Stochastic optimization in perishable food supply chain: a holistic approach

by

Meghna Maity

B.Tech., National Institute of Technology, Durgapur, 2015

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree.

DOCTOR OF PHILOSOPHY

Department of Industrial and Manufacturing Systems Engineering
Carl R. Ice College of Engineering

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Manhattan, Kansas

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Abstract

With continuous expansion in world population, total food demand across the globe is anticipated to increase by 56% within a span of 30 years. Predictions state that food production needs to increase by 70% and adhere to quality standards. Better informed consumers now want to have precise knowledge about the origin of food till it reaches the final shelves of the supermarket. Perishable food supply chain is a complex network involving multiple stakeholders and several interconnected stages. Presence of uncertainties like demand, outbreak, or contamination and a limited product shelf life adds further complexity and the need to uphold food quality and safety standards throughout the supply chain, from crop production to consumers. Without traceability in food supply chains, severe problems of product recall, consumer dissatisfaction, and contamination insecurities have occurred in the past. The lack of a transparent system resulted in food loss and aggravated the global challenge of feeding a growing population. In contrast to centralized systems which lack trustworthy information and deterministic optimization models, our goal is to incorporate a dynamic system like blockchain to monitor the quality of food, keeping the entire network transparent among the stakeholders, embedded with stochastic models to make it a robustly optimized supply chain.

This research develops stochastic optimization models to comprehensively combat uncertainty in item quality, transportation of perishable items (not limited to the ones considered below) and network transparency. We consider sausage, wheat, and cheese as perishable products for our research. First, we examine a five-level sausage supply chain where at each level, the output product is manufactured by combining/mixing correct proportions of the raw materials from the

previous stage. The demand for the final product is uncertain. We develop a two-stage stochastic model and analyze it using the L-shaped algorithm to improve traceability, optimize dispersion, and fulfil demand among the batches.

Next, to maintain safety standards, detailed wheat and cheese supply chains are analyzed separately to filter relevant parameters responsible for food quality at any point in the network. We implement Q-learning algorithm to optimize values of parameters based on which the decision maker can choose the best or worst decision in determining the quality of the perishable product.

Later, we analyze a large-scale rich tanker trailer routing problem with stochastic transit times for perishable bulk orders. Unlike classical transportation problems, bulk transportation falls under the umbrella of rich vehicle routing problems that involve several intermingled decisions. Typically, the bulk orders are characterized by a set of attributes consisting of an origin-destination location pair, pickup and delivery time windows, order specification, restrictions based on prior orders of food leading to incompatibility, and possibly special equipment (washed and prepped) or handling instructions. We propose concepts of a novel graph decomposition algorithm, column generation and shortest path to generate feasible optimal routes and account for incompatibility constraints.

We overcome the challenge of network transparency by storing supply chain data in a decentralized ledger, blockchain where data is visible to all stakeholders but immune to tampering, thus enabling transparency.

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Dedication

I dedicate my dissertation to my loving parents, Shrimati Mala Maity and Shrijukta Purnendu Bikash Maity, my sister Surela Maity and my husband Sauradeep Dasgupta for being the pillars of my strength. Your love, support, care, sacrifice and endless encouragement made this endeavor possible. To my loving parents-in-law who have been so supportive and proud of me.

To friends who became my family, thank you for boosting my confidence and encouraging me throughout my academic journey.

I also dedicate this work to my colleagues who made my experience at Kansas State University an unforgettable one.

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Chapter 1 - Introduction

According to the world population prospects report, 2022 the United Nations projects an increase of 1.7 billion people by the year 2050(Photo & Debebe, n.d.). The increase in population directly correlates to an increase in food demand. With more mouths to feed, strategies involving improvement in infrastructures, investing in production , enhancing supply chain efficiency under unpredictable fluctuations, and reducing food waste should be put into effect. Food scares intensify vulnerabilities and inadequacies of a global food system resulting in food loss. If we investigate the past, the food industry experienced numerous safety and contamination scares (Wilcock et al., 2004), (Doyle & Erickson, 2006). Global safety crisis incidents such as mad cow disease (Pennings et al., 2002), foot and mouth disease (Grubman & Baxt, 2004) and outbreaks of foodborne illnesses like salmonella, campylobacter, and E-coli are few examples of how the credibility of the food industry and its supply chain network has been threatened (Rangel et al., 2005), not to mention the reducing consumer confidence and trust. Food supply chains are complex dynamic networks, and their operations are continuously influenced by various interrelated factors and ongoing changes like seasonal demand pattern, consumer preference, natural disasters or pandemics, transportation delays , food contamination etc. This thesis is motivated by a pressing product safety concern and uncertainties involved at various stages from production and processing to distribution and retail. Our work aims to address the crisis by studying several food supply chain networks under stochastic environment and identifying ways to mitigate food quality degradation over time.

1.1 Perishable Food Supply Chain

Food supply chains present unique challenges compared to other product supply chains due to the perishable nature and limited shelf life of food products. Perishable products refer to all fresh foods like fruits, grains, vegetables, meat , dairy etc. that decay with time. Managing food supply chains is often more complex and demanding. Essential facilities and methods to maintain parameters (temperature for example), throughout the food supply chain, which includes production, harvesting, packaging, transportation, and final distribution to consumers, are crucial to ensure the perishable item is delivered in its optimum condition of freshness, nutritional value and taste (Aung & Chang, 2014). A simple representation of a perishable food supply chain is shown in Figure 1.1.

Figure 1.1 A perishable food supply chain

Perishable food supply chains experience variability in terms of quality due to several factors. Environmental conditions like climate, pests, rainfall, crop & animal disease etc., parameters (temperature or humidity) in storage areas, how the perishable product is transported could be the entry points of making the supply chain vulnerable.

1.2 Blockchain

The need to track and trace source of origin, shipping conditions and quality of an item for optimum consumer satisfaction, the food industry established traceability systems. Today's consumers consider transparency and traceability an important criterion of food safety and security (Roth et al. 2008). During the last two decades, RFID (Radio Frequency Identification) has evolved a prominent technology to identify and track tags attached to a wide range of objects, such as products, assets, or even living organisms throughout various stages of a supply chain.(Y. Tsang et al., n.d.). A simulation model to obtain benefits by integrating RFID in a supply chain was proposed by Ustundag & Tanyas in (2009). The study showed a performance improvement of the supply chain concerning efficiency, visibility, and accuracy. To improve transparency in supply chains using RFID-based logistics tracking and tracing model was proposed by Feng et al., (2013). Despite being a blessing, the RFID integration was found to be quite expensive and has a small memory capacity along with the safety concern (Want, 2006). It was time consuming to trace a single item throughout the supply chain.

Blockchain, a new emerging technology, can be a potential solution for the above problems- cost, memory, and security. This technology boosts the functionality of "Bitcoins" (a digital cryptocurrency)(Bariviera et al., 2017). According to Blockchain: Blueprint for a New Economy by Melanie Swan(2015), blockchains are digital public ledgers that have recorded all bitcoin transactions. These transactions are visible to each member present on the blockchain network, providing transparency across the network. It is a text file where anyone can read and write but forging or deleting transaction events is near to impossible (Mansfield-Devine, 2017). Using the same technology, supply chain-related transactions can be registered and confirmed on the

Blockchain, including order, inventory, and products, according to Helo & Hao, (2019). Düdder & Ross, (2017) presented a blockchain solution for the timber industry, which uses many raw materials, to record the entire process from forest to paper for tracing. Blockchain tracing in the food supply chain gained immense importance with food fraud issues worldwide. In the domain of perishable FSCs, Walmart partnered with IBM in 2016 to implement a blockchain-based system to obtain data such as farm origin, batch numbers, factory and processing data, expiration dates, and shipping details which were instantly available to all network members and enabled Walmart to track down the perishable food items immediately if there was a foodborne disease outbreak (Walmart, IBM Provide Blockchain Update). Many authors have embraced the plausibility of remarkable blockchain technology in perishable FSCs (Ahamed et al., 2021; Shahbazi & Byun, 2020; Y. P. Tsang et al., 2019). Fundamental units of Blockchain are the blocks containing transactions, which get added in chronological order after verification by a mathematical algorithm (Pilkington, 2016). Miners (a subset of peers in the blockchain network) is responsible for computing these mathematical algorithms by taking the original information or transaction data (as an input) and generating a hash (as an output) that is unique to every block in the chain (Pilkington, 2016). This hash is an irreversible encrypted form of the data stored in a block, which means once data is encrypted to the hash value, it cannot be retrieved back (Ferbrache, 2016). Each block has the hash value of its previous block along with its own hash value. This attribute of the blocks creates a linked chain-like structure. Slight tampering in the data as small as 1 bit in any block, leads to a change in the hash value of not only that particular block but all the blocks succeeding it. This is because each block contains hash data of the previous block, thus letting the peers know about the discrepancy. This makes the data manipulation in a blockchain difficult because the hash value of each succeeding block along with the manipulated block needs to be rehashed (computed through algorithms) and that too before a new block gets added to the chain to hide the discrepancy (Kume et al., 2017). Regarding the security of those transactions not being manipulated or deleted, a quantitative measure of this security is presented by (Nakamoto, n.d.).

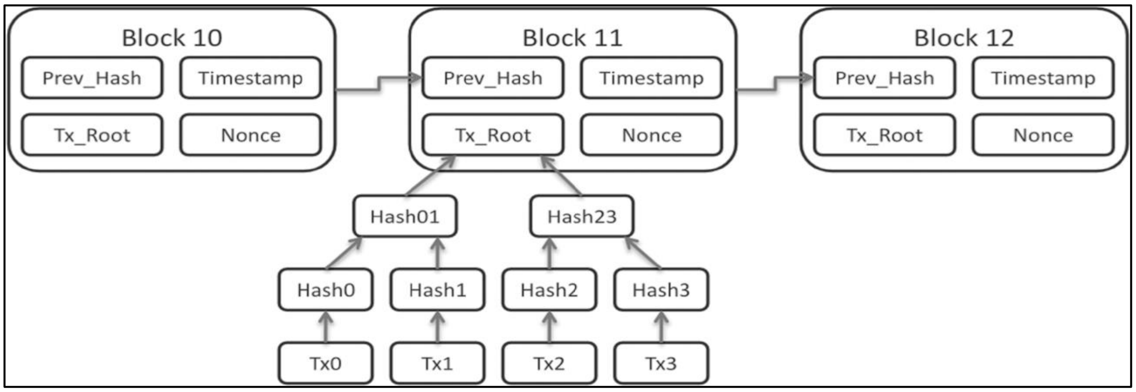

Figure 1.2 A typical blockchain (Adapted from Yermack, (2017))

A typical structure of Blockchain is presented in Figure 1.2. Components of the Blockchain are indicated in the figure. A block contains a hash value of its own as well as the previous block's hash value, which is associated with proof of work algorithm (Yermack, 2017) the transactions, and a timestamp to have an idea about when a particular event took place. We utilize the concept of Blockchain technology to answer research questions **RQ3** and **RQ6** in section 1.4.

1.3 Challenges

With global population explosion, COVID-19 pandemic and climate crisis, food supply chain has become vulnerable. The product’s journey from field-to-fork is prone to more disruptions and complexities than ever.

Uncertainty: Majority of the literature of reviewed papers focuses on the deterministic challenges faced by food supply chains, only a few proposed models considering uncertain parameters(Zhu et al., 2018). According to the review by Ahumada & Villalobos, (2009), planning models for perishable products in the past overlooked the inclusion of realistic stochastic elements within the various levels of the supply chain. This omission could be attributed to the increased complexity associated with finding solutions for the resulting models. Nevertheless, the few instances where researchers introduced reality-based stochastic features into their planning models demonstrated that the benefits outweighed the added complexity. These models were able to provide more accurate and effective decision-making support by considering the inherent uncertainties and perishability aspects of the supply chain. For example, Maia et al., (1997) modelled uncertainty in operating conditions with three scenarios of probability of occurrence. Kazaz, (2004) presented a Stochastic model for a company producing olive oil where demand and yield were considered uncertain. It is easier to model uncertainty if we assume to possess partial knowledge about it, for example if it follows any known distribution. It is considerably more challenging to model the quality of food as a variability, as it doesn't adhere to well-known distributions. According to Rahbari et al., (2019), there isn't much literature in terms of modelling uncertainty in perishability or freshness which subsequently determines the quality of a food item. Uncertainty also exists in transit times while shipping perishable food items from point of pickup to point of delivery in outbound vehicles(Rahbari et al., 2019). Travel times can be influenced by unpredicted elements such as adverse weather, car accidents, road constructions, traffic congestion etc. (Çimen & Soysal, 2017). Considering deterministic transit time would therefore be a strong simplification of reality.

Traceability: The absence of food traceability has led to severe problems like product recall, consumer dissatisfaction, and contamination insecurities in the past. Companies that produce, process, and deliver food are catering to an aware group of consumers who now like to know everything about the food they consume. The food industry has implemented traceability and transparency-related strategies (Feng et al., 2013) to improve its quality and safety and satisfy international standards and certification requirements. Moreover, due to increasing customer pressures, companies have started to invest in traceability and transparency techniques to ensure a safer and efficient food supply chain network (Roth et al., 2008). Traceability contributes to an effective food safety system and thereby helps companies recall contaminated food batches; in case the need arises.

Transparency: Transparency in the food supply chain would mean an architecture where food operators provide data about their products and operations and 3rd party service provider manages a transparent software system (Kassahun et al., 2016). Relying on centralized regulatory bodies to monitor operations and possess authority over the supply chain leads to low transparency and increased risk of security, data tampering, authentication and trustworthiness (Helo & Hao, 2019). Blockchain's fundamental characteristics remove the need of middleman unlike centralized systems and ensure stakeholders can track each activity across the entire network. In a Blockchain, manipulating a bit of data would inform about data discrepancy to all the participants present in the network.

In the next section, we discuss the driving factors and research inquiries that arise within the context of perishable food supply chains. We will delve into the motivations behind studying this area and outline the key research questions that researchers and practitioners seek to address.

1.4 Motivation and Research Questions

This thesis studies challenges about traceability and uncertainty in perishable food supply chain mentioned above through efficient stochastic mathematical models and propose emerging blockchain technology (Tian, 2016) as an approach to tackle transparency issues.

1.4.1 Dispersion and Demand Uncertainty in Sausage Supply Chain:

The inspiration of the proposed research to incorporate traceability, builds upon a five-level sausage supply chain model (Dupuy et al., 2005). At each level, the output product is manufactured by combining/mixing correct proportions (according to BoM or bill of materials) of the raw materials from the previous stages. Raw materials are obtained from different parts of the animal slaughtered, in the form of ham, side pieces, shoulder pieces etc. to yield sausages as final product. The phenomenon where individual items mixed or grouped together in a batch during the processing stage of supply chain is called batch dispersion and can result in product recalls (Dupuy et al., 2002). In a sausage industry for example, batch dispersion could be defined as the links between raw materials and finals products when no other scope of variability exists as shown in Figure 1.3.

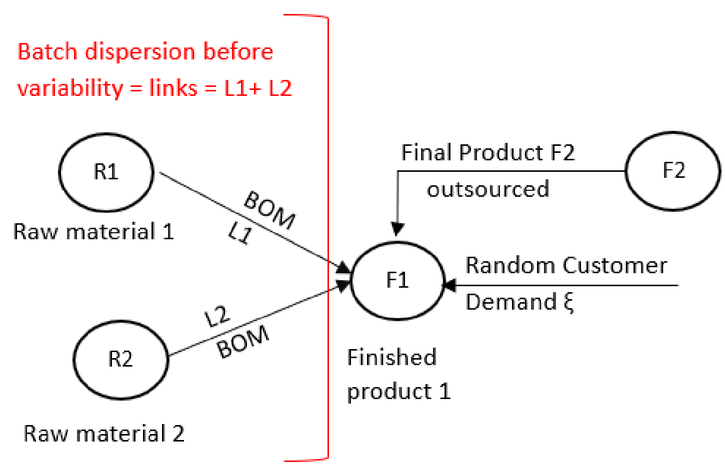

Figure 1.3 Batch dispersion

Variability can exist in the form of uncertain consumer demands and outsourcing finished products from other suppliers . To establish traceability under stochastic demand scenarios, we explore the research questions below.

RQ1: What is the optimum dispersion in batches obtained to make sure batch recalls are minimum in case of a bacterial contamination crisis?

RQ2: What are the variabilities considered while optimizing the batch dispersion model? How will the batch dispersion model behave under known random distributions of demand scenarios?

