order to increase the quality of the paper's main argument, hence their content was not fully reviewed in our study; 24 studies (β category) focus on partially exploring the original archetypes, along one of decision policies suggested (demand, lead time / WIP and pipeline policy); the remaining 89 papers (γ category) use the complete archetypes and their four decision policies.

In terms of the β category, a larger number of studies focus on lead time/WIP and findings highlight that forecasting has a direct impact on bullwhip generation, while lead-time visibility is essential to designing a high-quality production/distribution control system. The P controller is more widely used and appears to reduce the bullwhip effect, but the more complex PI and PID controllers received little attention in the literature. Further studies should particularly consider filling-in these gaps.

The γ category focused on studies adopting the IOBPCS family as a whole system or extending it to study supply chain dynamics. For these articles, a framework of dynamic system control was adopted in order to categorise contributions into the *sensing*, *assessing*, *selecting* and *acting* clusters, with a further *extension* cluster added to particularly encompass works that proposed developments of the original archetypes. During the sensing stage, various dynamic behaviours (e.g. the bullwhip effect, rogue seasonality, inventory resonance) were identified. Different criteria/sources of supply chain dynamics were then explored, including the stability property, batching and price fluctuation effect, although fewer studies were found at this stage. For the final action, the OUT inventory replenishment rule was examined due to this policy's popularity in the industry. Moreover, the authors of the reviewed papers agreed that information sharing and supply chain collaboration are effective for bullwhip mitigation, although many of the studies were theoretically-based and provided limited insights into the linear assumption for representation in a real system.

Overall, more studies incorporated the automatic WIP feedback group in the IOBPCS archetype (essentially the APIOBPCS or its variants) to understand supply chain dynamics. As stated in the original APIOBPCS paper (John et al., 1994), the inclusion of WIP damps the oscillations of COMRATE and reduces maximum overshoot, while eliminating the inventory drift through the assumption of full lead time visibility. Both are essential for a high-quality control system, although a slight increase in setting time is sometimes identified. This further confirms that the APIOBPCS archetype is a more general law, representing a variety of supply chain contexts (Zhou et al., 2010).

However, the original IOBPCS archetype still offers valuable insights into specific supply chain contexts without the use of WIP products, such as the MTO/pull systems, VIOBPCS for improving customer service and testing continuous or discrete time-based approaches. Future studies must combine traditional push/MTS systems and customer-oriented pull/MTO systems based on IOBPCS and its variants.

In terms of methods utilised, simulation was the preferred choice for assisting researchers in understanding the complex, dynamic nature of production and planning systems. However, simulation is argued to lack analytical insight. Many of the reviewed authors preferred linear-based control engineering approaches for system analysis, even though such methods cannot capture realistic supply chain systems in terms of their complex structure and nonlinearity. A lack of empirical studies is also noted.

Based on the findings, the following agenda for future research is presented:

1. *Cost and supply chain dynamics*: Most of the reviewed studies measured the performance of supply chain dynamics based on the bullwhip level and inventory variance. Two dimensions need to be particularly considered in future research: the cost function of dynamic behaviour and the impact of price fluctuation on supply chain dynamics based on the IOBPCS family.
2. *Sustainability dynamics*: Few studies considered the effect of supply chain dynamics on closed loop remanufacturing systems. Future research should focus on complex supply chain structures with realistic assumptions (multilevel, divergent networks and nonlinearity), as well as dimensions related to the sustainability of such systems (e.g. environmental cost, including pollutions and carbon emissions).
3. *Flexibility/resilience dimensions for supply chain dynamics*: The literature argues that supply chain systems must be flexible and resilient in order to cope with various risks or disruptions. These systems should also allow for customisation. However, it is often argued that there is a trade-off between flexibility/resilience and system on-cost triggered by the dynamics response. Future research should explore the applicability of the IOBPCS family in understanding the dynamic nature of supply chain models, such as hybrid Make-to-Order (MTO) and Make-to-Stock (MTS) or Assemble-to-Order (ATO) supply chains.
4. *The development of nonlinear methods:* Due to simulation's limited analytical capability, nonlinear methods should be further developed, such as linearization methods, exact solutions and graphical and stability approaches, to guide system improvement with realistic representations.
5. *Empirical studies of supply chain dynamics:* There is an acute need for more empirical research, particularly focusing on the final 'action' stage, after the rules-of-thumb have been theoretically developed based on the optimisation results. Future research should focus on the implementation of empirical methods, such as case studies and interviews, to gain more robust insight into the IOBPCS family.

