MPhil: Thesis

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Research Topic: How big data characteristics can help the manufacturing industry mitigate the bullwhip effect in their supply chain.

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Abstract.

For years, practitioners and academics have significantly studied the impact, causes, and remedies of the bullwhip effect in the supply chain. Numerous approaches have been developed throughout the years to help minimise demand amplification; these include order batching, the bear game, and demand forecasting. The bullwhip effect phenomenon is caused by numerous disruptions in the supply chain network, such as natural disasters, shortages, overproduction, overstocking of inventory, pandemics such as COVID-19, and political issues, for example, Brexit. This study examines the potential for big data to enhance supply chain procedures and decision-making to alleviate demand amplification. In addition, the study investigates how big data characteristics might be utilised in the manufacturing sector to reduce the situation. Numerous academic publications on big data and data analytics were evaluated critically to comprehend how big data has been utilised in the supply chain to mitigate the bullwhip impact.

The researcher has developed a Simulink model to examine the supply-chain system dynamics. The first model is generic and does not incorporate any big data properties; however, the other three models incorporate big data attributes, mathematical formulas, and other factors that can be modified during model execution. The model was repeatedly simulated with random or demand data. Simultaneously, results were collected and plotted on an Excel spreadsheet and other tools to generate factual data in graphs and numbers. Meaningful results or a quantitative research approach were employed to carry out the research, while a Simulink model was used as a primary research tool. Additionally, a model was employed to generate numerical data for analysis and to achieve study objectives. The outputs of each model were analysed since they all produce different results due to their varied incorporation of features. These results assist in identifying the most beneficial aspects of big data that have the potential to minimise the bullwhip effect.

Chapter 1

1.0 Introduction

Logistics and supply chain management is increasingly digitised and reliant on information sharing to enhance operational effectiveness (Grover et al., 2018). Scholars and practitioners have suggested that supply chain complexity has increased because of globalisation, which led to digitisation and a complex network of multiple players, including manufacturers, distributors, and retailers (Chopra, 2018). Digitalisation has compelled supply chain management to reconsider its competitive approach (Zacharia et al., 2011, Oliveira and Gimeno, 2014; Chopra, 2018). However, numerous organisations aim to exploit data from various sources for competitive advantages and performance enhancement (Yadav et al., 2018).

The significance of a company's performance in coordinating business activities and sharing information has increased in today's dynamic marketplace (Chan et al., 2017). Consequently, each entity's reputation differs based on the value of the data accessible to enhance their operational activities and the organisation's overall performance (Christopher, 2020); this helps enterprises to reduce demand amplification in the supply chain (Sople, 2012).

Based on past research, scholars suggest that utilising historical data in the supply chain is crucial because it helps mitigate demand amplification while boosting inventory levels, decreasing backorders, and smoothing output (Samdantsoodol et al., 2017; Abdallah and Nabass, 2018). Therefore, organisations have resorted to investing substantial resources in the development of IT infrastructures to enhance their capabilities (Ghasemaghaei, 2019a). In addition, organisations are spending more on big data since it is viewed as the future of information analysis to reduce business risks (Wamba et al., 2015; Akter et al., 2016). Moreover, analysing vast amounts of data facilitates the development of new techniques to increase productivity (Hofmann, 2017).

However, the use of data-driven decision-making processes has been prevalent and dominating for more than three decades (Chen et al., 2012; Picciano, 2012), and the volume of data is expanding because of globalisation, the prevalence of modern mobile devices, and the internet (Amankwah-Amoah, 2016; Durahim and Cokun, 2015; Liu et al., 2016). As a result, by 2020, data amounts will reach 40 trillion gigabytes. (Gantz and Reinsel, 2012). Furthermore, McAfee et al. (2012) note that while the number of data sources continues to grow, new technologies have substantially impacted data processing efficiency.

1.1.1 Bullwhip effect

The bullwhip effect refers to the supply chain phenomenon in which orders to the supplier have a more significant variance than sales to the buyer (Wang and Disney, 2016). Furthermore, this variation propagates upstream in a magnified way (Lee, Padmanabhan, and Whang, 1997; Wang and Disney, 2016). Wu and Katok (2005) stated that the bullwhip effect relates to the increasing diversity of orders in the supply chain as one approaches the source of production. Lee, Padmanabhan, and Whang (1997) popularised the bullwhip effect and its underlying reasons among academics. According to Hendricks and Singhal (2005), organisations affected by supply chain disruptions face both depleted inventory and excess inventory. As a result, stocks and orders fluctuate because of supply chain disruptions. Variable over time, this phenomenon is also known as dynamic disruption (Sokolov and Dolgui, 2014). However, several studies have observed that no analytical model has ever measured the effects of disruption (Solano and Campos, 2014; Ivanov, Sokolov, and Dolgui, 2014). Other writers like Kleindorfer and Saad, 2005; Wu, Blackhurst, and O'Grady, 2007; Tang, 2006; Tang and Musa, 2011; Thun and Hoening, 2011, stated that no specific consensus had been achieved on what should be analysed for the successful management of disruption risks (Kern et al., 2012). Riddalls and Bennett (2002) observed that if suitable safeguards cannot be implemented swiftly for demand amplification, the supply chain system will experience severe inventory and order fluctuations.

It has been stated that existing information management practices, including information sharing, collaborative forecasting, and replenishment planning, are often employed to alleviate risks of demand amplification (Lee, Padmanabhan, and Whang, 1997). Lee et al. (1997) contends that a bullwhip's primary symptoms in the supply chain include excessive inventories, decreased customer service levels owing to backorders, inadequate capacity planning, high shipping costs, and overstocking commodities. The bullwhip effect concept was initially introduced in J. W. Forrester's book Industrial Dynamics (1961). According to Forrester, the bullwhip effect occurs when there are delays and insufficient information along a chain. In 1961, he used industrial dynamics to demonstrate that changeable demand augmented the supply chain.

Following this, a simulation titled The Beer Game was created. In 1989, Sterman concluded that the reason for demand amplification is that decision-makers act irrationally. According to Akkermans and VOS (2009), the most crucial mechanisms in a supply chain for mitigating demand amplification are the effective coordination of information between stakeholders and the capacity to establish good connections with supply chain partners throughout the network. However, (Fransoo and Wouters, 2000) assert that delays in sending demand information and delivering actual items are significant sources of demand amplification in the supply chain. In addition, the lead-time constraint increases the variance of demand data from customers to suppliers, necessitating the elimination of demand data amplification (Chen et al., 2000).

Dai, Peng, and Li (2017) noted that the upstream stakeholders' lack of real-time customer demand data (mainly manufacturers) disrupts the supply chain. However, manufacturers rely on demand signal information from upstream partners, such as wholesalers and retailers, to make production decisions (Chopra, 2018). As a result, most data are inflated, resulting in demand amplification and the bullwhip effect (Chopra, 2018).

Prior study on the bullwhip effect has focused chiefly on elucidating the phenomenon's causes: this was accomplished through teamwork and IT solutions that improved communication among supply chain partners (Nagaraja and McElroy, 2016). According to Chao (2013), inventory rationalisation, order batching, and pricing volatility are the major sources of the bullwhip effect. However, Sterman (1989), Oliveira, and Gimeno (2014) noted that this phenomenon results from delays in decision-making on orders, backorders, a lack of primary power, and production capacity. As a result, organisations have begun to recognise the significance of reducing their internal costs of production, expenses of inventory and storage facilities, and the consequences of backorders, which affect profits, customer service levels, and market share (Wang and Huang, 2011). Due to these issues, businesses began implementing just-in-time (JIT), Kanban, and lean manufacturing strategies to meet increased demand and reduce time and money spent (Chopra, 2018). The figure below depicts demand amplification from one stage of the supply chain to the next. However, because the orders are inflated, these amplifications or swings are tiny downstream and increase as we move downstream.

Demand amplification at different stages in the supply chain.

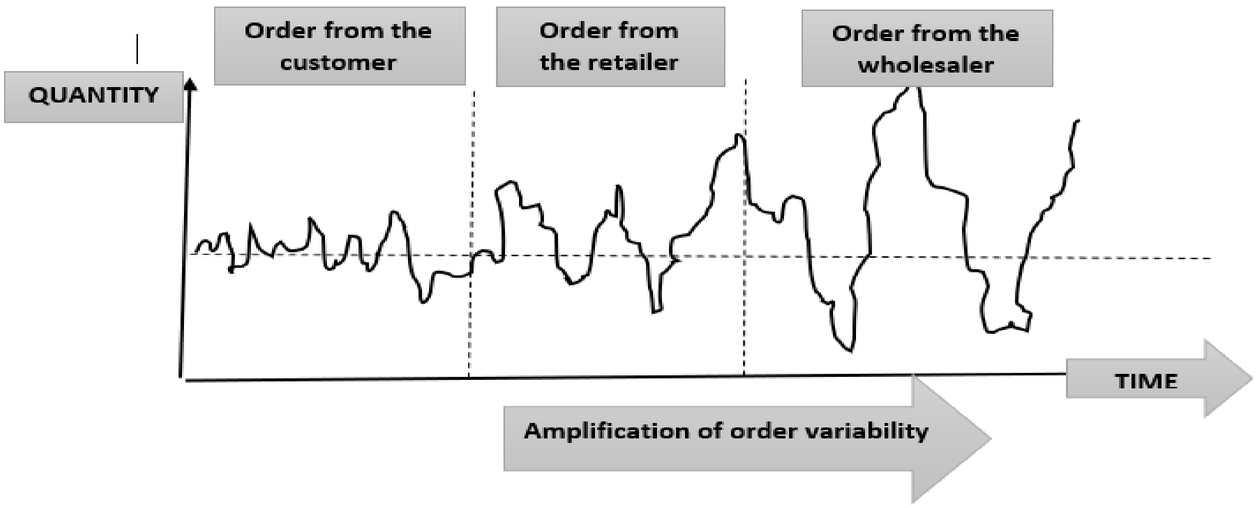


Figure 1.1: Demand amplification

Adapted from (source) - Bozarth and Handfield, 2008

According to Forrester, improved information technology, including electronic data interchange (EDI), vendor-managed inventory systems (VMI), and point-of-sale data, can assist improve the bullwhip effect (Dai, Peng, and Li, 2017). (Kristianto et al., 2012). (Wang and Huang, 2011) In addition, these logistics and supply chain technologies enable organisations to handle data and facilitate the real-time movement of information across the supply chain network.

1.1.2 Big data

Big data refers to the enormous amounts of structured and unstructured data generated daily by computers, machine sensors, and mobile devices (Oracle, 2013). Furthermore, logistics and supply chain companies today have sensors, tags, trackers, and other sophisticated devices that enable them to collect real-time data on various business activities (Schoenherr and Speier-Pero, 2015). In addition, improved IT infrastructures, such as cloud computing and virtualisation, promote the development of platforms capable of gathering, processing, and analysing massive amounts of data (Raghupathi and Raghupathi, 2014). additionally, the volume of big data continues to grow due to technological infrastructure, globalisation, and networking developments, and organisations continue to develop new ways to utilise the data (Hong, Hyoung, and Park, 2019; Chen et al., 2019, Daki et al., 2017). According to Mani et al., the quantity and complexity of big data make traditional data processing approaches challenging (2017). Furthermore, according to Makridakis (2017), large data has a mean and standard deviation and must be refined using analytic approaches.

Big data has applications in the supply chain, health sector, banking industry, government institutions, education, and security. For example, in the supply chain, big data applications have optimised big data analytics to mine new insights and generate value (Hatch and Cunliffe, 2013). According to Richey et al. (2016), data analytics can expand the volume of data used for business intelligence by utilising devices such as GSP, RFIDs, EDI, and IoT. In addition, big data analytics can be deployed to deliver supply chain insights based on the availability of specialised labour to assess the data and take the necessary steps (Sheng et al., 2017; Biswas and Sen, 2016). Raghupathi and Raghupathi (2014) observed that the medical and healthcare sectors refer to data sets with veracity, variety, and large amounts of complex data that are difficult to analyse and handle using conventional hardware to increase operational operations' efficacy. However, the ability of most organisations to utilise data is not dependent on the quantity or volume of data (Rai, 2019). Instead, its worth is defined by how well individuals can comprehend and exploit big data to gain a competitive advantage (Washington, 2014).

Practitioners believe businesses will fill the supply chain with data from several sources, such as digital streams, surveillance cameras, and social media. As a result, big data presents enormous opportunities (Wang et al., 2016; Waller and Fawcett, 2013).

However, corporations have successfully integrated big data into their operations and supply chain networks (Barker et al., 2016; Lamba and Singh, 2017); this gives them the unique opportunity to explore the effects of external factors.

1.1.3 The importance of big data

Big data has gained prominence as a source of growth and competitive advantage (Raymond et al., 2020). However, academics struggle to identify the functions that big data plays in the digitalisation of corporate operations (Saide and Sheng, 2020). However, according to Accenture (2016), academic and scientific institutions are analysing big data to uncover opportunities that have never been seen before. Additionally, businesses seek data mining and analysis technology to improve corporate performance and reduce demand amplification (Ramanathan et al., 2017). Capturing, collecting, aggregating, and analysing data is now required for firms trying to improve performance while minimising backorder risk (Lamba and Singh, 2018).

Big data could help businesses dramatically improve their entire business performance, including their demand forecasting capabilities, by enabling them to develop complex algorithms that improve the effectiveness and quality of their decision-making processes (Davenport and Harris, 2017; Ghasemaghaei and Calic, 2019a; Makridakis, 2017). According to the literature, big data is the new frontier for competition and productivity and will result in a management revolution (Wamba et al., 2015). In recent years, however, the enormous expansion of data has provided firms with a new frontier for productivity (Acharya et al., 2018; Ghasemaghaei, 2019a).

Businesses acquire large quantities of data from social networks to comprehend how their customers perceive their products. Businesses acquire large quantities of data from social networks to know how customers view their products. Therefore, large amounts of data may be processed to help firms gain a deeper understanding of consumer behaviour and boost their financial performance relative to their competitors (Brynjolfsson, Hu, and Rahman, 2013; Sun, Zhao, and Sun, 2018). Some of the acquired data contain analytical knowledge that can revolutionise corporate operations and reduce the risk of the supply chain bullwhip impact (Wamba et al., 2017). Big data is the solution, enabling organisations to monitor interrelated difficulties, sales, operational costs, and production (Daki et al., 2017). After analysing this data, organisations can govern operations and system dynamics (Wamba and Mishra, 2017). Big data, for example, can be utilised in the supply chain to track production and inventory, enabling firms to ensure they have sufficient inventory to meet demand (Ittmann, 2015).

Sakr et al. (2019) stated that novel strategies for managing, and processing data could result in high performance and scalability, enhancing operational activities and substantially reducing unforeseen risks. In addition, substantial economic development, business performance, and quality of life depend on maximising the potential benefits of huge data analysis (Office of Science and Technology Policy, 2012; Jamali and Abolhassani, 2006).

1.1.4 Big data analytics

Big data analytics is the practice of analysing vast volumes of data to uncover previously hidden patterns, correlations, market trends, and customer preferences that can help firms make informed business decisions and minimise supply chain risks. (Pehcevski, 2019; Ohlhorst, 2013). Advanced analytics is a programme that uses statistical analysis, simulations, models, data mining, and predictive analytics algorithms to address supply chain network problems (Chen et al., 2012). Dutta and Bose (2015) suggested that big data analytics could optimise and provide real-time visibility for all enterprise activities. In addition, it has generated a great deal of research to assess current ideas and enhance further improvements in demand forecasting, which helps reduce supply chain risks (Angappa, Papadopoulos, and Wamba, 2018).

Scholars believe that organisations must now concentrate on establishing non-technological resources, which includes developing big data analytics capabilities that are difficult to mimic (Davenport, 2013); this software includes advanced data simulation models. However, research has been performed to determine how big data analytics might improve disaster mitigation and recovery operations while limiting demand amplification in the supply chain (Redman, 2014). On the other hand, academics are investigating new ways to collect and gather data more efficiently while analysing it in real-time to provide businesses with valuable insight (Wamba et al., 2015; Wang, Gunasekaran, and Ngai, 2016). To monitor customer behaviour, which is vital for stakeholders, scholars and practitioners can now examine data sets and collect new data utilising point-of-sale (POS) data and electronic data interchange (EDI) (Pehcevski, 2019, Dutta and Bose, 2015). Consequently, big data analytics techniques are among the most efficient and novel approaches to addressing data-related issues (Wang et al., 2016).

The absence of earlier attempts to conceptualise these concepts has resulted in operational inefficiencies, financial loss, and demand amplification across the supply chain network (2016 IEEE International Conference on big data Analysis (ICDA), 2016). However, according to Hamister, Magazine, and Polak (2018), big data analytics needs significant expertise to evaluate diverse data architectures and infrastructure to reveal business-relevant trends, patterns, and data links (Ohlhorst, 2013). The procedure entails fast building prototypes, collecting and testing software, and validating vast quantities of data through experience (Pehcevski, 2019).

Capturing, storing, collecting, analysing, and extracting intelligence is becoming increasingly important for supply chain management to investigate internal and external environments since it gives an organisation a competitive edge (Wang, Gunasekaran, and Ngai, 2016). Consequently, big data analytics has gained popularity in industries as diverse as education, healthcare, manufacturing, and aerospace, enhancing efficiency and lowering risks (Gunasekaran et al., 2017). Wells and Sevilla (2003) state that huge volumes of data are routinely stored in ERP systems, Excel spreadsheets, and email. In addition, businesses gather data from external sources, such as trading partners, government organisations, and Google, to enhance their processes' effectiveness (Mubarik and Mohd, 2019). Therefore, big data will modify corporate processes and boost their capacity to prevent whiplash (Rai, 2019).

1.1.5 The impact of big data analytics

Existing research indicates that by analysing customer requirements, purchase history, and online behaviour, big data analytics can provide value to supply chain areas such as product development, production and information sharing to minimise supply chain risks (Wang, Gunasekaran, and Ngai, 2016; Christopher, 2020; Chopra, 2020; Tripathi, 2018; Wang et al., 2016). According to Accenture (2016), big data analytics could enable businesses to make more informed decisions by applying statistics, mathematics, econometrics, simulation models, and other technologies (Gunasekaran et al., 2017; Russom, 2011); integrating data analytics can increase transparency. However, it optimises the supply chain network, personnel, storage space, and production capacity, which could help mitigate demand amplification (Lamba and Singh, 2016; Zdrenka, 2017).

Over the years, the usage of big data analytics in the supply chain has increased significantly due to increased competitiveness, and it has helped businesses to minimise operational risks (Li et al., 2017). Queiroz and Telles, 2018; Tiwari et al., 2018; Wu et al., 2017 noted that by collecting data from numerous sources and refining it in real-time, companies could outperform competitors by utilising big data to construct analysis apps which can help organisations to reduce business risk (Wu et al., 2017). Some companies have accomplished this through customising programmes by leveraging platforms and components, enabling the system to fulfil various functions such as demand forecasting (Wang, Gunasekaran, and Ngai, 2016). However, leading third-party logistics providers, such as DHL and FEDEX, have acknowledged employing big data analytics to improve the efficiency and forecasting of their supply chains to mitigate disruption risks (Wang, Gunasekaran, and Ngai, 2016). According to Hamister, Magazine, and Polak (2018), big data analytics can also be utilised to enhance logistics storage, human resources, stock replenishment, and distribution system design.

Numerous organisations are currently utilising big data analytics to assist in integrated business planning, better comprehend market trends and consumer behaviour, and enhance business operations' agility to manage demand amplification (Wang et al., 2015). In addition, the rapid development of technologies such as the Internet, the Cloud, and the Internet of Things has enabled the creation of vast quantities of data across the supply chain network, which can subsequently be analysed using analytics (Chopra, 2018). Big data approaches enable businesses to collect and handle vast volumes of data and innovate, automate, and utilise data for enhanced decision-making, information sharing, and productivity (Gunasekaran et al., 2017). As a result, numerous organisations rely on big data analytics to assist with integrated business planning, better comprehend market trends and consumer behaviour, and boost the agility of business operations to reduce demand amplification (Wang et al., 2015). In addition, the rapid development of technologies such as the Internet, the Cloud, and the Internet of Things has enabled the supply chain network to generate vast quantities of data that can subsequently be analysed using analytics (Chopra, 2018).

The following table (Table 1.1) shows big data sources, the data types, the data quality, and its classification.

Table 1.1 Big data sources; big data type; structure, and big data quality.

Adapted from (sources): Waller and Fawcett (2013).

Sources	Data type	Structure of data	Data quality
ERP systems	Demand, sales, capacity, supply chain plans.	Structured	Medium
Barcode/RFID	Location, time, ID	Structured	High
Sensors/camera	Quality, humidity, temperature, images	Structured and unstructured	High
Archives	Financial statistics, price data	Structured	High/medium
Internet	Hits, click, streams, statistics, comments	Unstructured	Low/medium
Social network	Preference, texts, developments	Unstructured	Low

Table 1.2 Big data Classification

Adapted from (source): Waller and Fawcett (2013).

BIG DATA CLASSIFICATIONS		
Structured data	**Semi-structured data**	**Unstructured data**
Database	Emails	Videos
Excel files	Word documents	Images
Dates	Bibtex files	Media files
Numbers	XML (extensible mark-up language)	Audios
SQL database	Pdf	Web-pages
Names	Electronic data interchange	Graphics
Addresses	RDF(resource description framework)	Social media
Geolocation	HTML (hypertext mark-up language)	Live-chats

Big data analytics enables organisations to rapidly access and analyse untapped data via various platforms, some of which are publicly accessible (Hazen, Skipper, Ezell, and Boone, 2016). Internet connectivity generates infinite new company-product interactions (Papadopoulos et al., 2017). Cloud storage gives a place to store unprocessed data and boosts data accessibility (Hazen, Skipper, Ezell, and Boone, 2016). Other technologies, such as the Internet of Things, assist sensors and mobile devices in collecting data significantly.

Integrating systems help companies acquire and store massive amounts of data and analyse and visualise the data sets to reach the enhanced granularity and analytical power required for big data (Wang, Gunasekaran, and Ngai, 2016). The supply chain network can overcome the limits of legacy ERP and supply chain management by merging these technologies (Sople, 2012). Moreover, big data analytics gives the supply chain network and planning team in-depth accuracy and insights, resulting in more contextual intelligence shared across the supply chain to reduce demand amplification (Lamba and Singh, 2017). Integrating big data with big data analytics enables firms to develop a robust platform for engaging with stakeholders and minimising supply chain risks, such as waste and interruption (Mubarik and Mohd Rasi, 2019). Moreover, the same principle may be utilised to create real-time visibility, enabling firms to avoid supply chain demand amplification (Wang, Gunasekaran, and Ngai, 2016).

1.1.6 The relationship between big data and data analytics.

Big data and data analytics share several similarities in data processing and data analytics. However, big data fundamentally differs from analytics because it is complex and massive, necessitating advanced IT infrastructure and ample storage capacities for daily use (Mardani, 2013). In contrast, big data analytics is a scientific method or tool that evaluates and organises diverse data structures (Mazzei and Noble, 2019). According to Singh and El-Kassar (2019), analytics converts unstructured data into meaningful patterns and trends, which are then examined in real time for decision-making reasons.

According to Tripathi (2018), big data encompasses disciplines such as statistics, big data analytics, and big data visualisation. These disciplines help uncover valuable information that can be used to transform processes and the supply chain (a deductive approach). Big data analytics is a method or instrument for answering questions, and big data is the information that must be explored and analysed. Consequently, big data is required to employ analytical tools and skills to extract value from the data. Thus, big data analytics can help uncover and add value. Data analytics also employs various techniques and technologies to design and create reports and graphs using visualisation tools, enabling businesses to comprehend data more thoroughly (Tripathi, 2018).

1.1.7 Simulink model

Simulink is a collection of Matlab tools for producing simulation models, simulating data, and analysing system dynamics; the software offers a user interface for constructing models using block diagrams (Gao et al., 2010). Each block is controlled by several factors, including beginning initial values and ranges. It also provides an interactive, graphical environment for modelling (Mani and Pahl, 2015). Additionally, the system contains a complete library of pre-defined blocks, including complicated numerical and control theoretic computations; the software can simulate variations in demand signals, stock levels, and lead times (Kang, 2015). In addition, the application generates automatic codes and graphs about the variable demand signal or specified numbers for a given period. Management requirements will determine whether a change is necessary (Amogh et al., 2020).

A simulation is an interactive system that facilitates user access to decision models and data in support of business operations (Nguyen, Berning, and Djilali, 2004). Experiments are undertaken to simulate actual operating scenarios (Higuchi and Troutt, 2004). Among the objectives of modelling and simulation are performance evaluation and forecasting (Shannon, 1992, Axelrod, 2003). Researchers can assume the inherent complexity of organisational structures through simulation. Larson (1984) stated that simulation consists of a framework and rules that generate output based on variables.

Consequently, system dynamics (or continuous) simulation models are most suited for circumstances with many variables (Mani and Pahl, 2015; Berning and Djilali, 2004); they have been utilised to examine and analyse different inventory control systems (Larson, 1984). However, simulation has been implemented in inventory management in response to the need for a formal decision-making process that can account for the complexities and fluctuations of demand and business growth (Lewis and Foo, 1980).

A simulation model is a tool firm can use to improve the efficacy of its inventory control systems (Sinha et al., 1989). It permits constant lead times or demand levels for a particular distribution. In addition, the model examines backorders and how they should be remedied (Mani and Pahl, 2015; Badri, 1993). According to Bezivin (2005), block diagrams are the foundation for analysing Simulink models. In simulation research, data is supplied (input) into the model, and the model produces the output. The outcomes are then summarised using a frequency response plot (Mani and Pahl, 2015). First, a simulation will be run to determine the influence of characteristics of big data and additive manufacturing on the bullwhip effect. Then, the researcher will alter the inputs and conduct simulations to obtain varying results, which will be analysed and used to make inventory management operational decisions (Diouf, Maabout, and Musumbu, 2007).

A stochastic model is a system model whose behaviour is determined by one or more random variables (Sinha et al., 1989). Models are dynamic to the extent that time is an overarching factor in the model's behaviour. Similarly, to discrete event simulation, the variables describing the system's state must be defined (Thekdi and Santos, 2015). The researcher will duplicate Hofmann's Simulink model with a few modifications for a new purpose. Models are applicable to demand forecasting and related operational activities (Thekdi and Santos, 2015). They can model linear and nonlinear systems and transfer files between systems. The diagrams below (Figure 1.3) depict a Simulink model by Hofmann in which demand information (input) is supplied into the model and then simulated to analyse demand information. After that, the simulation will produce a result.

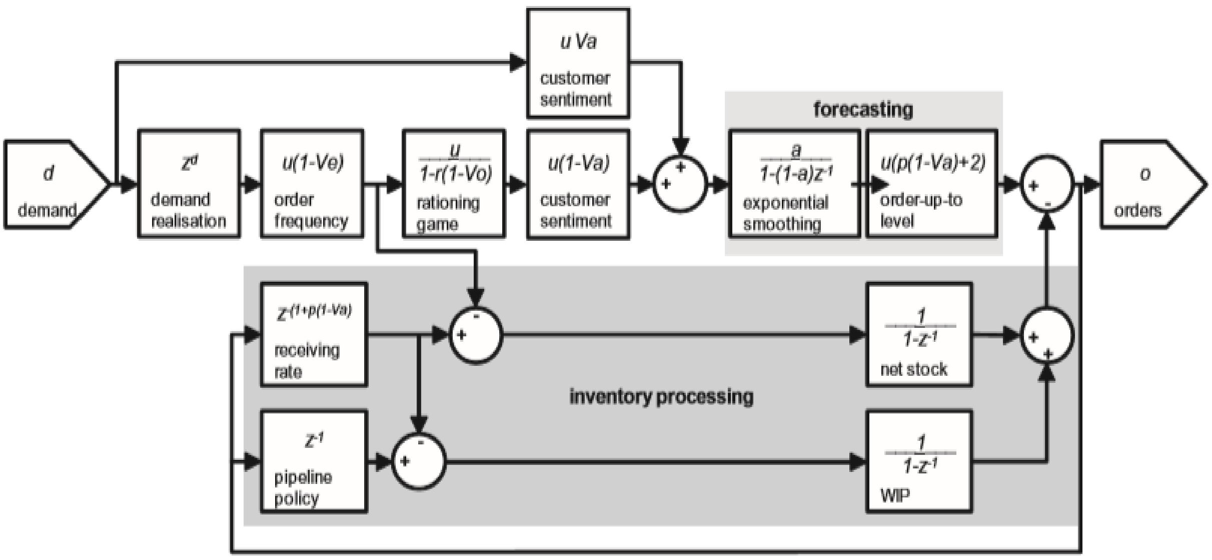


Figure 1.2. Block diagram of the Simulation model with a combination of Big Data characteristics. Adapted from (source): Erick Hofmann (2017)

1.1.8 Information sharing in the supply chain

According to Pujara and Kant (2015), sharing commercial information is at the core of supply chain collaboration because it enables businesses to enhance operational activities and customer service levels. However, attention is required to limit the risk of information distortion while communicating information (Wei and Huang, 2019). Integrating current information technology systems has enhanced the supply chain network, allowing stakeholders to coordinate and model operations to enhance corporate performance via information exchange (Wei and Huang, 2019; Ellinger et al., 2012; Yu et al., 2013; Huong Tran, Childerhouse, and Deakins, 2016). According to Roh et al. (2014), enhancing information technology infrastructure enables organisations to make supply chains more responsive to fluctuating client demands. Furthermore, when additional information becomes accessible within a supply chain, partners may profit from enhanced visibility to modify existing plans and formulate future operations (Tafti et al., 2013).

Sharing demand data, for instance, enables each supply chain participant to forecast demand accurately and prevent demand amplification (Lee et al., 2015, Mashiloane, Mafini, and Pooe, 2018). Additionally, if stakeholders share, uncertainty will be substantially reduced; these ambiguities include overstocking and backorders (Lioukas et al., 2016). In response to rising global rivalry, firms use their information integration approach to improve a smooth inventory flow throughout the supply chain (Flynn, Huo, and Zhao, 2010). However, internal integration and relationship commitment render exterior integration with consumers and suppliers subjective, according to Zhao et al. (2011).

Various forms of information are shared within a supply chain, including logistics, business, strategic, and tactical information. The procedure assists an organisation in mitigating unforeseen hazards (Chopra, 2018). For example, sharing inventory data between partners improves demand forecasting, reduces the risk of disruptions, and mitigates the "bullwhip" impact (Chinna and Madhusudanan, 2016). According to Ankersmita, Rezaeib, and Tavasszyb (2014), exchanging sales information with downstream partners enhances supply chain demand forecasting. To compete in today's global market, manufacturers must constantly develop, share, and disseminate information like sales and demand data (Singh, Garg, and Sachdeva, 2018). In addition, (Bahinipati and Deshmukh, 2012) share that sales data helps prevent orders from being messed up, reveal what customers want, and reduce losses caused by a product scarcity or surplus. Numerous companies are currently concentrating on enhancing their supply chains by implementing efficient processes and investing in human resources to obtain a competitive edge and reduce risk (Lotfi, Sahran, and Mukhtar, 2013).

However, some organisations are reticent to share information with trading partners due to perceived difficulties, risks, and costs (Kembro and Naslund, 2014). Furthermore, Tan et al. (2015) indicated that the risk associated with inter-organisational information sharing might increase as information volume increases. Many scholars and practitioners have noted that some organisations invest extensively in information technology but reap the little gain, whereas others invest comparably and have considerable success; this depends on the availability of resources to analyse the information (Lee, Johnson, & Tang, 2011).

According to Biloslavo et al. (2013) and Zhang and Cao (2016), information technology infrastructure, such as computers and telephones, is inexpensive to purchase. However, its optimal utilization has a significant benefit to organizations. Despite this, a lack of information technology implementation skills hinders the efficiency of information technology in enhancing business operations (Childerhouse and Deakins, 2016). Furthermore, it is believed that as global market competition intensifies, organizations create complex information systems to increase efficiency and capacities (Sithole, Silva, and Kavelj, 2016). Scholars contend that the issue is not with information technology but how firms use and integrate it with their strategic partners to mitigate supply chain risk (Kim & Lee, 2010). According to Roberts et al. (2012), outsourcing and collaboration in the supply chain have increased in recent years to improve efficiency.