RQ3: How to ensure perishable supply chain data is visible to all stakeholders but immune to tampering?

We provide answers to these questions in Chapter 3 of our thesis. Question RQ3 is also answered in Chapter 4.

1.4.2 Parametric Uncertainty in Wheat and Cheese Supply Chain

Unlike the demand uncertainty in the sausage supply chain that followed a known random distribution (Exponential, Poisson, Normal etc.), in real time environment the likelihood of obtaining partial or full knowledge of an uncertainty is questionable and computationally expensive (Zhang et al., 2009). There is uncertainty about the quality of food (which doesn't follow any known distribution) as it transits through different stages of the Supply Chain. We extend our research on implementing reinforcement learning model (as in Figure 1.4) in a wheat supply chain in such a stochastic environment and validate the same on real time data obtained for cheese supply chain. We focus on developing a dynamic monitoring system for wheat supply chains to reduce bacterial contamination and optimize parameters responsible for maintaining food quality. Initially, parameters that affect the quality of a perishable item (wheat in our case) due to bacterial contamination are selected. Such parameters can be temperature, humidity, pH of wheat in silos etc. leading to contamination or bacterial growth at any point along the chain—production, processing, preparation, and distribution. According to CDC, more than a 100 people were infected by a Salmonella outbreak in packaged sea food in 2021 and 1040 people affected due to onions containing bacterial growth in 2020 (Outbreaks Involving Salmonella | CDC, n.d.). Data was collected conventionally by reviewing records from restaurants and stores. Since past work mostly focused on how to trace or track batches that were already contaminated, we came up with a data-driven technology such as machine learning - Q-learning model (Sutton, R. S., & Barto, A. G., 2018) to optimize selected relevant parameters impacting food quality at all stages of the supply chain and ensure good quality of product. Therefore, as a decision maker the following research questions need to be addressed.

RQ4: What are the relevant parameters impacting perishable food quality?

RQ5: How can we determine the best course of action (in our case, values of parameters) as the product transits through different stages of the supply chain with an unknown transition probability and optimize them to satisfy quality standards?

RQ6: Can this model-free resilient model be applied for other perishable supply chains as well while securing the supply chain data?

Chapter 4 of our thesis contains the responses to these inquiries.

1.4.3 Stochastic Transit Times and Product Incompatibility in Liquid Food

Perishable liquid food like dairy products, liquid eggs, fruit juices, vegetable oils ,honey etc. consumed by people are shipped in food grade tankers (Kan-Haul, inc, ; Matlack Leasing, LLC)

Figure 1.4 Food grade tankers

Figure 1.4 displays examples of a few companies specializing in bulk liquid food transportation. Food Grade Tankers consist of a horizontally positioned cylindrical tank that is integrated into the body of the vehicle. To ensure product safety and integrity, it is essential to have a Safety Data Sheet (SDS) that provides detailed information about the characteristics of the product being shipped. According to Kan-Haul, inc, one such characteristic SDS contains is the information about the compatibility of a product with other substances, it could be compatibility between current and previous cargo or when carrying a mixed load for example. It is vital to prevent contamination and maintain the integrity of the product throughout transportation, adding complexity when selecting a feasible subset of tankers for a route. Another characteristic SDS contains is data regarding spoilage rate, which indicates how long the product can remain in a tank without deteriorating. This information is valuable as it allows for appropriate route planning in case of unforeseen or stochastic events such as storms or delays during transit. We investigate the following questions concerning a more realistic vehicle routing problem with stochastic travel time and order incompatibility constraints.

RQ7: How to choose feasible tankers for bulk liquid food transportation?

RQ8: How can we generate optimal routes, considering that the number of possibilities of choosing trailer route combinations with respect to compatible cargo could be in billions ?

We address the questions in Chapter 5.

1.5 Solution Approaches and Thesis Outline

We develop stochastic models in our thesis to analyze how perishable food supply chains behave in different types of uncertain environments. We derived theoretical results for our objectives and had the opportunity to validate our findings with real time data from an active cheese supply chain at Kansas State University.

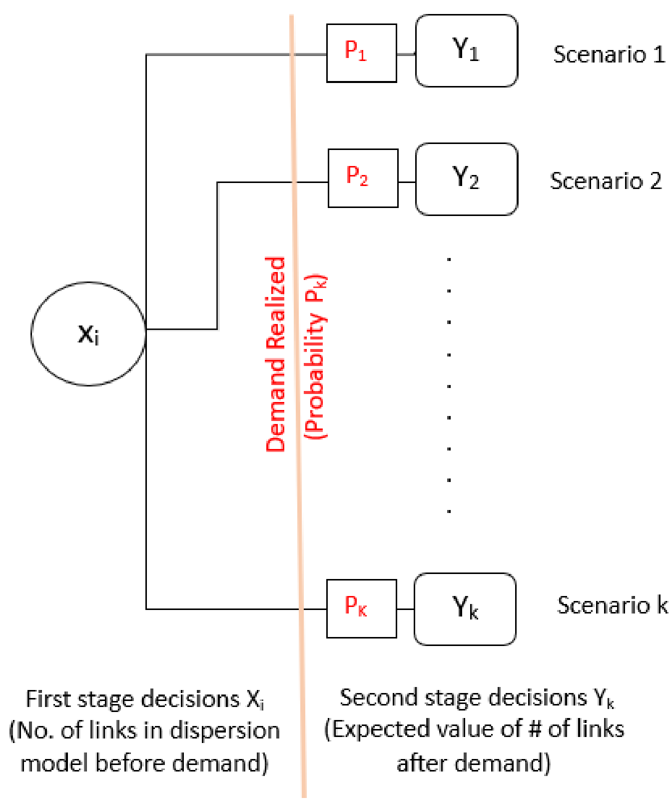

Figure 1.5 Decision making for two-stage stochastic model.

In **Chapter 3**, we investigate a sausage supply chain as an instance of perishable food supply chain under stochastic demand that follows a known random distribution. We apply the classical two-stage stochastic linear program as shown in Figure 1.5, with finite number of demand realizations (Birge & Louveaux, 2011) for **RQ1** and **RQ2**. The idea is to choose initial decisions for the variables not influenced by randomness as our first stage decisions. These decisions are deterministic. In the second stage, when actual values of uncertainty are revealed, recourse or corrective actions can be taken based on the first stage solutions. The objective value determines the minimized cost of initial decisions (calculated in first stage) plus the expected value of the recourse actions (second stage) over all realizations of uncertainty. Uncertainty of demand in the case of sausage supply chain follows a known random distribution with available information about the probability distribution for each scenario. **We have published our research findings from Chapter 3**(Maity et al., 2021).

Next, we extend our research to modelling parametric uncertainty in a wheat supply chain and validate our model with real time data obtained from cheese supply chain in **Chapter 4**. **Our findings with respect to wheat supply chain is a published work**(Maity et al., 2023) The quality of the perishable product as it travels through different stages of the supply chain, is considered random. The quality is dependent on relevant parameters and a reinforcement learning algorithm is applied to figure out the best course of action (values of parameters) to ensure good quality throughout the supply chain. Decision making in situations that involve sequential actions call for the application of the well-known Markov Decision Process framework(Bellman, 1957). In an MDP, a decision-maker known as the agent, interacts with an environment in discrete time steps. At each time step ‘t', the agent chooses an action ‘A_t’ from a set of available actions. One time-step later, the environment, in response to the action, rewards the agent numerically with 'R_{t+1}' and transitions the agent to a new state 'S_{t+1}' with a certain probability as shown in Figure 1.6. The objective of the agent is to maximize the cumulative rewards over time.

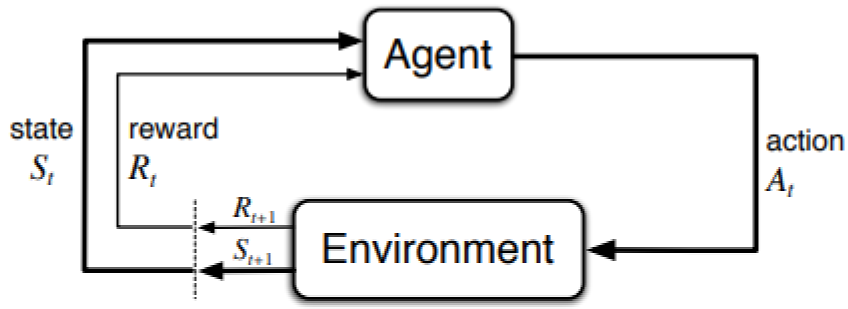

Figure 1.6 Agent-environnement interaction in MDP **(Sutton, R. S., & Barto, A. G., 2018)**

However, in reality, computing transition probability is not always feasible. We model uncertainty in such a scenario for the wheat and cheese supply chain in our thesis. Without transition probability, the environment becomes model-free, so we apply Q-learning, a model-free reinforcement learning algorithm. The agent learns action-value function or Q-value, that estimates the expected cumulative rewards for taking a particular action in a given state. The Q-value is updated iteratively based on the actions taken (**RQ4, RQ5, RQ6**).

In **Chapter 5**, we analyze logistics involved in perishable supply chains, liquid food to be specific. As we know, logistics plays a key role in selecting the appropriate transportation modes, routes, and carriers to move goods from suppliers to manufacturers, distribution centers, retailers, and end consumers. Efficient transportation management helps optimize delivery times, minimize costs, and ensure products are delivered to the right locations in their optimum conditions. We consider bulk liquid food being transported in tanker trailers with stochastic transit time and product incompatibility constraints (**Section 1.4.3**) as our last problem of investigation in perishable food supply chain. Options of selecting a combination of feasible trailers and the compatible products it can carry could be in billions as complexity and size of a problem increases exponentially when number of variables become more than the constraints involved. Generating thousands of feasible routes with customers and multiple compatible orders make it difficult to solve the problem using classic linear programming methods so we apply a novel integrated framework that combines shortest path concepts and efficient graph decomposition with column generation technique (Delli & Sinha, 2019) (**RQ7, RQ8**). Column generation is an indispensable tool in computational optimization to solve a mathematical program by iteratively adding the variables of the model (Feillet, 2010).

Chapter 6 concludes with a summary of the key findings and contributions of this dissertation, along with an exploration of potential areas for future research.

Chapter 2 - Literature Review

In this Chapter we identify and evaluate relevant literature. Our thesis focuses on modelling uncertainty in different perishable food supply chains (FSC). The chapter comprises of 3 sections. Section 2.1 talks about traceability and transparency as two key challenges in establishing FSC visibility. Section 2.2 focuses on reinforcement learning and how it can be applied to perishable FSC with randomness. Section 2.3 focuses on vehicle routing problems with respect to bulk liquid food transportation and its challenges.

2.1 Evolution of Visibility in Perishable Food Supply Chain

According to Lyles et al., (2008) and Tse & Tan, (2012), product recalls can occur due to two primary reasons. Firstly, manufacturing defects, where the product fails to meet the required specifications. Secondly, design defects, where the product does not comply with safety standards. Traceability and transparency are the two key aspects of supply chain (SC) visibility that enable companies to track and monitor their SC processes in real-time, from sourcing of raw materials to delivery of final product to the end consumer (Tse & Tan, 2012). It involves having a clear understanding of movement of goods and their quality, information, risks, and finances throughout the entire SC network. Absence of traceability-monitored-policies make product recall an extremely challenging task as there is additional burden of finding alternatives to ensure defective batches are withdrawn or disposed (Jayaraman et al., 2019).

We summarize studies related to evolution and development of traceability system in FSCc. Visibility in terms of traceability and transparency in FSCs is particularly important, as there is a continuous change in the quality of items which directly impact our health. The quality of an item significantly affected by factors like bacterial contamination, jeopardizes food security and leads to food borne illnesses and outbreaks. In 1994, USDA declared E.coli O157:H7, an adulterant of ground beef resulting in its mandatory recall. In 2006, 26 states reported 200 infected cases from the same E.coli variant due to consumption of fresh spinach and a similar incident associated with shredded lettuce was traced back to the accidental mixing of well water, intended for irrigation, with water from a dairy manure lagoon was reported in 2008(Bintsis, 2018). In 2016, Centers for Disease Control and Prevention (CDC) and the US Department of Agriculture's Animal and Plant Health Inspection Service investigated eight distinct outbreaks of Salmonella infections in humans from multiple states (CDC, 2016). Epidemiologic, traceback, and laboratory findings linked the eight outbreaks to people coming in contact with live poultry in backyard flocks sourced from multiple hatcheries. Around 900 people from 48 states were reported infected. These challenges triggered the importance of establishing a proper traceability system in FSCs.

The concept of a distinct traceable resource unit- TRU was first assumed by (Kim et al., 1995). It is the smallest, uniquely identified entity that is created during the internal production process. This work answers how given an entity and a state of enterprise, all necessary attributes that have a bearing on the quality of the given entity, can be traced and identified. Several other examples of traceability by many authors have been provided in the paper by Bosona & Gebresenbet, (2013) where a comprehensive literature review of 74 studies from 2000 to 2013 on food traceability issues was conducted. A new definition of food traceability being an integral component of logistics management that could capture, store, and transmit adequate information about a food, feed, food-producing animal, or substance at all stages of FSC was proposed as a part of the study so that the product could be checked for safety and quality control, traced upward, and tracked downward at any given point of time. To trace and track agricultural batch products, Ruiz-Garcia et al., 2010 implements a prototype where companies would be responsible for documenting the goods' whereabouts, how they are processed, and where they are transported. A key milestone was achieved with the involvement of Information Technology (IT) in reshaping product traceability (Sahin et al., 2002, Morrissey & Almonacid, 2005). IT provided a technological breakthrough to track livestock and products(Karlsen et al., 2013). Over the last two decades, radio frequency identification (RFID) has established its presence in almost every domain where tracking and tracing are necessary (Feng et al., 2013, Kumari et al., 2015). It has proven to be a promising tool to track products but could not track the number of recalled batches in case of contamination (Badia-Melis et al., 2015, Manos & Manikas, 2010). RFID traceability is suitable for detecting faulty batches, but not enough to reduce the number of batches recalls because traditionally RFID has been used only to track damaged items and correspondingly recall them (Chaves & Kerschbaum, 2008). Dupuy, Genoulaz & Guinet (2005) formulates an optimization model to reduce batch size dispersion which would lead to lesser recalls in the context of food (sausage) manufacturing. The model is a 3-level disassembling bill of materials (BOM), including raw materials, semi-finished and finished products. However, the paper does not deal with simultaneous packaging and distribution of the finished product.

Next, from a modelling perspective, we review perishable FSCs in deterministic and stochastic environment setting. Ahumada & Villalobos (2009) studies several supply chain planning models for perishable and non-perishable items where authors use traditional approaches such as linear and mixed integer programming, dynamic programming for deterministic parameters. Many researchers have focused on a deterministic model in the food supply chain literature and have not considered uncertainty in demand and production process (Kelepouris et al., 2007), (Tian, 2016) Kopanos, Puigjaner, and Georgiadis (2012) developes a deterministic model on the simultaneous optimization of detailed production and distribution operations. Novelty of the proposed mathematical formulation in the paper lied in the integration of three different modeling approaches: (i) a discrete-time approach for inventory and transported quantity calculation, (ii) a continuous-time approach for sequencing and timing decisions of similar products grouped into families, and (iii) lot-sizing type capacity constraints. The paper suggests oscillations in product demands and other operating and financial uncertainty factors to be considered as future research towards application of stochastic programming.

A handful of legislative measures have been taken to ensure food safety, but they do not always help in acquiring a successful food traceability system when uncertainty which is considered the sole source of perceived risk according to Choe (2009) is involved. Only a limited amount of literature exists where authors have utilized Stochastic programming for perishable FSCs (Ahumada & Villalobos, 2009). Maia et al., (1997) proposes a mixed integer programming model to optimize capital investment in food preservation facilities based on uncertain operating conditions with corresponding probabilities of occurrence. Scenario 1 with a probability of 0.3 represents pessimistic condition foreseeing high fraction of spoiled fruits, low demand, unfavorable selling price and poor yield. Similarly, scenarios 2 and 3 represent normal and optimistic operating conditions with 0.5 and 0.3 as probability of occurrence. Under a more realistic uncertainty condition of demand and yeild, Kazaz, (2004) investigates a Turkish company which produces olive oil. Demand in this paper is a function of unit sale price of olive oil and a random error uniformly distributed, representing noise. Randomness in yield follows a discrete uniform distribution as well. The choices in front of the company are either to lease olive trees or outsource them at a higher price under each scenario of stochasticity. Kazaz, (2004) provides a two-stage stochastic production plan. In the first stage, how much farm space must be leased is decided. The number of olives to be purchased from other growers and the total amount of olive oil to be produced are second stage decision variables.