This present work contributes to the body of research by exploring the extent to which two base frameworks for production planning and control (IOBPCS and APIOBPCS) have been adopted, exploited and adapted, and categorises developments, thereby highlighting notable gaps and providing directions for future researches. This study, however, is limited to the systematic citations review of the two original papers, Towill (1982) and John et al. (1994), and does not include papers that use a similar archetype without referencing the two original works. Future researches should consider using a keyword search and screening process.

## Appendix A. Four policies and transfer functions of APIOBPCS archetype (Laplace, continuous time version)

1) Demand Policy

$$AVCON_t = a \times (CON_t - AVCON_{t-1}) + AVCON_{t-1} \tag{1}$$

$$where\, a = \frac{1}{1 + \frac{T_a}{\triangle T}} \tag{2}$$

2) WIP policy

$$WIP_t = \frac{1}{T_w}(DWIP_t - AWIP_t) = \frac{1}{T_w}(AVCON_t \times T_P - AWIP_t) \tag{3}$$

3) Lead time policy

$$\frac{1}{1 + T_p S} \tag{4}$$

As we are interested in the relationship between CONS and AINV/COMRATE/WIP, the transfer function of APIOBPCS archetype are shown as follow:

$$\frac{AINV}{CONS} = -T_i \left| \frac{\frac{T_p - T_{p'}}{T_w} + \left(T_a + T_p + \frac{T_a T_p}{T_w}\right)s + T_a T_p S^2}{(1 + T_a s)\left(1 + \left(1 + \frac{T_p}{T_w}\right)T_i s + T_p T_i s^2\right)} \right| \tag{5}$$

$$\frac{COMRATE}{CONS} = \frac{1 + \left(T_a + T_i + \frac{T_{p'} T_i}{T_w}\right)s}{(1 + T_a s)\left(1 + \left(1 + \frac{T_p}{T_w}\right)T_i s + T_p T_i s^2\right)} \tag{6}$$

$$\frac{WIP}{CONS} = T_p \left| \frac{1 + \left(T_a + T_p + \frac{T_a T_p T_{p'}}{T_w}\right)s}{(1 + T_a s)\left(1 + \left(1 + \frac{T_p}{T_w}\right)T_i s + T_p T_i s^2\right)} \right| \tag{7}$$

It should be noted that equations above can represent the original IOBPCS by setting $T_w = \infty$. The Initial/final value theorem can be applied to the equation(5)

$$\frac{AINV}{CONS_{IVT}} = 0; \frac{AINV}{CONS_{FVT}} = \frac{T_i\left(T_{p'} - T_p\right)}{T_w} \tag{8}$$

The *noise bandwidth* can be represented as follow:

$$W_N = \int_0^\infty \left| \frac{COMRATE}{CONS}(jw) \right|^2 dw \tag{9}$$

## Appendix B. The categorization of three citations groups based on ABS discipline criteria

See Appendix Tables B1–B3.

**Table B1**
Categorization of citations to Towill (1982) only.

| | Journal title | α | β | γ | All |
|---|---|---|---|---|---|
| **Dependent citations** | International Journal of Production Economics (OTM 3) | 2 | 1 | 1 | 4 |
| | Production Planning & Control (OTM 3) | 2 | 0 | 0 | 2 |
| | European Journal Of Operational Research (ORMS 4) | 1 | 0 | 0 | 1 |
| | International Journal of Production Research (OTM 3) | 0 | 0 | 1 | 1 |
| | Computers in Industry (OTM 3) | 1 | 0 | 0 | 1 |
| | Supply Chain Management: An International Journal (OTM 3) | 1 | 0 | 0 | 1 |
| | Journal of the Operational Research Society (ORMS 3) | 1 | 0 | 0 | 1 |
| | Business Process Management Journal (OTM 2) | 1 | 0 | 0 | 1 |
| | IMA Journal of Management Mathematics (ORMS 2) | 0 | 0 | 1 | 1 |
| | International Journal of Computer Integrated Manufacturing (OTM 2) | 1 | 0 | 0 | 1 |
| | International Journal of Productivity and Performance Management (OTM 1) | 1 | 0 | 0 | 1 |
| | International Journal of Quality & Reliability Management (OTM 1) | 1 | 0 | 0 | 1 |