Recent information technology developments, including web and e-commerce technologies, allow companies to share infrastructure and coordinate costs (Tallon and Pinsonneault, 2011; Lee et al., 2015), Tan et al., 2015; Chinna and Madhusudanan, (2016) noted that sharing of infrastructure between stakeholders helps improve communication processes. In addition, information in a supply chain can also help firms in various ways, such as matching products to client preferences (Ngai et al., 2011; Tallon and Pinsonneault, 2011). The extensive use of advanced information technologies in supply chains, such as electronic data interchange and Web technologies, illustrates that businesses have realized the need for information integration. However, a lack of information sharing among supply chain stakeholders leads to numerous problems (Tafti et al., 2013). The schematic below, Figure 1.2, illustrates a generic framework for supply chain management based on current literature. The demand signal runs from the customer (downstream) to the raw material suppliers (upstream), whereas the flow of commodities is in the opposite direction. Figure 1.2 demonstrates the information flow inside the supply chain.

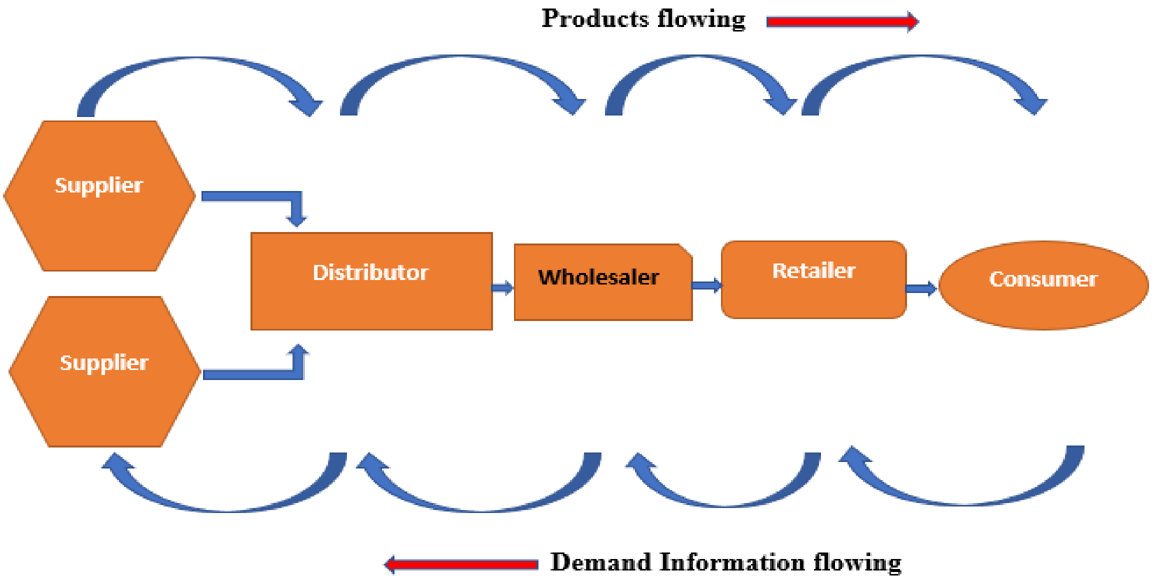


Figure 1.3: The flow of information in the supply chain

Adapted from (source) - Vrijhoef and Koskela (2000)

1.1.9 The overall aim of the research

The aim of this research is to investigate how big data can be implemented in the supply chain to mitigate the bullwhip effect.

1.2.0 Hypothesis

1. Big data and data analytics are fundamental tools to mitigate the bullwhip effect in the supply chain.
2. Operationalising a Simulink model in the supply chain can mitigate the bullwhip effect.
3. Big data and the Simulink model could help manufacturers to improve inventory levels while mitigate the bullwhip effect.

1.2.1 Research questions

1. Does big data and data analytics have the potential to mitigate the bullwhip effect?
2. What is the impact of big data on the bullwhip effect?
3. What is the relationship between big data, big data analytics and the bullwhip effect in the supply chain?

1.2.2 Research objectives

1. To develop a novel model to study the system dynamics and the bullwhip effect using big data.
2. To examine the impact of big data on bullwhip effect.
3. To explore big data optimisation methods to mitigate the bullwhip effect.

1.2.3 Conceptual framework

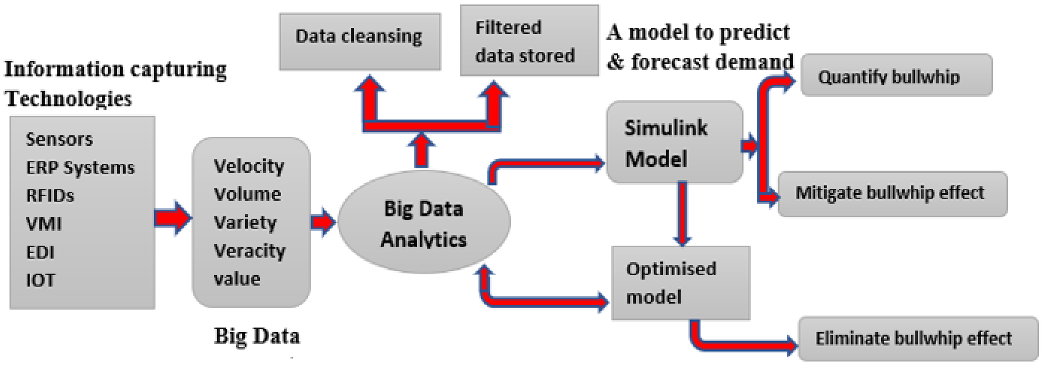


Figure 1.4: Conceptual Framework

Adapted from (source): Wang, Jie, and Abareshi (2015)

The researcher developed a conceptual framework that establishes a process flow and information flow in relation to the investigations (Shalij and Iqbal, 2016). Conceptual frameworks or models are utilised as analytical tools to enable visibility and capture actual events, it helps explain the existing knowledge, understand data to predict. A Simulink model can be used in supply chain management to simulate demand data to help examine the impact of order variations and to understand how supply chain activities can trigger demand amplification. However, independent variables are essential components that can be evaluated to understand how the system acts when variables are altered; doing so will help understand how the bullwhip effect can be mitigated by manipulating independent variables.

Figure 1.4 demonstrates how sales or demand data is utilised in the supply chain (using various technologies); capturing this requires big data qualities that are modelled using a Simulink model to analyse data. Throughout the process, data is cleansed and filtered in preparation for analysis. The conceptual framework for big data is comprised of the following five components:

1. Big data is harnessed using technologies like electronic data interchange (EDI), vendor management inventory (VMI), the Internet of Things (IoT), sensors, radio-frequency identification (RFID), and an enterprise resource planning system (ERP).
2. Big Data data analytics: Here data is analysed using different tools and methods such as Xplenty, Apache Hadoop, Cassandra, Knime, genetic algorithms, classification tree analysis, social network sentiment analysis, and regression analysis.

3. Data cleansing: data is filtered and stored for future use.
4. Simulink model: Several data simulations are performed using a Simulink model (software).
5. The results are then analysed to help make good or informed decisions to improve operational activities to mitigate the supply chain's bullwhip effect.

1.2.4 Overview of research methodologies

Existing theories and academic publications will be used to conduct this research; this will help explain the link between the variables and answer the research questions and objectives. Using existing publications to investigate the impact of big data in the supply chain helps understand the discrepancy between what has been previously achieved and the existing situation. Using a Simulink model, the researcher can increase predicting accuracy and knowledge by refining statistical data and literature (Creswell and Creswell, 2018). In contrast, external factors (orders) can be solved using a Simulink model since a model enables the researcher to construct new datasets, comprehend the system's overall behaviour, and assess the influence of big data characteristics on the bullwhip effect (Lewis, and Thornhill, 2016). Lastly, positivism is a philosophical approach in which the researcher employs observable instruments to generate law-like generalisations to gather facts (Saunders, Lewis, and Thornhill, 2016).

1.2.5 Research problem

The bullwhip effect is the most challenging phenomenon in supply chain management because it creates inefficiency, excess inventory, and supply chain interruptions (Shahabi et al., 2014). As a result of uncertainties and interruptions, organisations continue to face substantial issues with the bullwhip effect across the supply chain network. Based on business capabilities, organisations have been aided by prior research in mitigating the bullwhip impact (Lampret and Potoan, 2014). The following are some past research efforts undertaken to combat the problem. The flow of goods is managed by utilising demand forecasting tools, information exchange, the application of economic order quantity (EOQ) procedures, buffer stock, and sensors (Lampret and Potoan, 2014).

Researchers and organisations have identified the components that generate the bullwhip effect. These include demand signalling, inventory rationalisation, order batching, and price variation (Shee and Kaswi, 2015), promotions, extended lead times, information distortion, and backorders (Chen, Hu, and Yang, 2018), as well as seasonal pricing changes and backorders (Chen, Hu, and Yang, 2018). (Sterman, 1989; Croson and Donohue, 2004; Hofmann, 2017; Gattorna, Bozarth, and Handfield, 2008; Bray and Mendelson, 2013; Kristianto et al., 2012); (Sterman, 1989; Croson and Donohue, 2004; Hofmann, 2017); (Bray and Mendelson, 2013; Kristianto. These variables influence customer service, operating expenses, production, inventory levels, shipments, and investment returns.

Due to talent scarcity in the supply chain, businesses frequently outsource IT expertise. The shortage of skilled labourers affects productivity and the application of techniques to enhance the supply chain (KyungKyu and Sung, 2017). However, because most supply chain platforms do not connect, the employment of many platforms distorts supply network information (Tan, Sim, and Souza, 2014). Most earlier studies have focused on enhancing information exchange and integrating supply chain actors to lessen the bullwhip effect (Al-Odeh, 2016). Some scholarship, however, has focused on the uses of information systems (such as electronic data exchange and point-of-sale systems) (Tynjala, 2012). In addition, current methods for evaluating demand amplification did not account for incorporating big data into the simulation model to attenuate the bullwhip effect (Angappa, Papadopoulos, and Wamba, 2018; Kotevski, 2018).

Organisations that employ big data and big data analytics technology to counteract the bullwhip effect can raise their productivity by being innovative, enhancing process efficiency, enhancing customer service, and enhancing market responsiveness (Li, 2012). Additionally, some companies utilise demand forecasting tools, order batching, and rationing games to prevent demand amplification in their supply chains (Anderson, Jiang, and Shao, 2019). However, little is known about how big data can be utilised in the supply chain to lessen the bullwhip impact. Based on the limited literature on the significance of big data analytics and big data in the supply chain, a model will enable the researcher to analyse the significance and influence of big data on the bullwhip effect in the supply chain using stochastic demand data simulation (LaValle et al., 2013; Hu, 2019). In contrast, Hofmann (2017) asserts that big data can improve supply chain operations and performance, reducing the bullwhip impact.

The researcher has discovered the significance of big data and big data analytics in the supply chain for mitigating the bullwhip impact. Research on big data is essential because big data can revolutionise processes and enhance information sharing (Mishra et al., 2016). Wei and Huang (2019) and Singh and El-Kassar (2019) assert that using big data in the supply chain can result in competitive advantages and long-term capacities. According to Fosso Wamba and Akter (2019), big data and data analytics may help organisations redefine their operations, increase visibility, optimise order processing, enhance customer service, and outperform their competitors.

This paper explores the impact of big data characteristics on the bullwhip effect and the interaction between big data and data analytics in the supply chain to close a research gap. Using a Simulink simulation model, the researcher will also investigate how big data might be utilised to lessen the bullwhip effect along the supply chain. In addition, this study will examine the reasons for the bullwhip effect and demonstrate the significance of big data in the supply chain. Using stochastic demand signals, the researcher will design a novel model and include big data to examine system dynamics and the bullwhip effect; this enables the researcher to capture the system's behaviour and identify supply chain areas that need attention or change.

The simulation findings of the model will enable us to evaluate interruption risk and make informed judgments; this enables the researcher to capture the system's behaviour and identify supply chain areas that need attention or change. The simulation findings of the model will enable us to evaluate interruption risk and make informed judgments.

The study addresses a multi-echelon supply chain in which disruptions can occur at any point due to the interaction complexity of the supply chain, mainly when consumers employ different risk mitigation techniques. Motivated by a desire to explore and comprehend system dynamics and gain insight into how bullwhip effects are generated and minimised using a Simulink model, the researcher decided to investigate this topic. The research will aid the researcher in discovering and exploring new knowledge, testing, and developing existing hypotheses, and gaining new insights. The most recent investigation will help practitioners make informed judgments and mitigate the bullwhip effect. The researcher is also interested in answering research questions, analysing current theories, and employing a model to evaluate hypotheses and theories.

1.2.6 Contributions

This paper proposes an innovative, analytical, and methodological strategy for minimising the bullwhip effect through big data. Big data and big data analytics are topics of intense debate in the supply chain (Nguyen et al., 2018; Seyedan and Mafakheri, 2020). Theorists and practitioners believe that big data can be utilised to improve operations and increase supply chain efficiency, but additional research is required to gather the evidence (Wang, Gunasekaran, and Ngai, 2016; Liu et al., 2014). Despite prior research on mitigating the bullwhip impact through strategies such as (reduc[ing] lead-time, enhancing information sharing, supply chain collaboration, and supply chain integration), organisations continue to experience difficulties mitigating the bullwhip effect. Zhang and Cheng (2016); Wamba and Akter (2019). In real-time, big data will be modelled and simulated. Its influence will be analysed using a Simulink simulation model so that businesses may make educated decisions to enhance operational activities (Cigolini et al., 2014; Botha, Grobler and Yadavalli, 2017; Maulina and Natakusumah, 2020).

This project focuses on developing a new Simulink model to examine the behaviour of the bullwhip effect when big data is utilised. The model will incorporate a downstream echelon (the distributor and the retailer). In the initial stage of the model, the researcher will be able to simulate the model without using big data. This notion will help the researcher understand the bullwhip effect and its ramifications for the supply chain. In the second phase of the model, the researcher will be able to simulate random signal data utilising big data. The researcher will evaluate both models' outcomes. This concept will allow the researcher to determine how huge data affects the bullwhip effect. Simulink simulation models are utilised in numerous areas, including the manufacturing sector.

It captures the intricate interactions between vast quantities of changeable data, such as information and product flow. The researcher utilises random data since clients, primarily retailers and wholesalers, order varying quantities of restocking stock. For instance, ASDA may order 500 bottles of olive cooking oil from the manufacturer this week and 800 or 100 units of the same product the following week, based on demand.

The results from the model will give businesses an insight into how to improve their production and areas that require improvement in their supply chains to alleviate the bullwhip effect. The researcher analyses the results and trends from the simulation to gain insight into the impact of big data; these trends enable firms to make effective business decisions. The relationships and dependencies between these trends will determine whether big data can minimise demand amplification in the supply chain.

Chapter 2

2.0 Literature review

2.1.1 Demand forecasting

Demand forecasting is a supply chain operation that calculates orders based on modified numbers; the concept uses a history of previous orders from immediate customers (Oliveira and Gimeno, 2014). Therefore, when distributors or retailers employ manipulated statistics, demand information will be distorted, eventually producing demand amplification in the supply chain (Yao et al., 2007). Hofmann (2017) demonstrated that demand forecasting affects decision-making because manufacturers revise the demand prediction whenever a downstream member orders goods. As a result, the numbers will be inflated, leading to an excess of inventories. However, the final demand for the product that reaches the producer does not reflect the desire for the goods (Babai and Moon, 2011).

Due to this phenomenon, manufacturers' product scheduling, capacity planning, inventory management, and part procurement increase, resulting in multiple changes that distort information and ultimately contribute to demand amplification (Agrawal et al., 2009). Former methods for minimising the bullwhip effect concentrated mainly on mitigating the phenomena by directly accessing point-of-sale data from the downstream (retailers) (Chopra, 2020). Another method for mitigating this problem is to decrease production lead time. Based on the abovementioned problem (demand forecasting), a way to mitigate the bullwhip effect is through the big data characteristic variety. Processing historical data requires large sums of data (big data volume) from different sources and big data variety for analysis (Christopher, 2011). A large amount of processed information at high speed (velocity) will help analysts determine the problem through trends in historical data. In addition, visibility is needed so that information can be analysed in real time and decisions about production and buying raw materials can be made on time (Disney, 2006). However, firms should have advanced IT infrastructure to capture and process large amounts of data. Improving demand forecasting accuracy will help businesses (manufacturers) mitigate the bullwhip effect; it will also improve efficiency, minimise operational costs, and enhance customer service (Disney et al., 2006).

Another issue related to forecasting is that forecasting is based on aggregated figures. Previously, manufacturers were granted direct access to the downstream sales information to control the buyer's inventory (Chao, 2013; Nagaraja and McElroy, 2016). This notion made it possible for manufacturers to forecast and plan their production capacity. In addition, with vendor-managed inventory, suppliers can monitor the amount of inventory held by retailers; this eliminates the possibility of a customer having excess inventory.

Furthermore, the use of electronic data interchange (EDI) to mitigate demand amplification is more like point-of-sale data; the concept is ineffective when there is a sudden change in demand due to pandemics and population increases (Dai et al., 2017). An alternative solution to these problems is the ability to tap into big data's variety and velocity. Processing a variety of big data at high speed minimises the complexity while improving forecasting accuracy (Sun et al., 2018). Shortening the lead time was also a way of mitigating demand amplification. However, using and processing big data in various ways and at a fast pace can help manufacturers reduce the bullwhip effect and add value to their businesses.

2.1.2 Order batching

As inventory is depleted by demand, a supply chain organisation may stop continually ordering and stockpiling products from its source. Most companies order their stock monthly instead of recurring orders to reduce logistics costs (Kim et al., 2018). The manufacturing capabilities of a corporation can influence its ordering rules, capacity to manage orders, expenditures, and order processing time. As order cycles of varied clients tend to overlap randomly, the result is more inconsistent than the actual consumer demand causing the bullwhip effect (Kim et al., 2018). In addition, Metters (1997) stated that businesses always want to save operational expenses by consolidating deliveries to reduce shipping expenses. The same concept of building inventory can be generated by goods reaching their end of life, especially electronics. In the automotive industry, consumers tend to stockpile replacement parts for devices; this business model generates the bullwhip effect due to the unpredictability of demand. In addition, pandemics cause panic buying, with customers stockpiling products for personal use or resale, as was when COVID-19 was at its height (Shim et al., 2020).

The previous causes of order batching and the accumulation of bulk inventory owing to pandemics, product end-of-life, and seasonality are related to the absence of data point on-demand information (Chazan, 2012). Nevertheless, some sales are not recorded, and others are done in remote locations where businesses still rely on traditional methods of selling items and ordering stock. Order batching was therefore implemented to help clients reduce order transaction costs by consolidating inventories, increasing order frequency, and collecting more data points (Bloomberg, 2012). Nevertheless, utilising big data's variety, velocity, and veracity qualities is another method for mitigating the bullwhip effect generated by inventory accumulation (Larson and Chang, 2016).

Order batching challenges are mainly caused by forecasting based on deceptive figures, also known as exaggerated orders (Kristianto et al., 2012). As a result, the demand can either outpace production or cause overproduction. When the manufacturers fail to meet the demand due to inflated orders, buyers will order more than is required to sell the goods later, making abnormal profits (Sun et al., 2018).

The problem of order batching can be caused by a lack of enough data points in on-demand information. However, the former remedies to the problem tried to eliminate increased operational costs of order processing by increasing the cumulative order frequency and creating an extra point of sales data (Kristianto et al., 2012). Using information systems can help businesses improve the speed at which they process orders, eventually leading customers to order small amounts of inventory more quickly (Sun et al., 2018).

Suppliers should collect data from various sources (big data) and process it in real time to reduce the risk of backorders and overstock inventory for enterprises (Larson and Chang, 2016). Quickly capturing and processing data is necessary to derive value from information (big data velocity). Furthermore, the information sources should be highly dependable, and the data should be flawless and never altered or tampered with (Big data veracity). Furthermore, the capability to process big data at high velocity lessens the problem associated with order batching. It enhances frequency and customer service levels while mitigating the bullwhip effect in the supply chain (Kristianto et al., 2012). Big data velocity and variety will permit manufacturers to increase the speed at which they gather demand information for production purposes. As a result, firms can add value to their business operations by better predicting customer demand and giving better customer service. The idea enables the manufacturer to convey information from one function of the business to the other while minimising the distortion of information to mitigate the bullwhip effect (Chao, 2013).

The information's accuracy can help organisations minimise the information distortion induced by the bullwhip effect. In addition, the veracity or data accuracy concept permits organisations to rely more on reliable information sources, such as government databases (Brynjolfsson et al., 2013). Gathering and analysing historical data regarding past events such as pandemics, seasonal items, the influence of season changes, product end-of-life, inventory accumulation, and panic buying would necessitate massive data volumes (Ishwarappa and Anuradha, 2015). Large amounts of data and the rapidity with which the data is collected and analysed will give organisations a precise understanding of past occurrences. However, aspects of big data, such as velocity, can be exploited to lower the processing cost of inventory ordering. The capacity to rapidly process large data sets reduces order batching. In addition, velocity could assist clients in increasing their order frequency because every transaction will be completed in real-time, streamlining the ordering procedure (Grover et al., 2018).

2.1.3 Price fluctuation

Zabihi and Bafruei (2016) noted that distributors periodically had various schemes, promotions, and discounts to increase product sales. During such periods, the customer's buying pattern does not reflect the products' actual demand because some figures will be exaggerated (Hofmann 2017). However, this variation in buying pattern is much higher than the variation in the consumption rate. Promotions can also be an incentive to buy more than the demand requirements.

These promotions result in price fluctuations, which push the customer to buy more than required or wait for reduced prices before reordering. The concept yields temporary benefits for retailers but creates the bullwhip effect and increases costs upstream (Reimann and Ketchen, 2017). The former approach to this problem was to have sales promotions once a year for slow-moving products and have a minimum order quantity for fast-moving products.

Large volumes of data will be required to study the patterns and trends of sales resulting from promotions and discounts. These trends will help analysts develop informed decisions about mitigating the bullwhip effect (Yaqoob et al., 2016). Firms should have advanced IT infrastructure to harness information from various sources for analysis (big data variety) (Lam et al., 2017). This type of information requires agility in processing data (big data velocity). The process will help businesses understand the effects and solutions of the above problem.

2.1.4 Rationing game

The rationing game is demand forecasting based on exaggerated orders (Hofmann, 2017). When demand surpasses the production capacity, the manufacturers will not be able to meet the demand, causing the bullwhip effect in the supply chain. Therefore, manufacturers tend to allocate resources to stock their shelves based on chronological orders. As a result, the customer should order larger volumes of stocks than needed. Houlihan (1987) referred to this as "over-ordering"; by so doing, information flow is distorted, making it impossible to estimate the actual demand; supply chain practitioners argue that such business practice causes demand amplification in the supply chain (Chopra, 2018). In addition, it is believed that orders should be distributed based on historical purchasing data rather than the present orders; the notion encourages buyers to order exact quantities, reducing the customer's flexibility to exaggerate orders (Nagaraja and McElroy, 2016).

Sprague and Callarman (2010) argue that budget-driven organisations always create artificial demand, anticipating a price hike or a price reduction for the goods. As a result, the customer tends to pay more or less than the product's original price. In such cases, the bullwhip effect is visible in the form of excess inventory piling up in warehouses, poor customer service, a high cost of correction, and long waiting times for the product by the customer (Chao, 2013). Apart from price fluctuations and product rationing, forecasting, and ordering policies, significant factors affect the smooth information flow in the supply chains.

Dejonckheere et al. (2003) noted that the bullwhip effect caused by long lead times could be mitigated by reducing the lead time while sharing critical information between stakeholders. However, shorter lead times can be achieved by increasing production capacity, increasing the production line's throughput, manufacturing a few stock-keeping units (SKUs) or eliminating old SKUs from their production list.

Lee, Padmanabhan, and Whang (1997) mentioned the importance of direct marketing and eliminating intermediaries to improve the lead time. Furthermore, they also noted that the bullwhip effect could be mitigated by improving sales information flow (Lee, Padmanabhan, and Whang, 1997). This concept can be achieved through electronic data interchange systems (EDI) and the point-of-sale system (SOP); these systems provide the manufacturer access to demand or sales data.

Nagaraja and McElroy (2016) noted that demand amplification can be reduced using vendor-managed inventory systems (VMI); this business notion permits manufacturers to manage the distributors' inventory. The supplier will have direct access to demand or sales information downstream, eliminating the buyers' flexibility in the ordering process. The concept encourages customers to order quantities close to demand. Therefore, sharing production capability data and inventory levels with buyers will permit them to pre-order stocks in advance; this helps the suppliers plan their production while mitigating the bullwhip effect (Oliveira and Gimeno, 2014).

The author suggests using new sources of information presented by big data's five characteristics (the 5Vs) based on the problems presented above, the rationing game (which causes the bullwhip effect) is linked to forecasting based on exaggerated orders. This phenomenon's former approach emphasised curbing the customer's flexibility when placing orders by imposing a no-return policy and signing a contract, making exaggerated ordering impossible (Oliveira and Gimeno, 2014). Customers mainly inflate orders, hoping to get larger shares of the available stocks. The idea is to amplify demand by assigning resources based on historical sales records. Alternatively, the researcher suggests the utilisation of big data volume and big data veracity. Big data veracity refers to data accuracy, that is, data from reliable sources, and it should be pure and not tempered (Oracle, 2013). The ability to capture and process veracity data and large volumes of historical sales data from various sources helps businesses reduce the problems associated with rationing gaming (Hofmann, 2017). Processing bulky volumes of data in real-time situations can help firms make informed decisions on time.

2.1.5 Replenishment policies

Inventory replenishment is a collection of ideas, methods, and technologies that facilitate the management of the movement of stock from a central point to a downstream location to guarantee that stock continues to flow efficiently down the supply chain. Businesses can manage their inventory at various times due to replenishment procedures. Centralised or decentralised inventory management is the norm (Petrovic et al., 1999). Control is centralised within the organisation, where the decision-maker sets the optimal policy to minimise the costs of the entire supply chain. Members of the supply chain are accountable for local inventory decisions, such as replenishment decisions, under decentralised control.

Usually, decentralised control orders inventory in batches to save money on administrative processes and shipping costs; nonetheless, it generates demand amplification (Chen et al., 2016). On the other hand, a centralised replenishment strategy reduces the supply chain's total inventory cost and the danger of the bullwhip effect dramatically (Johari et al., 2018). Consequently, most manufacturers urge retailers and distributors to embrace vendor-managed inventory (VMI), which enables them to assume complete control of inventory management and potentially make replenishment decisions for customers (Rad et al., 2014; Kim and Shin, 2019). Additionally, utilising VMI in the supply chain can assist the manufacturer in precisely forecasting demand while limiting demand amplification, as VMI processes information in real-time. The main objective of inventory replenishment is:

- To avoid excessive overstock, which results in increased carrying/storage costs.
- To ensure on-time deliveries of commodities.
- To Minimize labour costs.
- To reduce stockout and slow-moving items
- To minimise distortion of information.
- To improve replenishment planning and demand forecasting.
- Maintain adequate safety/buffer stock levels.

However, there are several replenishment policies, such as periodic inventory replenishment, safety stock levels, economic order quantity, set order quantity, and periods of supply.

2.1.6 Big data veracity and the bullwhip effect

Veracity in big data refers to the reliability and consistency of the data, its significance, and confidence level based on the data source (Mishra et al., 2016). Géczy et al. (2007) noted that the veracity of big data is the quality aspect of data; this includes the correctness of the data, the truth of the data, and the elimination of precision waste. On the other note, Warthet et al. (2011) characterised big data veracity as data with limited dependability and little practical application; they stated that a company that collects data from both internal and external sources does so with limited visibility. However, data flows via several organisations and persons that can modify it using various tools and technologies. In addition, complexity emerges when large amounts of data arrive from various sources; consequently, it is necessary to link, match, cleanse, and convert data collected from these sources (Gandomi and Haider 2015). the authenticity of big data is the quality of data acquired and communicated throughout the chain. However, the quality and accuracy of the data depend on the credibility of the source; these sources can be extremely valuable for business decision-making processes, production processes, and related operational activities to prevent overstocking and backorders, which have a bullwhip effect on the supply chain (Mishra et al., 2016).

Fuzzy logic and fuzzy sets have created approaches and procedures for addressing the ambiguity and incompleteness of data (Hiba, 2020; Lamba and Singh, 2018). As a result, they will be crucial to determining how to deal with the vast ambiguity and incompleteness of big data (Kantardzic, 2011). The level of dependability that the data possesses is its veracity. Since a substantial portion of the data is unstructured and disconnected, big data must find a different approach to filter or translate it, as it is essential for business development (Sun, 2018). Conventional business intelligence solutions frequently gather data from multiple corporate systems. The collected data is structured correctly and derived from a trustworthy source system. The acquired information is cleansed and incorporated into a repository, such as a data warehouse or data mart (Owais and Hussein, 2016).

Consider the scenario in which businesses must combine structured data, such as customer information from corporate systems, with unstructured data, such as consumer emails and tweets. External data sources may not be verifiable, or the data, such as a tweet or an email, may be insufficient or deceptive (Zikopoulos, 2011). Therefore, organisations must assess the uncertainty of the data sources utilised for analysis in the decision-making process. For example, consider when a company debuts a new product and does a real-time analysis of how customers respond to it (Ghasemaghaei, 2019). Customers' views on a particular product or service can be gathered and analysed using sentiment analysis. However, the acquired data consists mainly of unstructured data such as tweets, comments, and posts from various social media networks (Anuradha and Ishwarappa, 2015). Even while real-time analysis can be a critical success factor, the number of data sources and the rate at which social media data is generated result in ambiguous and incomplete data. Therefore, before making decisions based on data analysis, it is necessary to tackle data veracity issues, such as uncertainty, incompleteness, and reliability (Owais and Hussein, 2016). Papadopoulos et al. (2017) suggested that the quality of information exchange is linked to network resilience in the supply chain, enabling organisations to establish network resilience and influence the supply chain. A suitable information system with multiple users, sharing information from diverse sources, and establishing a joint information centre can be used to evaluate the quality of information (JIC) (Chen et al., 2014; Gandomi and Haider, 2015).

For instance, sensors are utilised in numerous domains, including the Internet of Things, air quality monitoring, and weather forecasting (Anuradha & Ishwarappa, 2015). If the data supplied by these sensors is false, then analysing it will not produce a judgement that can be relied upon. Veracity refers to data biases, background noise, and outliers (Owais and Hussein, 2016; Yassin, 2014). In addition, the author stated that GSP data is more accurate and reliable for the supply chain business because businesses cannot temper with the GSP systems (Uddin et al., 2014; Lamba and Singh, 2018).

2.1.7 Importance of big data veracity

The authenticity of big data sources (big data veracity) plays a significant role because the supply chain relies on sharing vital information to minimise the risk of demand amplification. Firms have resorted to harnessing accurate data from sensors and related supply chain gadgets, including EDI and POS technologies, where data is gathered and transferred to the right people for analysis (Hiba, 2020). Analysing data from reliable sources gives businesses peace of mind and helps minimise the cost of data cleansing; it also helps businesses make informed decisions concerning their operations and production (Ristevski and Chen, 2018). Harnessing correct information from reliable sources helps improve demand forecasting (Kwon et., 2014). This data type is critical in the healthcare sector, security, banking, and other sensitive organisations. Using veracity data helps firms grow and improve sales and inventory levels. The researcher utilised a Simulink model to simulate big data veracity so that they could understand its impact on demand amplification. Finally, the results were harnessed and plotted into graphs for analysis and comparison with other big data characteristics.