While traceability ensures every movement of a TRU can be tracked back to its origin, transparency on the other hand would allow relevant information about the various stages, processes, and entities involved in a product's supply chain to be openly accessible and understandable to stakeholders, including consumers, businesses, and regulatory authorities. To gain supply chain visibility, it is necessary to employ both traceability and transparency. However, information currently relies on centralized systems exposing supply chain data to the risks of manipulation and single point of failure (Sunny et al., 2020). Blockchain technology, an ingenious solution can facilitate secure and immutable ledgers which are decentralized in nature. Kouhizadeh, (2019) studies and analyzes cases of blockchain application in industrial sectors with different adoption levels to identify potential for diverse organizational purposes. Each ongoing transaction or event in a supply chain can be chronologically added to the digital ledgers called blocks, where the network players (suppliers, distributors, customers etc.) can validate the authenticity of the information (**Section 1.2**).

Our research in **Chapter 3** is an extension of Dupuy et al., (2005) deterministic traceability model. We introduce stochastic customer demand as our research’s novel contribution to capture a holistic picture across the network. We also include the packaging stage or the final step of batch production to provide a 5-level disassembling BOM to optimize the batch dispersion and enhance TRU traceability. We develop the stochastic model to study batch dispersion and analyze the entire supply chain from its raw materials to packaging the batches under uncertainty in the demand of the end product and solve the model using L-shaped method (**RQ1,RQ2**). We present our supply chain dispersion problem as a two-stage stochastic optimization model (Kall et al., 1994) where the first stage determines the raw materials to use at each supply chain level. The second stage optimizes the flow across the arcs of the supply chain network. In a two-stage stochastic problem, the linear program can be written as,

$$\begin{aligned} \min z = \ & c^T x + E_\xi [\![Q(x,\xi)]\!] \\ \text{s.t. } & Ax = b, \\ & x \geq 0, \end{aligned} \tag{2.1}$$

where

$$Q(x,\xi) = \min\{q^T y \mid Wy = h(\xi) - T(\xi)x, \ \ y \geq 0\}. \tag{2.2}$$

In the formulation, ξ represents randomness, which is demand uncertainty in our model. First stage decisions x are deterministic and obtained keeping in mind the uncertainty. In the second stage, when actual values of uncertainty ξ is realized, corrective measures called recourse actions y are decided (Birge & Louveaux, 2011). This method has been used in various domains like supplier selections in supply chain and reservoir systems (Carpentier et al., 2015), production–transportation planning etc (You & Grossmann, 2013). Our research is the first one to include its unique implementation in the food supply chain. Many researchers have used machine learning techniques to estimate parameters, using machine learning to perform prediction or classification of random data (Deng et al., 2020, Zhao et al., 2019, 2020). However, we analyze multiple demand distributions and numerically highlight the optimal production decision's structure taking various demand scenarios. Using numerical studies, we also observe that the quantity of packaged goods follows similar distribution as random demand distribution to satisfy it. We integrate blockchain technology where data related to our perishable supply chain can be stored securely (**RQ3**).

2.2 Reinforcement Learning in Perishable FSC with Randomness

The quality of a perishable item is degradable with item and this factor makes perishable supply chains unique. Due to globalization of markets, products are moving throughout the country and exported. Population increase, unfortunate weather events, pandemic situations like COVID-19, bacterial contamination of products, rainfall, soil, temperature, humidity etc. are some of the controllable and uncontrollable parameters that places unprecedented disruptions in front of perishable food supply chains—bottlenecks in transport and logistics of perishable products, unexpected consumer demand, degraded quality and food loss to name a few. Monitoring dynamically changing quality while the product is exposed to uncertainty in supply chain transit is therefore a complex task. Ketzenberg et al., (2015) compare two cases, with and without availability of information on flow time and temperature history of products, which is used for determining shelf life. The authors formulate inventory management in perishable FSCs subjected to stochastic demand and lost sales, as Markov Decision Processes (MDP) under the two scenarios of availability of information. Fianu & Davis, (2018) modelled perishable FSC using MDP under stochastic supply and deterministic demand. Assumptions were made about the quality of the item being at par with the standards for food safety and distribution practices. However, none of the papers modelled quality as a parameter which is dynamically changing from one state to another at every point of supply chain and exposed to uncertain environmental factors. MDPs provide the framework for dynamic optimization problems are designed for decision making when the value of a certain probability known as ‘Transition probability’ is available and cardinality of the problem considered is small. The decision maker in an MDP, the ‘agent’, interacts with an external system called ‘environment’. The agent has an available set of options $a \in A$, called ‘actions’ to choose from. Actions could denote choosing values of parameters affecting quality of a perishable item. At each time step t, the agent is present in a representation of the environment called current state S_t. State is quality of perishable item in our problem of study in **Chapter 4**. Based on the selection of an action, one time step $'t+1'$ later, as a part of the consequence the agent moves to a new state S_{t+1} earning a numerical reward R_{t+1}. There is an associated probability of occurrence to the values of S_t and R_t based on the action chosen. This transition probability is a fundamental aspect in defining the dynamics of MDP (Sutton, R. S., & Barto, A. G., 2018) and is given by equation (2.3).

$$p(s',r|s,a) = Probability\{S_t = s', R_t = r | S_{t-1} = s, A_{t-1} = a\} \qquad (2.3)$$

In an increasing number of ‘state-action’ spaces, as in real-world applications, it is not practically possible to estimate the values transition probabilities. It is very computationally expensive too.

In the absence of transition probability function where explicit knowledge about the model is unknown, a class of RL algorithms called model-free algorithms are applied(Sutton, R. S., & Barto, A. G., 2018). We propose ‘Q-learning’, a model-free algorithm to overcome the crisis of obtaining transition probability while modelling quality of a perishable product exposed to parametric uncertainty in Chapter 4 (**RQ4,RQ5,RQ6**). The agent in model-free scenario must interact with the environment directly in a trial-and-error fashion to obtain information about how good an action is. Q value denoted as $Q(s, a)$ is the expected discount reward for executing such an action 'a' in state 's' and is updated after every trial.

2.3 Vehicle Routing Problem with Respect to Bulk Liquid Food Transportation

Logistic industry is expanding rapidly, 13% (Marsetiya et al., 2020) in the Unites States in the last few years. One of the most commonly investigated problems in logistics industry is the Vehicle Routing Problem (VRP) which determines the optimal routes carried out by a fleet of vehicles to serve a particular set of customers. Route determination by VRP becomes particularly daunting when perishable food items are involved due to their property of dynamically changing their quality over time. (Marsetiya et al., 2020) presents a systematic review of VRP involving perishable goods. The author provides an in-depth analysis of single and multi-objective problems based on the optimization methods and objective function for VRPs with perishable goods. Approximately 55 unique papers have been published in the last decade and a trend of an increasing interest to study VRPs of perishable goods is observed. According to (Oyola et al., 2017) several versions of VRPs exist depending upon the type of constraints and considerations included. For example, VRPTW (VRP with time-windows),VRPPD (VRP with pickup and delivery), VRPB (VRP with backhauling) etc. When real world parameters like traffic congestion, perishability of an item , accidents, or weather are included it gives rise to a new class of problems – SVRP (Stochastic VRP). VRPs can be solved using exact, heuristic, meta-heuristic, hybridization and simulation techniques. Most VRPs in the past have addressed single objective compared to multi-objective problems and considered minimizing the cost distribution as their objective. In Chapter 5, we aim to investigate a non-traditional goal of checking product order compatibility in bulk perishable liquid transportation.

Typically, in bulk transportation, customer orders are signified by a pair of origin destination location, pickup and delivery time windows, order specification, handling instructions. Pertaining to the product transported, there can be a request for possibility of special equipment like pneumatic trailer for bulk dry food, reefer tanks for temperature sensitive items (meat, dairy , fresh produce etc., or vapor recovery system for tankers carrying certain chemicals).An integral component in selecting a feasible tanker trailer is to ensure that its previous components are compatible with its current components or order compatibility exists when shipping mixed loads, even with consideration of intervening washes. According to FDA requirements for carriers is to comply with the provisions for the use of bulk vehicles pertaining to identifying the previous cargo transported in the vehicle and describing the most recent cleaning of the vehicle and for shippers to provide assurance that, for bulk cargo, a previous cargo will not make the food unsafe.(Fairfield, 2016). Prior cargo can provide information about containers that have come into contact with food allergens This compatibility may need to be checked with up to three previous orders, and requirements for seemingly compatible food items may also vary according to customers making it much harder to solve SVRPs with perishable food items.

In chapter 5, we consider a VRP carrying perishable item in tanker trailers, with stochastic transit time that follow the well-known Gamma distribution. The bulk transportation problem has compatibility constraints of orders, which increases the complexity of selecting feasible tankers and their tank wash locations. Due to the large-scale nature of this problem, we apply column generation technique, a detailed review on column generation is given by authors Ceselli et al., (2009) and Feillet, (2010), where we call MP (Master problem) , the linear relaxation of the original problem. We introduce $MP(\Omega_1)$, which is the restriction of master problem MP that considers a subset of decision variables ($\Omega \in \Omega_1$) We overcome order compatibility issue at determining the next set of routes in each iteration of column generation by applying the novel graph decomposition method (Chapter 5)(**RQ7, RQ8**)

Chapter 3 - Stochastic Batch Dispersion Model to Optimize Traceability and Enhance Transparency using Blockchain

3.1 Introduction

The food industry has experienced numerous safety and unprecedented contamination scares in the past. Demand variation, climatic conditions, consumer preferences, transportation delays are some other unpredictable fluctuations that can cause SC disruptions. Food products undergoing dynamic transformation throughout the supply chain network adds more complexity. To be able to track and trace food items back to their origin in case of recalls and monitor the condition of the perishable product at any stage of supply chain, an efficient traceability system is required. Vast literature is available on modelling perishable food supply chains under deterministic parameters as seen in Ahumada & Villalobos, (2009). But to make SC more resilient, modelling under uncertainty should be considered. Our research is motivated by Dupuy et al., (2005) batch dispersion model which originally optimizes traceability in a deterministic environment. Numerically, our paper studies optimal dispersion among batches of packaged goods for a large-scale problem. There are three major contributions to this research. Firstly, we extend the supply chain dispersion model of Dupuy et al., (2005) to a stochastic demand case and solve it using L shaped method a unique implementation in perishable FSC. We include packaging as the final step of sausage manufacturing and additional nodes to outsource finished products. Secondly, we theoretically show a relatively complete recourse structure in our proposed stochastic optimization model. This improves the performance of the L-shaped method by removing the need for feasibility cuts. Thirdly, we provide Blockchain technology as a potential solution to store the producers, retailers, and suppliers' information and enable transparency and traceability throughout the supply chain We establish traceability and transparency in the sausage supply chain where each batch of packaged product can be traced to its origin i.e., the raw material stage where meat is procured in the form of ham, belly, trimmings etc. from different animal farms while the relevant information is securely available to every FSC participant in a de-centralized digital platform.

The rest of the chapter is comprised of four sections. Section 3.2 presents the batch dispersion model with Blockchain under study. Section 3.3 provides the mathematical formulation of the model. Section 3.4 performs numerical experiments to test the validity of the model. Finally, Section 3.5 concludes with discussion.

3.2 Batch Dispersion Model in Food Supply Chain

We consider the sausage industry to model the problem of traceability and transparency in the food sector. Figure 3.1 shows the typical supply chain network of a meat/sausage industry. Narrowing down the terminology of traceability in context to a sausage/meat industry would mean insights on traceability attributes like the origin, composition, parentage identification and production practices(Loureiro & Umberger, 2007). Animals are grown in the farms to the appropriate age to be slaughtered. Their meat is then collected in ham, side pieces, shoulder pieces, and later refrigerated to preserve. It is then mixed and minced according to the desired proportions with the addition of additives. This is the primary manufacturing process.

Once cast into batches of sausages, they are then transferred to the packaging industry. The packed sausages obtained from small goods factories are transported to cold storage distribution centers (according to their demand) by the transport companies in a given time slot. The packages are transported to the supermarkets to be purchased by the end-customers from the distribution center, as shown in Figure 3.1. Next, we present models to analyze traceability & transparency in sausage supply chain.

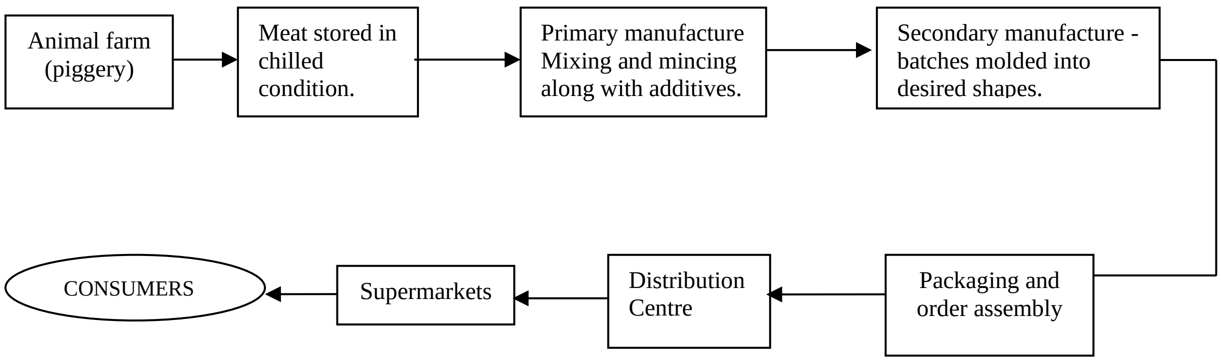

Figure 3.1 Meat supply chain network

3.2.1 Traceability in the Food Supply Chain:

The problem under study is a typical sausage supply chain where mixing and mincing of raw materials are done to yield the finished products. The sausage batch manufacturing process model is presented in Figure 3.2. The model is a 5-level bill of materials from raw materials to packaged products. The modular structure of the 5-level model is based on Gozinto graphs(Van Dorp & Nl, 2003).

Raw material batches (top node of the network) of pork meat, beef or chicken is collected in the form of ham, belly, trimmings, etc. These batches of raw materials are then cut into smaller component batches (2nd node of the network). Each raw material is supposed to provide components in fixed proportions or in other words, "disassembling bill of materials". These component batches undergo mixing and mincing again in fixed proportions- "assembling a bill of materials" to give multiple semi-finished product batches. Semi-finished products (3rd node) along with externally bought component batches, in fixed ratio gives batches of finished goods of the desired quantity. Finally, the finished product batches (4th node) are packed with other finished goods in fixed proportions, say sausages being packed with burger bread and cheese, or sausages from other suppliers to give packaged batches. Packaged batches occupy the last node. The edges of the Gozinto graph represent links connecting batches in this model.