**Table B1** (*continued*)

| | Journal title | α | β | γ | All |
|---|---|---|---|---|---|
| | Journal of Manufacturing Technology Management (OTM1) | 1 | 0 | 0 | 1 |
| | Logistics Information Management (IM 1) | 1 | 0 | 0 | 1 |
| UC (Non-ABS lists) | Transactions of the Institute of Measurement and Control | 1 | 0 | 0 | 1 |
| | International Journal of Risk Assessment and Management | 0 | 0 | 1 | 1 |
| | The International Journal of Advanced Manufacturing Technology | 1 | 0 | 0 | 1 |
| | Integrated Manufacturing Systems | 1 | 0 | 0 | 1 |
| | European Journal of Engineering Education | 1 | 0 | 0 | 1 |
| | CIRP Annals-Manufacturing Technology | 1 | 0 | 0 | 1 |
| **Independent citations** | International Journal of Production Research (OTM 3) | 7 | 2 | 3 | 12 |
| | International Journal of Production Economics (OTM 3) | 4 | 0 | 3 | 7 |
| | Production Planning & Control (OTM 3) | 3 | 0 | 0 | 3 |
| | Operations Research (ORMS 4*) | 1 | 0 | 0 | 1 |
| | European Journal Of Operational Research (ORMS 4) | 2 | 0 | 0 | 2 |
| | Human Resource Management (HRMES 4) | 1 | 0 | 0 | 1 |
| | Production and operations management (ORMS 4) | 1 | 0 | 0 | 1 |
| | Transportation Research Part E: Logistics and Transportation Review (SS 3) | 0 | 1 | 0 | 1 |
| | Annals of Operations Research (ORMS 3) | 1 | 0 | 0 | 1 |
| | Journal of Scheduling (OTM 3) | 1 | 0 | 0 | 1 |
| | Journal of the Operational Research Society (ORMS 3) | 1 | 0 | 0 | 1 |
| | International Journal of Computer Integrated Manufacturing (OTM 2) | 1 | 0 | 0 | 1 |
| | Computers & Industrial Engineering(OTM 2) | 0 | 0 | 1 | 1 |
| | International Journal of Technology Management (OTM 2) | 0 | 1 | 0 | 1 |
| | Business Process Management Journal (OTM 2) | 0 | 1 | 0 | 1 |
| | Kybernetes (ORMS 1) | 1 | 0 | 1 | 2 |
| | System Dynamics Review (ORMS 2) | 1 | 0 | 0 | 1 |
| | Systems Research and Behavioral Science (ORMS 2) | 0 | 1 | 0 | 1 |
| | Journal of Manufacturing Systems (OTM 1) | 1 | 0 | 1 | 2 |
| *UC (Non-ABS lists)* | Applied Mathematical Modelling | 0 | 0 | 1 | 1 |
| | Automatica | 0 | 1 | 0 | 1 |
| | Computer Aided Chemical Engineering | 1 | 0 | 0 | 1 |
| | Computers & Chemical Engineering | 3 | 0 | 0 | 3 |
| | Economia. Seria Management | 1 | 0 | 0 | 1 |
| | IEEE transaction on neural network | 1 | 0 | 0 | 1 |
| | Industrial & Engineering Chemistry Research | 3 | 0 | 0 | 3 |
| | International Journal of Business Performance and Supply Chain Modelling | 1 | 0 | 0 | 1 |
| | International Journal of Computer Applications in Technology | 1 | 0 | 0 | 1 |
| | international Journal Of industrial engineering and production research | 1 | 0 | cc | 1 |
| | International Journal Of Industrial Engineering-Theory Applications And Practice | 1 | 0 | 0 | 1 |
| | International Journal of Modelling and Optimisation | 0 | 0 | 1 | 1 |
| | International Journal of Modelling, Identification and Control | 1 | 0 | 0 | 1 |
| | International journal of networking and virtual organizations | 1 | 0 | 0 | 1 |
| | International Journal of Quality and Service Sciences | 1 | 0 | 0 | 1 |
| | International Journal of Scientific and Engineering Research | 2 | 0 | 0 | 2 |
| | International Journal of Intelligent Enterprise | 1 | 0 | 0 | 1 |
| | International Journal of Systems Science | 1 | 1 | 0 | 2 |
| | Journal of Automation and System Engineering | 1 | 0 | 0 | 1 |
| | Journal of Global Optimisation | 1 | 0 | 0 | 1 |
| | Journal of Industrial Engineering International | 0 | 0 | 1 | 1 |
| | Journal Of Process Control | 1 | 0 | 0 | 1 |
| | Journal Of the Chinese Institute Of Chemical Engineers | 1 | 0 | 0 | 1 |
| | Journal of the Franklin Institute | 1 | 0 | 0 | 1 |
| | Jurnal Teknologi | 0 | 0 | 1 | 1 |
| | KSME international journal | 1 | 0 | 0 | 1 |
| | Logistyka | 1 | 0 | 0 | 1 |
| | Mathematical Problems In Engineering | 1 | 0 | 0 | 1 |
| | Transactions of the Institute of Measurement and Control | 1 | 0 | 0 | 1 |
| | **Total citations for Towill (1982) only** | **74 (74%)** | **9 (9%)** | **17 (17%)** | **100** |

Source: the author.