2.1.8 Big data value and the bullwhip effect

Huang et al. (2017) argue that businesses sense globalisation and harness data to make the best possible business decisions. Big data has been proven to be a key business indicator and plays a pivotal role in driving value. Once companies understand the value of big data, they can reduce the increase in demand to make money (Dinov, 2016). A study by Papadopoulos et al. (2017) indicated value is created by analysing big data. Value has been referred to as the life span of data in the healthcare industry. Dinov (2016) stated that healthcare data sets' lifespan usually loses its value at an alarming rate. The value of big data refers to coherent analysis, which should be valuable to clinicians and patients. The value of data helps the supply chain network mitigate the bullwhip effect. On the other hand, low-quality data makes business operations more complicated and slows down decision-making. Lycett (2013) noted that data with errors and redundancy will not add value to organisations and may reduce business performance. Value is created through practical data analysis that employs advanced technologies to forecast demand (Ishwarappa and Anuradha, 2015; Ghasemaghaei, 2019). Supply chain value can also be created to mitigate demand amplification by sharing information in real-time (Chopra, 2018).

Mobile devices provide valuable real-time data that can be manipulated to help the manufacturing industry make informed decisions about the production and delivery of goods (Katal et al., 2013; Gandomi and Haider, 2015). These devices provide the geospatial location, demographics, and buying patterns while creating value for the supply chain. Social media also contains valuable information for businesses (Duan et al., 2019). However, big data is characterised by large volumes of data with relatively low-value density. The value of big data is unlocked only when it is leveraged to drive decision-making (Gandomi and Haider, 2015).

Businesses need effective processes to turn high volumes of fast-moving data into meaningful insights (Lycett, 2013). Firms should have the capabilities and resources to capture and process the data and make sense of it to mitigate demand amplification in the supply chain (Duan et al., 2019). Ghasemaghaei (2019) argues that data value can only be created by combining the forces of big data volume, velocity, and variety. The bullwhip effect is that big data volume, variety, and velocity are affiliated with a data value and collaborate (Ghasemaghaei, 2019). Low-quality data and data from unreliable sources (big data veracity) enhance the complexity of business operations and slow down decision-making processes throughout the organisation (Grover et al., 2018).

Singh and El-Kassar (2019) and Sanders (2014) mentioned that big data increases the firm's value when incorporated in collaboration with other organisational resources to alleviate the bullwhip effect in the supply chain network. However, it has been argued that big data analytics uses unique value creation processes to enhance business performance by improving decision-making (Sanders, 2014). Big data collected from different systems and sources must be linked to create value and meaningful information, which can be adopted to mitigate demand amplification (Duan et al., 2019). Additionally, integrating technologies with big data capabilities can create economic value and social responsibilities (Cukier and Schönberger, 2013).
Tiwari et al. (2018) noted that employing big data analytics (Simulink model) helps organisations to understand trends, patterns, and customer behaviour in the supply chain; understanding these will help to mitigate the bullwhip effect through improved decision-making. On the other hand, Zhong et al. (2016) mentioned that the value of big data is challenging to evaluate in supply chain management. Firstly, extracting value from big data is challenging because of the hurdles caused by the previous four factors. Second, examining the effects on both sectors' insights, benefits, and business processes are challenging.

Thirdly, the value of reports, statistics, and decisions obtained from big data is hard to measure due to the large influences on micro and macro perspectives (Anuradha and Ishwarappa, 2015). Large data sets are processed by industries using high-performance computing systems or technologies, and decision-makers interrogate these data for business value (Ghasemaghaei, 2019). Zikopoulos and Eton (2011) indicated that data visualisation and big data analytics are much more valuable and preferred by all businesses to help them make informed decisions and to mitigate demand amplification. However, data visualisation is the best way of converting data into meaningful information, adding value to the organisation. According to Kache and Seuring (2017), Amazon and Netflix employ big data as recommendation engines that provide client value by facilitating the search for what they need. Crowdsourcing and big data work together to answer issues such as what I can learn from other customers.

Customer behaviour is monitored in real-time and analysed to assess evidence and yield accurate results; this adds value to businesses and their customers and helps eliminate the bullwhip effect (Pellegrino and Carbonara, 2017). In addition, data analysis and modelling results are presented to the decision-makers so they can interpret the findings and extract sense and knowledge, adding more value to the business (Larson and Chang, 2016). American Airlines, Shoepassion.com, Priceline.com, and National Instruments use Datameer's big data customer analytics to improve their business operations. The tool provides an easy access point to unlock the power of Hadoop. American Airlines uses advanced analytics to gain insights from many data sources, which helped them calculate essential metrics (Wamba et al., 2018). Big data analytics helped retailers make sense of their data by optimising merchandising tactics, personalising the in-store experience with loyalty apps, and driving timely offers to attract consumers to complete purchases (Davenport, 2013). Shoepassion.com used the marketing metrics model to understand customer buying behaviour and create recommendations to mitigate the supply chain's bullwhip effect (Nagaraja and McElroy, 2016).

According to Kim et al. (2014), even though the primary tasks of businesses and governments are not in conflict, they have distinct objectives and values. The primary objective of business is to generate profits through supplying goods and services, gaining or maintaining a competitive advantage, and pleasing customers and other stakeholders by delivering value. In a competitive market with a restricted number of actors, most enterprises try to make short-term judgments. On the other hand, decision-making in government usually takes much longer. It is conducted through consultation and mutual consent of many diverse actors, including officials, interest groups, and ordinary citizens (Choi, 2013). Therefore, many well-defined steps are required to reduce risk and increase the efficiency and effectiveness of government decision-making. Chen and Zhang (2014) indicated that big data is precious to producing productivity in business and evolutionary breakthroughs in scientific disciplines, giving us many opportunities to make significant progress in many fields. As a result, big data has changed how we do business, management, and research.

According to the McKinsey Institute's report (2015), the effective use of big data has the underlying benefits of transforming economies and delivering a new wave of productive growth. Taking advantage of valuable knowledge beyond big data will become the primary competition for today's enterprises. In addition, it will create new competitors that can attract employees with critical skills in big data (Johnson et al., 2017). To capture big data's value, we must develop new techniques and technologies for analysing it (Rai, 2019). Scientists have devised numerous approaches and technologies to capture, create, analyse, and visualise big data.

These techniques and technologies span numerous fields of study, such as computer science, economics, mathematics, and statistics. Therefore, multidisciplinary methods are needed to discover valuable information from big data (Kwon et al., 2014).

It is believed that business resources help firms to achieve competitive advantages by creating bundles of strategic resources and capabilities. Resources can either be physical capital, human capital, technological capital, infrastructure and tangible or intangible When all these are combined, they will have a significant value (Gunasekaran et al., 2017). However, few studies have investigated the effect of the combination of resources and capabilities on demand amplification performance (Kwon et al., 2014). Yuan et al. (2019) mentioned that resources were combined to build capabilities and create connectivity and information sharing through different resources.

Premkumar and King (1994) defined information sharing as an organisation's capital that focuses on information flow. Furthermore, Hazen et al. (2014) argue that the utilisation of information sharing depends on data quality. However, Tiwari et al. (2018) stated that value reflects the economic benefits of big data, which can be used for mitigating the bullwhip effect in the supply chain (Forrester, 2012). Firms must acknowledge factual data and what is meaningful to be extracted for further analysis. For example, in supply chain management, Tesco has increased its operating margin while analysing big data on temperature and weather patterns, thereby conducting better forecasts of temperatures and associated changes in consumer demand (Patil and Szygenda, 2013). However, using IT and other devices in the supply chain adds value to the business.

Addo-Tenkorang and Helo (2016) indicated that the devices used in the supply chain industry help extract more value for businesses; this valuable information can be used to mitigate the bullwhip effect. In addition, these masses of data can be more valuable when analysed in real-time (visibility). The author also noted that big data analysis processing tools (cloud computing, master database, Hadoop, Cassandra, MapReduce, Pentaho, and Mahout) add value to the business. Other scholars believe that big data analysis and applications are essential tools that help big data add value to businesses (Vikaliana, 2018).

Wang et al. (2016) noted that big data is essential. It provides companies with better means to obtain value from an increasingly massive amount of data and gains a decisive competitive advantage (Chen et al., 2012). However, Kannan et al. (2018) emphasised that data is not quantitatively understood until it is used in an application; the output is evaluated for both competitive advantage and the mitigation of the bullwhip effect. Chen et al. (2012) also indicated that it is currently impossible to categorically estimate the value of firms' huge data stores.

Scholars argue that the correct data is a critical component at all decision-making stages and is a crucial part of the processing pipeline for descriptive, predictive, and prescriptive analytics, which helps the manufacturing industries mitigate the bullwhip effect (Kache and Seuring, 2017). Decision-makers are increasingly attempting to understand the value of the data they hold. It raises some fundamental questions about how the data is evaluated. However, data processing speed determines the value of data in real-time. It has been indicated that big data acquires value only when used (Wamba and Mishra, 2017). Unlike other assets, data only has an initial cost; once created, there is a marginal cost to using it in other applications. It is often created as an intermediate step in some other business process. Data has a processing cost regarding the effort involved in transforming the raw data into the application's format (Schoenherr and Speier-Pero, 2015). The value of data improves as it progresses through a processing pipeline. The same data can be used for multiple applications at different stages, improving the flow of information and reducing the need for more.

Sodhi and Tong (2010) indicated that raw data flowing across the web has limited economic value, disrupts the supply chain, and results in demand amplification. Therefore, to get value out of big data as a business, organisations should have the skill to manipulate big data sets through trained personnel and statistical and optimisation tools to have a clear insight into the data and improve operational activities. There is also a need to capture relevant data to address the fundamental problem, such as the bullwhip phenomenon. The attribute definition was derived from the International Data Center (IDC) on the definition of big data (Gantz, 2011). According to Gantz (2011), "big data technology describes a new era of technology and is designed to extract value from large-scale and diverse data through high-speed capture, discovery, and analysis techniques."The definition was widely accepted and embodied the "4V" feature of big data (volume, variety, velocity, and value) (Manyika et al., 2011; Oracle, 2012; Forrester, 2012). In addition, to emphasise the importance of data quality and the trust level in big data at a source, "veracity" was discussed and added to former definitions of big data (White, 2012).

In 2015, McKinsey Company defined big data as "a data set whose capabilities of data collection, storage, management, and analysis exceed those of a typical database software tool" (Manyika et al., 2011). Big data was also defined as large amounts of complex data being collected where traditional database management tools or data processing applications could not handle them (Fisher et al., 2012; Tseng, 2011; Lehmann and Voss, 2014). The following system definition was derived from the National Institute of Standards and Technology (NIST): "Big data refers to the data capacity; obtaining speed or representation limits the data analysis ability of traditional relational methods; and horizontal expansion mechanisms are needed to improve processing efficiency" (Tseng, 2011).

Also, many scholars and businesses discussed the definition of big data and came up with different definitions (Gandomi and Haider, 2015).

McAfee and Brynjolfsson (2012) interpreted the definition of big data from the supply chain perspective. They thought big data was a method of strengthening operations visualisation and improving enterprise performance measurement mechanisms to reconstruct decision-making processes. On the other hand, Wamba et al. (2015) believed that big data was "a holistic approach to manage, process, and analyse the 5 Vs to create action, enable insight for sustained value delivery, measure performance, and establish competitive advantages."

The bullwhip effect results from information distortion from different business functions, such as the marketing, advertising, and sales departments. This phenomenon leads to inefficiency, variabilities, excessive inventory, poor customer service, and inflected transport, labour, and storage costs (Lee, Padmanabhan, and Whang, 1997). Due to its profound impact on businesses, the bullwhip effect gained popularity, attracting researchers and scholars to unmask the myth (Dai et al., 2017). The present findings address the bullwhip effect in the supply chain, its causes, and its impact on organisations. Much attention has been paid to the subject matter, journals, and academic books. Case studies models and theories have been published over the years, but the problem still emanates from global trading standards, globalisation, procurement processes and a long supply chain. Furthermore, practitioners still lack a structured approach and a dialogue to address the problem at hand regardless of well-documented case studies (Croson and Donohue, 2003; Chatfield et al., 2004).

Zhang (2004) defined the bullwhip effect as a supply chain phenomenon where a slight change in demand from the customer results in significant variations as we move upstream. However, Kaipia et al. (2002) identified the two sources of the bullwhip effect. (1) The supplier delivery lead-time (2) The supplier's inventory levels are more significant than the market's actual demand. These factors contribute to an increase in capacity for production, resulting in higher safety stock levels. As a result, the business will be forced to make drastic decisions such as reducing prices and increasing warehouse capacity and related resources (Kaipia et al. 2002). Sahin and Robinson (2002) mentioned that demand amplification results from information distortion and long lead times, which eventually cause the Forrester effect. They also argued that seasonal sales variations, advertising, price discounts, and warehouse capacity limitations affect the demand pattern and cause the bullwhip effect.

Chen et al. (2000) stated that price discounts and related incentives attract customers to increase sales, causing the bullwhip effect to move upstream. However, these amplifications point to irrational decision-making when placing orders. Therefore, organisations are forced to modify their business model and supply chain. Zhang (2004) indicated that business managers would start analysing demand data, forecasting methods, and related trends to improve how they mitigate the bullwhip effect. However, Forrester (1961) and Sterman (1989) demonstrated that the absence of demand visibility and information distortion are sources of delay during the production process, including lead times, breakdowns, and a lack of resources to meet the demand. The pair emphasised that stakeholders must collaborate and coordinate effectively to eliminate information distortion. Collaboration helps improve the quality of demand information and minimises lead time variability.

The term "bullwhip effect" was devised by Procter and Gamble (P&G), referring to the order variance amplification phenomenon detected within its supply chain. However, Schisgall (1981) indicated that the bullwhip effect phenomenon was first documented in the 1960s. In 1958, Forrester stated that the bullwhip effect occurred due to delays and a lack of adequate information flow throughout the chain. However, in 1961, Forrester used industrial dynamics to validate variance amplification in the supply chain. He also crafted a simulation highlighting the effects of decision-making in the supply chain, known as the Beer Game. In 1989, Sterman referred to the causes of amplification as irrational behaviour caused by decision-makers. Based on these early insights, Babai et al. (2015) indicated that work backlogs and backorder variability manifest the bullwhip effect in the supply chain. It has been argued that, as the workload increases, companies increase their staff to cope with the backlogs. All the forms of delay were observed as early signs of ignorance on the part of the management team. Furthermore, Kristianto et al. (2012). stated that the interaction between workload, quality and customer expectations can amplify the bullwhip effect.

Dave and Kamal (2017) stated that big data is critical for information sharing and enables businesses to mitigate the bullwhip effect. However, most businesses find it challenging to identify the value of data because of the lack of knowledge and facilities to harness it in real-time (Ahmed et al., 2018). Kwon and Sim (2013) indicated that big data value is a crucial feature of information, defined by the added value that the gathered data can contribute to the organisation's activities and processes. However, it is not only the amount of data we process to extract valuable meaning from it. To gain insights, a large amount of trusted, reliable, and trustworthy data must be stored, processed, and analysed (Zhaohao and Sun, 2018).

Oracle introduced value as a defining attribute of big data (Gandomi and Haider, 2015). Big data is stored and analysed to improve business processes. The significance of big data depends on the organisation and the collected data.

For example, data from a person's continuous monitoring in an intensive care unit is tracked and analysed for lifesaving measures. In contrast, data generated from a wearable device can monitor walking speeds and sleeping patterns, which can be analysed for a healthy lifestyle. Data is stored and analysed for its intended purposes. Anuradha and Ishwarappa (2015) defined "big data value" as the extent to which data is collected, analysed, and used in the supply chain. Furthermore, Kaisler et al. (2013) indicated that its impact measures the value of big data to mitigate the supply chain's bullwhip effect.

Wu et al. (2016) stated that value answers the question, "Does the data contain any valuable information for my business needs?" Meanwhile, Anuradha and Ishwarappa (2015) consider value the most important aspect of big data because it helps improve processes in the supply chain. If the big data collected does not hold value, it is considered useless. Thiyagarajan and Venkatachalapathy (2014) described value as the desired outcome of big data processing. Examples of the value of big data in different organisations are: In the banking sector, big data analytics is used for fraud detection and illegal trading. In the US Food and Drug Administration (FDA), big data is used for detecting and understanding illnesses and diseases caused by food. In contrast, in retail and wholesale trading, big data is used for inventory analysis and to understand customers" shopping patterns. however, in the transportation industry, big data provides value in route planning and traffic control (Sivakumar, 2015). Wamba et al. (2015) defined value as "the extent to which big data generates economically worthy insights or benefits through extraction, and transformation international Data Corporation's (IDC) estimated revenue opportunities for the industries in 2019 are: discrete manufacturing ($22.8 billion), banking ($22.1 billion), process manufacturing ($16.4 billion), and more than $10 billion in retail, telecommunications, the federal government, and professional services.

2.1.9 Big data volume and the bullwhip effect.

Hofmann (2017) stated that volume is the ability to successfully process a large amount of data in real time, including harnessing valuable data using IT systems. In addition, he noted that businesses have access to voluminous data from various sources but lack the competence to analyse it, so the data may be utilised to mitigate disruption risk. Armours et al. (2013) emphasised the significance of organisations getting data from credible sources because some data may have been filtered and lacked validity, causing information distortion in the supply chain. However, what matters most is not the quantity of data collected but its value and effect on business operations and growth (Ghasemaghaei, 2019). Although internal and external data sources can be merged and analysed for competitive advantage (Papadopoulos et al., 2017), integrating data sources enhances the volume and value of data being processed to mitigate supply chain disruption risk (Chen and Zhang, 2014). To reduce demand amplification throughout the supply chain, a company must manage large amounts of data and act on it promptly to increase efficiency and stock levels (Garg, 2013); this can be achieved by simulating big data volume, gathering data, and analysing it.

Tiwari et al. (2018) stated that building information and computer-aided design models generate vast data in the engineering industry. By combining these systems, the industry can generate vast quantities of data that will enhance its effectiveness, procedures, and business practices. However, manufacturers collect and analyse vast amounts of data from the shop floor and other facilities; this enables the firm to improve demand forecasts, manufacturing, and other business activities such as transportation, inventory management, and storage capabilities (Singh and El-Kassar, 2019). The enormous quantity of data helps the supply chain to develop novel simulation techniques for resolving issues. It has been demonstrated that enormous volumes of data and optimisation approach aid the supply chain in understanding the complexity that impacts performance and business. Utilising large volumes of data can assist the manufacturing industry in mitigating the bullwhip effect created by overestimated orders placed by customers in anticipation of future demand. However, the manufacturing industry may also use the same data to optimise operations and make strategic decisions in real-time to prevent demand amplification (Zhang and Cheng). The probability of complexity grows when there are enormous volumes of data; hence, organisations should strengthen their IT infrastructure to increase data processing efficiency (Huang et al., 2017).

According to Kim et al. (2014), in 2002, the United States government collaborated with IBM to develop a clustered, massively scalable infrastructure for managing the real-time processing of high-volume streaming data. Therefore, IBM InfoSphere Stream and IBM Big Data Center are widely utilised by government agencies and businesses in the United States. These platforms include application development, Hadoop-based system management, stream computing, and data warehouses for discovering and visualising data from thousands of real-time sources (Wang et al., 2016).

For example, as of February 2014, the National Health Institute had accumulated hundreds of terabytes of data regarding human genetic variations on Amazon Web Services, enabling researchers to access and analyse massive volumes of data without needing to acquire supercomputing capabilities (Boone et al., 2019). Furthermore, by analysing big data sets to comprehend the trends in large data volumes, this method has helped U.S. corporations mitigate the bullwhip impact (Davenport, Barth, and Bean, 2012).

Additionally, the Internal Revenue Service has initiated the integration of big data analytics into its Return Review Program (RRP). As a result, the IRS can detect, prevent, and resolve tax evasion and fraud cases by analysing vast amounts of data (Hiba et al., 2020). Governments are also spending millions of dollars on big data-related projects; one goal is to build autonomous robotic systems (learning machines) by analysing extensive data to prevent demand amplification (Kanna, 2018). For example, the Michigan Department of Information Technology built a data warehouse to provide multiple government agencies and organisations with a single source of information about Michigan residents to improve their services (Kim, Trimi, and Chung, 2014).

The Japanese government has initiated numerous data-intensive programmes. For example, from 2005 to 2011, the Ministry of Education, Sports, Culture, Science, and Technology (MEXT) managed the New IT Infrastructure for the Information-explosion Era (so-called Info-plosion) initiative in collaboration with universities and research organisations (Hiba et al., 2020). Furthermore, since 2011, the government has prioritised resolving the consequences of the 2011 Fukushima earthquake, tsunami, and nuclear-power-plant accident, including the reconstruction and rehabilitation of affected areas and the alleviation of related social and economic effects (Pence, 2015). Analysing these data sets has helped scientists appreciate the disaster's causes, ramifications, and consequences. These insights can be utilised to mitigate supply chain interruptions and, consequently, the bullwhip effect.

Boone et al. (2019) believe that the vast quantities of data collected and analysed in near real-time can improve our understanding of consumer behaviour, increase demand forecasting, and facilitate the bullwhip effect. Big data can enhance product forecasts and identify consumer behaviour patterns. Despite these possible benefits, demand planners confront substantial difficulties. Initially, the sheer volume of data may be overwhelming. For instance, Walmart gathers millions of records daily (Davenport et al., 2012). However, the organisation analyses only 0.5% of its obtained data. Theoretically, big data and analytics lead to more accurate forecasts and less of the bullwhip effect.

Dijcks (2012) described substantial data volume as exponential information content. He stressed that the content should reflect the numerous joint distributions of the underlying processes inside the healthcare industry.

For example, considerable biological data may reflect the unknown distribution of the clinical disease of interest. By combining empirical observation data and analytic models, this concept will facilitate the proper analysis of people's clinical conditions. In contrast, Archenaa and Anita (2015) referred to enormous data quantities as significant data volumes and exponential information content. He stressed that the content should reflect the numerous joint distributions of the underlying processes inside the healthcare industry. For example, considerable biological data may reflect the unknown distribution of the clinical disease of interest. By combining empirical observation data and analytic models, this concept will facilitate the proper analysis of people's clinical conditions. Archenaa and Anita (2015) stated, however, that big data volume refers to the amount of data that can be acquired from various specialities in the medicine and healthcare sectors to assist practitioners in comprehending the causes of illness and how they can be promptly cured to save lives. Utilising data has minimised the bullwhip effect within their supply chain.

Ghasemaghaei (2019) noted that big data volume refers to the size of data, which is expanding due to globalisation and economic activity. The author claims that firms began gathering and analysing massive amounts of data to improve their knowledge and decision-making processes to limit demand amplification (Ghasemaghaei and Calic, 2019; Larson and Chang, 2016). Businesses can better comprehend customers' behaviours, products, and purchasing power by collecting vast amounts of data through social networks (Brynjolfsson, Hu, and Rahman, 2013; Sun, Zhao, and Sun, 2018). Moreover, (Géczy et al., 2012) defined "big data volume" as the quantity of data in standard information measures, which is extremely helpful for minimising demand amplification. The storage facilities and data processing processes are crucial because they enable businesses to collect as much data as possible and analyse it as necessary. To limit demand amplification, the manufacturing division will make corresponding decisions (Sun et al., 2018).

Ishwarappa and Anuradha (2015) indicated that the magnitude of big data poses a challenge to traditional IT systems. Most organisations have amassed vast amounts of data but are incapable of processing and analysing it. Nonetheless, there are various advantages to processing vast amounts of data; Bullwhip is diminished by big data analysis. In addition, organisations can make informed decisions regarding operational activities, such as stock levels and manufacturing capabilities, to minimise demand amplification in their supply chain networks (Davenport et al., 2012). However, according to Singh and El-Kassar (2019), the volume of information flows from various sources, such as sales in quantities sold, specific items sold, date and time of sale, and payment methods. Consumers also receive information regarding customer preferences, purchasing behaviour, and frequency. The quantity and location of inventory delivery are additional examples of large data volumes. These data volumes enable firms to estimate their demand and production correctly; as a result, they will cut their supply chain lead time while limiting demand amplification (Kanna, 2018).

Retailers have resorted to the use of various supply chain devices, such as radio frequency identification (RFID), beacons, and electronic data interchange (EDI), in conjunction with the Internet and information technology (IT) to harness vast amounts of data in order to combat the phenomenon of demand amplification (Wang et al., 2016). However, Wang et al. (2016) claim that a vast amount of data acquired through vendor management inventory (VMI) and electronic data interchange (EDI) assists organisations in predicting demand, reducing inventory levels, and lowering the cost of maintaining inventory. These programmes provide visibility and real-time data to enable management to make accurate judgments. In addition, integrating new data volume sources can aid an organisation in minimising demand amplification in their supply chain. On the other hand, it has been stated that enormous data volumes generate noise, high computing costs, and algorithmic instability (Dijcks, 2012).

As defined by Huang et al. (2017), big data is the collection of enormous quantities and complicated data sets from various sources. Among the sources are, to name a few, surfing history, social media, shopping history, medical records, and geolocations. The author described the volume as gigabytes to yottabytes worth of data. However, big data computers can process both structured and unstructured data, mitigating the bullwhip effect. Singh and El-Kassar (2019) noted that organisations' generation and collection of excessive data is getting more difficult for decision-makers. Businesses need to be able to process and analyse data in real-time to avoid demand amplification. Large volumes of data are seen as significant business assets due to their potential to mitigate the bullwhip effect. Despite their imperfections, imprecision, and inconsistency, large data flows challenge traditional theories and techniques (Davenport et al., 2012).

According to Papadopoulos et al. (2017), 80% of the overall data volume is unstructured. It has been demonstrated, however, that large data sets have volume-related features (the amount of data). These volumes of data may be analysed so firms can comprehend their trends, make educated decisions, and mitigate the bullwhip effect. Ristevski and Chen (2018) suggest that a vast volume of data is produced from structured, semi-structured, and unstructured sources, making it exceedingly difficult to manage client usage data. These data must be retrieved, processed, and loaded to examine customer behaviour and interaction patterns. This action is essential for businesses because it enables them to recognise the bullwhip effect before it occurs. Customer input can help businesses improve their performance (Kanna, 2018). A poll based on big data reveals their current position in the market.

According to Pramanik et al. (2017), each component of a smart city utilises large-scale data analytics to display public safety, economic growth, and traffic conditions. In addition, the author noted that the volume of healthcare data in the United States would soon surpass zettabytes (ZB).

However, the data set has a non-uniform data distribution and parallel processing, and many variables are handled inefficiently by existing analytic approaches. Consequently, an intelligent system is described as one that uses technology to sense, analyse, process, and integrate enormous quantities of useful information to limit demand amplification (Rai, 2019).

To minimise the bullwhip effect, Philip et al. (2014) asserted that big data necessitates excellent ways to efficiently analyse vast amounts of data within constrained runtimes. Reasonably, specific applications govern dig data approaches (Queiroz and Telles, 2018). For instance, Walmart uses machine learning and statistical methods to examine patterns in their vast transaction data volume (Mishra et al., 2016). These patterns can gain a competitive edge in pricing strategies and advertising efforts (Boone et al., 2019).

For instance, Taobao (a Chinese company like eBay) deploys sophisticated stream data mining techniques on users who browse recorded data on their website and extracts a substantial quantity of vital information to support their decision-making (Gunasekaran et al., 2017). As a result, businesses have been able to add value to their supply chains and reduce demand amplification due to utilising vast volumes of data. Big data techniques include statistics, data mining, machine learning, neural networks, social network analysis, signal processing, pattern identification, optimisation strategies, and visualisation approaches (Mishra et al., 2016). There are numerous data processing techniques in various disciplines, and they overlap (Mobertz, 2013).

Tiwari et al. (2018) reported that volume indicates the size of data, which has exploded in recent years. Big data can range in size from many terabytes to petabytes. Wamba et al. (2015) defined volume as a vast quantity of data that requires a tremendous amount of storage space. As the amount of data traversing the Internet each second has dramatically expanded, businesses may now work with petabytes of data in a single data set (Ghasemaghaei et al., 2017). Data from radio-frequency identification and other types of sensors used for identifying and transporting products or components, cell phone global positioning system signals, and purchase transaction records are examples of high-volume data in supply chain management (Wang et al., 2016). This data was utilised to comprehend the demand to mitigate the supply chain's bullwhip effect. For instance, Walmart is projected to collect more than 2.5 petabytes of data per hour from client transactions (McAfee and Brynjolfsson 2012).

Addo-Tenkorang and Helo (2016) argue that the overall created and copied data volumes worldwide were 1.8ZB, which then increased nine times within five years. By 2010, the world generated 1 ZB of data and 7 ZB by 2014. These massive amounts of data are retrieved in many forms, including unstructured, semi-structured, and structured data so that they can be analysed in real-time for decision-making purposes while businesses limit the bullwhip impact.

Kannan et al. (2018) stated that large amounts of data drive the development of new analytic techniques in machine learning, which increases the demand for more data for model creation and validation. In addition, the open-source domain offers a rising quantity of data sets. Consequently, those constructing data models may have access to many data sets to enhance their prediction and reduce demand amplification.

However, Gandomi and Haider (2015) stated that the amount of data is the most significant factor in big data. The research characterised the magnitude as generally variable concerning time and data type; to gain a competitive edge, it is essential to analyse and act upon the amount and rate of data generation. The data volume is applicable across all dimensions. Nonetheless, the restrictions vary based on the organisation's size, industry, and location. In addition, alterations to the supply chain result in the accumulation of data over time. Therefore, firms can still learn about the demand for their products despite the abundance of available data (Pence, 2015).

Davenport, Barth, and Bean (2012) also emphasised the significance of achieving a balance between analytical precision, the volume of incoming data, and the required processing speed. Additionally, Sun et al. (2016) mentioned that big data quantitative analysis helps firms figure out patterns and connections between different data sets to make smart decisions and stop demand from growing in supply chains. The results are used for additional numerical comparisons and operations to establish relationships. In addition, the author emphasised that qualitative analysis of extensive data relies on human input to define data patterns and linkages. Consequently, the data samples are smaller than the volume of data analysed using quantitative analysis. Ghasemaghaei and Calic (2019) define data volume as the amount of data utilised to improve existing knowledge and decision-making to mitigate the bullwhip effect. Brynjolfsson et al. (2013) and Sun et al. (2018) stated that vast amounts of data from social media may be used to comprehend how customers feel about products and services and to gain a deeper comprehension of how customers behave.

Hiba and Ruhana (2020) define data volume as the amount of data that can be stored as logs. This pair believes this data type necessitates a sophisticated IT infrastructure to manage and process massive data volumes. Furthermore, massive volumes of data threaten competitors when adequately handled and utilised since it can mitigate the bullwhip effect to increase earnings and market share. However, due to the processes, skills, and techniques necessary to derive value from massive amounts of data, analysing such data can be time-consuming (Ishwarappa and Anuradha, 2015). Hashem et al. (2015) noted that a considerable amount of data is often gathered from multiple sources; these sources should be reputable to avoid the risk of data distortion. Likewise, Cano (2014) stated that countless applications and devices, such as smartphones, sensors, and social media platforms, generate vast quantities of digital data.

However, a company's capabilities will determine its effectiveness in mining, purifying, and utilising the data to minimise disruption threats. Hashem et al. (2015) emphasised that big data volume is the amazing amount of information produced every minute from social media, cell phones, autos, credit cards, sensors, photos, videos, and so on. Therefore, businesses need the technology to store and analyse vast amounts of data to make production decisions and mitigate the bullwhip impact. In addition, some social media sites, such as Facebook and Instagram, create approximately one billion messages in a fraction of a second, and corporations can benefit from this information (Su et al., 2016).

2.2.0 Big data velocity and the bullwhip effects

According to Hofmann (2017), velocity is a company's capacity to digest data and rapidly make timely, educated decisions. In addition, the author suggested that enhanced applications increase the rate at which data may be recorded and transmitted across stakeholders to lessen the bullwhip effect. Computers manage massive data collections and process information swiftly (Cecere, 2013). As Armor et al. (2013) stated, data velocity quantifies the data production, streaming, and aggregation rate. Velocity can be implemented in various data processing locations to boost overall speed, allowing users to access the most recent data sets. According to Davenport et al. (2012), big data companies utilise real-time information from sensors, radio frequency identification (RFID), and other identifying devices to respond to changes.