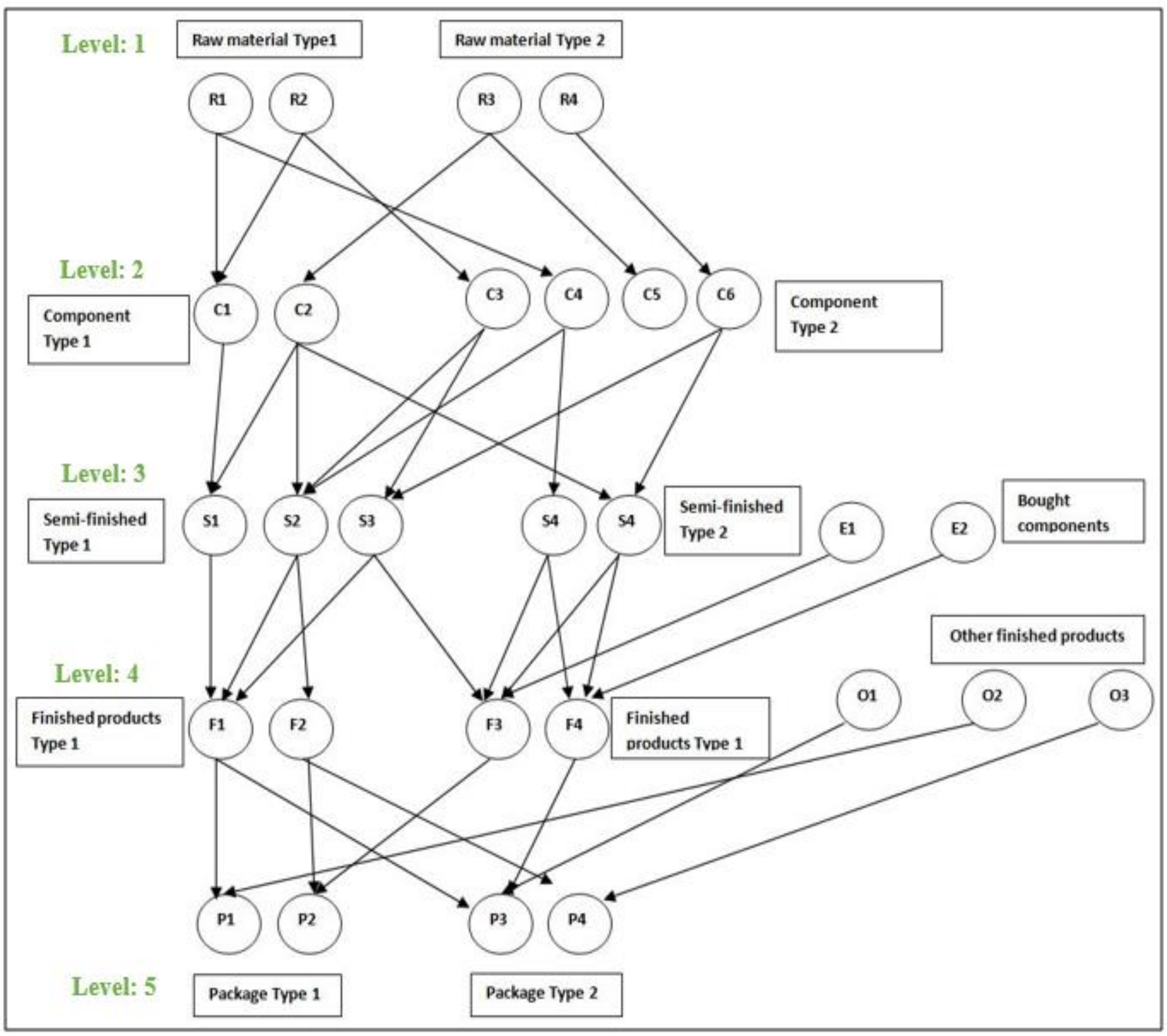

Figure 3.2 A 5-level batch dispersion model

The structure in Figure 3.2 is analogous to the classical transshipment problem with fixed costs. Raw materials are analogous to the sources, and packaged goods to the destination. The arc in the transshipment problem represents the links (disassembling and assembling a bill of materials) between several batches.

The model minimizes the sum of the links between the raw materials and the packaged goods, and the dispersion caused due to external components and finished goods from other sources. This analogy can support that the batch dispersion model is an NP-Hard problem (Palekar et al., 1990). We present a stochastic model that aims to reduce the batch size dispersion or the mixing of raw materials so that a minimum number or quantity of recalls could be made at the time of crisis, thus optimizing traceability. It includes a random demand, which must be satisfied by the amount of the final number of batches produced.

3.2.2 Transparency in the Food Supply Chain:

Traceability information related to the transformation of products and their flow throughout the supply chain is generally maintained in a centralized agriculture database (Bechini et al., 2005). At all stages of the production, food supply chain participants remain highly protective of their data. Each participant is responsible for maintaining their data confidentiality and reveals a relevant amount of data to other participants as required. A private third party called 'data trustee' is involved as an intermediary between the supply chain participants and other external entities: government, companies, individuals, etc. to verify contracts and transactions. This leads to certain drawbacks like trust issues, trade disruption among the members involved in the supply chain, delay in response time, cost concerns due to 3rd parties (Bechini et al., 2005). The focus of the paper is on integrating traceable data with blockchain technology to enhance transparency. Blockchain database holds the record of information or transactions of products like their composition, location, and history. The data stored is accessible to every peer involved in the network, as shown in Figure 3.3. This transparency can only be valid if data inside the blockchain is immutable; anybody can modify/alter the data and lead to discrepancies. The transparency in the supply chain can be enhanced using a decentralized database because customers get to have the details of the entire product details right from its origin to consumption. If a dishonest peer alters the data in block 'P-1' (Figure 3.3), a hash of block 'P' will immediately change. Since each block is connected to its next block, a hash of the succeeding block ‘P+1’also changes. With the change of hash in ‘P-1’, hash of ‘P’, ‘P+1’, ‘P+2’, and so on will change. Every other peer present in the network will get notified of this alteration of data.

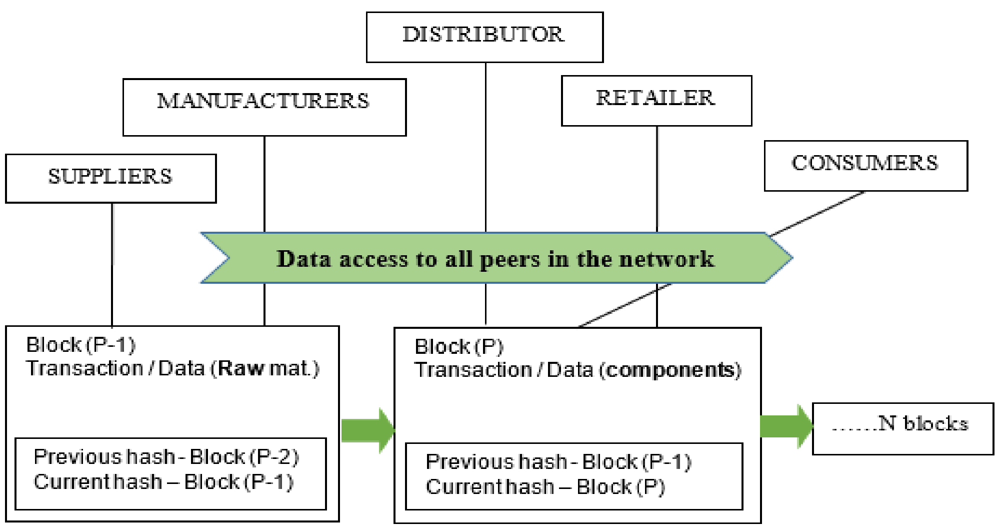

Figure 3.3 Supply chain in a blockchain

A scenario of an attacker or a dishonest peer in the blockchain network trying to tamper with an existing honest chain is considered in our problem. The attacker has to modify his target block; they have to modify all succeeding blocks before a new block is formed in the chain, which again increases the complexity of altering the data. The competition between attacked and honest chain is analogous to a ‘Binomial Random Walk’ (Nakamoto, n.d.). An attacker's probability of not succeeding to tamper with the blockchain is similar to negative binomial distribution (NBD). A negative binomial distribution gives us the probability of viewing say f number of failures before the s number of success is obtained (Krishnamoorthy (2016). Using this probability, we can calculate an attacker's failure progress when he tries to attack the blockchain head (the most recent block in the Blockchain).

3.3 Mathematical Formulation:

In this section we provide mathematical formulation of the two-stage stochastic model for batch dispersion model of sausage manufacturing industry.

3.3.1 Batch Dispersion Model for Traceability:

We consider a sausage supply chain with five levels, as represented in Figure 3.2. The first level is raw materials (meat such as ham, belly, trimmings, etc.) where each raw material $r, r \epsilon R$ can be used in required proportions to obtain the next level of components $c, c \epsilon C$. A binary variable $X_{RC}(r,c)$ is 1 if raw materials r is present in component c**.** Parameter $Qraw(r)$ is the quantity of each raw material we use and can handle reasonable values like 100 units or 2000 units etc. Note that these values entirely depend on the user. However, the model can handle any values, but for the sake of demonstration of the proposed model and approach, we have randomly chosen these values to show how the insights change with the parameters. Similarly, $Qfin(f)$ is the quantity of each finished product and can have reasonable values less than or equal to raw materials value (because higher nodes in the network produce the lower nodes). We define a parameter $BomRC$ that represents the proportion of raw materials of each type needed to obtain components of both the types. The values of the BoM parameters represent the amount of an entity used to manufacture the next stage. The amount used is less than or equal to 100% of the entity. Hence the amount of materials used for the next step should sum up to less than or at max equal to 100% of the total quantity. Again, it's a random selection; however, the model can handle any value of BoM parameter between 0 and 100 as proportions in general. We have taken two sets of values in Table 3.4 and Table 3.5 for BoM parameters to clarify that the model is robust enough to handle any values between 0 and 100%. We assign values similar to other BoM parameters like $BomCS$, $BomSF$, $BomFP$.

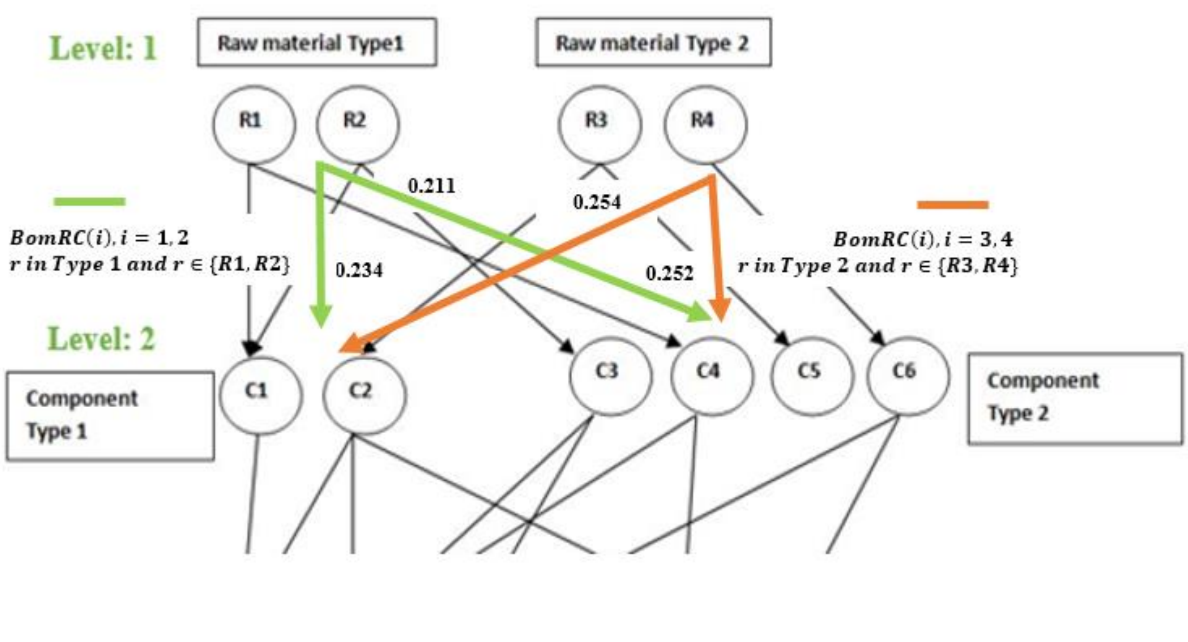

Figure 3.4 A two-level dispersion model

Figure 3.4 shows two levels: raw materials & components. Similarly, components in correct proportions combine to yield semi-finished products$s, s \epsilon S$, represented by $BomCS$. Semi-finished products and externally bought component $e, e \epsilon E$ batches in a fixed ratio produces batches of finished the goods$f, f \epsilon F$ represented by $BomSF$. Finally, the batches of the finished product are packed with other finished goods $o, o \epsilon O$ in fixed proportions, say sausages being packed with burger bread and cheese, or sausages from other suppliers to give packaged batches $p, p \epsilon P$ represented by $BomFP$ which eventually satisfies random customer demand.

Demand $D(\xi)$ is defined as a random distribution for (ξ) scenarios. We have taken 2 cases, one as a normal distribution and the other as exponential. $\rho(\xi)$ is the probability distribution function for the above demand. We develop a two-stage stochastic mathematical model below, where firstly, the decisions are made to have fixed proportions represented by BoM (bill of materials) of each raw material, components, semi-components are distributed to obtain finished products and packaged ready for customers. Secondly, we decide how much to order from other sources of finished products to be packaged to satisfy customer demand. The detailed description of parameters of the batch dispersion model is given below in Table 3.1, followed by the objective function and the corresponding constraints.

Table 3.1 Notation of batch dispersion model

Notation	Definitions	
Sets & Indices:		
$\boldsymbol{R}$	Set of raw material batches of two types	$r, \boldsymbol{r} \epsilon \boldsymbol{R}$
C	Set of component batches of two types	$\boldsymbol{c}, \boldsymbol{c} \epsilon \boldsymbol{C}$
S	Set of semi-finished product batches of two types	$\boldsymbol{s}, \boldsymbol{s} \epsilon \boldsymbol{S}$
$\boldsymbol{F}$	Set of finished product batches of two types	$\boldsymbol{f}, \boldsymbol{f} \epsilon \boldsymbol{F}$

$\boldsymbol{E}$	Set of external bought component batches of single type	$\boldsymbol{e}, \boldsymbol{e} \in \boldsymbol{E}$
$\boldsymbol{O}$	Set of other finished batches of single type from different sources	$\boldsymbol{o}, \boldsymbol{o} \in \boldsymbol{O}$
$\boldsymbol{P}$	Set of packaged batches of two types	$\boldsymbol{p}, \boldsymbol{p} \in \boldsymbol{P}$
$\boldsymbol{i}$	Different types of batches from previous level to the next.	
$\boldsymbol{j}$	Number of items in each type of batches.	
M	Very big number	

Parameters*:*

$\boldsymbol{Qraw}(\boldsymbol{r})$	Quantity of each raw material r , $\boldsymbol{r} \in \boldsymbol{R}$
$\boldsymbol{Qfin}(\boldsymbol{f})$	Quantity of each finished product $\boldsymbol{f}, \boldsymbol{f} \in \boldsymbol{F}$
$\boldsymbol{D(\xi)}$	Demand of Quantity of packed goods batch in each scenario $\boldsymbol{\xi}$
$\boldsymbol{\rho}(\boldsymbol{\xi})$	Probability distribution function of demand for $\boldsymbol{\xi}$ scenarios
$\boldsymbol{BomRC}$	Proportion of raw materials of each type going in component materials of each type
$\boldsymbol{BomCS}$	Proportion of semi-finished products of each type coming from components of each type
$\boldsymbol{BomSF}$	Proportion semi-finished products of each type going in finished products of each type
$\boldsymbol{BomFP}$	Proportion of finished products of each type going in packaged goods of each type

Binary Variables:

$\boldsymbol{X_{RC}}(\boldsymbol{r}, \boldsymbol{c})$ $\quad \begin{matrix} \mathbf{1}, & \boldsymbol{if\ raw\ material\ \ r\ is\ present\ in\ component\ c} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{matrix}$

$\boldsymbol{X_{CS}}(\boldsymbol{c}, \boldsymbol{s})$ $\quad \begin{matrix} \mathbf{1}, & \boldsymbol{if\ component\ c\ is\ present\ in\ semi-finished\ component\ s} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{matrix}$

$\boldsymbol{X_{SF}}(\boldsymbol{s}, \boldsymbol{f})$ $\quad \begin{matrix} \mathbf{1}, & \boldsymbol{if\ semi\ finished\ product\ s\ is\ present\ in\ finished\ product\ f} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{matrix}$

$\boldsymbol{X_{EF}}(\boldsymbol{e}, \boldsymbol{f})$ $\quad \begin{matrix} \mathbf{1}, & \boldsymbol{if\ external\ bought\ component\ e\ \ is\ present\ in\ finished\ batch\ f} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{matrix}$

$\boldsymbol{Y_{RF}}(\boldsymbol{r}, \boldsymbol{f})$ $\quad \begin{matrix} \mathbf{1}, & \boldsymbol{if\ if\ raw\ material\ batch\ r\ is\ present\ in\ finished\ batch\ f} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{matrix}$

$\boldsymbol{X_{FP}}(\boldsymbol{f}, \boldsymbol{p})$ $\quad \begin{cases} \mathbf{1}, & \boldsymbol{if\ \ finished\ batch\ f\ is\ present\ in\ packaged\ good\ p} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{cases}$

$\boldsymbol{X_{OP\xi}}(\boldsymbol{o}, \boldsymbol{p}, \boldsymbol{\xi})$ $\quad \begin{cases} \mathbf{1}, & \boldsymbol{if\ other\ finished\ batch\ o\ is\ present\ in\ packaged\ good\ p\ in\ scenario\ \xi} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{cases}$