**Table B2**
Categorization of citations to John et al. (1994) only.

| | Journal title | α | β | γ | All |
|---|---|---|---|---|---|
| **Dependent citations** | International Journal of Production Economics (OTM 3) | 0 | 0 | 7 | 7 |
| *UC (0)* | International Journal of Production Research (OTM 3) | 0 | 1 | 2 | 3 |
| | Supply Chain Management: An International Journal (OTM 3) | 0 | 0 | 2 | 2 |
| | European Journal Of Operational Research (ORMS 4) | 0 | 0 | 1 | 1 |
| | International Journal of Operations & Production Management (OTM 4) | 0 | 0 | 1 | 1 |
| | Omega (ORMS 3) | 0 | 0 | 1 | 1 |
| | Transportation Research Part E: Logistics and Transportation Review (SS 3) | 0 | 1 | 0 | 1 |
| | International Journal of Physical Distribution & Logistics Management (OTM 2) | 0 | 0 | 1 | 1 |
| | Business Process Management Journal (OTM 2) | 0 | 0 | 1 | 1 |
| | The International Journal of Logistics Management (OTM 1) | 0 | 0 | 1 | 1 |
| | Journal of Manufacturing Technology Management (OTM1) | 0 | 0 | 1 | 1 |

**Table B2** (*continued*)

| | Journal title | α | β | γ | All |
|---|---|---|---|---|---|
| **Independent citations** | Logistics Information Management (IM 1) | 0 | 0 | 1 | 1 |
| | International Journal of Logistics Research and Applications (OTM 1) | 0 | 1 | 0 | 1 |
| | European Journal of Operational Research (ORMS 4) | 2 | 0 | 1 | 3 |
| | International Journal of Production Economics (OTM 3) | 0 | 0 | 2 | 2 |
| | International Journal of Production Research (OTM 3) | 0 | 1 | 1 | 2 |
| | International Journal of Physical Distribution & Logistics Management (OTM 2) | 1 | 0 | 1 | 2 |
| | Production and operations management (OTM 4) | 1 | 0 | 0 | 1 |
| | Production Planning & Control (OTM 3) | 1 | 0 | 0 | 1 |
| | IIE Transactions (ORMS 3) | 1 | 0 | 0 | 1 |
| | Expert Systems with Applications (IM 3) | 0 | 0 | 1 | 1 |
| | Journal of Purchasing and Supply Management (OTM 2) | 1 | 0 | 0 | 1 |
| | International journal of flexible manufacturing systems (OTM 1) | 1 | 0 | 0 | 1 |
| | International Journal of Logistics Research and Applications (OTM 1) | 1 | 0 | 0 | 1 |
| | Journal of Manufacturing Systems (OTM 1) | 1 | 0 | 0 | 1 |
| *UC* (*Non-ABS lists*) | Acta Technica Jaurinensis | 0 | 0 | 1 | 1 |
| | Applied Mathematical Modelling | 0 | 0 | 1 | 1 |
| | Automation Science and Engineering, IEEE Transactions on | 1 | 0 | 0 | 1 |
| | CIRP Annals-Manufacturing Technology | 2 | 0 | 0 | 2 |
| | Discrete Dynamics in Nature and Society | 0 | 0 | 1 | 1 |
| | IEEE Transactions on Automation Science And Engineering | 1 | 0 | 0 | 1 |
| | International Journal of Innovation, Management and Technology | 0 | 1 | 0 | 1 |
| | International Journal Of Innovative Computing Information And Control | 1 | 0 | 0 | 1 |
| | International Journal of Logistics Systems and Management | 1 | 0 | 0 | 1 |
| | International Journal of Manufacturing Research | 1 | 0 | 0 | 1 |
| | International Journal of Manufacturing Technology and Management | 1 | 0 | 0 | 1 |
| | International Journal of Modelling and Simulation | 1 | 0 | 0 | 1 |
| | International Journal of Simulation and Process Modelling | 1 | 0 | 2 | 3 |
| | International Journal of Systems Science | 1 | 0 | 0 | 1 |
| | The IUP Journal of Supply Chain Management | 0 | 1 | 0 | 1 |
| | Journal of Modelling in Management | 0 | 1 | 0 | 1 |
| | Latin American Applied Research | 0 | 0 | 1 | 1 |
| | Nonlinear Dynamics and Systems Theory | 1 | 0 | 0 | 1 |
| | Promet-Traffic & Transportation | 0 | 1 | 1 | 2 |
| | Siam Journal on Applied Dynamical Systems | 1 | 0 | 0 | 1 |
| | WSEAS Transactions on Systems | 0 | 0 | 1 | 1 |
| | **Total citations for John et al. (1994) only** | **23 (37%)** | **8 (12%)** | **33 (51%)** | **64** |