Ghasemaghaei and Calic (2019b) defined velocity as the rate at which data is generated and how organisations utilise it to enhance operations. The author said that organisations utilise big data to optimise processes, adjust quickly to changes, obtain a greater understanding of the market, and boost innovation. It has been suggested. However, that velocity enables businesses to acquire current and updated data in real time. Therefore, big data velocity may be used to shorten supply chain wait times, enabling manufacturers to counteract the bullwhip impact (Sun., 2018). Dubey et al. (2019) reported that big data velocity enables organisations to increase supply chain agility and decision-making processes while minimising the bullwhip effect; furthermore, businesses utilise big data analytics as a dynamic capacity. In addition to enhancing company performance and supply chain competencies, big data and predictive analytics help boost business performance. Nonetheless, organisations are utilising big data analytics to comprehend customer behaviour by analysing purchasing patterns and trends. Its capabilities aid in accelerating complicated organisational decision-making in supply chains and surroundings. Nonetheless, businesses have begun to recognise data technology as a crucial instrument for assisting managers in detecting rapid changes and responding swiftly to limit demand amplification.

Papadopoulos et al. (2017) argued that rapid information sharing, and collaboration are crucial facilitators for the supply chain to combat misleading data. It is claimed that velocity refers to the frequency or speed with which data is generated and delivered to reduce demand amplification. The degree of a company's adaptability also depends on how rapidly it can acquire, process, and use data to its benefit. Zhong et al. (2016) stated that big data analysis necessitates rapid streaming data processing and batch analysis of already-stored data for identifying trends and patterns. It has been suggested, however, that the speed of receiving data is crucial since it enables businesses to acquire vast volumes of data quickly. In addition, Zhong et al. (2016) concurred that processing a vast amount of data from supply chain management is crucial since decisions must be made rapidly based on data.

Tiwari et al. (2018) contended that big data analysis facilitates real-time visibility for monitoring the supply chain and highlighting business areas requiring attention. The methodology also expedites the mining and analysis of data for decision-making and mitigates the bullwhip effect. However, it has been argued that real-time support offers supply chain decision-making flexibility and a higher return on investment. According to Ghasemaghaei et al. (2017), velocity is mainly affected by how quickly data is acquired, how dependable data transfer is, how well data is kept, how quickly new knowledge is discovered, and how well decision-making models and algorithm’s function. Big data typically involves vast, unstructured, diverse, and heterogeneous data collections that require speedy and adequate storage. The velocity of computing and analysis of massive amounts of data is a crucial challenge that cannot be resolved using more powerful supercomputers. Traditional sequential algorithms, concepts, and methods are inefficient for massive data sets. To lessen the bullwhip effect, new data parallelism and advanced methodologies are desirable in data processing, such as cleansing, compressing, and classifying firms (Ghasemaghaei and Calic, 2019a). The efficacy and precision of data processing are essential to the success of data analysis.

Properties of big data, such as velocity, are gathered or generated at intervals ranging from monthly to weekly to daily to hourly. An organisation's IT infrastructure controls the data set's speed, and these systems are crucial for identifying obstacles and mitigating demand amplification. Sharing their IT system with stakeholders and agents allows some organisations to collect data swiftly along the supply chain (Sivakumar, 2015). For instance, DHL is always in a superior position to know the number of goods processed each hour and their destination. This "velocity" gives them a competitive advantage in terms of transport planning, effective operations, efficiency, minimising delivery lead time, and lessening the bullwhip impact. In addition, DHL's willingness to invest in systems technology to improve its company operations has made this business model a valuable tool for identifying issues in real-time situations (Geczy, 2014).

Tiwari et al. (2018) noted that velocity is the rate at which data are generated, utilised to reduce the bullwhip effect, and the speed at which they should be analysed and acted upon (Gandomi and Haider, 2015). Data is accelerated due to the rapid expansion of digitisation, which supports real-time analytics and evidence-based planning. Since standard data management solutions are ineffective at managing enormous data sets, big data technologies serve as a safeguard by enabling businesses to generate real-time intelligence from large quantities of perishable data (Gandomi and Haider, 2015). Amazon is an example of supply chain management since it maintains a daily flux of products, suppliers, consumers, and promotions while being trustworthy (Wamba et al., 2015).

Addo-Tenkorang and Helo (2016) state that organisations must collect massive volumes of data from many sources through rapid discovery, storage, and analysis (Mayer-Schonberger and Cukier, 2013). Businesses and academics agree that technology must be enhanced year after year to meet the needs of businesses and increase their operational speed due to the increasing volume of data. It has been asserted that frequency is one of the characteristics of big data that determines how data can be collected and utilised to minimise demand amplification in supply chain networks. However, it is considered that the velocity of big data is not always constant. Instead, it is believed to be periodic, meaning that at different periods it moves at the quickest and slowest rates (Gandomi and Haider, 2015).

According to Pramanik et al. (2017), the diverse nature of big healthcare data and the speed at which it must be managed make it disastrous. The healthcare industry's big data applications have the potential to cut costs, improve services, minimise waste, increase efficiency, and streamline operations. In contrast, it assists the industry in identifying supply difficulties. Dinov (2016) refers to the velocity of big data as the vitality of integrated data archives. The author noted that the rate at which data should be obtained in the healthcare industry might substantially impact patients' responsiveness, agility, and the elimination of the "whiplash" effect. In addition, the speed at which data is collected and processed assists businesses in preventing information from being distorted.

Ristevski and Chen (2018) define big data velocity as the speed and frequency of data creation, processing, and analysis and the data in motion from various medical sector sources. The idea enables businesses to establish favourable and long-lasting partnerships for sharing business knowledge, mitigating the bullwhip effect. According to Ghasemaghaei and Calic (2019), velocity is the data collection, generation, and analysis rate. It enables businesses to recognise obstacles and take the required steps to lessen the bullwhip impact. The usage of digital devices in the supply chain, such as sensors and smartphones, increases the rate at which data can be generated, hence increasing the demand for real-time data analysis (Gandomi & Haider, 2015). The increased use of digital devices in the supply chain has resulted in a unique data generation rate inside the supply chain.

Firms should be able to upload data and exchange it in real-time within seconds so that information can spread globally. Velocity enables organisations to make formal decisions between internal and external stakeholders (Ishwarappa and Anuradha, 2005). (2015). Moreover, (Katal et al., 2013) claimed that supply chain velocity reflects the rapid rate at which data is created, mined, and analysed, allowing firms to make precise decisions on time to minimise demand amplification regarding orders, manufacturing, and other operational activities. However, the storage capacity and IT infrastructure availability required to handle data provide a problem for velocity.

Data velocity is the rate organisations capture, generate, and analyse data using various approaches to create significant value; it is also the speed with which data may be utilised in the supply chain to prevent demand amplification following the completion of analyses (Michele et al., 2020). According to scholars, data velocity is the rate at which data is produced, gathered, and analysed. The pace is governed by the organisation's IT systems and capacity to get information from dependable sources, store it, and make it accessible at a specific time. However, skills and knowledge of the data's nature are essential for business applications (Onukwugha, 2016). Manyika et al. (2018) emphasised that rapidly generated data must be processed promptly to offer value to the business. Furthermore, since data is produced rapidly, it must be analysed in real-time.

Using digital devices such as sensors and cell phones increases the data collection rate; this makes it more difficult to analyse data in real-time, becoming increasingly crucial (Gandomi and Haider, 2015). For instance, real-time analysis of consumer behaviour, such as purchasing patterns, gross income, and geolocation position, contributes to the creation of value (Ghasemaghaei and Calic, 2019).

According to Zikopoulos and Eaton (2011), velocity is the movement of data from one location to another; it is also the time taken to process the data. Some activities require an immediate response; that is why fast data processing is required. The information must be analysed and used as it streams into the business to maximise the data's value. However, Oracle (2013) argues that the velocity of data depends not just on the speed at which the data is fluxing but also on how it must be gathered, analysed, and recovered (Kwon and Sim, 2013). Primarily, the pace of data flow is determined by the availability of capable IT infrastructure, skilled labour, and data sources. Examining the information as rapidly as possible is vital to get the most out of rushed data. According to IBM (2016), a two-minute wait could be too long to detect fraud or protect human life. Therefore, a method that efficiently collects and processes data fast possesses the most sufficient and efficient computational resources. However, Fink et al. (2017) noted that business intelligence hopes to leverage big data velocity to acquire relevant data and analyse it to deliver critical information that enables rapid response for competitive advantage.

The primary objective of big data velocity is to reduce the time required to gather essential information swiftly, analyse data, and make an informed business decision (Bose and Mahapatra, 2001; Borne, 2014). Therefore, the requirement to process high-speed data more effectively is the most critical driver driving organisations to invest extensively in IT systems, particularly for industries with complicated supply chain networks, the aerospace sector, and the healthcare industry (Townsend, 2018).

According to Sathi (2013), big data velocity is connected to data throughput and latency. Throughput and velocity indicate data entering and exiting the networked systems in real-time (Betser and Belanger, 2014). According to Borne (2014), velocity is the rate at which data and information flow into and out of interconnected systems; consequently, "big data velocity" is more significant than big data volume for real-world applications (McAfee and Brynjolfsson, 2012). Furthermore, Internet systems are rarely utilised in some developing nations due to their sluggish speed. These technical issues will hinder the speed of big data. Lastly, velocity has an exceptional function compared to the other features of big data. Therefore, the most crucial aspect of large data is faster delivery when required (Zhaohao and Sun, 2018).

2.2.0 Big data variety and the bullwhip effect.

Hofmann (2017) noted that variety (Va) is a firm's ability to integrate various data sources successfully. This characteristic refers to the different kinds of sources for data that can be attained and utilised to mitigate demand amplification. Data variety indicates how text, images, video, and audio are incorporated into the data representation (Armor et al., 2013). Frank (2012) noted that a variety of big data provides value to business intelligence and helps organisations lower the risk of supply chain disruption. In this regard, Baars and Kemper (2008) investigated various options for managing structured and unstructured data in support system management. Huang (2017) defined diversity as diverse data sources used by big data analytics systems (BDAS). He/she indicated that big data might be collected from several data storages, including various data types such as databases, films, Excel sheets, and short messaging services.

Dubey (2018) asserts that competitive advantage might come from various sources. As diversity, Gandomi and Haider (2015) identified many data types and sources. The couple mentioned diversity as a structural heterogeneity (quality) inside the dataset. However, only 5% of the existing data are structured (Cukier, 2010); these strategies involve real-time usage for visibility and pre-recording and are primarily employed in call centres and supermarket CCTV cameras to monitor customer behaviour and gather other commercial intelligence. In aerospace, data from numerous sensors can be mined to evaluate aircraft performance.

In addition, Kamenov (2018) stated that visual analysis generates data from many sources and processes it for analytical objectives. According to Zhong et al. (2016), supply chain management data is typically inconsistent due to its different sources and formats. With intelligent technology, multiple sensors utilised in manufacturing facilities, roadways, retail establishments, and dwellings will produce a proliferation of new data types. Integrating such different materials into standard formats necessitates a wider and more intricate composition. Although businesses can harvest data from various sources in vast numbers, most of them cannot analyse this data.

According to Kache and Seuring (2017), Lufthansa Group, a renowned airline, use Teradata software to manage its broad sector of airlines and services and integrate data to achieve operational excellence and maximise revenue. Since they feel that money cannot be earned just from data, they built a common data language from multiple sources. However, analysing each customer's trip experience requires big data and crowdsourced analytics to comprehend its data. Singh, Shukla, and Mishra (2018) contend that big data information flows from various organisational sources and stakeholders. These include direct sales, distributors, the Internet, international, and competitors' sales. These sources are vital to minimising the bullwhip effect. For example, client data can be gathered from product reviews and demand for the product. In addition, inventory and manufacturing performance contribute to the generation of business data sets.

Boone et al. (2019) mentioned that information related to big data is compiled from numerous sources. When data is connected, it is utilised for forecasting and analysing customer behaviour. Included in these sources is user-generated content. Examples include Google Search, Facebook, Instagram, and social media platforms. Moreover, data can be collected by in-store path data using augmented reality and beacons; they track the number of people who visit the store (Gandomi and Haider 2015). Examples include Google Search, Facebook, Instagram, periodicals, and social media platforms.

Moreover, data can be acquired through in-store path data utilising augmented reality and beacons; they record the number of individuals who visit the store (Gandomi and Haider 2015). Point-of-sale data is an additional source of information exchange that allows organisations to analyse sales data for reasons of forecasting and production. However, data diversity can be utilised to mitigate demand amplification in the supply chain. Tiwari et al. (2018) concurred with Gandomi and Haider (2015) in their definition of variety as the structural heterogeneity of a data set. According to the study by Russom (2011), variety in big data is characterised by the presence of multidimensional data fields in data collected from a broader diversity of sources and formats (Wamba et al., 2015). Structured, semi-structured, and unstructured data are all utilised by businesses. For example, tabular information found in spreadsheets is structured data. However, it only accounts for 5% of the available information (Cukier, 2010).

Structured, semi-structured, and unstructured data are all utilised by businesses; structured data refers to the tabular data available in spreadsheets and accounts for only five percent of all existing data (Cukier 2010). Text, images, music, and video are more prevalent than structured data in comparison. There are no standards for semi-structured data, which exists on a continuum between structured and unstructured data. The Internet data-exchange language Extensible Markup Language (XML) is a typical example of semi-structured data (Pence, 2015). Tata Motors examines over four million monthly SMS messages in its supply chain management to help them reduce risks. These include product complaints and reminders about servicing appointments, news on new items, and customer satisfaction surveys (Wamba et al., 2015).

According to Addo-Tenkorang and Helo (2016), the supply chain industry uses a variety of data streams from several devices, such as embedded sensors, smartphones, computer systems, and computerised devices. However, these data sources make organisations difficult (Kantardzic, 2011). Among these obstacles are data analysis, standardisation, and storage. From upstream sources, several data can be extracted. Wang et al. (2016) observed that the huge amount of data collected by various supply chain devices, such as radio-frequency identification tags, mobile devices, and electronic data exchange, might be utilised for logistics planning (Swaminathan, 2012). Shipping prices, supply capacity estimates at a supplier's company, demand projections at demand points, and network capacity forecasts are all examples of logistics data sources (Najafi et al., 2013). According to the author, a large diversity of data necessitates various procedures and methodologies. The difficulties cause heterogeneity, experimental variances, and statistical biases.

Ristevski and Chen (2018) stated that the complexity and heterogeneity of multiple data sources, which can be structured, semi-structured, and unstructured, are various. Different data, on the other hand, assist firms in having a wide range of information to analyse data to make informed decisions about operational activities and avoid the bullwhip effect. Grover et al. (2018) argue that big data variety refers to the type of data, ranging from structured, unstructured, and semi-structured data. This type of data is created internally and comes from external sources. However, unstructured data comes in different formats, such as pictures, audio, and customer reviews, to mention a few. Analysis of unstructured data needs to be done by experts because the nature of the data makes it more likely that information will be misinterpreted (Del, 2016). Géczy et al. (2007) noted that various data refers to various element types within the data. The author argues that big data variety comes from different sources by using different techniques to gather demand signals from downstream (Sakr et al., 2019). Data from different sources adds richness, but it also comes with a price due to the complexities of processing and analysing the data. Therefore, the author argues that various data are essential, and it equips firms with all the necessary data about the demand.

However, according to Ishwarappa and Anuradha (2015), big data variety is the data structure; these structures depend on how data is gathered, and the devices used for capturing data. Various data helps businesses make predictions and effective decisions about operational activities and alleviate demand amplification. However, most data are unstructured, making it complicated for businesses to store, process, and analyse them (Sakr et al., 2019). Therefore, variety is also associated with big data because with such data; one must handle structured, semi-structured collectively, and unstructured data, which makes it big data. Therefore, firms can mitigate demand amplification in their supply chain using combined data and practical analysis (Katal et al., 2013).

Kim et al. (2014) emphasised that the United States initiated big data in 2009 as a move toward government transparency and accountability. As of August 2012, it is a repository including 420,894 datasets relating to transportation, the economy, health care, education, human services, and data sources for numerous applications. In 2012, however, the Obama administration announced the Big Data Research and Development Initiative, a $200 million investment involving numerous federal departments and agencies, including the White House Office of Science and Technology Policy, the National Science Foundation (NSF), the National Institutes of Health (NIH), the Department of Defense (DoD), the Defense Advanced Research Projects Agency, the Department of Energy, Health and Human Services, and the US Geological Survey (Dubey et al., 2013). The primary goals were to enhance the state-of-the-art core big data technologies, accelerate discovery in science and engineering, bolster national security, transform teaching and learning, and grow the workforce required to develop and exploit big-data technologies (Gandomi and Haider, 2015).

The EU countries and IBM started the DOME project to construct a supercomputing system capable of handling enormous data sets generated by the Square Kilometer Array (SKA) radio telescope (Troester, 2013). The project studies emerging technologies for exascale computing, data transmission and storage, and streaming analytics necessary for reading, storing, and analysing all the raw data collected daily (Geczy, 2014). Several Asian countries, including South Korea, Singapore, and Japan, received good rankings in the United Nations' 2012 E-Government Survey. Australia also ranked. These leaders have initiated varied big data efforts and implemented numerous projects: TechAmerica Foundation (2012) refers to "big data diversity" because of the heterogeneity of data kinds in text, photos, commercial transactions, social media, audio, and video. However, the majority of these are unstructured. According to Liu and Park (2014), veracity is the extent to which business leaders and organisations believe the information and its sources.

Data variety, according to Ghasemaghaei and Calic (2019), is the diversity of data kinds, which includes structured, unstructured, and semi-structured data. Structured, semi-structured, and unstructured data are the categories that Liu and Park (2014) use to describe the information types that big data can contain. While such data is available in various forms and formats, including text, sensor data, audio, video, click streams, and log files, its analysis is complicated and time-consuming. IBM, however, stated that the data exists in both organised and unorganised formats (Xu, 2013).

Big data diversity refers to the different data sources and structures from which they originated and the sorts of data available to everyone (Betser and Belanger, 2013). However, there are three sorts of big data: structured, semi-structured, and unstructured. Relational database systems, such as Oracle, store structured data. The data accessible over the Internet is unstructured. 80% of the info in the world is unstructured (Sathi, 2013). Tweets and social media are not structured data since they contain several vernacular words in a multiethnic and multilingual setting (Bakshi, 2014). Big data diversity is a formidable barrier to storage, mining, and analytics (Kumar, 2015).

Variety denotes the various data structures formed (De Mauro et al., 2015). In traditional data, the generated data is structured; however, in big data, the generated data is frequently semi-structured or unstructured, such as photos, audio, video, transactions, and log data (Owais & Hussein, 2016). For instance, the development of internet-enabled social media platforms such as Facebook, Twitter, and Instagram generate data in images (JPEG, GIF, 3D), videos, and audio files and promotes hashtags. In addition, sensors serve a variety of functions in research and industry. They generate data such as temperature, air quality, water quality, traffic speed, and the movement of commodities. Images taken from satellites for weather forecasting or surveillance, data generated for scientific studies such as tide/wave motions and earth rotation patterns, and videos generated for security and traffic purposes are examples of unstructured data (Hurwitz et al., 2013). For instance, automobile sensors produce speed, engine temperature, and fuel level data. Smartphone sensors such as the Global Positioning System (GPS) create geolocation data (Davis, 2015). In agriculture, sensors measure soil water content, soil fertility, the number of herbicides and insecticides required, and plant growth (Hurwitz et al., 2013). One use of the Internet of Things is wearable devices with sensors that create a range of data about a person, such as sleeping patterns, heart rate, walking pace, food intake, water consumed, and calories burned. In addition, in e-commerce, the customer's behaviours on the website, such as time spent, browsing pattern, and purchase history, are recorded and analysed as data (IBM, 2016).

Chapter 3

3.0 Introduction to the chapter

This chapter discusses all the elements of research methodology, including a quantitative research method, research questions, methodology flow diagram, and a Simulink model. The chapter also explains all the components of the conceptual framework and how big data properties can be implemented in the supply chain using a simulation model. This research aims to investigate how big data characteristics can be implemented in the manufacturing industry to mitigate the bullwhip effect. Additionally, the researcher developed a novel Simulink model to simulate stochastic data and analyse the impact of big data properties on demand amplification. Previous research has been conducted to help firms minimise the bullwhip demand amplification, but the problem persists. However, there is a lack of prior literature on the impact of big data on mitigating the bullwhip effect in supply chain management. Therefore, the identified research questions, research hypotheses, and objectives for this study are:

- Big data and data analytics are fundamental tools to mitigate the bullwhip effect in the supply chain.
- Operationalising a Simulink model in the supply chain can mitigate the bullwhip effect.
- Big data and the Simulink model could help manufacturers mitigate the bullwhip effect.
- Does big data and data analytics have the potential to mitigate the bullwhip effect?
- What is the impact of big data on the bullwhip effect?
- What is the relationship between big data, big data analytics and the bullwhip effect in the supply chain?
- To develop a novel model to study the system dynamics and the bullwhip effect using big data.
- To examine the impact of big data on bullwhip effect.
- To explore big data optimisation methods to mitigate the bullwhip effect.

3.1.1 Research methodology

A research methodology is a systematic framework connected to a set of paradigmatic assumptions that are used to conduct research. It is also an organised procedure for investigating a specific topic to find a solution; it outlines the processes, approaches, techniques, research procedures, and tools (Sekaran, 2000; Kothari, 2008). The approaches allowed the researcher to evaluate a study's overall credibility and scope, and they should correspond with the research objectives (Kothari, 2008; Creswell, 2011; Allan and Randy, 2005).

The researcher employed a quantitative research strategy to collect data; this technique assisted in elucidating the bullwhip effect by analysing numerical data using mathematical approaches and a Simulink model (Stafford, 2011; Saunders, Lewis, and Thornhill, 2016). Quantitative analysis techniques enable the researcher to study, present, describe, and analyse the data's correlations and trends to make predictions (Stafford, 2011; Swanson and Holton, 2005; Mohajan, 2020). Random demand data will be fed into a Simulink model, also considered a deduction tool. Quantitative research methods are appropriate when factual data are required to address research issues. For example, before collecting data for the study, broad information about viewpoints is acquired, variables are identified, defined, and linked to hypotheses (Burns and Grove, 2005), and a deductive process is employed to establish relationships between existing theories (Creswell, 2015).

The researcher utilised a Simulink model to simulate stochastic or fluctuating data to determine how the model would respond anytime there was a demand. The demand signal and simulation results will be evaluated to make an informed decision on production, distribution, and related operational operations to mitigate demand amplification. In addition, according to Savkovic and Stevanovic (2015), simulation findings aid in determining whether there are correlations between the variables.

The simulation results are then transferred to an Excel spreadsheet to generate graphs that may be used to study trends and determine the onset of demand amplification. Identifying the variables that generate the bullwhip effect can be facilitated by analysing these trends and patterns. By analysing these tendencies, the researcher can develop an experimental model that incorporates the traits and variables of large data.

The researcher will analyse and evaluate big data papers to generate recommendations and ideas for the methodologies and technologies to implement. In addition, before adopting big data as the primary data source, the researcher will perform a more in-depth investigation of the supply chain issues brought by big data, its benefits, and the technological obstacles. In conclusion, the concept will study several technologies that can be utilised to manage large volumes of data and reduce the bullwhip effect on supply chain management.

3.1.2 Research Design (RD)

A research design is a defined list of processes and standards for directing research and an organised strategy for gathering and analysing data (Heppner et al., 1992). In addition, a research design has many aspects or instruments for data collection (Lincoln and Guba, 1985), such as experiments, interviews, surveys, secondary data analysis, and observations. There are other research designs, such as exploratory, descriptive, explanatory, and evaluative (Yin, 1989). This study employs a Simulink model to mimic random input, generating factual data in graphical form. Then, these numbers, graphs, and trends are analysed to find the most beneficial qualities of big data and how they might be utilised to lessen the bullwhip impact. Using numerical and graphical data, Simulink models assist researchers in identifying supply chain solutions. Simulation results were critically examined and explained in detail, and further suggestions were made. This researcher employed stochastic demand data because when manufacturers receive orders, they all come randomly.

The researcher has adopted a research onion to steer the study; the onion depicts the numerous options, tactics, and paradigms utilised during the research process. The concepts address information sources, the growth of knowledge, and how data should be collected, processed, and used to conclude (Saunders, Lewis, and Thornhill, 20116). This methodology permits the researcher to critically evaluate a study's overall credibility and scope (Kothari, 2008; Creswell, 2011). The notion also aids the researcher in comprehending the significance of analytical instruments and data collection methods (Saunders, Lewis, and Thornhill, 2016). The diagram below depicts a research onion.

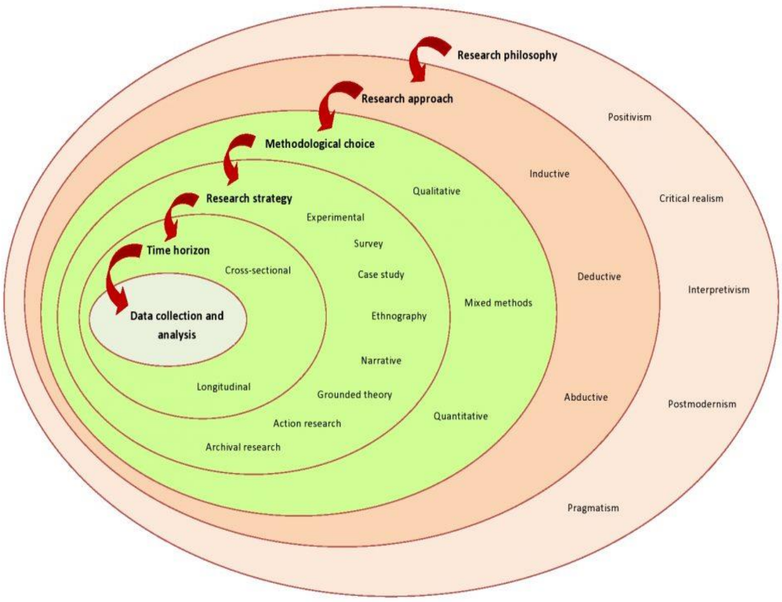


Figure 3.1: Research onion

Adapted from (sources): Saunders, Lewis, and Thornhill, 2016

3.1.3 Positivism

The method adopted in this study is positivism. Positivism uses scientific evidence such as experiments, analytical methods, and statistics to answer the research question and achieve the study's research objectives (Alexander, 2014). The concept will allow the researcher to observe the model's properties and generate new evidence and understanding (Saunders, Lewis, and Thornhill, 2016). According to Burns and Grove (2005), positivism involves constructing strict, linear, and methodical ideas based on facts. Bryman (2016) claimed that natural science studies social issues, and positivists emphasise empirical findings. This concept asserts that researchers can only get knowledge of observable and measurable phenomena.

According to Park, Konge, and Artino (2020), positivism relies on the hypothesis-deductive process to validate a priori hypotheses. Their causal and explanatory relationships with outcomes are deduced from their functional correlations. Although a deductive technique helps construct theories, the positivist paradigm identifies and explores the relationship between the components that contribute to generalisations by utilising the deductive process (Alexander, 2014; Orlikowski and Baroudi, 1990). However, the research philosophical paradigm views the researcher as an analyst and implies that the researcher is independent of the study subject (Saunders, Lewis, and Thornhill, 2016). Typically, the conclusion is observable and quantifiable, indicating that the research is founded solely on facts. Scholars claim that positivists employ existing theories to construct hypotheses that are then tested (Saunders, Lewis, and Thornhill, 2016). According to Park, Konge, and Artino (2020), positivism is predicated on a purely scientific empiricist process intended to provide objective data and facts unaffected by human interpretation or bias.

As a positivist, the researcher created a novel Simulink model to generate random demand based on numbers, patterns, and trends; the primary objective is to generate causal linkages that ultimately lead to predictions for controlling the phenomenon. This philosophical position includes producing law-like generalisations from observable social reality (Saunders, Lewis, and Thornhill, 2016). A positivist approach seeks objective truth, facts, and laws as its fundamental goal. According to Collis and Husey (2009), science observes, measures, and describes occurrences. These phenomena will be observed while independent variables are modified in real-time, and their performance is analysed for enhancement.

The researcher simulated random demand data to generate facts, including mean and standard deviation. Simulating random order data generates factual data and gives researchers insight into the system's dynamics by rendering the information meaningful. Utilising quantitative analytic methodologies permits the researcher to explore, present, describe, and investigate the data.

The researcher assumes that the properties of big data can alter the system's dynamics, significantly impacting the supply chain's whiplash effect. New theoretical work and real-time visibility using a Simulink model for analysing big data attributes' behaviour following simulation is possible. (Stafford, 2011). Quantitative approaches are empirical and represent paradigmatic thought and the formulation of laws and regulations. The Simulink model gives visibility when facts are obtained; after the data simulation, the researcher will use deductive methods to collect specific data. The facts ultimately led to interpretations and forecasts based on statistical and testable theories and assumptions. (Remenyi, 2010; Bryman, 2015).

The hypothesis will be tested by a cross-sectional analysis in which quantitative data will be gathered and analysed using deductive approaches. Diverse dig data characteristic ratios will be used to provide distinct insights that can be examined in real-time. For simulation purposes, quantitative data will likewise be created randomly, providing that directives to the upstream are also fabricated arbitrarily. This study's hypotheses will aid the researcher in gathering additional information regarding reducing demand amplification with big data. Nevertheless, positivism places the following values first:

- It states that logic of inquiry is identical across all branches of science.
- The goals must be plain, predict and discover.
- The research should be observed empirically with the human sense.
- Studies are logical and must remain free of values.
- Knowledge is arrived at by gathering facts that provide the basis for the laws.
- Theories generate hypotheses and are tested and explained by specific laws.
- Science must be conducted via an objective approach. Scientific and normative statements have a clear distinction, and the former is the actual domain of a scientist (Cooper et al., 2003).

3.1.4 Deductive approach (Research approach).

The researcher has used a Simulink model as a deductive tool; the approach helps to conclude the simulation of data. The logical method known as "top to bottom" begins with examining and evaluating current theories (academic journals and related publications from reliable sources such as government institutes). After gathering and analysing relevant data, theories are derived or refined to greater precision before formulating hypotheses. The diagram below Figure 3.1 Shows a deductive research approach and the sequence it takes.

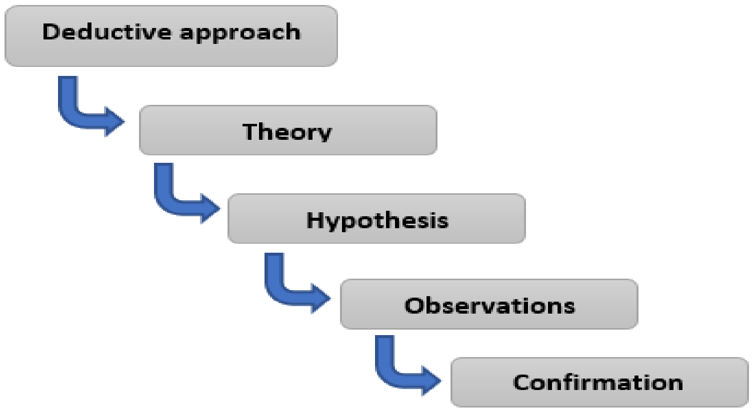


Figure 3.2: A deductive approach (sequential progression).

Adapted from (sources): Bryman (2016) and Saunders et al. (2003)

As described in the previous chapter, the researcher analysed current theories to understand the origins and issues of the bullwhip effect, the impact of big data and big data analytics, and how this could be coordinated to limit the bullwhip effect in supply chain management. The concept enables the researcher to identify research gaps and conduct a fact-based analysis of the subject. Analysing scholarly articles will serve as a strategic plan and facilitate accomplishing the study objective. Existing theories guided the study and offered a framework for the researcher (Creswell, 2011); they also helped the researcher understand the causal relationship between big data, big data analytics, and the bullwhip effect. The researcher employed a logical strategy in which the law explains the basis predicts the occurrence, and allows its control (Burns and Grove, 2005).