Continuous variables

$\boldsymbol{Qcomp}(c)$	Quantity of each component $\boldsymbol{c}, \boldsymbol{c} \in \boldsymbol{C}$
$\boldsymbol{Qsemi}(\boldsymbol{s})$	Quantity of each semi-finished product s, $\boldsymbol{s} \in \boldsymbol{S}$
$\boldsymbol{Qpack}(\boldsymbol{p}, \boldsymbol{\xi})$	Quantity of packaged good $\boldsymbol{p}$ in each demand scenario $\boldsymbol{\xi}$

$\boldsymbol{Q_{RC}(r,c)}$	Quantity of raw material r present in component $\boldsymbol{c}$
$\boldsymbol{Q_{CS}(c,s)}$	Quantity of component $\boldsymbol{c}$ present in semi-finished product s
$\boldsymbol{Q_{SF}(s,f)}$	Quantity of semi-finished product $\boldsymbol{s}$ present in finished product f
$\boldsymbol{Q_{EF}(e,f)}$	Quantity of external bought component $\boldsymbol{e}$ present in finished product $\boldsymbol{f}$
$\boldsymbol{Q_{FP}(f,p)}$	Quantity of finished product f present in packaged good $\boldsymbol{p}$
$\boldsymbol{Q_{OP}(o,p,\xi)}$	Quantity of other finished product $\boldsymbol{o}$ present in packaged good $\boldsymbol{p}$ in demand scenario $\boldsymbol{\xi}$

Next, we define the mathematical formulation of the proposed food supply chain.

$$Z = min \sum_{r=1}^{R}\sum_{\boldsymbol{f=1}}^{F} Y_{RF}(r,f) + \sum_{e=1}^{E}\sum_{f=1}^{F} X_{EF}(e,f) + \sum_{f=1}^{F}\sum_{p=1}^{P} X_{FP}(f,p) + E_{\xi}[\![Q(X,\xi)]\!] \quad \textbf{(3.1)}$$

Subject to:

$$\sum_{i=1}^{2}\sum_{r=1}^{j} BomRC(i)Qraw(r) + \sum_{i=3}^{4}\sum_{r=(j+1)}^{R} BomRC(i)Qraw(r) = \sum_{c=1}^{C} Q_{RC}(r,c) \quad \forall r = 1 \dots . R \quad \textbf{(3.2)}$$

$$Qcomp(c) = \sum_{r=1}^{R} Q_{RC}(r,c) \quad \forall c = 1 \dots . C \quad \textbf{(3.3)}$$

$$\sum_{c=1}^{C} Q_{RC}(r,c) = Qraw(r) \quad \forall r = 1 \dots . R \quad \textbf{(3.4)}$$

$$X_{RC}(r,c) = \begin{cases} 1, & Q_{RC} > 0 \\ 0, & otherwise \end{cases} \quad \forall r = 1 \dots . R, \forall c = 1 \dots . C \quad \textbf{(3.5)}$$

$$\sum_{i=1}^{2}\sum_{c=1}^{j} BomCS(i)Qcomp(c) + \sum_{i=3}^{4}\sum_{c=(j+1)}^{C} BomCS(i)Qcomp(c) = \sum_{c=1}^{C} Q_{CS}(c,s) \quad \forall s = 1 \dots . S \quad \textbf{(3.6)}$$

$$Qsemi(s) = \sum_{c=1}^{C} Q_{CS}(c,s) \quad \forall s = 1 \dots . S \quad \textbf{(3.7)}$$

$$\sum_{s=1}^{S} Q_{CS}(c,s) = Qcomp(c) \quad \forall c = 1 \ldots . C \tag{3.8}$$

$$X_{CS}(c,s) = \begin{cases} 1, & Q_{CS} > 0 \\ 0, & otherwise \end{cases} \quad \forall c = 1 \ldots . C, \forall s = 1 \ldots . S \tag{3.9}$$

$$\sum_{i=1}^{2} \sum_{s=1}^{j} BomSF(i)Qsemi(s) + \sum_{i=3}^{4} \sum_{s=(j+1)}^{S} BomSF(i)Qsemi(s) = \sum_{s=1}^{S} Q_{SF}(s,f) \qquad \forall f = 1 \ldots . F \tag{3.10}$$

$$Qfin(f) = \sum_{s=1}^{S} Q_{SF}(s,f) + \sum_{e=1}^{E} Q_{EF}(e,f) \quad \forall f = 1 \ldots . F \tag{3.11}$$

$$\sum_{f=1}^{F} Q_{SF}(s,f) = Qsemi(s) \quad \forall s = 1 \ldots . S \tag{3.12}$$

$$X_{SF}(s,f) = \begin{cases} 1, & Q_{SF} > 0 \\ 0, & otherwise \end{cases} \quad \forall s = 1 \ldots . S, \forall f = 1 \ldots . F \tag{3.13}$$

$$X_{EF}(e,f) = \begin{cases} 1, & Q_{EF} > 0 \\ 0, & otherwise \end{cases} \quad \forall e = 1 \ldots . E, \forall f = 1 \ldots . F \tag{3.14}$$

$$\sum_{i=1}^{2} \sum_{p=1}^{j} BomFP(i)Fin(f) + \sum_{i=3}^{4} \sum_{p=(j+1)}^{P} BomFP(i)Fin(p) = \sum_{f=1}^{F} Q_{FP}(f,p) \quad \forall p = 1 \ldots . P \tag{3.15}$$

$$X_{FP}(f,p) = \begin{cases} 1, & Q_{FP} > 0 \\ 0, & otherwise \end{cases} \qquad \forall f = 1 \ldots . F, \forall p = 1 \ldots . P \tag{3.16}$$

The objective function (3.1) minimizes the batch dispersion or the links between the five stages of the proposed food supply chain dispersion model. It comprises of four terms. The first binary term $\boldsymbol{Y_{RF}}$ is 1 if raw material batch ***r*** is present in finished batch ***f***. The second binary term $\boldsymbol{X_{EF}}$ represents the amount of dispersion caused due to externally bought components ***e*** and is equal to 1 if there exists a link between externally bought items ***e*** and finished good batches ***f***. The third term X_{FP} represents the arcs from finished batch ***f*** to packaged goods ***p*** and equals 1 if there is a link between them. Finally, the fourth term is given by $E_{\xi}[\![Q(X,\xi)]\!]$ is the expected value of sum of arcs from other finished goods to packaged goods over a possible set of demand scenarios. Constraints (3.2, 3.6, 3.10, and 3.15) fulfil the assembling and disassembling BOM requirements to ensure a required proportion of the material is going to the batches. For a manufacturing problem, constraints (3.3, 3.4, 3.7, 3.8, 3.11, and 3.12) take care of the quantity conservation, which means components are obtained from only raw materials, semi-components from components, and final products are obtained from semi-components and external bought components. Equations (3.5), (3.9), (3.13), (3.14) and (3.16) denote binary variables $\boldsymbol{X_{RC}}$, $\boldsymbol{X_{CS}}$, $\boldsymbol{X_{SF}}$, $\boldsymbol{X_{EF}}$, $\boldsymbol{X_{FP}}$ are equal to 1 if $\boldsymbol{Q_{RC}}$, $\boldsymbol{Q_{CS}}$, $\boldsymbol{Q_{SF}}$, $\boldsymbol{Q_{EF}}$, $\boldsymbol{Q_{FP}}$ are not null. These decisions are first-stage decisions which are taken before the demand has been realized.

Corrective actions or the second stage decisions represented by the fourth term of the objective function (3.1) is decided on receiving full information of the random demand vector $\boldsymbol{\xi}$ (which is stochastic demand according to our problem statement and we have analyzed 1000 demand scenarios in our model) Using decision values from first stage, the expected value of dispersion from other finished goods to packaged products due to a stochastic demand scenario is obtained in the second stage of the problem given in Equation (3.17).

$$Q(X,\xi\ ) = min \sum_{\xi=1}^{1000} \sum_{o=1}^{O} \sum_{p=1}^{P} X_{OPS}(o,p,\xi) * \rho(\xi) \qquad \textbf{(3.17)}$$

Subject to

$$Qpack(p,\xi) = \sum_{f=1}^{F} Q_{FP}(f,p) + \sum_{o=1}^{O} Q_{OP\xi}(o,p,\xi) \quad \forall p = 1 \dots . P, \forall \xi$$

(3.18)

$$= 1 \dots .1000$$

$$X_{OP\xi}(o,p,\xi) = \begin{cases} 1, & Q_{OP\xi} > 0 \\ 0, & otherwise \end{cases} \quad \forall o = 1 \dots . O, \forall p = 1 \dots . P, \forall \xi$$

(3.19)

$$= 1 \dots .1000$$

(3.20)

$$Qpack(p,\xi) \geq D(\xi) \quad \forall p = 1 \dots . P, \forall \xi = 1 \dots .1000$$

The objective function (3.17) provides the optimum value of batch dispersion/links between the other finished goods $\boldsymbol{o}$ and packaged products $\boldsymbol{p}$ for all demand scenario $\boldsymbol{\xi}$ with a probability distribution function $\boldsymbol{\rho(\xi)}$**.** Quantity conservation constraint (3.18) implies that packaged products are obtained from finished goods from both sources. Equation (3.19) denotes binary variable $\boldsymbol{X_{OP\xi}}$, which is equal to 1 if $\boldsymbol{Q_{OP\xi}}$ is not null. Equation (3.20) ensures the quantity of packaged goods produced fulfils the demand requirement with any random distribution function.

3.3.2 Optimality and Feasibility Cuts

Equation (3.19) can be re-written as:

(3.19a)

$$\sum_{o=1}^{O} Q_{OP\xi}(o,p,\xi) + \delta(1 - X_{OP\xi}(o,p,\xi) \;\geq\; \delta \qquad \forall p = 1 \dots . P, \forall \xi = 1 \dots 1000$$

(3.19b)

$$\sum_{o=1}^{O} Q_{OP\xi}(o,p,\xi) + (M + \delta) X_{OP\xi}(o,p,\xi) \;\leq\; \lambda \qquad \forall p = 1 \dots . P, \forall \xi = 1 \dots .1000$$

Let $\pi_{\xi}(3.18), \pi_{\xi}(3.19a), \pi_{\xi}(3.19b), \pi_{\xi}(3.20)$ be the dual values associated with the 2nd stage Equations (3.18), (3.19a & 3.19b), and (3.20), respectively. Let $\theta = E_{\xi}[\![Q(X,\xi)]\!]$. Let Ế represent the set of scenarios in general.

We define:

$$E_{\xi}(3.18) = \sum_{\xi=1}^{\Xi} -\rho(\xi).\,\pi_{\xi}(3.18) \tag{3.21}$$

$$e_{\xi} = \sum_{\xi=1}^{\Xi} (\rho(\xi).\,\pi_{\xi}(3.20).\,D(\xi) + \ \rho(\xi).\,\pi_{\xi}(3.19a).\,\delta + \rho(\xi).\,\pi_{\xi}(3.19b).\,\lambda \tag{3.22}$$

where δ and λ are very small values. The optimality cut is thus represented as:

$$\begin{aligned} E_{\xi}(3.18) = \sum_{\xi=1}^{\Xi} -\rho(\xi).\,\pi_{\xi}(3.18) + \theta \\ \geq \sum_{\xi=1}^{\Xi} (\rho(\xi).\,\pi_{\xi}(3{,}20).\,D(\xi) + \ \rho(\xi).\,\pi_{\xi}(3.19a).\,\delta \\ + \rho(\xi).\,\pi_{\xi}(3.19b).\,\lambda \end{aligned} \tag{3.23}$$

In the next section, we show that the model has a relatively complete recourse structure, and the L-shaped method does not require feasibility cuts.

3.3.3 Stochastic Program with Relatively Complete Recourse

A model is relatively complete recourse when the second-stage problem is feasible for any feasible first-stage solution. When first-stage decision variable $X(X \in \mu_1)$ is not inside μ which represents a set of feasible solutions for first stage, we add feasibility cuts to make the second stage feasible.

In other words, if the second stage becomes infeasible, we build a feasibility cut, an equation, for the first stage and go back to solve sub problem of that stage again. By assuming other packaged goods ***o*** has an infinite capacity to supply, we can show that the second stage is always feasible with respect to every solution of the first stage in our stochastic model, thus it is relatively complete recourse ($\mu_1 \subset \mu_2$). The complexity of L-shaped method can be fairly assumed to be linear. But with increasing number of constraints and variables used in the model, the model can't be solved in linear time. Insight on the proof of time complexity is given in "Introduction to Stochastic Programming" (Birge & Louveaux, 2011). An algorithm's computation time can be improved since this alternative, skips finding dual values of subproblem to generate feasibility cuts for the master problem.

Let $\mu1 = \{\, Q_{RC}(r,c), Q_{CS}(c,s),\ Q_{SF}(s,f),\ Q_{EF}(e,f), Q_{FP}(f,p),\ Qsemi(s),\ Qcomp(c),$
$X_{RC}(r,c),\ X_{CS}(c,s),\ X_{SF}(s,f),\ \ Y_{RF}(r,f), X_{EF}(e,f)\ , X_{FP}(f,p)\quad |Contraints\ (3.2)\ to\ (3.16)\ where$
$X_{RC}(r,c),\ X_{CS}(c,s),\ X_{SF}(s,f),\ \ Y_{RF}(r,f),\qquad X_{EF}(e,f)\ , X_{FP}(f,p)\ \in \{0,1\}\quad \forall r,c,s,f,p,e$
$\in R,C,S,F,P,E\}$

Let µ1 represent all possible values of 1st stage variables that make the first stage feasible. Let $\mu_2 = \{1st\ stage\ variables\ |Constraints\ (3.18)\ to\ (3.20)\}$ be all possible values of 1st stage variables that make the second stage formulation given by Equation (3.17) feasible. Using Lemma 1, we show the proposed two stage optimization has relatively complete recourse and does not need feasibility cuts.

Lemma 1: If the stochastic optimization model represented in Equation (3.17) has a solution for all values of binary variables $X_{RC}(r,c)$, $X_{CS}(c,s)$, $X_{SF}(s,f)$, $Y_{RF}(r,f)$, $X_{EF}(e,f)$, $X_{FP}(f,p)$ then it is relatively complete recourse, i.e. $\mu_1 \in \mu_2$.

Proof: To prove this lemma, we need to show that all solutions in the set μ_1 are present in the set μ_2. Equation (3.18) is satisfied as it is a trivial balance constraint considering unlimited capacity from other finished goods o. So, for all values of continuous variable $Q_{FP}(f,p) \epsilon \mathbb{R}^+$, Equation (3.18) is feasible. Constraint (3.20) is demand satisfiability constraint. So, for every existing solution of $Q_{FP}(f,p) \epsilon \mathbb{R}^+$, constraint (3.20) is feasible. In constraint (3.19), decision variable $X_{OP\xi}(o,p,\xi)$ takes the value of 0 or 1 if continuous variable $Q_{OP\xi}(o,p,\xi)$ is null or not. Therefore, for all 1st stage decision variables in μ_1 i.e. $\{0,1\}$ constraints of 2nd stage is satisfied. Value of 2nd stage decision variable $X_{OP\xi}(o,p,\xi)\ belongs\ to\ \{0,1\}$ as decision variable $X_{OP\xi}(o,p,\xi)$ in Equation (3.19) takes the value of 0 or 1 if continuous variable $Q_{OP\xi}(o,p,\xi)$ is null or not. Thus, $\mu_1 \in \mu_2$ and hence concludes the proof.

3.3.4 Data Immutability of Batch Dispersion Model

Once traceability of the supply chain is enhanced, the data related to origin, history, the composition of products during different stages in a network such as processing, distribution, and delivery need to be stored in a database. If the database is a centralized one, it will entail trust issues, and risk of data manipulation since one controlling party solely has access to it. Blockchain being a decentralized database, gives access to every peer in the network and tampering the data inside the ledger would inform about the data discrepancy to all the participants thus ensuring transparency of the supply chain model.

Typical components of a blockchain (in Figure 1.2) are blocks, or digital ledgers. We store data related to raw materials in blocks $B_{raw(r)}, \forall r = 1 \ldots . R$. Similarly, data related to components, semi-components, finished, and packaged batches are stored in blocks: $B_{comp(c)}\ \forall c = 1 \ldots . C$; $B_{semi\ (s)}\ \forall s = 1 \ldots . S$; $B_{fin(f)}\ \forall f = 1 \ldots . F$; $B_{pack(p)}\ \forall p = 1 \ldots . P$ respectively.