Source: the author.

**Table B3**
Categorization of citations to both Towill (1982) and John et al. (1994).

| | Journal title | α | β | γ | All |
|---|---|---|---|---|---|
| **Dependent citations** | International Journal of Production Economics (OTM 3) | 0 | 2 | 7 | 9 |
| *UC* (0) | European Journal of Operational Research (ORMS 4) | 1 | 1 | 2 | 4 |
| | International Journal of Production Research (OTM 3) | 1 | 0 | 3 | 4 |
| | Omega (ORMS 3) | 1 | 0 | 2 | 3 |
| | Production Planning & Control (OTM 3) | 2 | 1 | 0 | 3 |
| | Engineering Management, IEEE Transactions on (OTM3) | 0 | 0 | 1 | 1 |
| | OR Spectrum (ORMS 3) | 0 | 0 | 1 | 1 |
| | Transportation Research Part E: Logistics and Transportation Review (SS 3) | 0 | 0 | 1 | 1 |
| | Computers & Industrial Engineering (OTM 2) | 0 | 0 | 1 | 1 |
| | International Journal of Physical Distribution & Logistics Management (OTM 2) | 0 | 0 | 1 | 1 |
| | Journal of Purchasing and Supply Management (OTM 2) | 1 | 0 | 0 | 1 |
| | The International Journal of Logistics Management (OTM 1) | 0 | 1 | 0 | 1 |
| **Independent citations** | International Journal of Production Economics (OTM 3) | 2 | 1 | 3 | 6 |
| | International Journal of Production Research (OTM 3) | 1 | 0 | 3 | 4 |
| | International Journal of Physical Distribution & Logistics Management (OTM 2) | 0 | 0 | 2 | 2 |
| | International Journal of Logistics Research and Applications (OTM 1) | 0 | 0 | 2 | 2 |
| | European Journal of Operational Research (ORMS 4) | 0 | 0 | 1 | 1 |
| | Computers & Operations Research (ORMS 3) | 1 | 0 | 0 | 1 |
| | IIE Transactions (ORMS 3) | 1 | 0 | 1 | 2 |
| | Production Planning & Control (OTM 3) | 0 | 0 | 1 | 1 |
| | International Journal of Computer Integrated Manufacturing (OTM 2) | 0 | 0 | 1 | 1 |
| | Journal of Manufacturing Systems (OTM 1) | 1 | 0 | 0 | 1 |
| | International Transactions In Operational Research (ORMS 1) | 0 | 0 | 1 | 1 |
| | Journal of Manufacturing Technology Management (OTM1) | 0 | 0 | 1 | 1 |
| | Kybernetes (ORMS 1) | 1 | 0 | 0 | 1 |
| | Supply Chain Forum (OTM 1) | 0 | 0 | 1 | 1 |
| *UC* (*Non-ABS lists*) | Automatic Control, IEEE Transactions on | 1 | 0 | 0 | 1 |
| | Automation Science and Engineering, IEEE Transactions on | 1 | 0 | 0 | 1 |
| | Innovation and Supply Chain Management | 0 | 0 | 1 | 1 |
| | International Journal Of Advanced Manufacturing Technology | 1 | 0 | 1 | 2 |

**Table B3** (continued)

| Journal title | α | β | γ | All |
|---|---|---|---|---|
| International Journal of Simulation and Process Modelling | 1 | 0 | 0 | 1 |
| International Information Institute (Tokyo). Information | 0 | 1 | 0 | 1 |
| Maritime Policy & Management | 1 | 0 | 0 | 1 |
| European Journal of Industrial Engineering | 0 | 0 | 1 | 1 |
| Decision Models in Engineering and Management | 1 | 0 | 0 | 1 |
| **Total citations for both** Towill (1982) **and** John et al. (1994) | **19 (30%)** | **6 (9%)** | **39 (61%)** | **6** |

Source: the author.

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