By simulating demand signals, the researcher employed a Simulink model to improve the accuracy of forecasting. The model can minimise the scope of the study's hypotheses using a deductive strategy. This research began with extensive data and narrowed it down to more precise information (a deductive method) by analysing and refining the data prior to hypothesis testing. A deductive approach refines rather than builds theories (Creswell and Creswell, 2018). The researcher will then gather secondary data to develop a model and simulate random data. Finally, the outcomes and patterns of the simulation are analysed and discussed to assist well-informed decision making. The variables constituting hypotheses are then defined to validate theories and build the model further.

As stated previously, the researcher seeks to construct a novel Simulink model to examine how big data qualities might be utilised in supply chain management to reduce the bullwhip impact (analytical tool). The model will aid in investigating and enabling system dynamics and efficient manufacturing processes. The researcher's system of beliefs and hypotheses on the development of knowledge can influence the anticipated results of the investigation.

To interpret this study, however, needs the application of personal knowledge and experience-based assumptions (epistemological assumptions) (Saunders, Lewis, and Thornhill, 2016; Morgan, 2016). The Simulink paradigm facilitates data creation and necessitates addressing the physical and observable nature of the problem. This will also aid the researcher in quantifying and comprehending the phenomenon.

Data collection for this study consists of measurable and numerical facts. The simulation results (dependent variable) will be observed in real-time while independent variables or demand signals are manipulated, and the facts are harnessed for analysis. The researcher detaches himself from this study, which makes him neutral or value-free. As a positivist, the researcher will depend on quantifiable observations that will lead to statistical analyses. The hypothetico-deductive method will let the researcher check a priori hypotheses, which are often stated quantitatively, where functional relationships can be found between causal and explanatory factors (independent variables) and outcomes (dependent variables).

As a positivist, the researcher will rely on empirical observations to find and examine the relationship that leads to generalisation via logical processes for constructing theories. To fulfil the study objectives, the researcher will derive hypotheses from the existing literature, developing ideas that other researchers can test. In addition, a hypothesis facilitates the testing of current information and the elimination of presumptions. This study's hypotheses will aid the researcher in gathering additional information regarding reducing demand amplification with big data. Nevertheless, positivism takes the following values into account: Since the researcher is an objectivist, his philosophical position is positivism. However, this study's data collection comprises quantifiable facts and numbers.

- It asserts that the logic of inquiry is identical across all scientific disciplines.
- The objectives must be apparent, predictable, and discoverable.
- The inquiry should be empirically seen with the human senses.
- Studies are rational and must be devoid of values.
- Knowledge is obtained by collecting facts as the basis for laws.
- Theories generate hypotheses, which are tested and explicated by specific rules.
- Science must be conducted using an objective methodology. There is a clear contrast between scientific and normative claims, with the former being the valid area of a scientist (Cooper et al., 2003).

3.1.5 Data collection tools

The researcher conducted his investigation using secondary data. The instrument enables the researcher to collect the required data for constructing a Simulink simulation model to process data, answer research questions, and accomplish the project's objectives and overarching aim. Moreover, secondary data can provide informative and cost-effective answers to various concerns (Cowton, 1998; Harris, 2001). Others collect secondary data for purposes other than research (Steward, 1992); copyright and patent restrictions do not apply to these data (Frankfort and Nachmias, 1992).

The data (secondary data) can be used to establish a baseline after an event and aid the researcher in evaluating changes and analysing lessons learnt from previous interventions (Cowton, 1998). Typically, initiatives begin with a literature review to assess the nature of the problem and examine previously addressed concerns (Alexander, 2014; Saunders, Lewis, and Thornhill, 2016). However, secondary data enables the researcher to discover the study gap in the literature and establish a baseline by analysing the information and alterations made in comparable studies (Fowler, 2014).

The researcher could comprehend system dynamics using Matlab Simulink, online articles, and textbooks. The benefit of secondary data's precision and reliability benefit (Klee, 2019). In addition, secondary data are cost-effective and reliable for comprehending the research problem (Swanson and Holton, 2005; Wong, 2014). secondary data are essential for hypothesis formation (White and Millar, 2014). Figure 3.2 depicts a Simulink library and its constituent pieces.

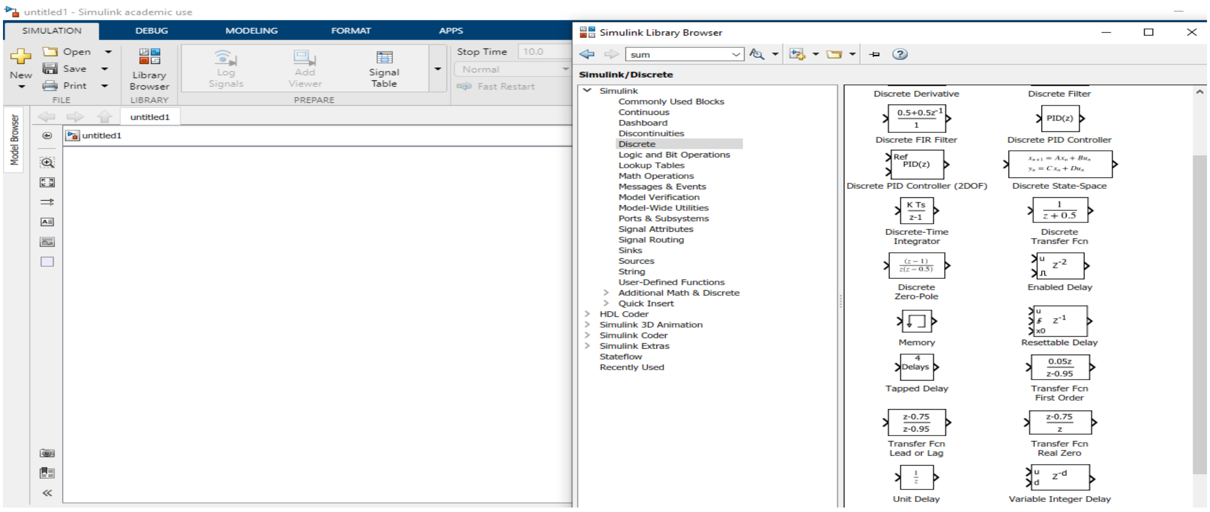


Figure 3.3: Matlab Simulink Screen

Adapted from (source): Matlab (2020 version)

The researcher developed a model consisting of multiple block diagrams to facilitate the flow of information and items from inception to delivery. The movement of information and goods from one stage of the model to the next is illustrated by arrows. In addition, running time and stop time were added to the model and adjusted by a discrete integrator or demand signal to ensure the researcher receives accurate data. The scope blocks present simulation results graphically and numerically in real time. The algorithm then transmits data to a Microsoft Excel spreadsheet for trend and pattern analysis for real-time decision-making.

The researcher utilised Microsoft Excel as it is an excellent tool for creating and plotting organised data. The tool is user-friendly and offers access to vital data (Yamane and Ito, 2017). The programme is effective and intuitive (Yamane and Ito, 2017). In addition, it allows the researcher to spread the data. The software helps develop organised data, interpret the link between variable findings, and execute studies such as predictive analysis by visualising data (Tanavalee, Luksanapruksa, and Singhatanadgige, 2016).

The researcher, in stages, constructed the model. The initial phase includes the store and the producer (no big data involved). Using a model, the researcher can examine the system dynamics and comprehend the effects of the bullwhip effect without relying on massive amounts of data. In the subsequent step, the model will contain big data; this will aid the researcher in gaining insight, becoming better informed about the dynamics, and mitigating risk in their analysis and decision-making by analysing the simulation outcome. Lastly, collecting this insight through simulation findings will aid the study in determining the impact of big data on the bullwhip effect. The model includes various segments, including (1) Simin, where orders are received, fed into the system, and processed using an integrator block; (2) the production section, where the production integrator processes orders based on the programmed time-lead; (3) the warehouse; and (4) output or delivery (5).

3.1.6 Justifying the use of the positivism approach for this study.

A positivist technique was adopted to meet the objectives of this study's research. A positivist methodology will allow the researcher to build a theoretical framework that supports him in answering the research question and reaching the overarching purpose of the research. In addition, the framework will characterise the system's dynamics and the variable that has the greatest influence on the phenomena. The framework finally links the researcher to existing information gleaned from primary data, secondary data, and published works.

The positivist researcher will employ a confirmatory strategy. Consequently, the investigation commences with hypotheses regarding the causes of the bullwhip effect and the available remedies for minimising its occurrence. In addition, the study evaluated the influence of big data journals on the supply chain. Finally, a Simulink model was utilised to test hypotheses and examine the impact of big data on the bullwhip effect (Saunders, Lewis, and Thornhill, 2016).

A positivist worldview is based on physical science and follows the scientific method of inquiry (Aliyu et al., 2014). Hughes (2001) argued that the positivist worldview considers the universe to be unchanging and governed by universal laws; the universal laws explain this. The positivist paradigm results in a scientific, methodical study approach, producing quantitative methods (Bryman, 2015). The objective of the quantitative technique is to measure, count, or determine something's size (Hughes, 2001; Bryman, 2015). Therefore, to comprehend the universal law, we must observe and record events and phenomena and then determine the underlying principles that caused them (Saunders, Lewis, and Thornhill, 2016). Nevertheless, Johnson and Genevieve (2005) emphasised that positivist researchers must adhere to accepted norms and practises. Essential features of scientific techniques include:

1. The collection of data.
2. Looking for patterns and developing theories.
3. Forming a hypothesis to test theories.
4. Researching to test the hypothesis (Coolican, 2004).

Simulation of data will help the researcher analyse the output data. At the same time, trends will aid the researcher in comprehending the most effective qualities of big data with the highest likelihood of neutralising or alleviating the bullwhip impact. In addition, by analysing patterns and results, the firm can make more informed decisions and precise demand forecasts.

Chapter 4

4.0 Developing a model.

Simulation is an essential tool to explain how supply chain performance indicators react in the face of controllable and environmental factors. Experiments can be done with different input values (demand signals) and with several simulation model structures (representing various ordering policies) (Spall, 2003). For example, Simulink simulation models may offer an idea about the causes of demand amplification, its effects on the supply, and what inputs significantly affect what outputs. In addition, simulation can help understand causality (Kelton et al. 2004). A Simulink simulation model is a computer-based, quantitative, and mathematical software (Wangphanich et al., 2010). It is a dynamic model with applications in the supply chain, manufacturing, banking, and medical industries (Stefanovic et al., 2009). It has at least one equation with at least one variable, referencing at least two different time points (for example, differential equations). Furthermore, the simulation provides a secure solution, allowing us to observe the outcomes of model input values and model structure outputs. The primary purpose of systems dynamics is to comprehend the structural factors that affect system performance (Martin, 2006).

The researcher has devised a model to investigate the system dynamics and the bullwhip impact on the supply chain; the concept aids the manufacturer in making informed decisions regarding production and inventory levels. A model may be used to simulate complex systems that exhibit chaotic behaviour; therefore, simulation must provide a more comprehensive perspective of the system (Kelton et al. 2004). According to Wangphanich et al. (2010), a model represents real-world events and can depict a system at different abstraction levels. System dynamics are the most important variables (Spall, 2003); these include inventory levels, standing orders, manufacturing capacity, data, and product flow. A model is a crucial business instrument used to manage information flow, inventory, demand forecasts, and the number of items produced. Systems dynamics govern the entire operation by adjusting the ratio of the variables (such as production and sales), so altering flows (and consequently stocks) (Law and Kelton, 2000). It provides the manufacturer with a more compiling and accessible interpretation of the model's predictions by removing obstacles to the seamless flow of operational activities (Sterman, 2000). It examines the system's dynamics and employs minute details in decision-making to lessen the whiplash impact. In addition, a model gives visual tools to find, investigate, and process complicated supply chain events (Kleijnen and Smits, 2003). The model will enable producers to examine real-time supply chain effects visually. It also clearly indicates which variables require greater attention. According to Stefanovic et al. (2009), firms can accelerate their efforts to manage, plan resources, and prevent rapid demand growth in the supply chain if they have access to this information.

The model's scalability enables the user to simulate the model and make modifications while analysing the data and getting insight into the dynamics (Campuzano et al., 2010, 2011). In addition, the model's scalability lets the user repeatedly simulate data while applying additional validation tweaks (Spall, 2003). The concept of scalability will enable the manufacturer or model users to optimise their supply chain by giving them a clear view of what occurs after the manufacturer begins accepting orders (Kleijnen, 2005). To minimise the bullwhip effect, all risks of delays and overproduction can be detected and mitigated on time. The orders are held in the integrator before being released after a sampling time correlated with the lead time. Scope blocks monitor all actions from one stage to the next, allowing manufacturers to analyse data and make operational decisions in real time (Campuzano et al., 2011).

Due to the accumulation of standing orders in the integrator, bullwhip oscillations will increase as orders and uncertainties increase exponentially. However, the standing orders trigger production swiftly so that the manufacturer can satisfy demand; before building an adequate model, the manufacturer must comprehend their supply chain issues. In addition, the model user must comprehend how to programme aspects of large data, such as demand volumes. To attain effective simulation results, the model users must understand the information flow concept to determine the model's speed (Daganzo, 2003). It is crucial to understand the impact of the system's initial values or buffer stock and its effect on standing orders to minimise the amplification. The lead times are the key areas where the manufacturers anticipate delays, which causes the bullwhip effect (Ro, Su and Chen, 2016). The challenges encountered while developing the model are:

- The selection of Simulink blocks. There is a need to understand the blocks and where to place them.
- The user should know how to manipulate blocks because using the wrong data could affect the simulation results.
- The user should know how to connect the blocks to facilitate the flow of information and goods.
- Analysing the patterns and trends within the scope can be challenging.
- Coding demand signal data can be challenging because every block has different coding.
- Incorporating big data characteristics in the model is time-consuming and confusing.
- The selection of Simulink blocks can be challenging. Some blocks are for other applications.
- The user should understand the impact of using wrong information when manipulating the blocks.

Using wrong blocks will lead to severe problems such as increased operational costs, overproduction, inventory shortages and delays (Campuzano et al., 2011). All these factors will trigger the bullwhip effect. However, the objective of a supply chain simulation is:

- To improve the supply chain's operational processes, identify the stages where the bullwhip effect starts occurring so that measures are taken on time.
- To develop and validate improvements.
- Reproducing and testing different decision-based alternatives. Determining a priori the level of optimisation and robustness of a strategy without interrupting the real supply chain.
- Quantifying benefits. In general, simulation is important because it could help quantify the benefits resulting from the supply chain management supporting decision making at the strategic decision level.

4.1.1 Basic model

The notions made in the model are derived from the following information: The observed supply chain network encompasses a single retailer and a single manufacturer. The retailer orders goods in different quantities at different time intervals. The manufacturer's lead time is strictly observed as a company policy, which determines production capacity and the initial stock levels. The customer is always informed of the lead time to improve customer service levels while reducing the risk of information distortion in the supply chain; this concept encourages customers to order stock on time and avoid stockouts. The manufacturer only has one production line to fulfil the orders. Production throughput (the speed at which the production line runs) can be adjusted depending on the demand volumes, but there is a risk of breakdowns. Due to the company policy and the nature of the goods, the manufacturer can only afford to stock limited volumes per SKU (buffer stock). The distortion of information is one of the factors that cause delays, long lead-time and production breakdowns, a lack of storage space, and demand amplification (Otto and Kotzab, 2003).

Retailers closely monitor their stock levels and will eventually place new orders when their inventory levels reach a safe stock level. However, the manufacturer uses different big data techniques to improve operational performance and mitigate the bullwhip effect; this includes demand forecasting and rationing game. Replacing the former ordering process, such as rationing games and demand forecasting, enables manufacturers to reduce the retailer's flexibility to exaggerate orders (Daganzo, 2003, Melo et al., 2009). The diagram below, Figure 4.1, illustrates the first stage of the model.

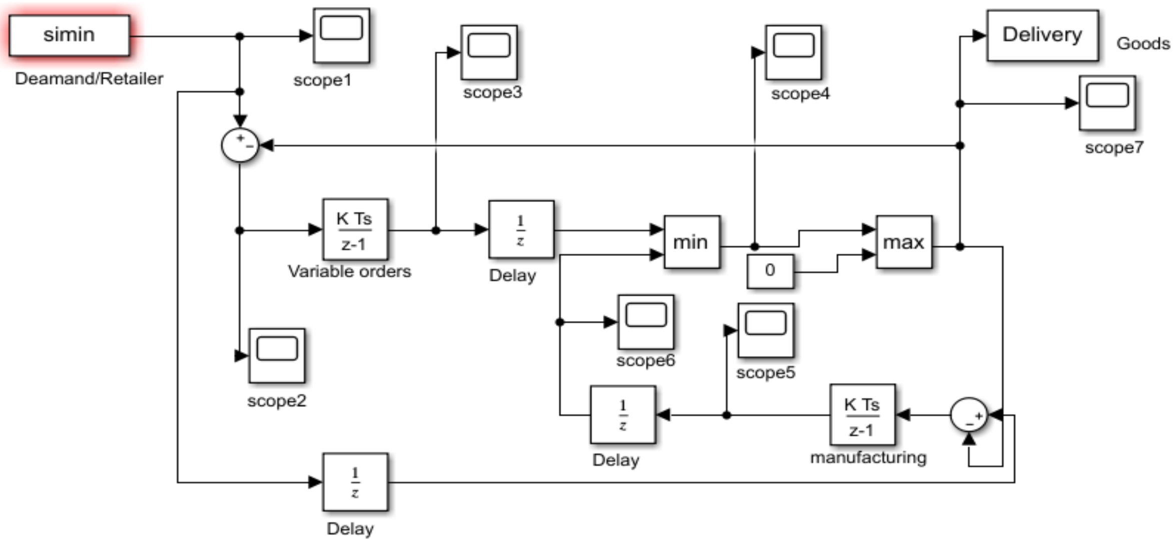


Figure 4.1: Simulink model: (Retailer and manufacturer)

Adapted from (source)- Hofmann (2017)

The researcher developed the model without incorporating big data to study the systems' behaviour using random demand data. The elimination of big data helps the researcher understand the bullwhip effect and its impacts on the supply chain. The model shows how information (variable data or demand signals) flows from retailers to manufacturers and how goods flow from factories to buyers. The first integrator processes demand signals before passing the information to the production plant; this concept helps the planning team minimise information distortion. Next, a discrete-time integrator represents the production plant. Finally, the integrator processes the initial values and the lead time according to the company policy; the block also incorporates the gain values; these are represented with the letter K, and time is signified with the letter Ts also known as (lead-time). Delay blocks help monitor the lead time, and the scope blocks show the flow of goods and information from one point to another; this progress can be visualised in a real-time situation in the form of diagrams and figures, as mentioned earlier (see Figure 4.3 below). However, the lead time determines the output or the production values on a first-in, first-out (FIFO) basis. After production, the information is cleared from the system, paving the way for new demand data. Finally, after harnessing data from the simulation results, the information is migrated to an Excel spreadsheet for analysis and decision-making purposes (see table 4.1 below). Figure 4.2 below shows how orders are transmitted into the system as they come through.

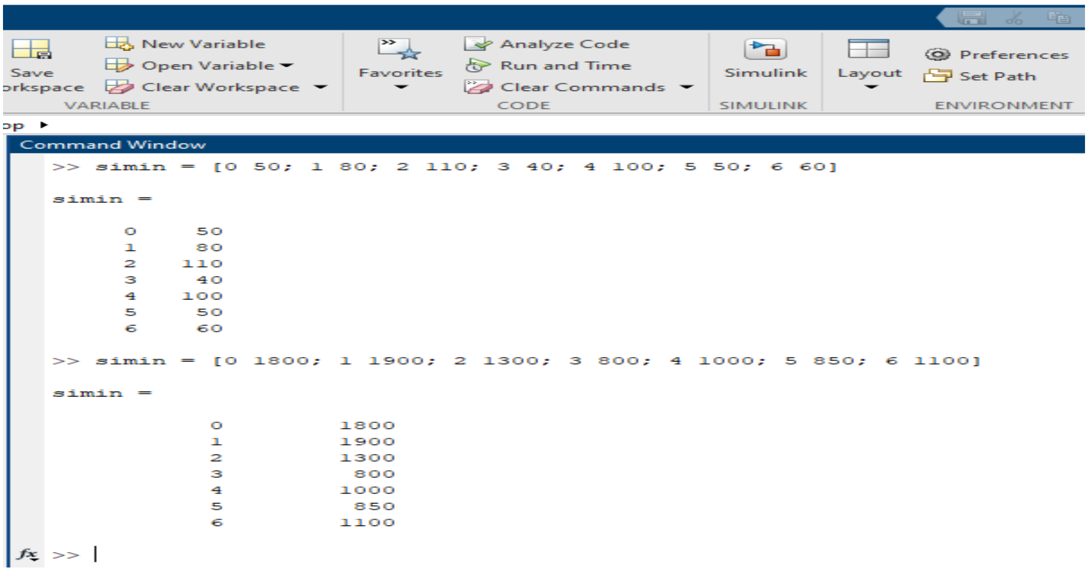
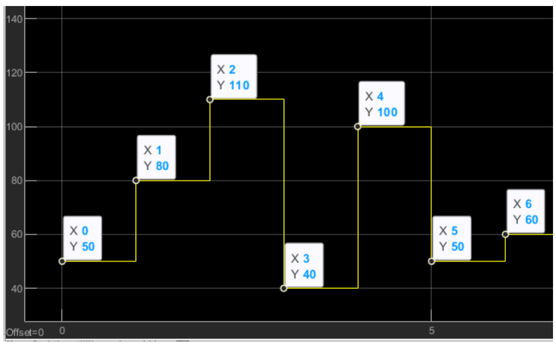


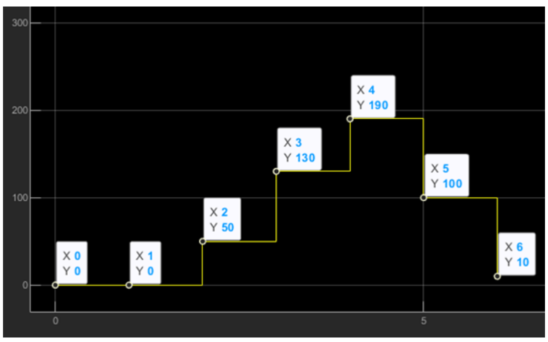
Figure 4.2: Matlab Simulink -command window

Adapted from (source) – Matlab Simulink (2020)

Orders = Simin (total daily orders are automatically calculated as they are received into the system). Total orders for day (0) are therefore 50 units, day (1) are 80 units, day (2) are 110 units, day (3) are 40 units, day (4) are 100 units, and day (5) are 50 units, and day (6) are 60 units. However, the initial stock value or buffer stock is consistently maintained at 200 units (a business strategy to improve cash flow). The manufacturer maintains buffer stock to protect against unanticipated inventory shortages, typically escalating demand amplification throughout the supply chain. However, excessive buffer stock can lead to expensive inventory carrying costs, and insufficient stock can result in backorders; a delicate balance must be maintained between the two. Figure 4.3 depicts simulation results obtained from scope blocks, which are subsequently plotted on a Microsoft Excel spreadsheet (tables). The simulation results provide the manufacturer with an understanding of the system's dynamics, allowing them to make well-informed decisions regarding operating activities to mitigate the bullwhip effect.



Simulation results (scope 1 of the first model).



Simulation results (scope 7 of the first model)

Figure 4.3: Scope blocks- Simulation results

Adapted from: (source) – Matlab Simulink (2020)

Table 4.1: Simulation results migrated from the first model to Excel spreadsheet. Adapted from (source) - Matlab Simulink (2020)

Day	Time	Time	Initial value	Scope 1	SCOPE 2	SCOPE 3	SCOPE 4	SCOPE 5	SCOPE 6	SCOPE 7
0	6 mins	2 days	200	50	50	0	0	200	0	0
1	6 mins	2 days	200	80	80	50	0	200	200	0
2	6 mins	2 days	200	110	80	140	50	250	200	50
3	6 mins	2 days	200	40	60	190	130	280	250	130
4	6 mins	2 days	200	100	-90	100	190	260	280	190
5	6 mins	2 days	200	50	-50	10	100	110	260	100
6	6 mins	2 days	200	60	50	-40	10	110	110	10

Table 4.1 above shows simulation results from the first phase of the model. However, figures under Scope 1 represent stochastic orders (demand signals) from the retailer to the manufacturer. The model will automatically process all the orders based on the manufacturer's capabilities and the lead time determined by the manufacturer. Orders from Scope 1 are transferred to the integrator as standing orders awaiting production; as the orders begin to stack up, production is triggered depending on the volumes, which also define the production throughput. Scope 2, days 4 and 5 and scope 3 days 6 demonstrate the manufacturer's capacity to ramp up production to meet demand. However, Scope 7 indicates that the manufacturer can deliver incomplete orders, leaving the customer with backorders and causing the supply chain to experience a bullwhip effect.

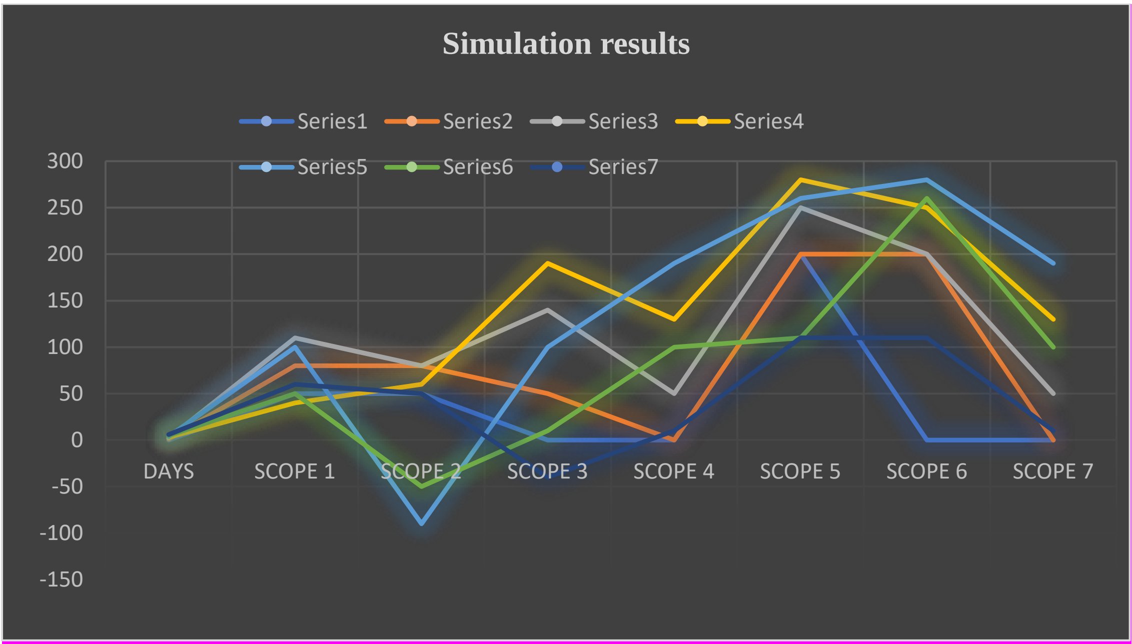


Figure 4.4: Simulink results- (Table 4.1 depicted in a pictorial graph)
Adapted from: (source) - Matlab Simulink (2020)

Figure 4.4 displays simulation results in graphical format, allowing the researcher to analyse a range of data; analysing this data will give the researcher a clear idea of how orders might be processed and fulfilled.

4.1.2 A summary for Table 4.1

The integrator released complete orders on day 0 and day 1 due to a 200-unit buffer stock (also known as initial values). The integrator then releases an additional 140 units on days 2 and 3. (day two, scope 3). Finally, on days 4 and 5, scope 2 displays -90 orders, -50 orders, and -40 orders; the manufacturer can raise production capacity to fulfil demand from a supply chain perspective. However, the company is harmed by the bullwhip effect in its supply chain, which is produced by inaccurate data, delays, and other processes.

However, scope 4 considers the delays and lead times indicated in the delay block, even though nothing is given on days one and two; this is reflected in scope 7, days 0 and 1, since the manufacturer takes the lead time into account. Between days 2 and 6, the manufacturer will initiate the shipping. Nevertheless, several items are currently on backorder (see scope 7). The simulation findings in Table 4.1 reveal the bullwhip effect in the supply chain due to the lack of big data in the manufacturer's supplier networks. Big data may have helped the producer mitigate the danger of demand amplification due to shortages. However, table 4.2 presents statistics generated from table 4.1 using Microsoft Excel; these numbers can be plotted on graphs to assist the company in understanding the levels and impacts of the bullwhip effect on its supply chain.

Table 4.2: Simulation results: calculations from table 4.1

Adapted from: (sources) - Matlab Simulink (2020)

Day	Stop Time	Lead Time	Buffer Initial value	Demand Scope 1	Scope 2	Scope 3	Scope 4	Scope 5	Scope 6	Scope 7
0	6 mins	2 days	200	50	100	50	50	250	50	50
1	6 mins	2 days	200	80	160	130	80	280	280	80
2	6 mins	2 days	200	110	190	250	160	360	310	160
3	6 mins	2 days	200	40	100	230	170	320	290	170
4	6 mins	2 days	200	100	10	200	290	360	380	290
5	6 mins	2 days	200	50	0	60	150	160	310	150
6	6 mins	2 days	200	60	110	20	70	170	170	70

The preceding table (4.2) for scope 1 and scope 2, days four and five, indicates that the manufacturer can minimise the bullwhip effect without using big data. Nonetheless, as the quantity of orders increases, the manufacturer will begin to miss deliveries and have backorders, resulting in the bullwhip effect in the supply chain. However, scopes 5, 6, and 7 represent standing orders resulting from missed deliveries. Therefore, the manufacturer can be forced to increase production to meet the demand; this can be accomplished by increasing the throughput and risk breakdowns or increasing working hours (overtime) at an extra cost.

The data in table 4.2 (above scope 1, scope 2, scope 5, and scope 7) from day zero to day six have been displayed on a graph (figures 4.5 and 4.6 below) to examine the impact of the bullwhip effect on the supply chain. Combining simulation model findings with demand signals resulted in the creation of Table 4.2. (Simin orders: 50, 80, 110, 40, 100, 50, and 60). (Scope 2 to scope 7). The calculations for simulation outcomes in scopes 2, 3, and 7 of the initial models are depicted in tables 4.2 and 4.3 below.

Table 4.3: Simulation results: Calculations for table 4.2

Adapted from: (sources) - Matlab Simulink (2020)

Demand		BWE
Scope 1	Scope 2	curve
50	+ 50	= 100
80	+ 80	= 160
110	+ 80	= 190
40	+ 60	= 100
100	+ (-90)	= 10
50	+(-50)	= 0
60	+ 50	= 110

Demand		BWE
Scope 1	Scope 3	curve
50	+ 0	= 50
80	+ 50	= 130
110	+ 140	= 250
40	+ 190	= 230
100	+ 100	= 200
50	+ 10	= 60
60	+ (-40)	= 20

Demand		BWE
Scope 1	Scope 7	curve
50	+ 0	= 50
80	+ 0	= 80
110	+ 50	= 160
40	+ 130	= 170
100	+ 190	= 290
50	+ 100	=150
60	+ 10	= 70

Data from the above tables 4.3 is plotted on a graph to enable the researcher further analyse the bullwhip effect's impact in the supply chain.

Figure 4.5: The bullwhip effect: Day two scope 7
Adapted from: (source)- Matlab Simulink (2020)

Figure 4.5 depicts elements of the bullwhip effect. The manufacturer cannot meet demand: Consequently, standing orders have accumulated from 50 to 160 units (day two, scope 7), resulting in a backorder of 110 units.