Blocks $B_{ext(e)}\ \forall e = 1 \ldots . E$ and $B_{other(o)}\ \forall o = 1 \ldots . O$; store data related to externally bought components and other finished goods. The total number of blocks in our model is given by equation (3.24). It is the sum of all blocks and is represented by B_{total}.

$$B_{total} = \sum_{r=1}^{R} B_{raw(r)} + \sum_{c=1}^{C} B_{comp(c)}) + \sum_{s=1}^{S} B_{semi\ (s)} \\ + \sum_{f=1}^{F} B_{fin\ (f)} + \sum_{p=1}^{P} B_{pack(p)} + \sum_{e=1}^{E} B_{ext(e)} + \sum_{e=1}^{E} B_{ext(e)} \qquad \textbf{(3.24)}$$

From equation (3.24), we can comprehend that number of blocks in the blockchain increases with increasing raw materials, components, or general nodes in the supply chain network. In other words, each block has a fixed storage capacity. With the increment of data being stored or transactions carried out, the number of blocks increase.

A dishonest peer a, is trying to tamper with an honest block chain with B_{total} the number of blocks. The attacker must not only modify his target block but also modify all succeeding blocks before another honest new block H gets linked to the existing honest chain. The mathematical model we developed below shows how far an attacker could progress in terms of his failure before successfully tampering the first block. In other words, the model provides a quantitative measure to draw insight on transparency and security against a data breach. A detailed description of parameters of the blockchain model is given in Table 3.2.

Table 3.2 Notation of block chain model.

Variables	***Definitions***
$P_A(B_{total})$	Probability, the attacker attacks a chain already having B_{total} blocks behind him.
P_H	Probability an honest node, H finds the next block
P_a	Probability an attacker, a finds the next block.
B_{total}	Number of blocks containing data in the blockchain, after which the attacker starts attacking.
$P_{failure}$	Probability, the attacker will fail or will never catch up from 'B' blocks behind
$F_{progress}$	Measure of progress made by the attacker in terms of its failure.

Assumption:

The probability of an honest node finding the next block is greater than the probability of an attacker finding the next block, i.e. $P_H \geq P_a$ *, otherwise, a new block would never form, and the blockchain would not exist.*

$$P_A(B_{total}) = \begin{Bmatrix} 1 & if \;\; P_H \leq P_a \\ \left(\frac{P_a}{P_H}\right)^{B_{total}} & if \;\; P_H > P_a \end{Bmatrix} \qquad \textbf{(3.25)}$$

$$P_{failure} = \binom{r+k-1}{k} {P_H}^r . {P_a}^k \left(1 - \frac{P_a}{P_H}\right)^k \; where \;\; k \leq B_{total} \tag{3.26}$$

$$F_{progress} = \sum_{k=0}^{B_{total}} P_{failure} \tag{3.27}$$

Probability, the attacker will succeed or will ever catch up from B_{total} the number of blocks behind is given by Equation (3.25). Given our assumption that $P_H \geq P_a$, the probability drops exponentially as the number of blocks the attacker must catch up with increases. With the odds against him, if he doesn't make a forward movement early on, his chances become vanishingly small as he falls further behind.

Probability of viewing k failures before the attacker achieves his r^{th} success is obtained by multiplying the negative binomial distribution with the attacker's failure probability of $\left(1 - \frac{P_a}{P_H}\right)$ as in Equation (3.26). Further, Equation (3.26) with $r = 1$ modifies to Equation (3.28) and becomes:

$$P_{failure} = \binom{k}{k} P_H . (P_a)^k \left(1 - \frac{P_a}{P_H}\right)^k \; where \;\; k \leq B_{total} \tag{3.28}$$

Once the attacker can modify the chain successfully for the first time, the entire chain comes under the attacker's control. So, we are concerned with k number of failures before his 1^s success is obtained. The exact amount of progress the attacker makes is not known, but assuming the honest blocks took the average expected time per block, the attacker's progress in terms of failure while attacking the chain is obtained by summing up the negative binomial distribution at every step of the attack. The expected value is given by Equation (3.27).

3.4 Numerical Experiments:

To test the validity of the model regarding traceability & transparency, we will perform three experiments. In Experiments 1, we analyze the impact of stochasticity in demand on the optimal number of batches. In Experiment 2, we assume a deterministic demand. Experiment 3 shows insights with regard to transparency. For Experiments 1 and 2, we assume four batches of raw materials categorized into two groups of type 1 and type 2. Similarly, throughout the network, two types of components, semi-finished products, finished products, and packaged products, are considered for simplicity. Quantity parameters for each level of our model are presented in Table 3.3.

Table 3.3 Quantity parameters

	Raw materials	Quantity of Raw materials	Comp-onents	Semi-components	Finished goods	Quantity of Finished goods	Packaged Goods	Quantity of Packaged Goods
Type 1	R1	1000	C1	S1	F1	2300	P1	3000
	R2	1500	C2	S2	F2	2106	P2	4000
Type 2	R3	3000	C3	S3	F3	3000	P3	4500
	R4	4500	C4	S4	F4	3000	P4	3570

Externally bought components and finished goods from other sources are taken as infinite capacity parameters to complete the network. They do not have type variations, or in other words, they are of a single type. Bill of materials at each level of batch dispersion model (Figure 3.2) defines the percentage of ingredient quantity of type a going in the ingredient of type b. We have taken two sets of BoM for experimental purposes and to justify that our model is robust enough to handle random but logical values (within 0 and 100%). The values of percentages for bill of materials in set I, assumed for our model, are mentioned in Table 3.4.

Table 3.4 Percentage values (bill of materials) – Set I

$BomRC$ Sum of BomRC (R→C) = [0.243+0.211+0.252+0.254]=96%	Raw Materials/ Components	Type 1	Type 2
	Type 1	0.234	0.211
	Type2	0.252	0.254
$BomCS$ Sum of BomCS (C→S) = [0.226+0.268+0.252+0.254]=100%	Components/Semi-components	Type 1	Type 2
	Type 1	0.226	0.268
	Type 2	0.252	0.254
$BomSF$ Sum of BomSF (S→F) = [0.234+0.211+0.252+0.254]=95.1%	Semi-components/ Finished	Type 1	Type 2
	Type 1	0.234	0.211
	Type 2	0.252	0.254
$BomFP$ Sum of BomFP (F→P) = [0.234+0.211+0.252+0.254]=95.1%	Finished/ Packaged	Type 1	Type 2
	Type 1	0.234	0.211
	Type 2	0.252	0.254

The values of percentages for bill of materials in set II, assumed for our model, are mentioned in Table 3.5.

Table 3.5 Percentage values (bill of materials) – Set II

$BomRC$ Sum of BomRC (R→C) = [0.25+0.25+0.25+0.25]=100%	Raw Materials/ Components	Type 1	Type 2
	Type 1	0.25	0.25
	Type2	0.25	0.25
$BomCS$ Sum of BomCS (C→S) = [0.25+0.10+0.25+0.10]=70%	Components/Semi-components	Type 1	Type 2
	Type 1	0.10	0.25
	Type 2	0.25	0.10
$BomSF$ Sum of BomSF (S→F) = [0.15+0.25+0.25+0.15]=80%	Semi-components/ Finished	Type 1	Type 2
	Type 1	0.15	0.25
	Type 2	0.25	0.15
$BomFP$ Sum of BomFP (F→P) = [0.25+0.25+0.25+0.25]=100%	Finished/ Packaged	Type 1	Type 2
	Type 1	0.25	0.25
	Type 2	0.25	0.25

3.4.1 Experiment 3.1: Impact of Stochasticity in Demand

For Experiment 1, we investigate two demand distributions: Normal distribution and Exponential distribution and compute the total number of arcs in the batch dispersion model as the objective and study the variation of the produced quantities of packages produced under a normal distribution of customer demand. We perform the experiment considering the BoM values given in Table 3.4. The main purpose of considering demand as an exponential is the evident utility of the distributions in discrete systems simulation and its effectiveness for modeling the random arrival pattern represented in a Poisson process. Exponential smoothing or normal distribution has proven to be a robust forecasting method and is probably the most used of the statistical approaches to forecasting intermittent demand (Cox & Snell, 1968; Willemain et al., 2004). For each type of packaged products (type 1 & type 2), variations of packaged product P1 of type 1 and P3 of type 2 are observed and plotted in Figure 3.5 and 3.6, respectively against 50 demand scenarios (normally distributed). From the graph we can deduce that the quantity produced follows the demand pattern throughout.

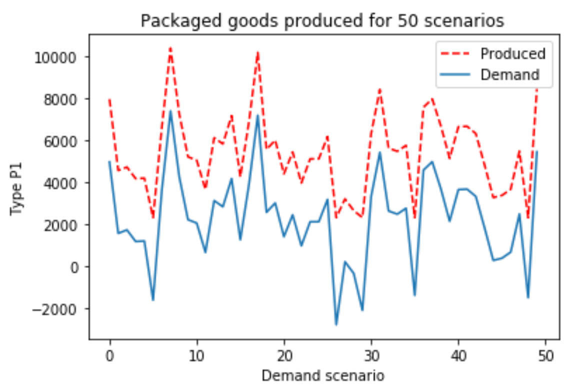

Figure 3.5 Variation in package P1(category: type 1) against normal demand scenarios

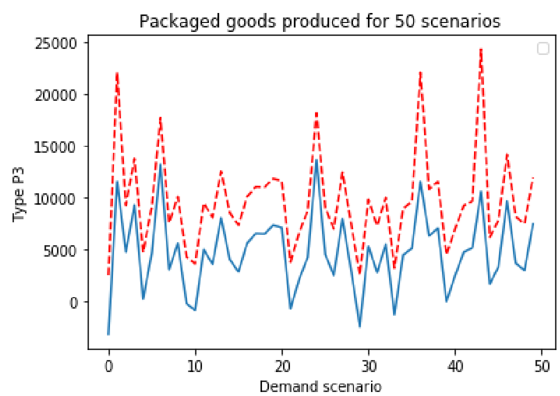

Figure 3.6 Variation in package P3(category: type 2) against normal demand scenarios

With exponential distribution of customer demand for each type of packaged products, variations of packaged product are plotted in Figures 3.7 and 3.8 respectively against 50 demand scenarios.

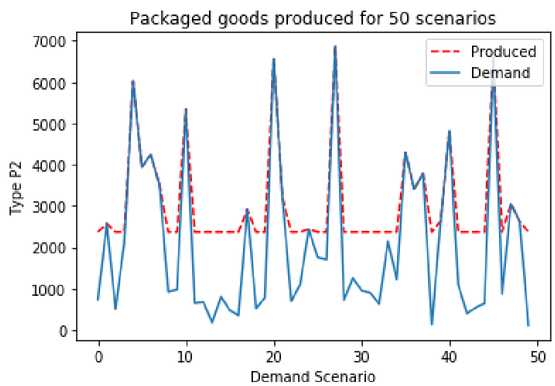

Figure 3.7 Variation in package P2 (category: type 1) against exponential demand scenarios

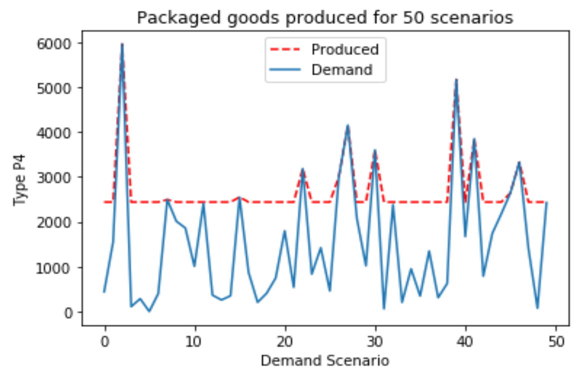

Figure 3.8 Variation in package P4 (category: type 2) against exponential demand scenarios

Similar observations can be gathered about the relation between the quantity produced and the customer demand pattern for experiment 2 too. Both the above experiments are performed under 50, 100, 500 and 1000 scenarios to see how the objective function is affected with increasing scenarios. Observations are recorded in Table 3.6. Another important observation is that the quantity of packaged items produced has to satisfy the BoM criteria regardless of the demand. It is a 1st stage decision that takes place before the demand is realized. So, even if the demand is low, the model doesn’t produce less than the required quantity of packaged goods that should be produced due to BoM.

3.4.2 Experiment 3.2: Deterministic Case

In this experiment, we assume a fixed quantity of packaged products of both types at the end of the network. Using the same parameters as Tables 3.3, 3.4 and 3.5, we determine the optimal number of arcs (see Table 3.6). Under the deterministic model, the dispersion is less compared to the stochastic cases. We can conclude that a deterministic model underestimates the objective value in this problem as the variation is zero. As the demand variation increases, more suppliers are needed to satisfy the demand. The model run time also improves significantly with a relatively complete resource structure.

After obtaining supply chain data on traceability, it is stored in the online ledger – Blockchain. As suggested in the paper, Blockchain improves data immutability as its length increases. To show how transparent our supply chain can be in regard to data access to all peers present in the network, we perform the last experiment.

Table 3.6 Observations of experiments.

Scenarios	Exponential Demand dist. exp(λ))		Normal Demand dist. (N (μ, σ))	
	Objective values with Bill of Materials - Set I (from Table 3.4)			
	Objective	Run Time (seconds)	Objective	Run Time (seconds)
50	24.264	0.156	25.018	0.203
100	24.183	0.156	24.764	0.203
500	24.192	0.266	24.807	0.25
1000	24.202	0.266	24.787	0.312
	Objective values with Bill of Materials - Set II (from Table 3.5)			
10	25	0.156	31.280	0.187
5	26.238	0.157	30.112	0.157
	The objective value for Deterministic demand is: 20			

3.4.3 Experiment 3.3: Transparency in the Model using Blockchain.

For this experiment, a scenario of a dishonest peer trying to attack the Blockchain containing the batch dispersion problem data is assumed. Random instances of attacker probability of finding the next block are considered and their corresponding ‘progress’ is plotted against the number of blocks of the Blockchain. The observations are recorded in Fig 3.9. It suggests that with an increasing number of blocks, chances of the attacker’s success keeps reducing thus making the data inside the ledger immutable.

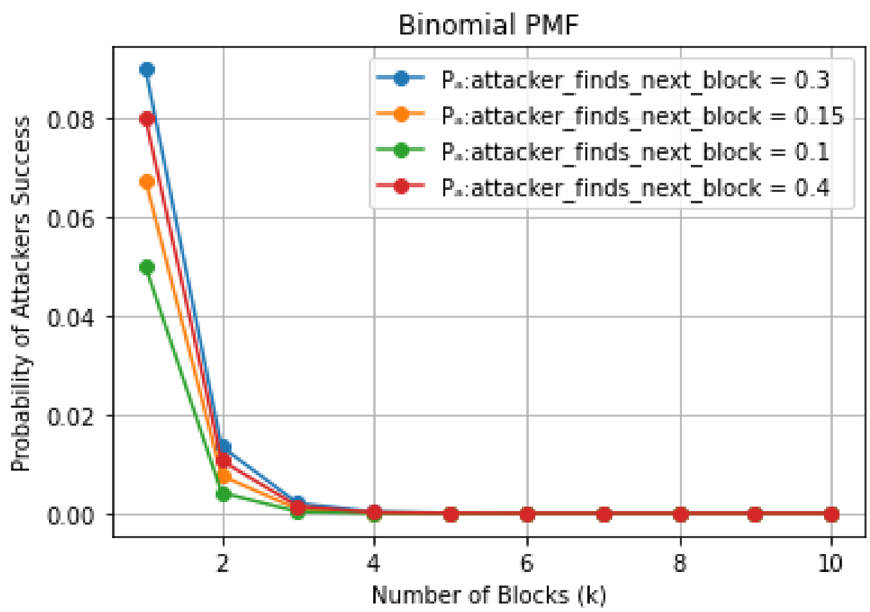

Figure 3.9 Relationship between attacker’s success and number of blocks in a block chain

Transparency is ensured by integrating Blockchain as an online database. Once data traceability is obtained, the information can be uploaded in the decentralized ledger. Depending upon the size of the information loaded, the number of blocks will increase. A linear relation is considered between the data size and the number of blocks of the Blockchain as explained in the mathematical formulation. It is observed that with the increment of number of blocks the probability of the attacker failing to alter the data of blockchain increases or succeeding to alter data decreases, thus reducing the chances of tampering the data and increasing the privacy and security or immutability of the Blockchain as shown in Fig 3.9. The bigger the block chain, lesser are the chances of altering/deleting its data, making it more secure.

3.5 Discussion

In this research, we investigate a stochastic five-level batch dispersion problem with application of blockchain technology. The first part of the problem reduces the amount of mixing and mincing among the batches to reduce the net amount of dispersion. If food contamination occurs, the number of batches to be recalled decreases, thus reducing the recall cost. The solution to this problem is achieved by formulating a stochastic mathematical model whose objective is to optimize batch dispersion and improve traceability considering a random probability distribution of customer demand. Dispersion models proposed in the past were deterministic with either 3-levels or 4-levels excluding packaging. (Dupuy et al., 2005). The stochastic model and the optimum batch size give an insight into the composition of each product batches. The relation between the demand for product batches and the quantity produced investigated in the paper makes it more realistic. Exponential smoothing or normal distribution has proven to be a robust forecasting method and is probably the most used of the statistical approaches to forecasting intermittent demand. The quantity of our final product, i.e., packaged sausage batches, follows the pattern of random demand in both exponential and normal distribution scenarios.

After attaining traceability, ‘batch dispersion problem’ data is integrated with Blockchain to achieve transparency. The second part of the problem is to ensure the safety of this data inside the ‘distributed ledger’. A mathematical model based on negative binomial distribution is proposed, which proves the more the amount of data is fed in the Blockchain, the safer it becomes. The main motivation of this paper was to mitigate a fatal food scare by a unique stochastic optimization method and linking the data of ‘batch dispersion problem’ to the Blockchain. The paper attempts to explore transparency and traceability levels with the inclusion of data related to each level to the Blockchain, thus preventing breach and manipulation of classified data.

Chapter 4 - Q-learning Approach to Mitigate Bacterial Contamination in Food Supply Chain

4.1 Introduction

With a predicted increment in population all over the globe, there is also an increase in the requirement of food availability. Due to globalization of markets, products are moving throughout the country and exported. Food safety hence is a global concern. During the last 10 -15 years, about 1 out of 6 individuals in North America experienced foodborne illnesses annually, amounting to around 48 million cases. As a consequence of food product recalls, the food processing industry incurs significant financial losses, reaching billions of dollars (CDC, 2011). In the food industry, it is widely recognized that food supply chains are grappling with substantial losses attributed to food deterioration. This issue not only leads to financial burdens but also contributes to heightened environmental costs throughout the supply chains. One of the applicable options to reduce food deterioration is to invest in preservation technologies during process, storage, transportation, and retail. Another option could be vertical cooperation, where the entire supply chain acts like a company to reduce production and transportation lead time and optimize inventory and sale strategies. We suggest dynamic quality monitoring as an option to optimize values of relevant parameters affecting food quality at any stage of the perishable supply chain to reduce deterioration ((Maity et al., 2023)

For our research we investigate wheat and cheese supply chains closely. About 6-7 percent of the world's total wheat is produced by United States alone and it is a major exporter (11 percent) of wheat too(USDA ERS). Wheat is the third most grown product after corn and soybeans in the United States. It is the principal source of grain consumption in the country and hence our point of interest. We focus on developing a dynamic monitoring system for a wheat supply chain to reduce bacterial contamination and maintain food quality. Research has proceeded profoundly in terms of traceability of products- RFID tags used for temperature tracking(Amador & Emond, 2010) to blockchain technology by Walmart and nestle to monitor quality(Caro et al., 2018) and satisfy consumer expectations. The in-sights from the model reveal that the use of decentralized database could make these data accessible to the peers (retailers, suppliers, manufacturers) while mitigating data tampering by virtue of blockchain technology. This not only ensures transparency among the peers but also privacy and immutability of the data present in the decentralized database of different supply chain networks. Once the data is securely stored in the decentralized ledger, our next step is to select parameters that affect the quality of a perishable item (wheat in our case) due to bacterial contamination. Such parameters can be temperature, humidity, pH of wheat in silos etc. leading to contamination or bacterial growth at any point along the chain—production, processing, preparation, and distribution. According to CDC, more than a 100 people were infected by a Salmonella outbreak in packaged sea food in 2021 and 1040 people affected due to onions containing bacterial growth in 2020(CDC). Data was collected conventionally by reviewing records from restaurants and stores. Since past work mostly focused on how to trace or track batches that were already contaminated, we came up with a data-driven technology such as machine learning (Q-learning model) to filter relevant parameters impacting food quality at all stages of the supply chain and optimize them to ensure good quality.

The purpose of our research is to develop a holistic approach to make a perishable food supply chain resilient by ensuring a secure way of storing and monitoring supply chain data and identifying and optimizing the relevant factors that lead to bacterial contamination in food supply chain under uncertainty. Blockchain technology ensures the privacy or resistance to data immutability of a decentralized database in case an attacker tries to alter or delete data inside the blockchain. We developed a blockchain UI to add, validate, and send data related to detailed wheat supply chain from farmers growing crops to harvesting, storing in the silos or elevators, then processors for milling and sifting to develop end products (bread, biscuit, buns, tortillas, etc.) and distribute to retailers who finally sell them to consumers. After the data is securely stored in the decentralized ledger, in our next step, we came up with data-driven technology such as machine learning (Q-learning model) to filter relevant parameters impacting food.

Next, we extend our research by applying the Q-learning model on real-time data obtained from an active cheese supply chain at Kansas State University to check the validity of the model. The rest of the chapter is comprised of four sections. Sub-Sections 4.1.2 and 4.1.3 study two perishable supply chains in detail - wheat and cheese respectively. Section 4.2 provides the Q-learning model to monitor parameters in both the FSCs. Section 4.3 performs numerical experiments and analysis to test the validity of the model. Finally, Section 4.4 concludes with discussion.

4.1.2 A Detailed Wheat Supply Chain

In Figure 4.1, we create a detailed wheat supply chain in United States. Wheat is grown by farmers during the planting, mostly during fall or early winter season depending on the region and harvested at peak time which is late summer. The timing of harvest is crucial to obtain optimum quality of grains. Harvested wheat then undergoes cleaning and separating of debris which are post-harvest handling processes. The grains are transported by truck or rail logistics throughout the country and stored in country elevators. In the US, country elevators are modest-sized grain storage facilities situated alongside railroad tracks, spread out at regular intervals throughout rural areas. These elevators offer storage solutions to farmers with limited on-farm storage capacity to accommodate their entire harvest. Additionally, they facilitate the loading of grain into train cars, which transport the grain to domestic processing plants or export (terminal) elevators(Bullock & Desquilbet, 2002). Grains for export are transported in overseas vessels to an overseas importer as shown in Figure 4.1. The overseas importers may distribute them within their own country or sell them to other businesses or consumers. They act as intermediaries in the global supply chain, connecting foreign producers with domestic markets and contributing to the flow of goods and services on a global scale.

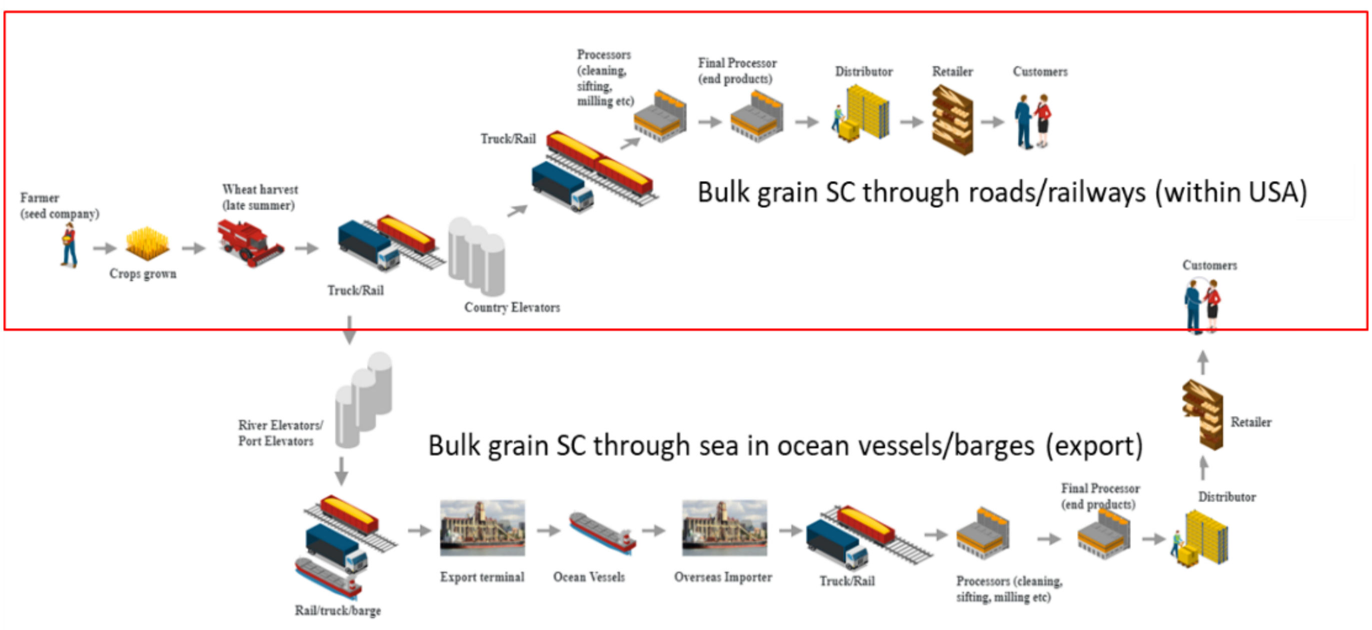

Figure 4.1 A detailed wheat supply chain

Our scope of study includes the upper half (boxed in red) of the wheat supply chain in Figure 4.1, which focuses on the domestic supply chain, examining the intricate processes and activities that govern the movement of grains within the country. Once the grains are harvested ,the biggest challenge faced is storing wheat while keeping its quality intact in silos or elevators. Wheat, mostly in the storage areas, is exposed to various parameters like temperature, CO2 level, humidity, pressure leading to bacterial or fungal growth affecting the quality of the product. From the country elevators it is further transported for cleaning, sifting, milling in processing units. Distributors collect the processed wheat in the form of bread, biscuit, buns, tortillas, pasta, noodles etc. and send it to retailers like Kroger, Walmart, Aldi etc. Customers then can collect the final item which is ready to consume.

4.1.3 Process Flow in Cheese-making

Millions of people worldwide depend on a diverse range of dairy products and foods that include fluid beverage milk, cheese, butter, ice cream, yogurt, dry milk products, condensed milk, and whey products to add both taste and nutrition to their daily diet (USDA ERS). Dairy-based foods offer a nourishing combination of proteins, fats, micronutrients, prebiotics, and probiotics, making them valuable for enhancing food security and promoting human well-being. In recent decades, consumption of dairy products has risen faster than the growth in population in the U.S. although there is significant variation in the type of dairy product preferred by each individual(USDA ERS). For instance, total U.S. per capita consumption of fluid milk has declined likely due to increased competition from other beverages and a declining share of children in the population. In contrast, there has been a spike in demand for cheese consumption which could be attributed to availability of diverse cheese varieties, increased dining out, and the rising trend of ethnic cuisines that prominently feature cheese. Mozzarella has emerged as the most favored variety in recent years, closely followed by Cheddar. Cheese has become a significant part of the diet of U.S consumers, thus motivating our area of interest. We present detailed production process of cheddar cheese in Figure 4.2.

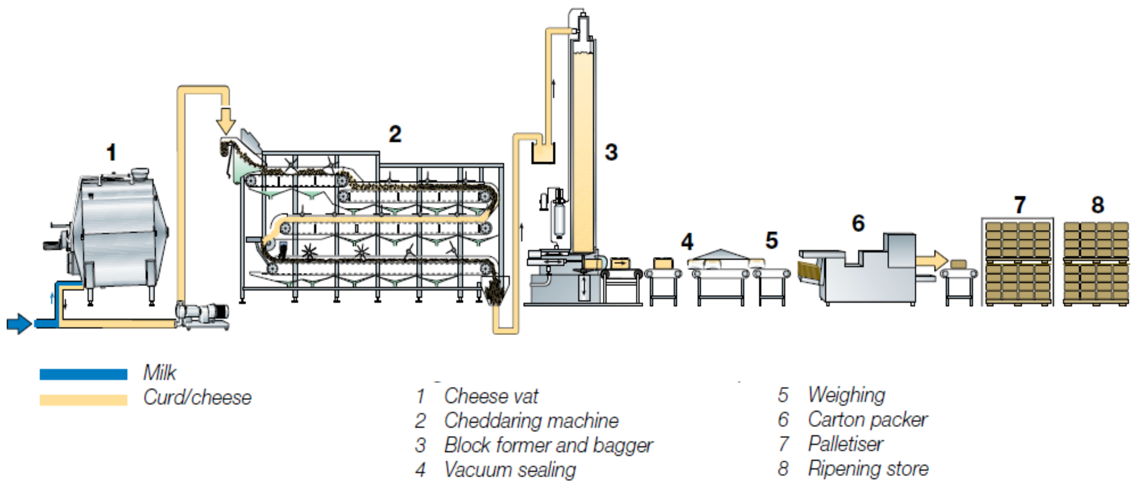

Figure 4.2 Mechanized production of cheddar cheese (Bylund, G. 2003)

The classical method of raw milk collection from dairy farms early morning is followed by pasteurization to kill the bacteria. Pasteurized milk undergoes a separation or standardization procedure where the protein and fat contents of the raw milk are measured (this process follows throughout the year) and the ratio between them is standardized according to requirement Bylund, G. 2003). Treated milk is then piped into large clean containers called cheese vat (1 in Figure 4.2). A critical step in cheese-making is the addition of essential substances. These are starter culture and a complex enzyme called **rennet**, obtained from the inner lining of the stomach of ruminant mammals. The additives result in coagulation of the milk and formation of cheese curds. These curds are gently cut using specific tools followed by whey drainage (in some types of cheese)

– a valuable byproduct. At this stage the required firmness, moisture content and acidity are thoroughly checked. The cheese curds are pre-pressed to remove excess whey and water by applying pressure. A simpler flow chart is presented in Figure 4.3. Real-time image of an active cheese-making process is presented side by side in figure 4.4 for better clarity.

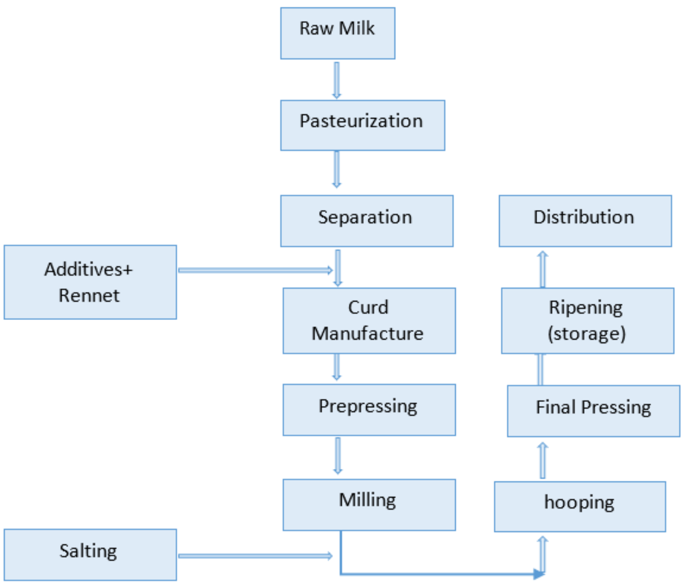

Figure 4.3 Process flow in manufacturing of hard cheese

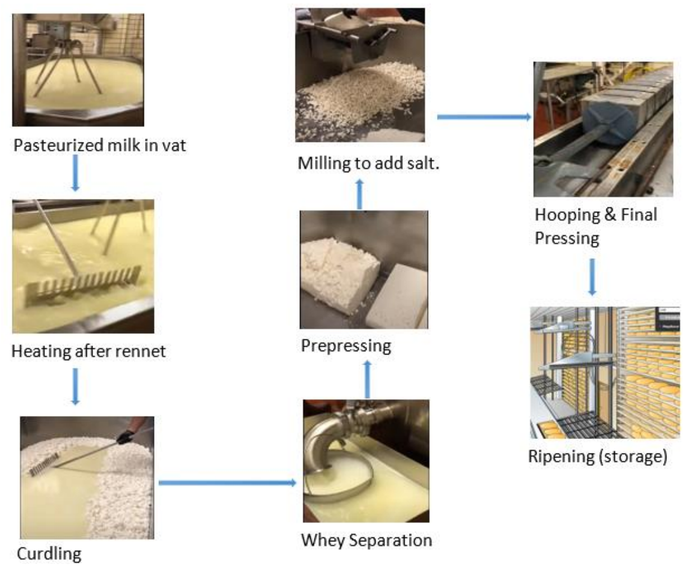

Figure 4.4 Kansas State University production of cheddar cheese in real-time

Pre-pressed cheese curds undergo cheddaring process (milling) where salt is added while the curds are milled to smaller finer pieces called chips. The salted chips transferred to desirable molds (hooping), where they finally pressed using automated or manual pressing systems depending upon the size of the industry. Final pressing assists in final whey expulsion, provide texture and shape. The ripening or aging stage of cheese is characterized by the decomposition of protein which affects the quality of the cheese to a very considerable extent to develop its flavor, texture, and taste. The purpose of storage is to create and maintain specific external conditions (specific temperature, humidity etc.) that are essential for controlling the ripening cycle of the cheese.