Figure 4.6: The bullwhip effect: Day four scope 7
Adapted from: (source)- Matlab Simulink (2020)

Figure 4.6 demonstrates that standing orders are not being filled; thus, backorders have accumulated from 190 to 290 units (day four, scope 7), resulting in a 100-unit shortfall for the manufacturer.

4.1.3 Big data volume (Vo) (Rationing game simulation).

Figure 4.7 depicts a Simulink model incorporating a rationing game and big data volume (Vo). The rationing game (Rg) contributes to the supply chain's bullwhip effect. The model was simulated numerous times after being fed large volumes of data from the rationing game to study the system's dynamics. The simulation results shown in Table 4.4 below are compared to the first model's (Figure 4.1 above). The results will provide the researcher insight into the impact of big data volume on the rationing game and the supply chain's bullwhip effect. In addition, the analyses will help the manufacturers make an informed decision about whether to invest in big data technology to help the company deal with the bullwhip effect.

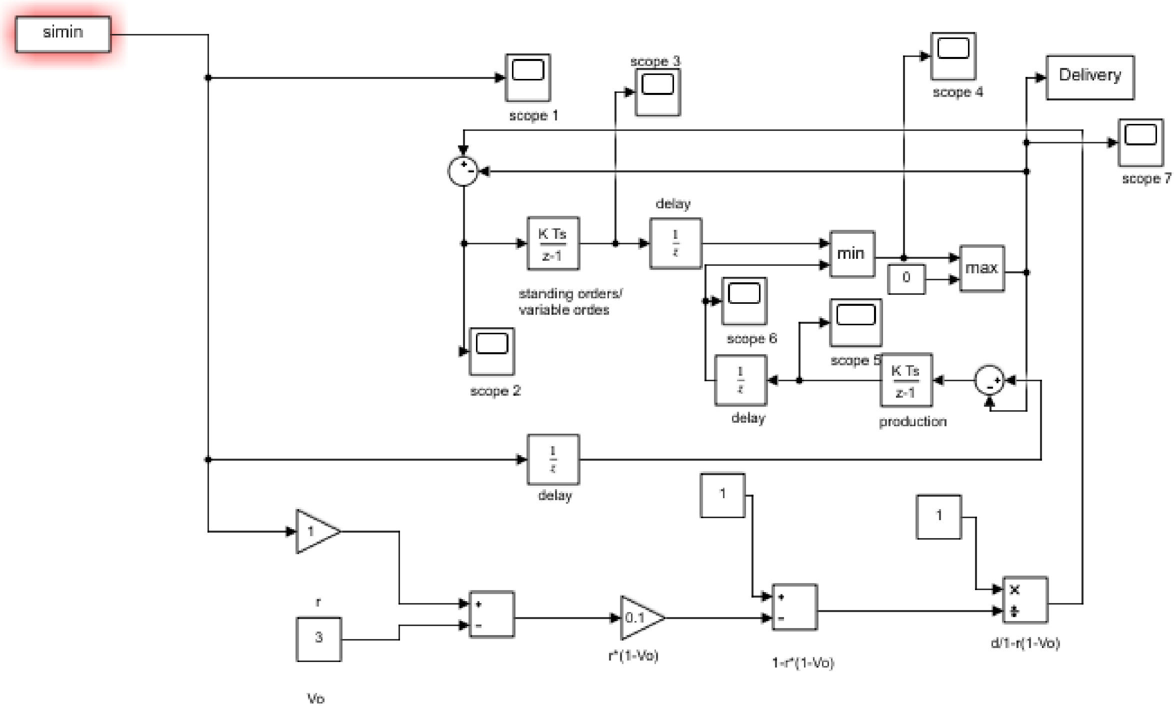
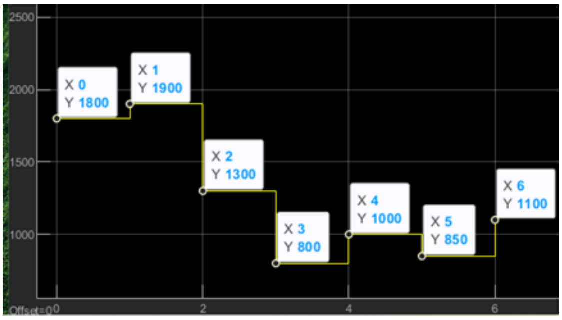


Figure 4.7: Model 2: Rationing game and big data volume
Adapted from: (source) - Matlab Simulink (2020)

The manufacturer relies upon demand information from its customers for production purposes. However, the manufacturer is aware that customers (retailers) always exaggerate their orders and cancel part of the orders; this leaves the manufacturer with excess stock. Therefore, the model accounts for the causes of the bullwhip effect. The manufacturer receives orders or demand signal (d) information between Monday and Friday. The data is fed into the system when orders are received, and the model adds up the quantities. Orders are filled based on lead times (Lt) and initial values (x1), also known as buffer stock. As a result, the model considers the standing orders (So).

The outcome is on a scale between 0 and 1, determined with the ratio ($R_{1, 3, 5,9}$). $d - (x1) = stock\ levels.$ The mathematical formula for volume is $Vo = \frac{d}{R1 - Rg\ (Vo - Rg)}$, this means a stronger the big data Vo ration will lessen the R_g or bullwhip effect.

Simulation results scope 1 (second model).



Simulation results scope 7 (second model)

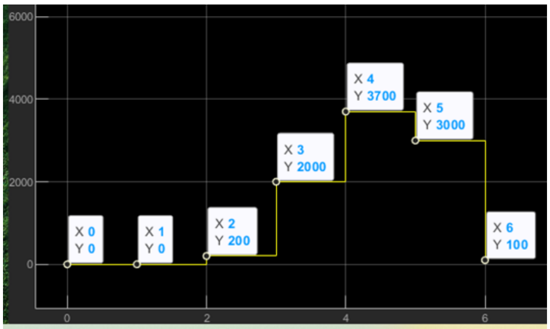


Figure 4.8: Scope blocks- Simulation Results

Adapted from: (source) – Matlab Simulink (2020)

Figure 4.8 above shows simulation results from the second model; the information was harnessed from some of the scope blocks and then plotted on table 4.4 below.

Table 4.4: Second model-simulation results

Adapted from: (sources) - Matlab Simulink (2020)

r1 Vo ratio= 1

Day	Time	Time	Initial value	Scope 1	SCOPE 2	SCOPE 3	SCOPE 4	SCOPE 5	SCOPE 6	SCOPE 7
0	6 mins	2 days	200	50	0.02564	0	0	200	0	0
1	6 mins	2 days	200	80	-0.1449	-0.2564	0	200	200	0
2	6 mins	2 days	200	110	-0.101	-0.4013	-0.2564	250	200	0
3	6 mins	2 days	200	40	-0.3448	-0.5013	-0.4013	330	250	0
4	6 mins	2 days	200	100	-0.1124	-0.8472	-0.5023	440	330	0
5	6 mins	2 days	200	50	-0.2564	-0.9595	-0.8472	480	440	0
6	6 mins	2 days	200	60	-0.2041	-1.216	-0.9595	580	480	0

The preceding table (table 4.4) results indicate that big data volume can reduce the bullwhip effect. The data in Table 4.4, Scope 2, 3, and 4 from day 1 to day 6 demonstrate that the manufacturer may reduce the bullwhip effect by utilising big data (Vo). Scope 7 indicates that no orders were left to be delivered from day 1 to day 6 (scope 7).

The same information is presented in table 4.5, demonstrating that the manufacturer could meet all delivery deadlines. Figure 4.9 is a graphical representation of the results presented in Table 4.4. The approach can aid data analysts in analysing data from numerous sources. Nonetheless, the model was simulated using the same demand signal values or stochastic data as the original model (50, 80, 110, 40, 100, 50, 60).

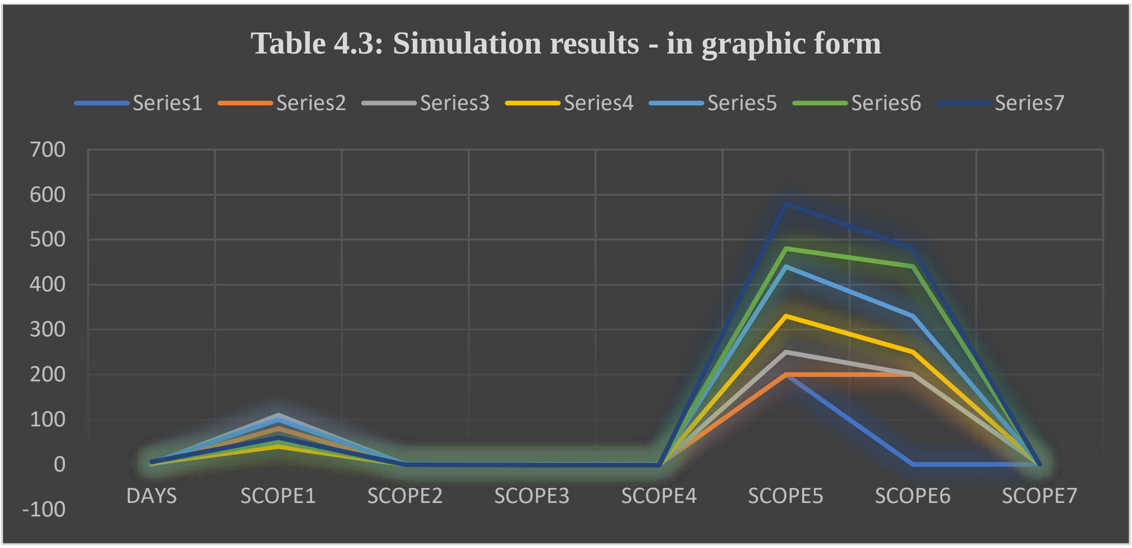


Figure 4.9 Second model simulation results (Table 4.4 depicted into a pictorial graph)

Adapted from: (source) Matlab Simulink (2020)

Table 4.5: Simulation results: calculations from table 4.4

Adapted from: (sources) - Matlab Simulink (2020)

Day	Time	Time	Initial value	Demand signal Scope 1	SCOPE 2	SCOPE 3	SCOPE 4	SCOPE 5	SCOPE 6	SCOPE 7
0	6 mins	2 days	200	50	49.97436	50	50	250	50	50
1	6 mins	2 days	200	80	79.8551	79.7436	80	280	280	80
2	6 mins	2 days	200	110	109.899	109.5987	109.7436	360	310	110
3	6 mins	2 days	200	40	39.6552	39.4987	39.5987	370	290	40
4	6 mins	2 days	200	100	99.8876	99.1528	99.4977	540	430	100
5	6 mins	2 days	200	50	49.7436	49.0405	49.1528	530	490	50
6	6 mins	2 days	200	60	59.7959	58.784	59.0405	640	540	60

Data in table 4.5 above was plotted from the simulation results in table 4.4; the concept will enable the researcher to analyse data in a meaningful way to understand further how big data volume can impact demand amplification. The figures in the table were reached by adding the demand signals (scope 1) with the figures in the rest of the scopes using Microsoft Excel.

However, table 4.6 below illustrates how the calculations were carried out, including the effects of big data (Vo) on the bullwhip effect. Scope 2 and 3 in table 4.6 illustrate the impact of intensifying big data in the supply chain and how it can minimise the bullwhip effect; in other words, intensifying big data (Vo) helps speed up the process of mitigating the risk.

Table 4.6: Simulation results: Calculations for table 4.5

Adapted from: (sources) - Matlab Simulink (2020)

Demand Scope 1	Scope 2	BWE
50	+ (-0.02564)	49.9736
80	+ (-0.1449)	79.8551
110	+ (-0.101)	109.899
40	+ (-0.3448)	39.6552
100	+ (-0.1124)	99.8876
50	+ (-0.2564)	49.7436
60	+ (-0.2041)	59.7959

Demand Scope 1	Scope 3	BWE
50	+ 0	50
80	+ (-0.2564)	79.7436
110	+ (-0.4013)	109.5987
40	+ (-0.5013)	39.4987
100	+ (-0.8472)	99.1528
50	+ (-0.9595)	49.7436
60	+ (-1.216)	59.7959

Demand Scope 1	Scope 7	BWE
50	+ 0	50
80	+ 0	80
110	+ 0	110
40	+ 0	40
100	+ 0	100
50	+ 0	50
60	+ 0	60

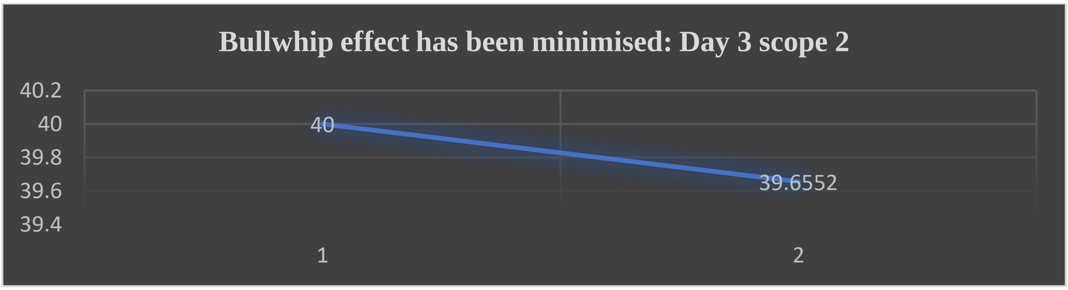


Figure 4.10: **The bullwhip effect: Day three scope 2**
Adapted from: (source)- Matlab Simulink (2020)

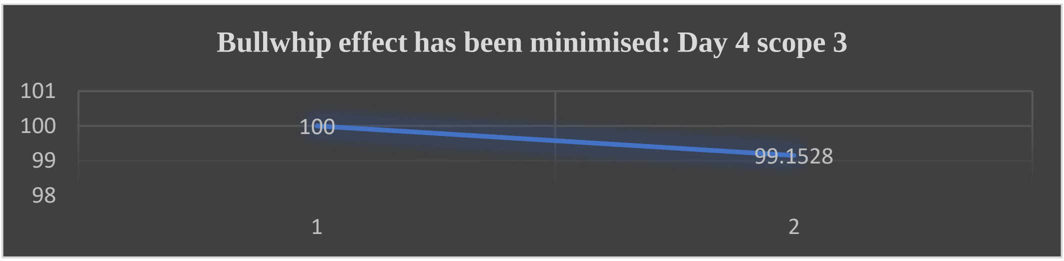


Figure 4.11: **The bullwhip effect: Day four scope 3**
Adapted from: (source)- Matlab Simulink (2020)

Figures 4.10 and 4.11 demonstrate a reduction in the bullwhip effect from 40 to 39.6552 and 100 to 99.1528; this was achieved through big data volume (ratio of 1). Nonetheless, several simulations revealed that increasing the big data Vo ratio from one to five substantially affected the bullwhip effect.

The results from modelling the second model with various big data ratios are displayed in Table 4.7 below (Vo r1; Vo r3; Vo r5; Vo r9). The statistics indicate a considerable decrease in the bullwhip effect as the ratio increases. For instance, the first simulation (Scenario 1) was conducted at a ratio of 1, and the bullwhip effect fell from 50 to 49.97436; as the ratio was increased to 9, the bullwhip effect decreased from 50 to 49.6774, and orders will be delivered on time. If the ratio is increased from (Vo9) to (Vo50), the supply chain will experience remarkable results.

Table 4.7: Simulation results: Data captured from four different scenarios of model 2. Adapted from (source)- Matlab Simulink (2020)

DAYS	DEMAND	SCENARIO 1 (r1)	SCENARIO 2 (r2)	SCENARIO 3 (r3)	SCENARIO 3 (r4)				
	SIGNAL	Vo Ratio = 1	Vo Ratio = 3	Vo Ratio = 5	Vo Ratio = 9	Vo 1	Vo3	Vo5	Vo9
		SCOPE 2	SCOPE 2	SCOPE 2	SCOPE 2	SCOPE 7	SCOPE 7	SCOPE 7	SCOPE 7
0	50	49.97436	49.7297	49.7143	49.6774	50	50	50	50
1	80	79.8551	79.8507	79.8462	79.8361	80	80	80	80
2	110	109.899	109.8969	109.8947	109.8901	110	110	110	110
3	40	39.6552	39.6296	39.6	39.5238	40	40	40	40
4	100	99.8876	99.8851	99.8824	99.8765	100	100	100	100
5	50	49.7436	49.7297	49.7143	49.6774	50	50	50	50
6	60	59.7959	59.7872	59.7778	59.7561	60	60	60	60

4.1. 4 Big data velocity (Ve) (Order batching simulation)

As previously mentioned, one of the phenomena responsible for the amplification of demand in the supply chain is order batching, which is formed by placing orders in batches (Chazan, 2012). Clustering items for purchase, shipping, or production distorts data and results in excess stock and backorders. Furthermore, due to supply chain network uncertainties and backlog expenses, order fulfilment is directly proportional to inventory levels (Bloomberg, 2012). Sometimes, distributors and retailers order bulk to take advantage of quantity discounts and reduce transportation costs. On the other note, producers can achieve economies of scale (EOS) by mass-producing identical goods, reducing production costs while increasing inventory costs.

However, order batching increases demand by rounding actual demand to the nearest whole batch for production and ordering from distributors (Kim et al., 2018). Suppose, for instance, the actual demand for a product is thirteen single units, but the minimum order or production batch size is fifty single units in a sealed pack. The minimum order quantity or production run size for this scenario is fifty sealed items.

Recently, advanced techniques, such as genetic algorithms to determine the optimal way to sort at each level (O'Donnell et al., 2006), fuzzy inventory controllers (Xiong and Helo, 2006), and distributed intelligence (De La Fuente and Lozano, 2007), have been employed to do this.

Although it is commonly accepted that batch size should be reduced to help mitigate the bullwhip effect in the supply chain (Burbidge, 1981), few studies have explored the effect of batch size on demand amplification. In this section, the researcher will replicate the velocity of big data using different velocity ratios to examine the impact of velocity on supply chain batch sizes (Ishwarappa and Anuradha, 2015). As stated earlier, the second big data feature to replicate is big data velocity (Ve), which is the organisation's ability to handle data quickly and efficiently using advanced IT software and systems (Oliveira and Gimeno, 2014). As a result, organisations are more exposed to supply chain disruptions caused by unpredictability, pandemics, and increasing product demand. Consumers, in contrast, overstate their orders to maintain consistent supply levels (Reimann and Ketchen, 2017). Therefore, an excessive number of orders increases demand, making it more difficult for the manufacturer or supplier to estimate demand (Kim et al., 2018).

In addition, certain consumers are likely to order products to stock due to long lead times, poor communication between stakeholders, and associated operational costs (Grover et al., 2018). In supply chain management, the idea of order-to-stock inventory generates the bullwhip effect. However, research indicates that a better IT system can increase communication and prevent supply chain disruptions (Hofmann, 2017). Hofmann (2017) asserts that businesses must raise the velocity (Ve) at which they process data to optimise operational activities such as production, delivery time, and lead time and prevent demand amplification throughout the supply chain. Consequently, enhanced operational activity and communication can help suppliers eliminate supply chain backorders and amplify demand.

This notion permits the researcher to examine the behaviour of both independent variables (r) and dependent variables (d) (s). When the independent variable (r) is modified, we should examine the dependent values (s) to determine how they respond to the change. Consequently, if there is a relationship between the variables r and S, we can analyse the data to determine its causes and effects. d = demand signal:

r = independent variables

s = dependent variable (order quantities)

d = demand signal	We assume demand remains constant
r = independent variables	variable can be changed (independent variable)
s = order supplied in batches	This represents dependent variable

The researcher considers that demand (d) is deterministic, and in this situation, we assume that demand is 68 980 batches every month. The ratio (r) or velocity (Ve) ranges from zero to one. When the r/Ve = 0, the manufacturer is not using big data velocity in their supply chain. Therefore, the ratio can be changed based on the manufacturer's manufacturing capabilities and resources. These ratio changes can range from 0.5 to 9 or more. Various ratios are used to investigate the effect of velocity on dependent variables. When the ratio is increased, the order quantity (s) decreases, demonstrating the impact of big data velocity in the supply chain in alleviating the bullwhip effect. The concept will assist supply chain members, or customers improve their cash flows. It is also a positive indication of the impact of an improved IT system and communication between stakeholders in minimising supply chain disruption, allowing customers to order stock in small batches at a faster rate.

The following formula can be operationalised in the Simulink model to study the impact of velocity in the supply chain.

d-r*(r1-Ve): This mathematical formula means (demand signal minus independent variable multiplied by the ratio of one minus velocity.

$\frac{d=68\,980\ (demand\ is\ deterministic)}{r1=(\ ratio)}$=s (dependent variable).

$\frac{68\,980}{0}$ This means there is no big data implemented in the supply chain

$\frac{68\,980}{0.5}$ =137,960 (batches supplied every month using big data velocity ratio (r) of 0.5.

$\frac{68\,980}{3}$ = 22,993 (batches supplied every month using big data velocity ratio (r) of 3.

The data presented above indicate that the big data velocity ratio (r) was increased from 0.5 to 3. Also, the results show that the number of order batches went from 137,960 to 22,993 over time. This shows that velocity can have a big effect on how orders are grouped in the supply chain, and the ratio used can show this. Figure 4.12 displays a Simulink model that contains big data velocity; by simulating big data velocity, the researcher will be able to examine the effect of velocity on order batching in the supply chain. Nonetheless, the model was simulated using the same demand signal values as the first two models while intensifying the ratio of big data velocity (50, 80, 110, 40, 100, 50, and 60).

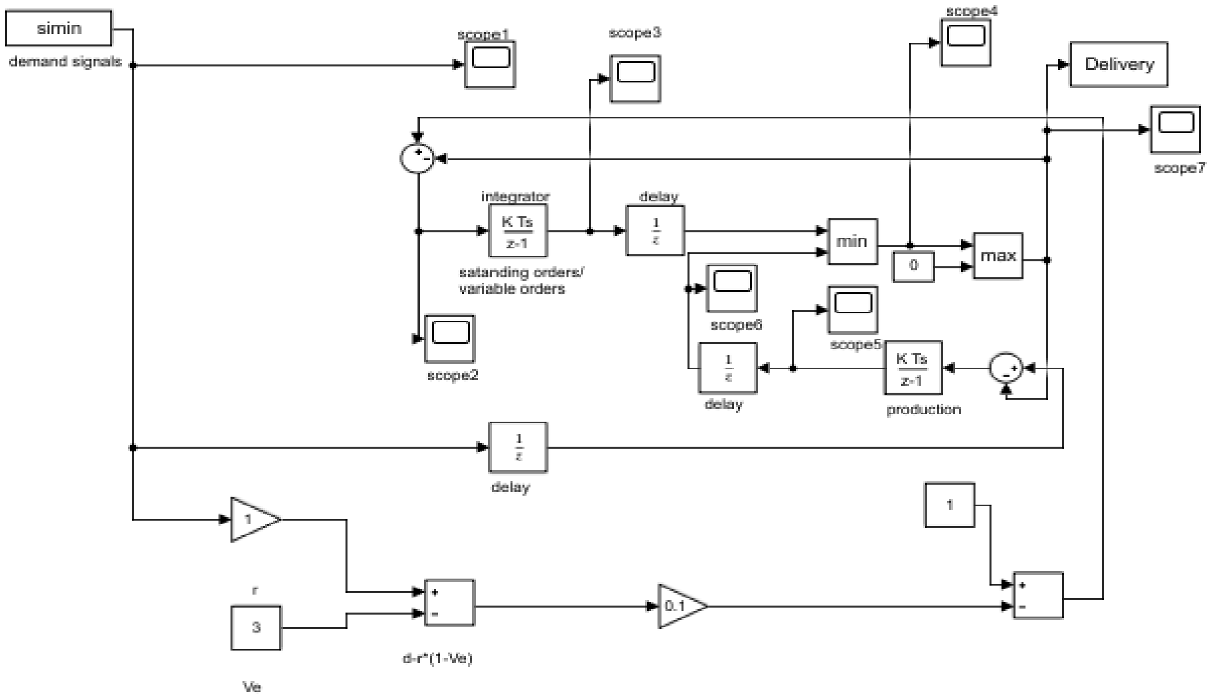
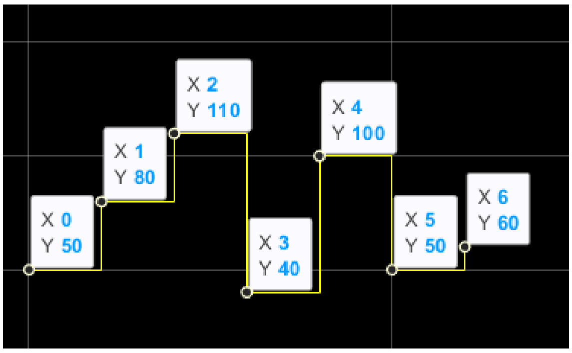
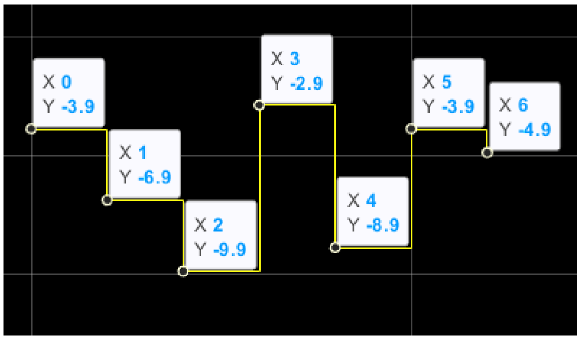


Figure 4.12: Model 3: Order batching and big data velocity
Adapted from: (source) - Matlab Simulink (2020)

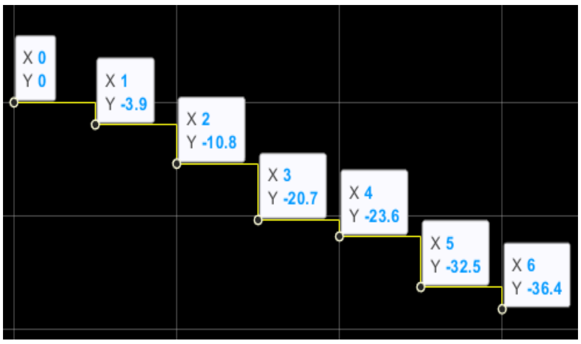
The data presented in Figure 4.13 are simulation results derived from the simulation scope. These results were obtained after simulating the big data velocity (Ve) ratio (r1).



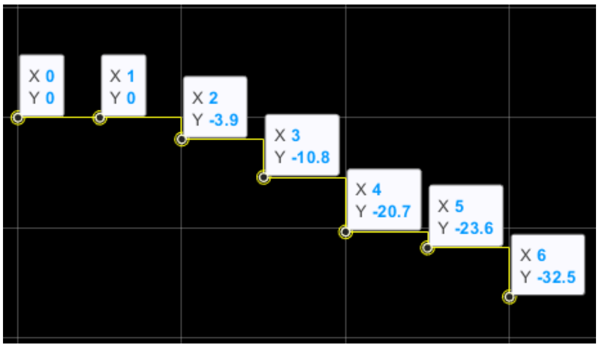
Scope1 big data Ve (r1)



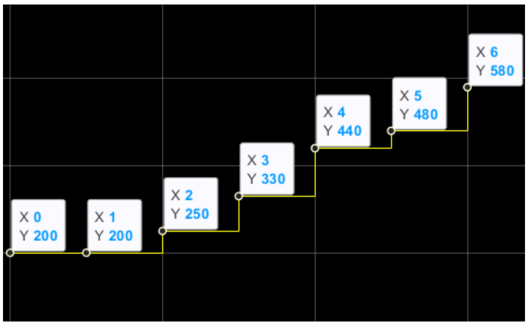
Scope2 big data Ve (r1)

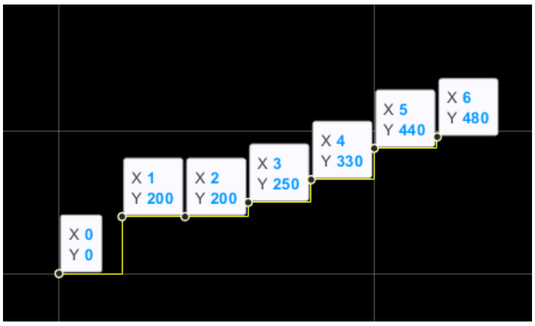


Scope3 big data Ve (r1)



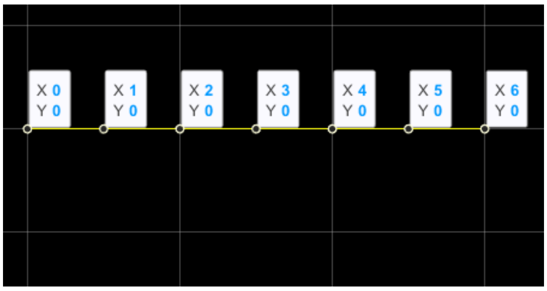
Scope4 big data Ve (r1)





Scope5 big data Ve (r1)

Scope6 big data Ve (r1)



Scope7 big data Ve (r1)

Figure 4.13: The bullwhip effect (Ve): scope 1 – 7 from day 1 – day 6
Adapted from: (source)- Matlab Simulink (2020)

After collecting the relevant data for scopes 1 through 7 from figure 4.13, the information was plotted in an Excel spreadsheet for data analysis. Table 4.8a, for instance, illustrates the simulation outcomes of Model 3 incorporating big data velocity using the ratio of 1. In comparison, Table 4.8b displays the simulation outcomes of Model 3, adding big data velocity with a ratio of 3. Moreover, figures 4.14a and 4.14b represent simulations depicted in tables 4.8a and 4.8b as illustrative graphs; this notion gives analysts various data from which to investigate trends. Tables 4.8a and 4.8b display simulation findings, while Table 4.8c illustrates a shapely reduction in numbers after raising the large data velocity from Ve (r1) to Ve (r2). Tables 4.8a and 4.8b, Scope 2, 3, and 4 indicate that the manufacturer can improve big data velocity to achieve a competitive advantage. Simulations demonstrate that the velocity of big data can influence the bullwhip effect in supply chain management.

Table 4.8a: Simulation results: Data captured from all seven scopes of model 3 (r1).

Adapted from (source)- Matlab Simulink (2020)

Ve r1

Day	time	lead-time	Initial values	Scope1	scope2	scope3	scope4	scope5	scope6	scope7
0	6 mins	2 days	200	50	-3.9	0	0	200	0	0
1	6 mins	2 days	200	80	-6.9	-3.9	0	200	200	0
2	6 mins	2 days	200	110	-9.9	-10.8	-3.9	250	200	0
3	6 mins	2 days	200	40	-2.9	-20.7	-10.8	330	250	0
4	6 mins	2 days	200	100	-8.9	-23.6	-20.7	440	330	0
5	6 mins	2 days	200	50	-3.9	-32.5	-23.6	480	440	0
6	6 mins	2 days	200	60	-4.9	-36.4	-32.5	580	480	0

scope1	scope1	BWE
50	-3.9	46.1
80	-6.9	73.1
110	-9.9	100.1
40	-2.9	37.1
100	-8.9	91.1
50	-3.9	46.1
60	-4.9	55.1

scope1	scope2	BWE
50	0	50
80	-3.9	76.1
110	-10.8	99.2
40	-20.7	19.3
100	-23.6	76.4
50	-32.5	17.5
60	-36.4	23.6

Scope1	Scope3	BWE
50	0	50
80	0	80
110	-3.9	106.1
40	-10.8	29.2
100	-20.7	79.3
50	-23.6	26.4
60	-32.5	27.5

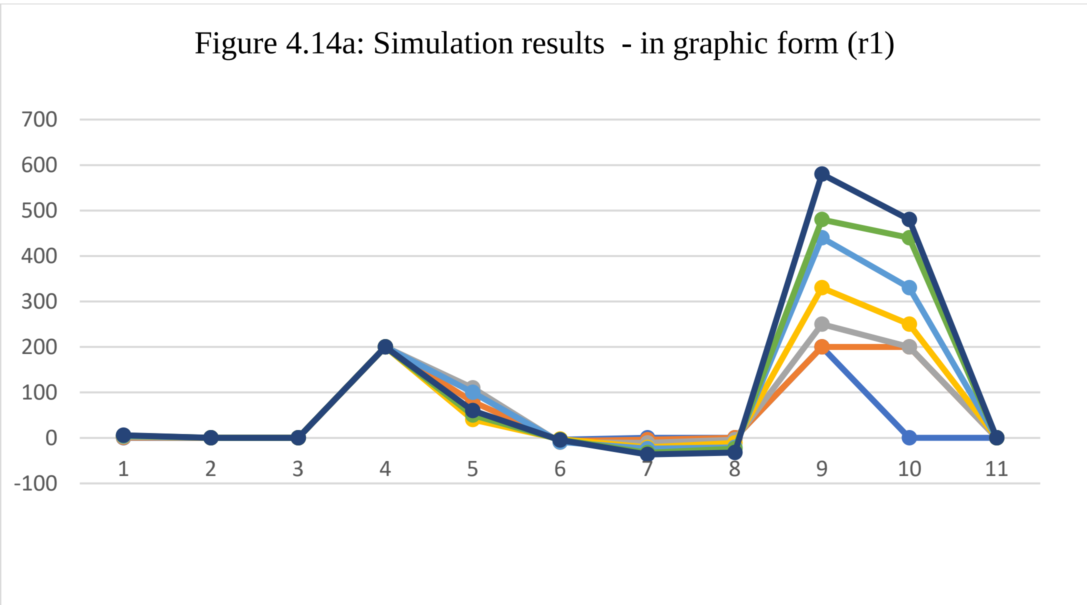


Figure 4.14a Second model simulation results (Table 4.8a depicted into a pictorial graph)

Adapted from: (source) Matlab Simulink (2020

Table 4.8b: Simulation results: Data captured from all seven scopes of model 3 (r3).

Adapted from (source)- Matlab Simulink (2020)

Ve r3

Day	time	lead-time	Initial values	Scope1	scope2	scope3	scope4	scope5	scope6	scope7
0	6 mins	2 days	200	50	-3.7	0	0	200	0	0
1	6 mins	2 days	200	80	-6.7	-3.7	0	200	200	0
2	6 mins	2 days	200	110	-9.7	-10.4	-3.7	250	200	0
3	6 mins	2 days	200	40	-2.7	-20.1	-10.4	330	250	0
4	6 mins	2 days	200	100	-8.7	-22.8	-20.1	440	330	0
5	6 mins	2 days	200	50	-3.7	-31.5	-22.8	480	440	0
6	6 mins	2 days	200	60	-4.7	-35.2	-31.5	580	480	0

scope1	Scope2	BWE
50	-3.7	46.3
80	-6.7	73.3
110	-9.7	100.3
40	-2.7	37.3
100	-8.7	91.3
50	-3.7	46.3
60	-4.7	55.3

scope1	Scope3	BWE
50	0	50
80	-3.7	76.3
110	-10.4	99.6
40	-20.1	19.9
100	-22.8	77.2
50	-31.5	18.5
60	-35.2	24.8

Scope1	Scope4	BWE
50	0	50
80	0	80
110	-3.7	106.3
40	-10.4	29.6
100	-20.1	79.9
50	-22.8	27.2
60	-31.5	28.5

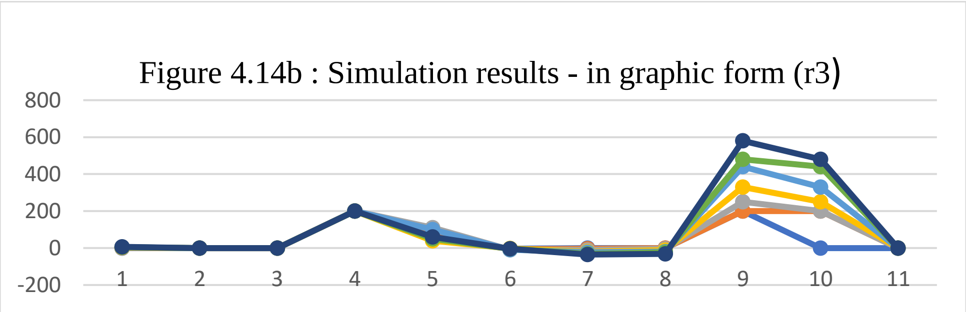


Figure 4.14b Second model simulation results (Table 4.8b depicted into a pictorial graph)

Adapted from: (source) Matlab Simulink (2020)

The results in Tables 4.8a and 4.8b were plotted using Microsoft Excel. According to the facts presented, utilising big data velocity for order batching is advantageous. We discovered a substantial influence of big data velocity on order batching in supply chain management when the big data velocity ratio increases from Ve (r1) to Ve (r2) scopes 2, 3, and 4. Scope 5's tables 4.8a and 4.8b reveal that the manufacturer is operating at total capacity and that demand can be fulfilled without producing surplus storage inventory. Scope 6 shows that orders are released from production following the lead-time policy. In contrast, Scope 7 shows that orders are provided in small batches faster and with no backorders.

Table 4.9: Simulation results: (Combined results)

Ve r1

Day	time	lead-time	Initial values	Scope1	scope2	scope3	scope4	scope5	scope6	scope7
0	6 mins	2 days	200	50	46.1	50	50	250	50	50
1	6 mins	2 days	200	80	73.1	76.1	80	280	280	80
2	6 mins	2 days	200	110	100.1	99.2	106.1	360	310	110
3	6 mins	2 days	200	40	37.1	19.3	29.2	370	290	40
4	6 mins	2 days	200	100	91.1	76.4	79.3	540	430	100
5	6 mins	2 days	200	50	46.1	17.5	26.4	530	490	50
6	6 mins	2 days	200	60	55.1	23.6	27.5	640	540	60

Table 4.10: Simulation results: calculation from table 4.8a of model 3 (r1).

Adapted from (source)- Matlab Simulink (2020)

Scope1 (Demand)	scope2 (standing orders)	A decrease in BWE
50	+(-3.9)	46.1
80	+(-6.9)	73.1
110	+(-9.9)	100.1
40	+(-2.9)	37.1
100	+(-8.9)	91.1
50	+(-3.9)	46.1
60	+(-4.9)	55.1

Scope1 (Deman	scope3	A decrease in BWE
50	+0	50
80	+(-3.9)	76.1
110	+(-10.8)	99.2
40	+(-20.7)	19.3
100	+(-23.6)	76.4
50	+(-32.5)	17.5
60	+(-36.4)	23.6

Table 4.11: Simulation results: Scope 2,3,4,6 & 7 model 3 Ve (r1).

Adapted from (source)- Matlab Simulink (2020)

Days	Scope 1	scope2	Days	Scope 1	scope3	Days	Scope 1	scope4	Days	scope6	scope7
0	50	46.1	0	50	50	0	50	50	0	50	50
1	80	73.1	1	80	76.1	1	80	80	1	280	80
2	110	100.1	2	110	99.2	2	110	106.1	2	310	110
3	40	37.1	3	40	19.3	3	40	29.2	3	290	40
4	100	91.1	4	100	76.4	4	100	79.3	4	430	100
5	50	46.1	5	50	17.5	5	50	26.4	5	490	50
6	60	55.1	6	60	23.6	6	60	27.5	6	540	60

Based on simulation findings, the table above 4.11 shows a drop in numbers, a positive indicator for using big data velocity to mitigate demand amplification. Scope 6 shows a system dynamic and the manufacturer's capabilities to facilitate production. As a result, the manufacturer can continue to deliver goods on time as the number of orders increases. However, data plotted in figures 4.15a and 4.1a to 4.15d shows a decline in figures (bullwhip effect); this illustrates that implementing big data velocity can affect order batches throughout the supply chain. There is a 3.9 decrease in figures on scope 2 day 0, a further 6.9 decrease on scope 2 day 1, and a further 9.9 decrease on scope 2 day 2. However, on day 3 of scope 3, there is a staggering decrease in number by 20.7, followed by a further decrease of 32.5 on day 5 of scope 3, and finally a 36.4 decrease in number on day 6 of scope 3. As a result, the manufacturer managed to supply all the orders shown on scope 7 from day 0 to day 6.

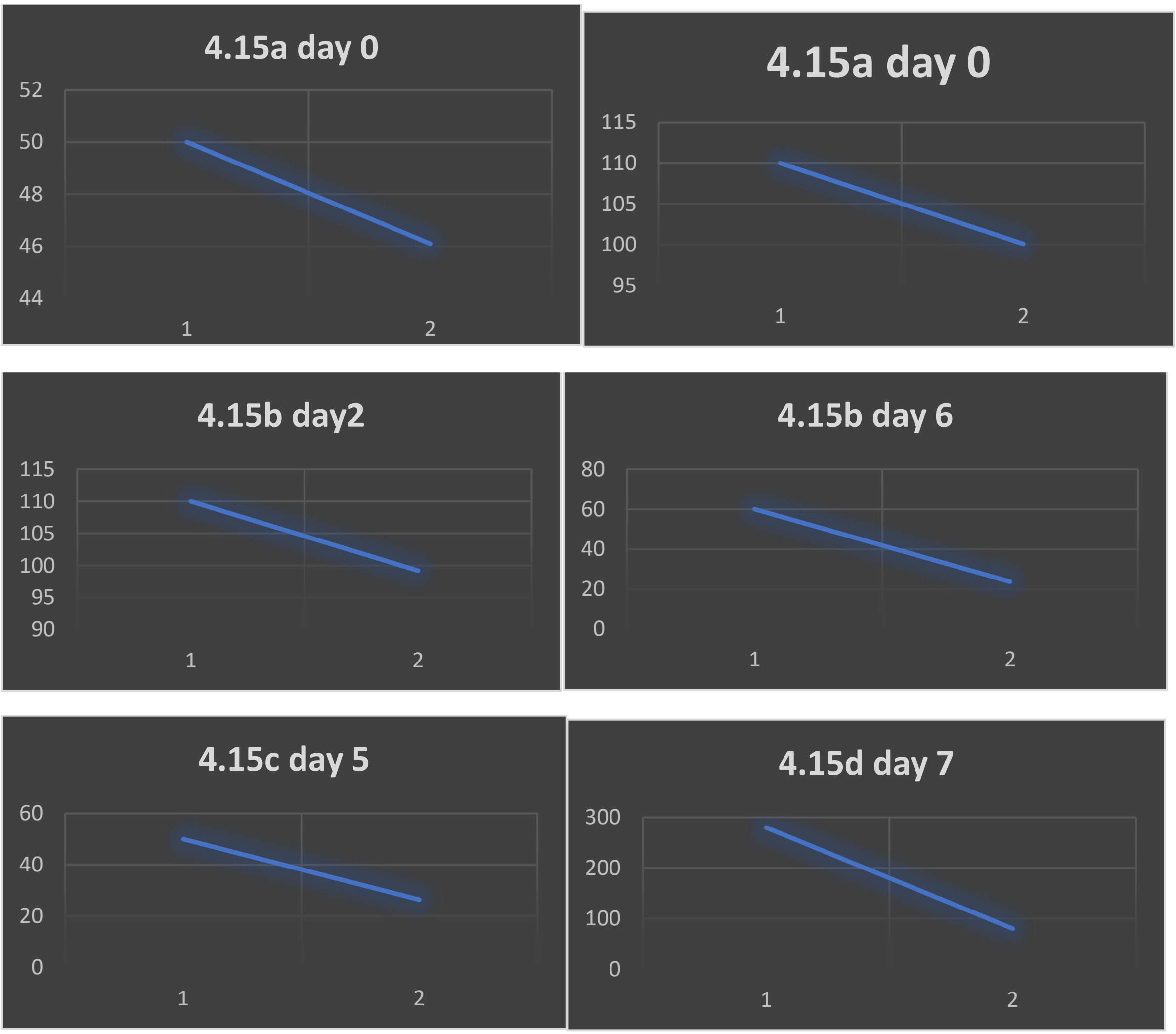


Figure 4.15a, b,c& d Second model simulation results (Table 4.11 depicted into a pictorial graph)
Adapted from: (source) Matlab Simulink (2020)

4.1.5 Big data variety (Va) (Demand forecasting).

Forecasting employs historical sales data to predict the number of goods or services expected to be demanded within a specific period. (Babai et al., 2016). Divakar, Rotchford, and Shankar (2014, 2017, 2016, 2015) emphasised that supply chain management needed predictive analytics to maximise inventory management. Consequently, accurate demand forecasting provides supply chain management with vital information that facilitates planning and decision-making. Nonetheless, several uncertainties and complexities, including natural disasters, COVID-19, and Brexit, contribute to supply chain bottlenecks. Moreover, due to the bullwhip effect, businesses must invest in various demand forecasting tools (Armstrong and Green, 2017). Babai et al. (2016) state that accurate demand forecasting can be attained by monitoring social media, point-of-sale data, and electronic data sharing. A system based on consumer sentiment is necessary to enhance demand forecasting. To add demand estimates into a Simulink model, use the following formula.

Formula: (d=Va) d(r1+Va)

d=demand

Va= Big data variety

r1=variety ratio

The assumption is that as the variety of big data intensifies or increases, big data will positively impact supply chain management, and, as a result, demand forecasting will improve. Figure 4.16 depicts a Simulink model 4. The model includes big data variety (Va); simulating big data variety will allow the researcher to investigate the impact of variation on demand forecasting in the supply chain. The model was simulated with the same demand signal values as the first two, which can be changed (50, 80, 110, 40, 100, 50, and 60).

Va (r1)

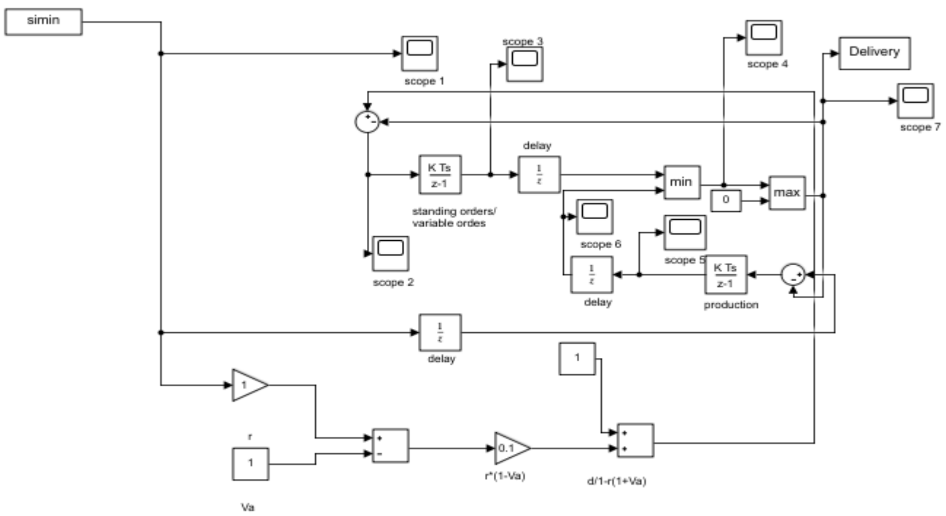
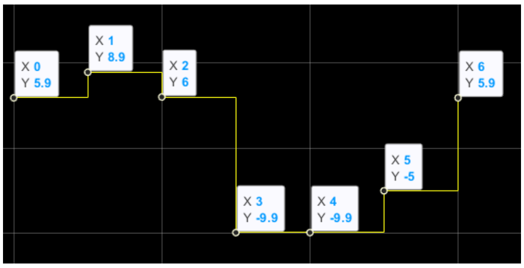


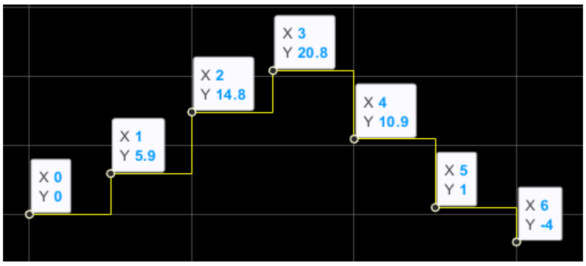
Figure 4.16: Model 4: Demand forecasting and big data variety
Adapted from: (source) - Matlab Simulink (2020)

Figure 4.17 displays simulation results in graphical representation; the data is then transferred to a spreadsheet for further analysis. Results were obtained by applying a variety of ratios for big data variety. However, simulations were also conducted for ratios r2 and r6 so the researcher could compare the outcomes.

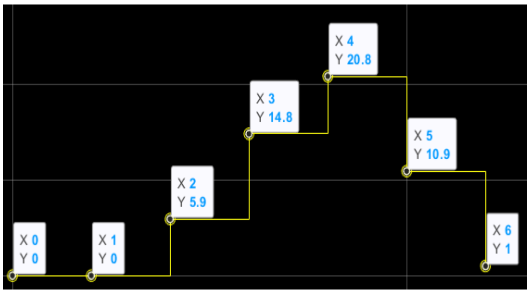
Va (r1) scope 2



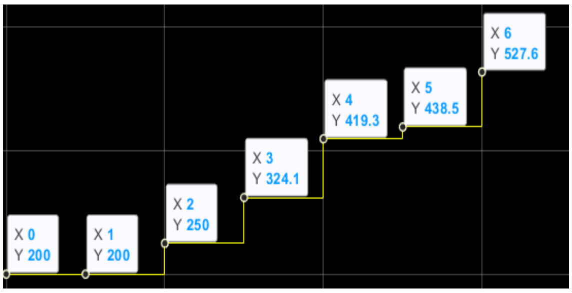
Va (r1) scope 3



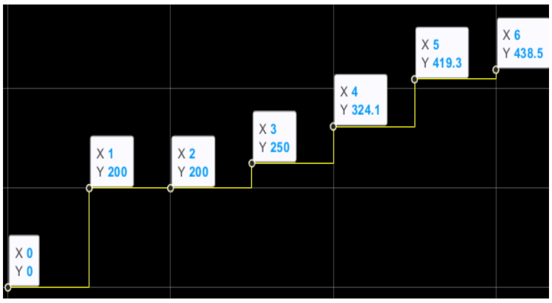
Va (r1) scope 4



Va (r1) scope 5



Va (r1) scope 6



Va (r1) scope 7

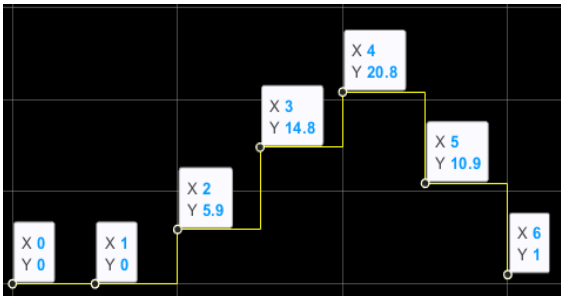


Figure 4.17: The bullwhip effect (Va): scope 2 – 7 from day 1 – day 6
Adapted from: (source)- Matlab Simulink (2020)

Tables 4.12 below display simulation results for big data variety acquired from scopes 1 to 7 utilising big data variety ratios 1. Scopes 2, 3, and 4 demonstrate the impact of big data variety on demand forecasting. However, scope 5 reveals inventory levels after the information was moved from the integrator, scope 6 reveals inventory levels with a unit delay which is the company policy in relation to lead time, and scope 7 reveals a company's capacity to fulfil orders without backorders.

Simulating four different Simulink models using different big data properties has permitted the researcher to explore the impact of big data on the supply chain. As a result, the researcher has managed to identify the potential of big data characteristics and how they can be implemented to mitigate demand amplification. Although big data have numerous properties that can be important in the supply chain, some are critical. They can significantly improve the supply chain by employing the right variables and mathematical formulas. However, integrating big data characteristics can also transform business operations and reduce risk. For instance, big data volume, variety and velocity can be modelled to study its impact because they seem to have one thing in common.

Table 4.12: Big data variety Simulation results: model 4 Va (r1). Adapted from (source)- Matlab Simulink (2020)

Day	time	lead-time	Initial values	Scope1	scope2	scope3	scope4	scope5	scope6	scope7
0	6 mins	2 days	200	50	5.9	0	0	200	0	0
1	6 mins	2 days	200	80	8.9	5.9	0	200	200	0
2	6 mins	2 days	200	110	6	14.8	5.9	250	200	5.9
3	6 mins	2 days	200	40	-9.9	20.8	14.8	324.1	250	14.8
4	6 mins	2 days	200	100	-9.9	10.9	20.8	419.3	324.1	20.8
5	6 mins	2 days	200	50	-5	1	10.9	438.5	419.3	10.9
6	6 mins	2 days	200	60	5.9	-4	1	525.6	438.5	1

Tables 4.13 below shows the effects of utilising big data Va. These results are also plotted on graphs for advanced analysis purpose.

Table 4.13: Big data variety calculations from table 4.12: model 4 Va (r1). Adapted from (source)- Matlab Simulink (2020)

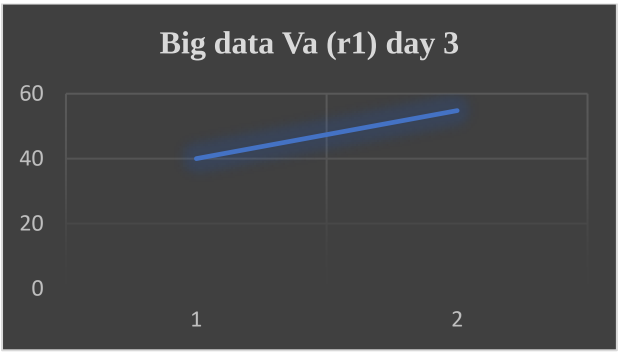
scope1	scope2	BWE
50	5.9	55.9
80	8.9	88.9
110	6	116
40	-9.9	30.1
100	-9.9	90.1
50	-5	45
60	5.9	65.9

scope1	scope3	BWE
50	0	50
80	5.9	85.9
110	14.8	124.8
40	20.8	60.8
100	10.9	110.9
50	1	51
60	-4	56

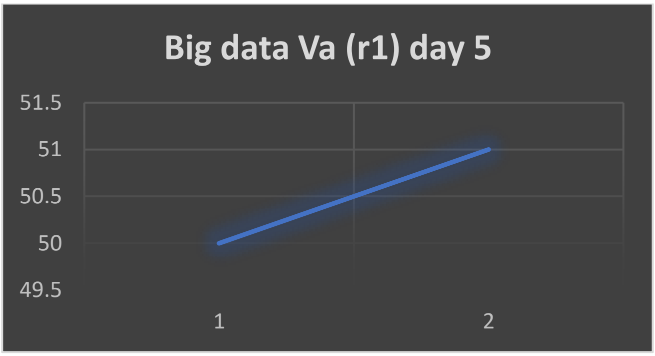
scope1	scope4	BWE
50	0	50
80	0	80
110	5.9	115.9
40	14.8	54.8
100	20.8	120.8
50	10.9	60.9
60	1	61

Figure 4.18 depicts the simulation results reported in Table 4.13. The simulation results indicate that big data variety has a negative effect on the bullwhip effect, as shown in table 4.13, scopes 3 and 4, and days 3 and 5.

Nonetheless, table 4.13, scope 2 days 3, 4, and 5 indicates that the manufacturer may be able to lessen the bullwhip effect by increasing the diversity of big data by utilising extensity ratios. Table 4.12, Scope 2 Days 3, 4, and 5, and Scope 3 Day 6 reveal a positive indication of the bullwhip effect's diversity based on large data. Based on these findings, it is possible to enhance the variety of big data to achieve better results. Despite having 200 initial values in the system, Scope 7 exhibits signs of the bullwhip effect due to the manufacturer's inability to meet demand.



Va (r1) Day 3 scope 3



Va (r1) Day 5 scope 4

Figure 4.18: Big data Va (r1) day 3 scope 3 and day 5 scope 4.
Adapted from: (source)- Matlab Simulink (2020)

Chapter 5

5.0 Conclusion

Only a few academic studies have attempted to investigate and demonstrate the in-depth impact of big data characteristics on the bullwhip effect in the supply chain. Most studies indicate that big data and data analytics can be combined and used to improve business processes and decision-making in supply chain management (Hussain and Drake, 2011; Gaalman, 2014). However, the analysis revealed that big data as an analytical category needs to be unpacked and extensively exploited to find the best possible ways to implement it into the supply chain to alleviate demand amplification (Hofmann, 2017).

Even though big data can be used in the supply chain to help improve various activities, such as demand forecasting and delivery times, Gaalman (2014). noted that big data could reduce the communication gap between stakeholders, reduce costs, and improve service levels. However, businesses struggle to find talent with big data and analytics expertise (Hofmann, 2017). Using Simulink models to operationalise big data properties in real-time could help transform the supply chain and mitigate the risk of the bullwhip effect. Furthermore, big data does not share the same qualities; however, some properties, such as big data volume and big data variety, share the same sentimental value and operate in parallel (Hussain and Drake, 2011; Gaalman, 2014).

The researcher developed multiple models using Matlab software to help generate data using constraints such as order quantities, different big data characteristics ratios, lead times, and delays to explore system dynamics and the bullwhip effect. Changing parameters on the model helped the researcher understand the variables' impact on the bullwhip effect. Furthermore, the models helped determine the most critical big data properties that significantly impact the supply chain. The researcher simulated each model numerous times, and data were collected and analysed for decision-making. Furthermore, the researcher explored optimisation strategies that can be utilised to mitigate the bullwhip effect; these include mathematical functions. The concept helped the researcher to achieve research objectives and answer research questions. However, based on the results obtained from simulating the model, the researcher has proved that using a Simulink model in the supply chain can lessen the bullwhip effect and that the Simulink model can assist the supply chain in improving inventory levels. The researcher also experimented with Simulink models by linking Module blocks that facilitate data flow from one stage of the model to the next. As a result, the researcher could generate data and comprehend the trends, correlations, and patterns inside enormous data, which would have been difficult to see without computer power, by manipulating the settings of Simulink blocks.

5.1.1 Results

This study incorporates four distinct models that assisted the researcher in investigating how big data characteristics can help the manufacturing industry mitigate the bullwhip effect in their supply chain. Furthermore, the researcher used the same random data or demand signal, simulated at different intervals; these include [50, 80, 110, 40, 100, 50, 60]. Using the same random data throughout the study helped the researcher stay on track and minimise the risk of being biased.

1. Model 1 does not incorporate big data to study the system's dynamics.
2. Model 2 incorporates big data volume.
3. Model 3 incorporates big data velocity.
4. Model 4 incorporates big data variety.

Based on the data collected throughout the studies, the research demonstrates that big data volume (Vo), big data variety (Va), and big data veracity (Ve) have distinct qualities that can enhance supply chain value to mitigate the bullwhip impact. Using the same stochastic demand signals [50, 80, 110, 40, 100, 50, and 60], the table below 5.1 displays data acquired by simulating big data Vo, big data Va, and big data Ve at various intervals. Nevertheless, the simulation was conducted from day 0 to day 6, with a lead time of 2 days for the entire process, while the initial values or buffer stock remained at 200 units. Using big data Vo ratio 1 (r1), scope 2, 3, and 4, and big data va scope 2, 3, and 4 (r1), and big data Ve (r1), scope 2, 3, and 4, the initial simulation results were obtained; this is where demand was intensified and then dropped. This concept helped the researcher comprehend how the dynamics of systems behave when demand is higher and then drops. The researcher then simulated big data Vo, Va, and Ve using a ratio (r3) between scopes 2 and 4. The procedure was conducted to comprehend the system's behaviour as the ratio increased.

Changes in ratios and related parameters, like demand signals, lead time, and delays, might impact the bullwhip effect. Some variables, including designed delays and throughput, have less effect than others. However, these parameters can be modified when the company is thriving. Changing ratios, such as from r1 to r3, has a substantial impact on the characteristics of big data. When there are no significant changes, the manufacturer must increase its interaction with its stakeholders to promote information sharing; this notion will aid the manufacturer in enhancing demand forecasting (Hussain and Drake, 2011). However, when the producer cannot interact with customers, they may increase their use of big data.

Figure 5.1 of table 5.1 demonstrates a modest reduction in the bullwhip impact from scope 2 to scope 3 of big data Vo and big data Va when utilising ratio 1 (r1). However, big data Vo produces better outcomes than big data Va, except for days 3, 4, and 5 of big data Va (r1) and day 6 of scope 5 of big data Va, where it shows a massive reduction in the bullwhip effect because of an increase in orders.

As for big data Ve ratio 1 scope 2 to scope 3 from days 0 to 6, the table shows phenomenal results compared to big data Vo and big data Va. Intensifying big data ratios from (r1) to (r3) could be an advantage for the manufacturer. However, the bullwhip effect will be minimised at a decreasing rate; for example, in big data Ve (r1) scope 2 days 0 to 6, the results are [-3.9, -6.9, -9.9, -2.9, -8.9, -3.9, and -4.9]. In contrast, the results for big data Ve (3) scope days 0 to 6 are [-3,7, -6.7, -9.7, -2.7, -8.7, -3.7, -4.7]. These results show that increasing the big data ratio can have a significant benefit, but the bullwhip effect will decrease at a decreasing rate. Therefore, the manufacturer should know the ratios to use, which could benefit the business. However, when utilising big data velocity, the manufacturer can meet demand without standing orders or backorders, as demonstrated in table 4.9, scope 7, where all orders were delivered.

Table 5.1: Big data volume, velocity & variety bullwhip effect results

Adapted from (source)- Matlab Simulink (2020)

Key input data for the simulation				Bullwhip effect for big data volume, velocity & variety ratio 2, ratio 3 & ratio 4								
Days	Lead time	Initial values	Demand Siginal	Vo(r1) scope2	Vo(r1) scope3	Vo(r1) scope4	Ve(r1) scope2	Ve(r1) scope3	Ve(r1) scope4	Va(r1) scope2	Va(r1) scope3	Va(r1) scope4
0	2 days	200	50	-0.0256	0	0	-3.9	0	0	5.9	0	0
1	2 days	200	80	-0.1449	-0.2564	0	-6.9	-3.9	0	8.9	5.9	0
2	2 days	200	110	-0.101	-0.4013	-0.2564	-9.9	-10.8	-3.9	6	14.8	5.9
3	2 days	200	40	-0.3448	-0.5013	-0.4013	-2.9	-20.7	-10.8	-9.9	20.8	14.8
4	2 days	200	100	-0.1124	-0.8472	-0.5023	-8.9	-23.6	-20.7	-9.9	10.9	20.8
5	2 days	200	50	-0.2564	-0.9595	-0.8472	-3.9	-32.5	-23.6	-5	1	10.9
6	2 days	200	60	-0.2041	-1.216	-0.9595	-4.9	-36.4	-36.4	5.9	-4	1
Days	Lead time	Initial values	Demand Siginal	Vo(r3) scope2	Vo(r3) scope3	Vo(r3) scope4	Ve(r3) scope2	Ve(r3) scope3	Ve(r3) scope4	Va(r3) scope2	Va(r3) scope3	Va(r3) scope4
0	2 days	200	50	-0.2703	0	0	-3.7	0	0	5.7	0	0
1	2 days	200	80	-0.1493	-0.2703	0	-6.7	-3.7	0	8.7	5.7	0
2	2 days	200	110	-0.1031	-0.4195	-0.2703	-9.7	-10.7	-3.7	6	14.4	5.7
3	2 days	200	40	-0.3704	-0.5226	-0.4195	-2.7	-20.1	-10.4	-9.7	20.4	14.4
4	2 days	200	100	-0.1149	-0.893	-0.5226	-8.7	-22.8	-20.1	-9.7	10.7	20.4
5	2 days	200	50	-0.2703	-1.008	-0.893	-3.7	-31.5	-22.8	-5	1	10.7
6	2 days	200	60	-0.2128	-1.278	-1.008	-4.7	-35.2	-31.5	5.7	-4	1

5.1.2 Limitations

The primary focus of this study was to investigate how big data characteristics can be implemented in the manufacturing industry to mitigate the bullwhip effect in their supply chain. A Simulink model was used to allow the researcher to manipulate various parameters and investigate how the model reacts to data changes such as unit delays, lead time changes, and the rate at which changes are made. Understanding how to operationalise mathematical functions in the model linking the Simulink blocks for effective results was one of the difficulties encountered during this study.

Another limitation encountered in this research was a lack of academic publication on how to mitigate the bullwhip effect using big data characteristics and the relative novelty of big data, making it difficult to find empirical evidence and scientific contributions on the subject. As a result, because it is a new subject in the supply chain, empirical data on the impact of big data characteristics on mitigating the bullwhip effect in supply chain management is very limited. Furthermore, nine big data properties (volume, variety, veracity, value, velocity, variability, validity, volatility, vulnerability, and visualisation) should be modelled and analysed to arrive at an unbiased conclusion.

As a result, additional research is required to model all big data characteristics. Furthermore, more analyses incorporating big data properties with existing bullwhip effect remedies such as electronic data interchange, point-of-sale technology, and vendor-managed inventory are required (Ma et al., 2013; Li, Disney, and Gaalman, 2014). Nonetheless, the researcher overcame the limitations by evaluating numerous journals on the subject, running the model, and making changes as needed; studying the system dynamics assisted the researcher in gaining an in-depth understanding of which parameters to manipulate.

5.1.3 Future research

More research into the veracity and utility of big data is required to comprehend the influence of big data on the supply chain. In addition, it is required to combine all the attributes of big data into a single model to investigate the behaviour of these properties when demand signal data is simulated. The approach could generate unique data that can be utilised to make judgments regarding how to mitigate demand amplification. In addition, the data can be used to compare single models to models that utilise all five properties of big data to determine whether this improves the bullwhip effect.

Previous studies on bullwhip effect remedies, such as using a point-of-sale system and electronic data interchange, can also be operationalised on the Simulink model. Furthermore, the model should be simulated on multiple occasions to analyse the trends and patterns in the results. Lastly, this study looked at what happened when different parameters in the model were changed. Changing these parameters can help the researcher figure out which variables are most important and need to be paid attention to. However, the study did not address other issues, such as the cost of managing the model and the skills needed to manage simulation data. As previously stated, future research should incorporate all the big data properties and test the model with large numbers of orders from multiple customers.

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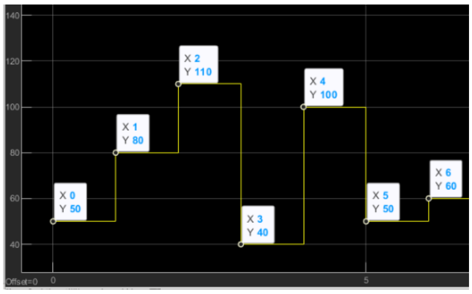
Appendix

Appendix

Appendix

Scope1



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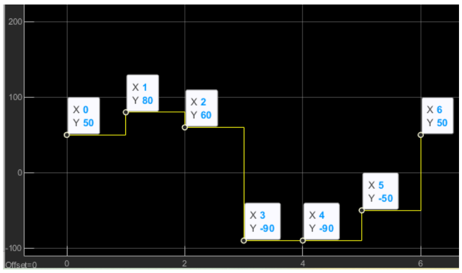

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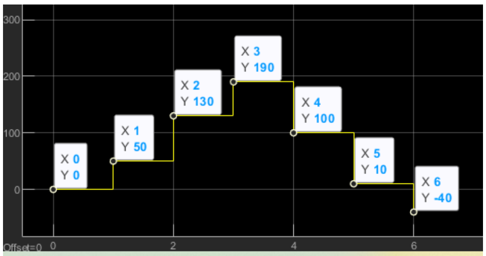

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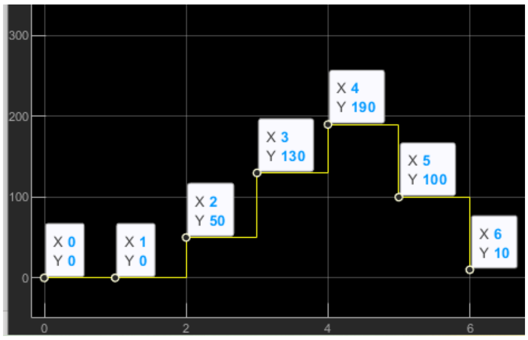

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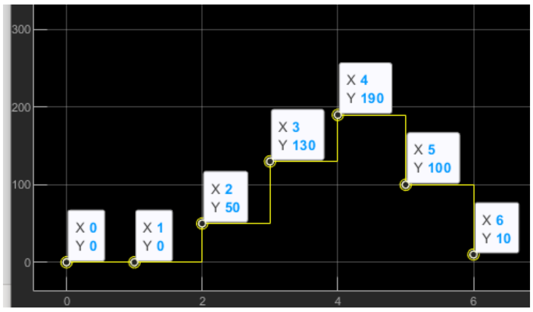

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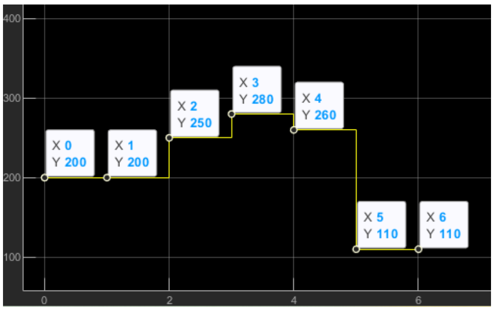

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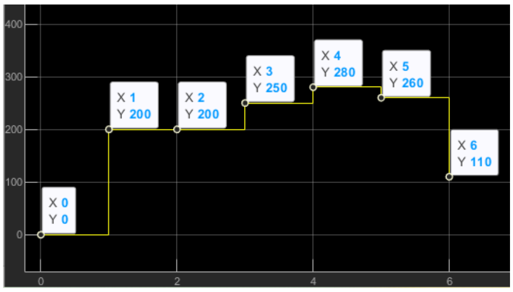

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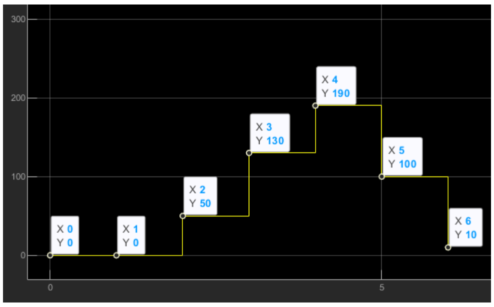
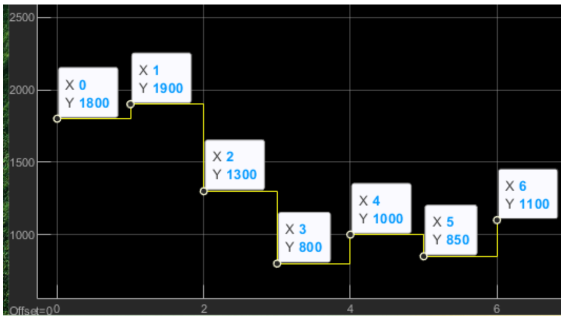
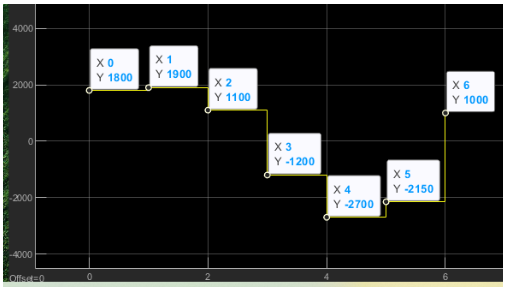


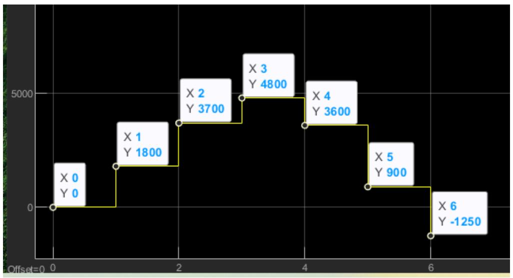
Scope 1



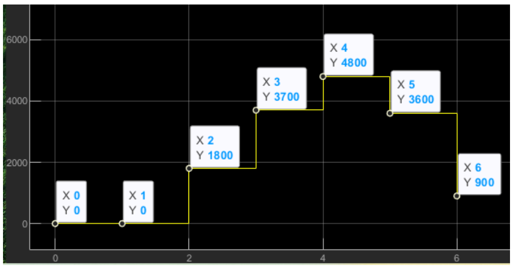
Scope 2



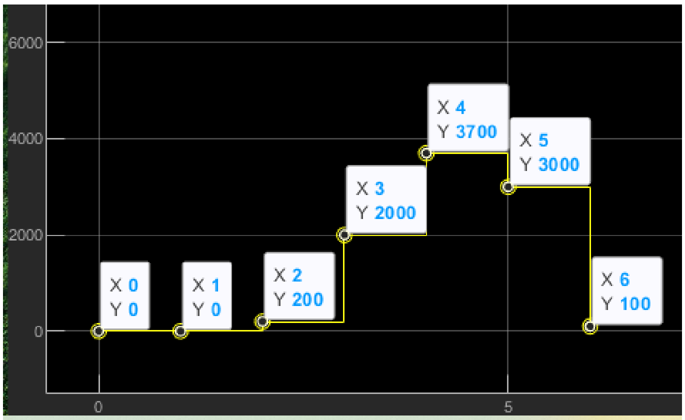
Scope3



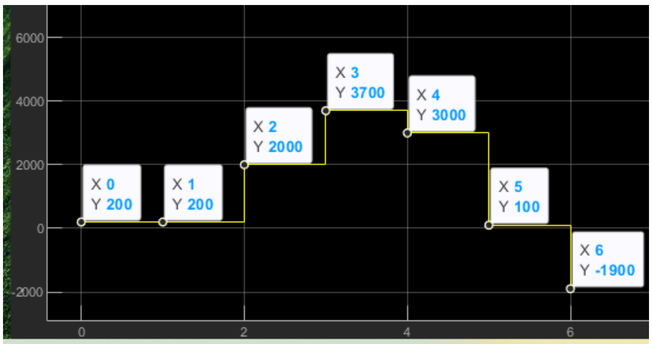
Scope 4



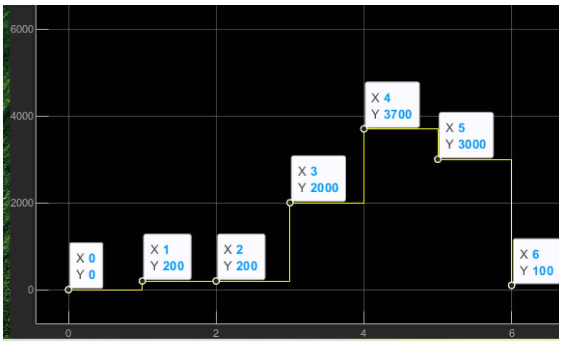
Scope 5



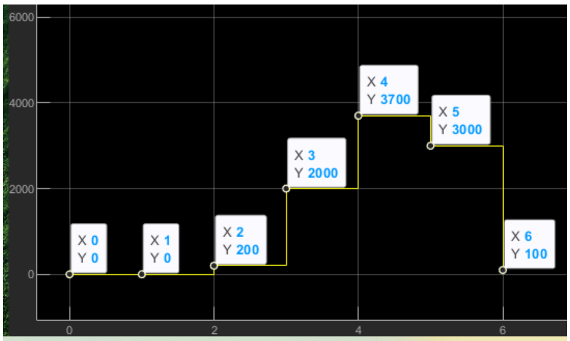
Scope 6



Scope 7



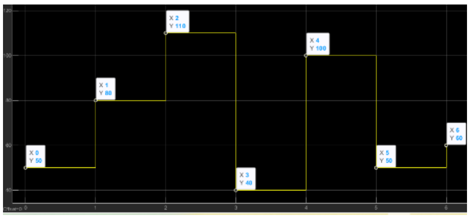
Scope 8



Appendixes 2

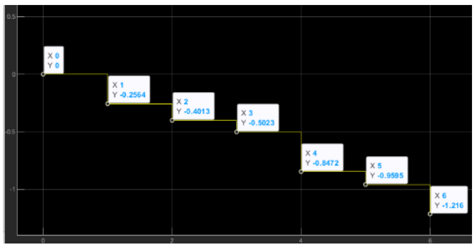
Rationing game r1 (1)

Scope1

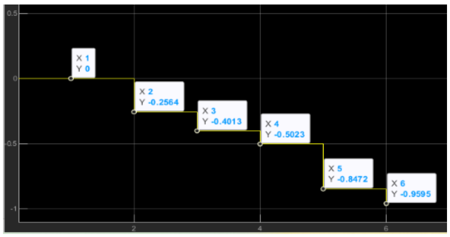


Scope 2

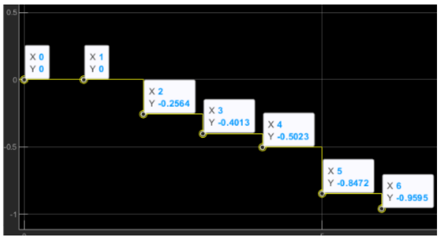
Scope3



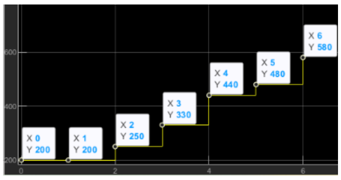
Scope4



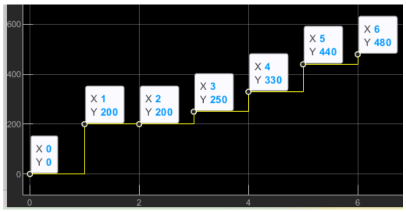
Scope5



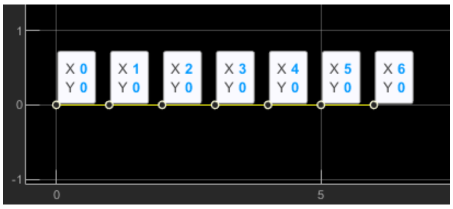
Scope6



Scope7



Scope8



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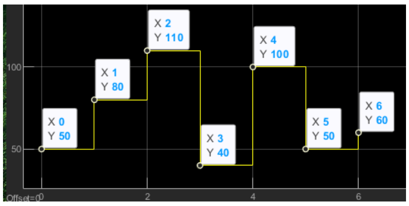
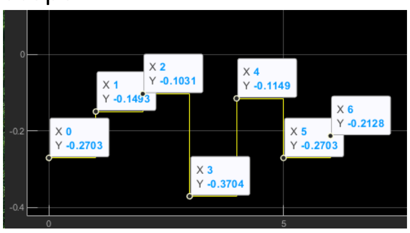
Rationing game r2 (3)

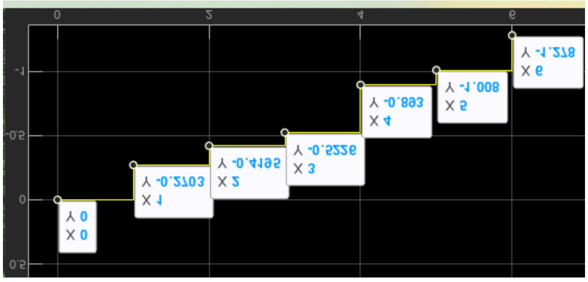
Scope1



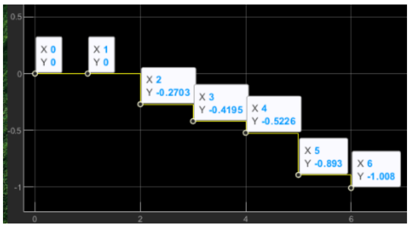
Scope2



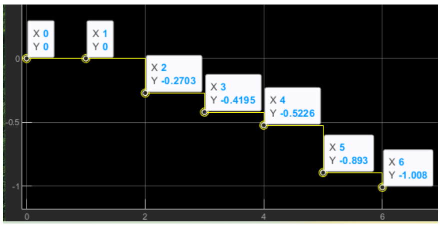
Scope3



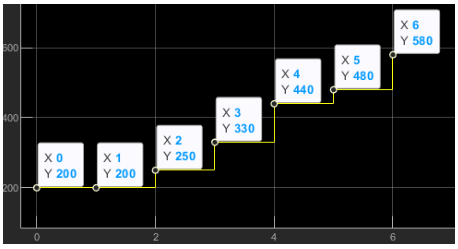
Scope4



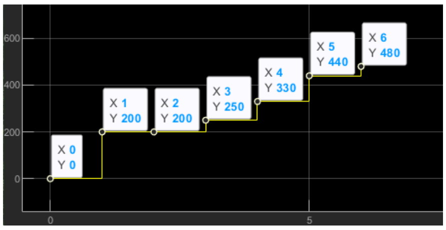
Scope5



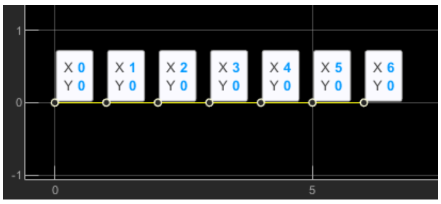
Scope6



Scope7



Scope8



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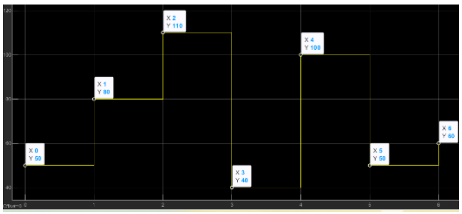
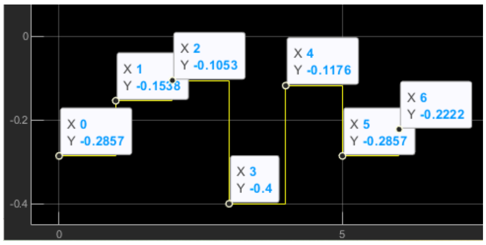
Rationing game r3 (5)

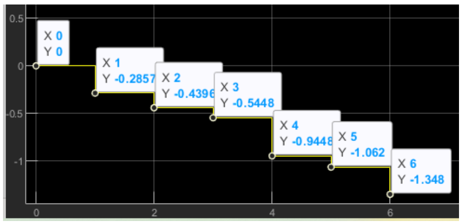
Scope1



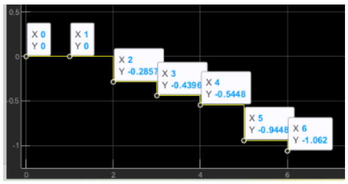
Scope2



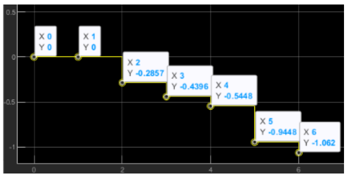
Scope3



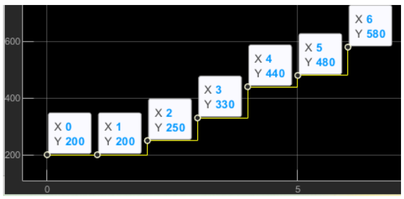
Scope4



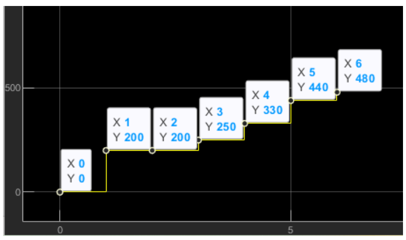
Scope5



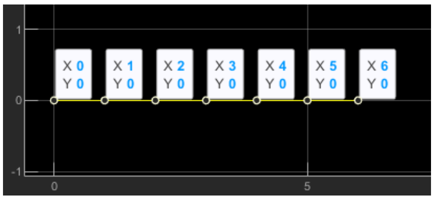
Scope6



Scope7



Scope8



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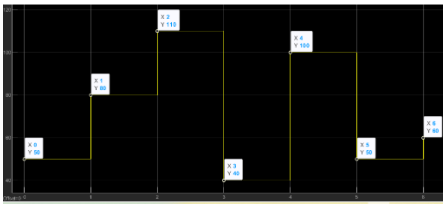
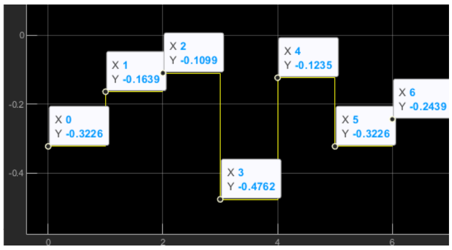
Rationing game r4 (9)

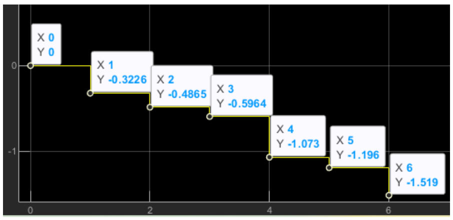
Scope1



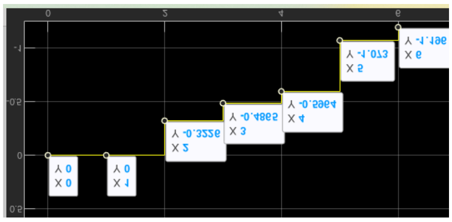
Scope2



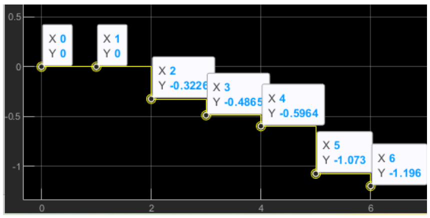
Scope3



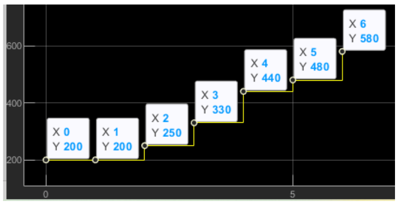
Scope4



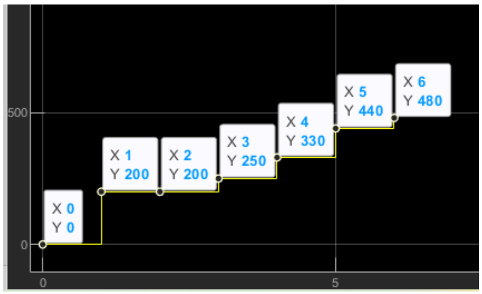
Scope5



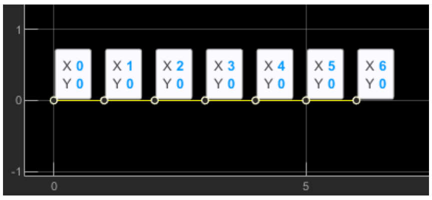
Scope6



Scope7



Scope8



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	r2	Vo3					
DAYS	SCOPE1	SCOPE2	SCOPE3	SCOPE4	SCOPE5	SCOPE6	SCOPE7
0	50	-0.2703	0	0	200	0	0
1	80	-0.1493	-0.2703	0	200	200	0
2	110	-0.1031	-0.4195	-0.2703	250	200	0
3	40	-0.3704	-0.5226	-0.4195	330	250	0
4	100	-0.1149	-0.893	-0.5226	440	330	0
5	50	-0.2703	-1.008	-0.893	480	440	0
6	60	-0.2128	-1.278	-1.008	580	480	0

DAYS	SCOPE1	SCOPE2	SCOPE3	SCOPE4	SCOPE5	SCOPE6	SCOPE7
0	50	49.7297	50	50	250	50	50
1	80	79.8507	79.7297	80	280	280	80
2	110	109.8969	109.5805	109.7297	360	310	110
3	40	39.6296	39.4774	39.5805	370	290	40
4	100	99.8851	99.107	99.4774	540	430	100
5	50	49.7297	48.992	49.107	530	490	50
6	60	59.7872	58.722	58.992	640	540	60

Table illustrates Big Data volume (volume rate 5.0)

	r3	Vo rate=5					
DAYS	SCOPE1	SCOPE2	SCOPE3	SCOPE4	SCOPE5	SCOPE6	SCOPE7
0	50	-0.2857	0	0	200	0	0
1	80	-0.1538	-0.2857	0	200	200	0
2	110	-0.1053	-0.4396	-0.2857	250	200	0

3	40	-0.4	-0.5448	-0.4396	330	250	0
4	100	-0.1176	-0.9448	-0.5448	440	330	0
5	50	-0.2857	-1.062	-0.9448	480	440	0
6	60	-0.2222	-1.348	-1.062	580	480	0

Table C2

DAYS	SCOPE1	SCOPE2	SCOPE3	SCOPE4	SCOPE5	SCOPE6	SCOPE7
0	50	49.7143	50	50	250	50	50
1	80	79.8462	79.7143	80	280	280	80
2	110	109.8947	109.5604	109.7143	360	310	110
3	40	39.6	39.4552	39.5604	370	290	40
4	100	99.8824	99.0552	99.4552	540	430	100
5	50	49.7143	48.938	49.0552	530	490	50
6	60	59.7778	58.652	58.938	640	540	60

The table below (table D1) shows Big Data volume (volume rate 9.0), while table D2 shows the calculations for demand amplification from table D1.

	r4	Vo rate=9	**Table D1**				
DAYS	SCOPE1	SCOPE2	SCOPE3	SCOPE4	SCOPE5	SCOPE6	SCOPE7
0	50	-0.3226	0	0	200	0	0
1	80	-0.1639	-0.3226	0	200	200	0
2	110	-0.1099	-0.4865	-0.3226	250	200	0
3	40	-0.4762	-0.5964	-0.4865	330	250	0
4	100	-0.1235	-1.073	-0.5964	440	330	0
5	50	-0.3226	-1.196	-1.073	480	440	0
6	60	-0.2439	-1.519	-1.196	580	480	0

Table D2

DAYS	SCOPE1	SCOPE2	SCOPE3	SCOPE4	SCOPE5	SCOPE6	SCOPE7
0	50	49.6774	50	50	250	50	50
1	80	79.8361	79.6774	80	280	280	80
2	110	109.8901	109.5135	109.6774	360	310	110
3	40	39.5238	39.4036	39.5135	370	290	40
4	100	99.8765	98.927	99.4036	540	430	100
5	50	49.6774	48.804	48.927	530	490	50
6	60	59.7561	58.481	58.804	640	540	60

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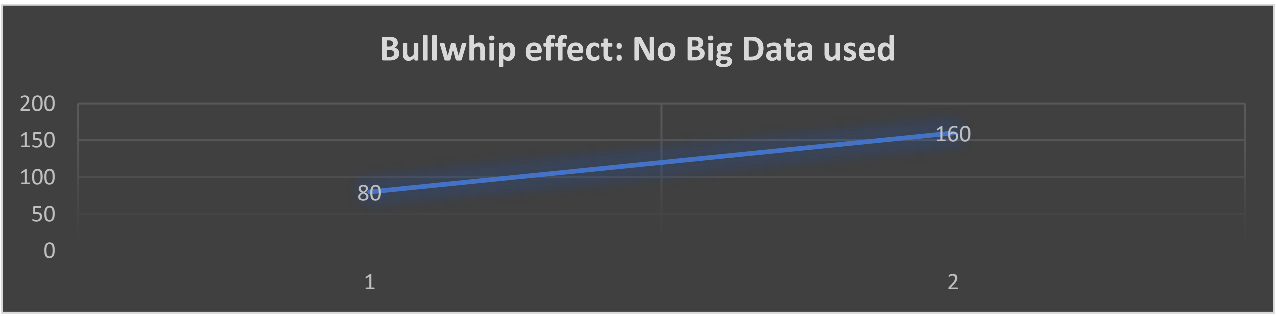
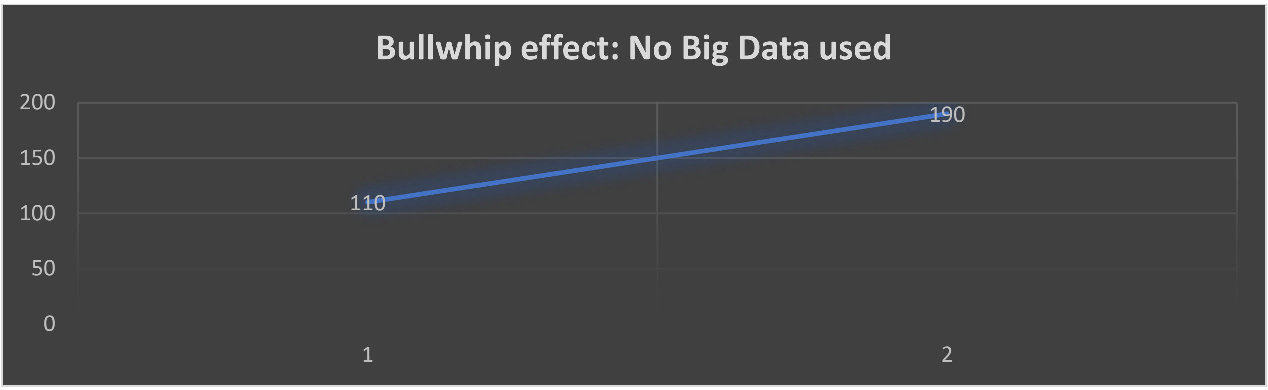
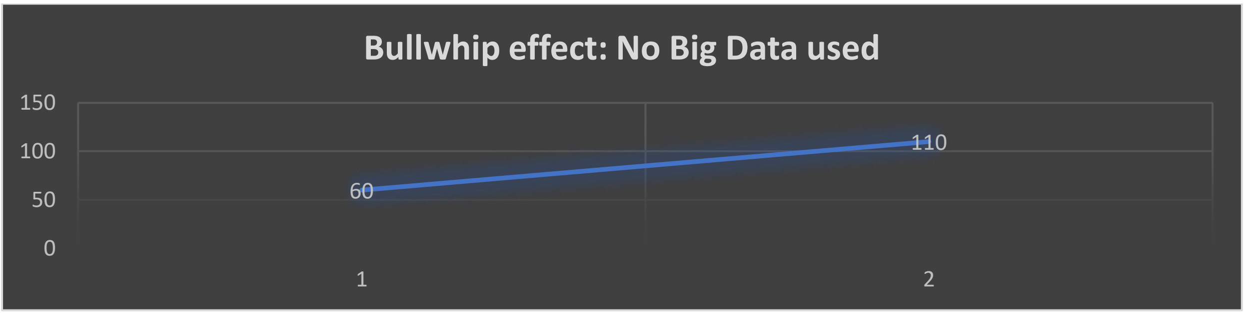
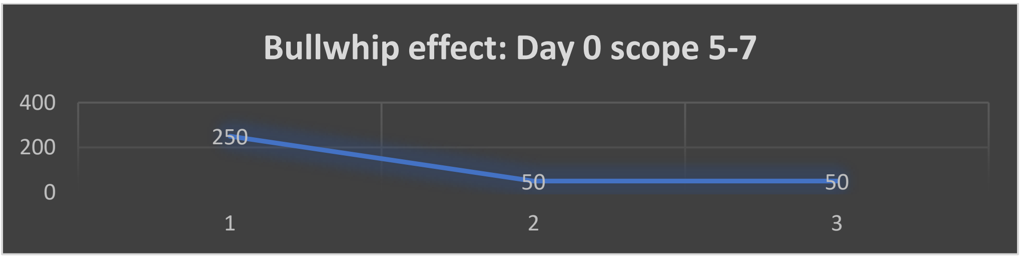


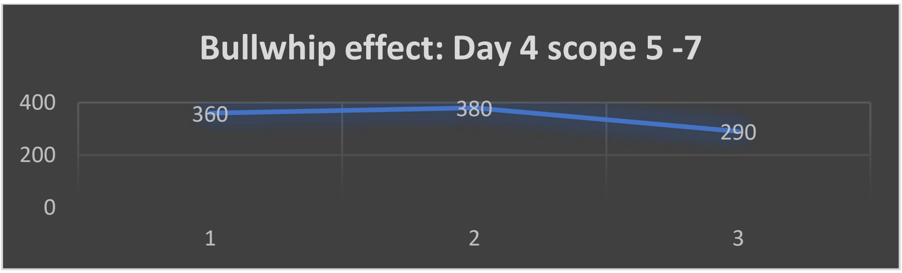
Day1 scope 1 and 2.



Day2 scope 1 and 2.







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