4.2 Monitoring Parameters and Optimal Actions : Q - learning Model

Our point of investigation concerns areas where managing the quality of the perishable product is quintessential. This section outlines the Q-learning model in supply chain network to monitor the quality of wheat at potential risk areas. The quality of wheat in our scope of study is affected by parameters that control the growth of bacteria. We consider five levels of bacterial contamination which result in very high quality of wheat that has lowest contamination to very low quality of wheat that has the highest contamination. Temperature and humidity have been the most significant parameters in aiding the growth of micro-organisms in wheat when they are in the storage elevators (Wegulo, 2012; J. Zhang et al., 2022). Hence for simplicity, we perform our experiments based on these two parameters, temperature and humidity, to prevent deterioration of wheat quality due to the growth of bacteria.

Following are the key elements in Q- learning model formulation in determining the best course of action that would ensure good quality of wheat as it travels through the entire supply chain. Environment: It is the abstract world through which the agent moves. The Environment takes the current state and action of the agent as input and returns its next state and appropriate reward as the output.

States: The specific place at which an agent is present is called a state. This can either be the current situation of the agent in the environment or any of the future situations. A set of states S_k is defined as a tuple (k, q_k) where k is each step of supply chain starting from farming to harvesting, truck/rail, country elevators, processing units to finally customers. Quality of wheat in each step k ranges from lowest quality of wheat, value represented by 1, to highest quality of wheat, represented by 5, such that quality level q_k = (very low, low, medium, high, very high). Table 4.1 shows a few possible states of our model. Here S_3=(3,4) represents the state truck/rail(state value = 3) and quality of wheat inside is high(quality value = 4) according to figure 4.1.

Table 4.1 Possible set of state space

S_k	k	q_k
S_1	1	1
S_2	1	2
S_3	3	4
S_4	5	4
S_5	5	5

Actions: We define the action space as a tuple of temperature and humidity as parameters affecting bacterial contamination/quality of a state represented as $A_m = (t, h)$ where m is the action number. Temperature value and humidity values are represented by t and h respectively. Values of t and h vary from $10°C\ to\ 50°C$ and $10\%\ to\ 50\%$ respectively with step size of 1. Performing action $A_m = (t, h)$, the quality of wheat transitions from S_k to state S_l as shown in Figure 4.5.

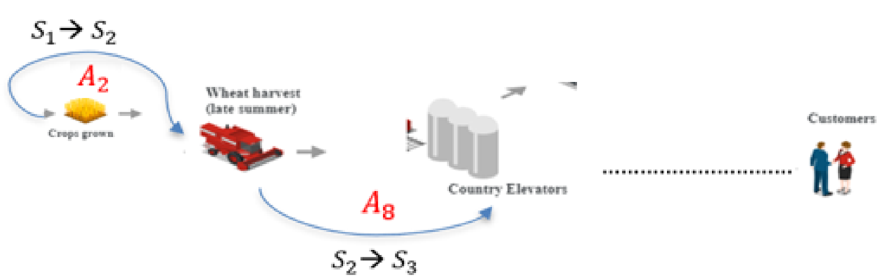

Figure 4.5 Transition of one state to another by taking actions A_2 and A_8

Table 4.2 shows 5 possible actions for our model. Here action $A_1 = (10,30)$ represents first action where the temperature and humidity at a stage of supply chain is $10°C$ and 30% respectively. Note that combination of 41 values of temperature and humidity make 41*41 = 1681 possible actions.

Table 4.2 Possible set of action space

A_m	t	h
A_1	10	30
A_2	20	29
A_3	35	10
A_4	17	20
A_5	50	32

Reward: The system is in S_k and decision maker chooses any action A_m available in state S_k resulting in a new state S_l in the next time period and giving the decision maker a corresponding reward $R_{A_m}(S_k)$. Reward in our problem is a linear cost function of temperature and humidity.

The Q learning algorithm calculates the quality of a state–action combination given by the standard equation (4.1).

$$Q^{new}(S_k, A_m) \leftarrow Q(S_k, A_m) + \alpha[R_{A_m}(S_k) + \gamma * max_{\forall A} Q(S_l, A) - Q(S_k, A_m)] \quad (4.1)$$

Note that $Q: S \times A \rightarrow R$, where S, A and R are states, actions, and reward respectively. Q learning works when we don't know which states are good or bad, or by taking an action which state we land on, in other words the value of transition probability. It works by estimating values of Q^{new} by exploring and exploiting. The model must try out state action pairs from the data to figure out the best course of action that yields maximum expected discounted reward denoted by the Q-value which is updated after every iteration. γ is the discount factor and α is the rate at which the model learns. Both values of γ and α range from 0 to 1. Setting α to 0 means that the Q-values are never updated, hence the model learns nothing. Setting a high value of α such as 0.8 means that learning can occur quickly updating the Q-values aggressively.

4.3 Experiments and Analysis on Wheat Supply Chain

For our experiment, we considered 8 steps (as shown in figure 4.6) and 5 quality levels at each step giving a possibility of 40 states that wheat can be in.

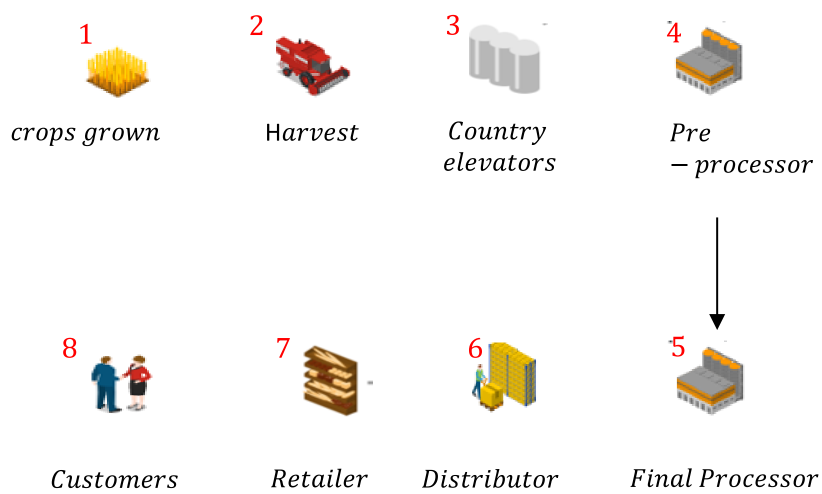

Figure 4.6 8 Steps of wheat supply chain

We performed an experiment at the country elevator stage of the wheat supply chain with a learning rate of $\alpha = 0.5$ to learn the best and worst possible values of temperature and humidity for all 5 quality levels of the wheat. For country elevators, best and worst temperature values explored for 5 quality levels according to the Q function are represented in Figure 4.7.

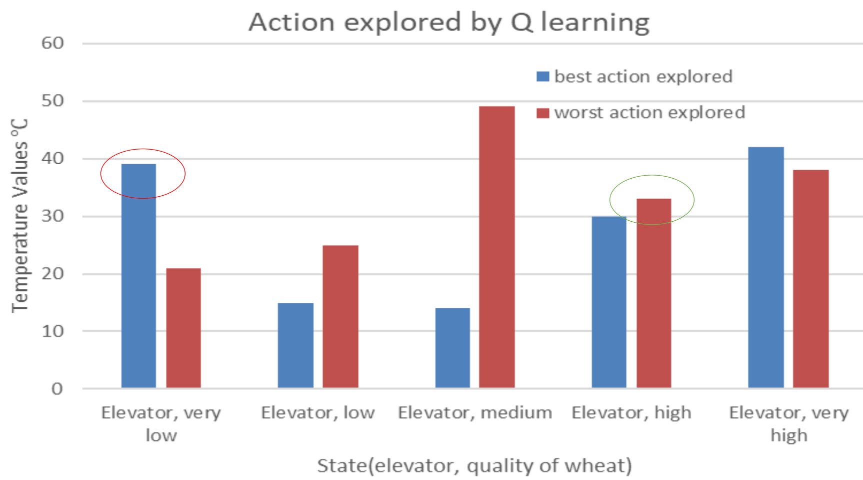

Figure 4.7. Temperature values to select/avoid

If the elevator has very low quality of wheat (numerical value of state = 3,quality = 0), the best decision would be to maintain temperature as 39℃(highlighted in red). If elevator has high quality of wheat (numerical value of state = 3,quality = 5), worst decision would be to maintain temperature as 33℃(highlighted in green). Similarly, for country elevators the best and worst humidity values explored according to the Q function are represented in Figure 4.8.

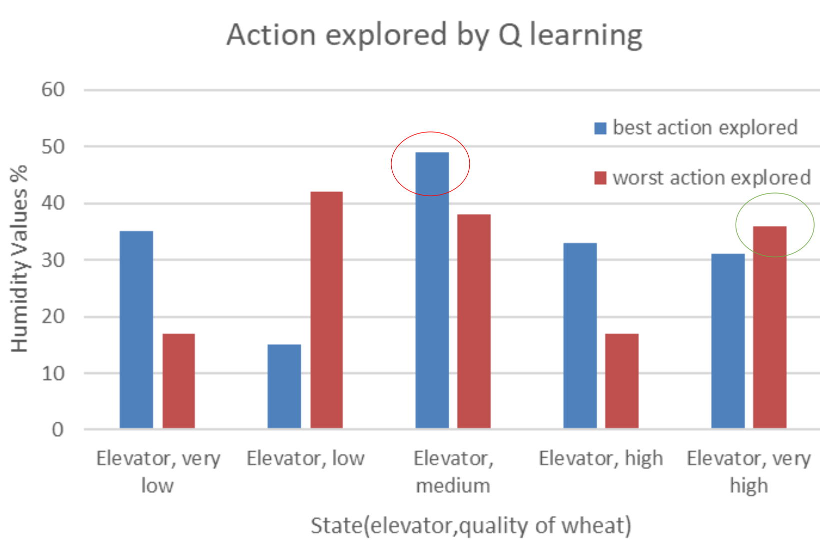

Figure 4.8 Humidity values to select/avoid

If Elevator has medium quality of wheat, best decision would be to maintain humidity at 49%. If the elevator had very high quality of wheat, worst decision would be humidity at 36%.

4.4 Model Validation on Real-time Data

We extend our analysis on real-time data obtained from the cheese processing unit at Kansas State University. We define states, actions, and rewards for cheese processing similar to the wheat supply chain above. Based on the data obtained we consider 8 stages of cheese processing, from obtaining raw milk in cheese vat to adding starter culture and rennet, until finishing the process of draining whey. A snippet of the real-time data is provided in figure 4.9.

OPERATION	TIME	TEM	ACID
RECEIVED IN VAT	5:00	64	
STARTER ADDED	7:00	88	0.18
RENNET ADDED	7:35	90	
CUT CURD	7:55	90	
BEGAN HEATING	8:00		
COOKING TEMP REACHED	8:30	102	0.12
BEGAN DRAINING WHEY	8:50	101	0.13
FINISHED DRAINING WHEY	10:10	100	0.14

Figure 4.9 Cheese-processing data

States: We define a set of states S_i for cheese processing based on obtained data similarly to the wheat supply chain studied above. It is defined as a tuple (i, q_i) where i is each step of cheese processing from raw milk in cheese vat to draining whey units and finally customers. Quality of cheese in each step i ranges from lowest quality of cheese, value represented by 1, to highest quality of cheese, represented by 5, such that quality level q_i = (very low, low, medium, high, very high). Note that in our model there are 8 states according to real-time data and 5 quality levels giving a possibility of 40 states that cheese can be in. **Example**: State number (ranging from 0 to

39) is a tuple. So, let's say state 14 is a tuple (2,4) where '2' denotes the cheese processing state ('Starter Added in our case') and '4' denotes high quality of cheese.

Temperature and titratable acidity (TA) significantly impact cheese flavor, quality, and growth of pathogenic microorganisms. Titratable acidity is related to pH such that the more acid developed, the higher the TA. We define our action space, like wheat supply chain, considering temperature and TA as two parameters impacting cheese quality. *Actions:* A set of actions, $A_j = (t, a)$ where j is the action number. Temperature value and acidity values are represented by t and a respectively. Values of t and a are obtained from dataset and synthetically more data is analyzed for better learning. Performing action $A_j = (t, a)$, the quality of cheese transitions from S_i to state S_l. **Example:** Action number (an integer value) '20' is a tuple (68,0.12) where '68' is the value of temperature and '0.12' denotes value of titratable acidity. Temperature in our experiment ranges from 68°F to 105°F and TA from 0.09 to 0.18 respectively.

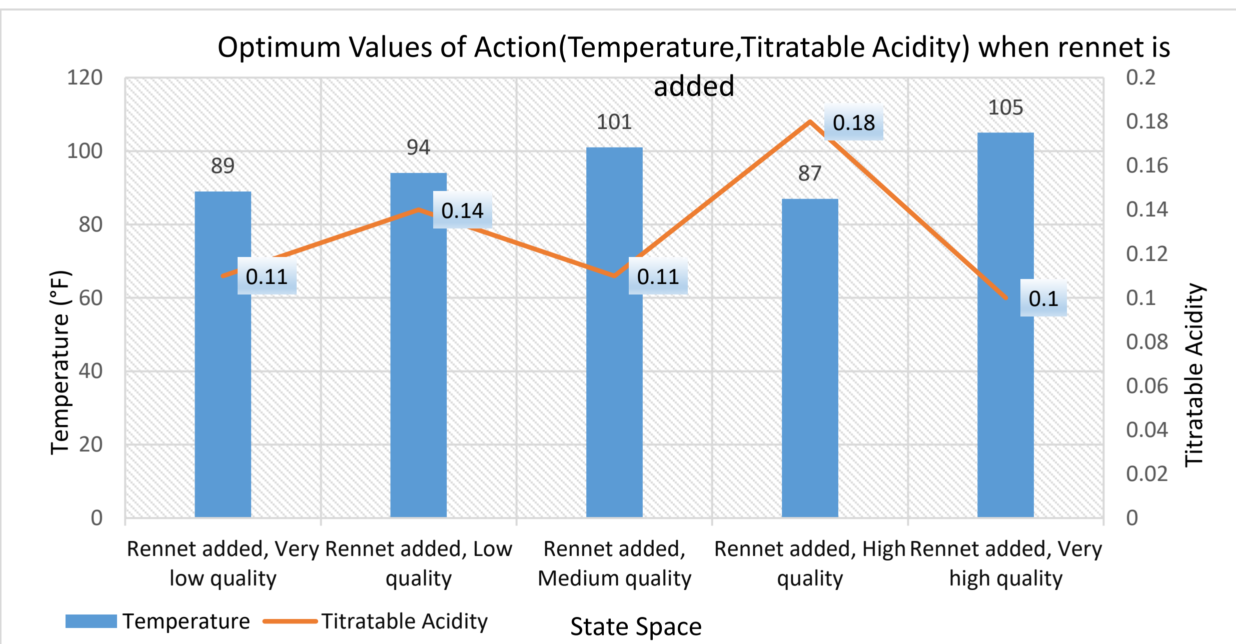

Figure 4.10 Optimal values of temperature and TA at rennet addition stage

Figure 4.10 shows optimum values of parameters or optimal actions/decisions obtained by Q-learning for the third stage cheese processing where rennet is added to the cheese vat. If in this stage, cheese has very low quality, best decision would be to maintain temperature as 89°F and TA at 0.11.

We repeat the experiment for another stage of cheese production for the 1st stage when raw milk is received in cheese vat. If in this stage, cheese is very low quality, best decision would be to maintain temperature as 80°F and TA at 0.16. Optimal decisions are obtained for each quality level of cheese in the 1st stage as shown in figure 4.11. For every state from 0 to 39, we obtain an optimal action number based on Q values, an integer, which is a tuple containing optimum values of (temperature, TA).

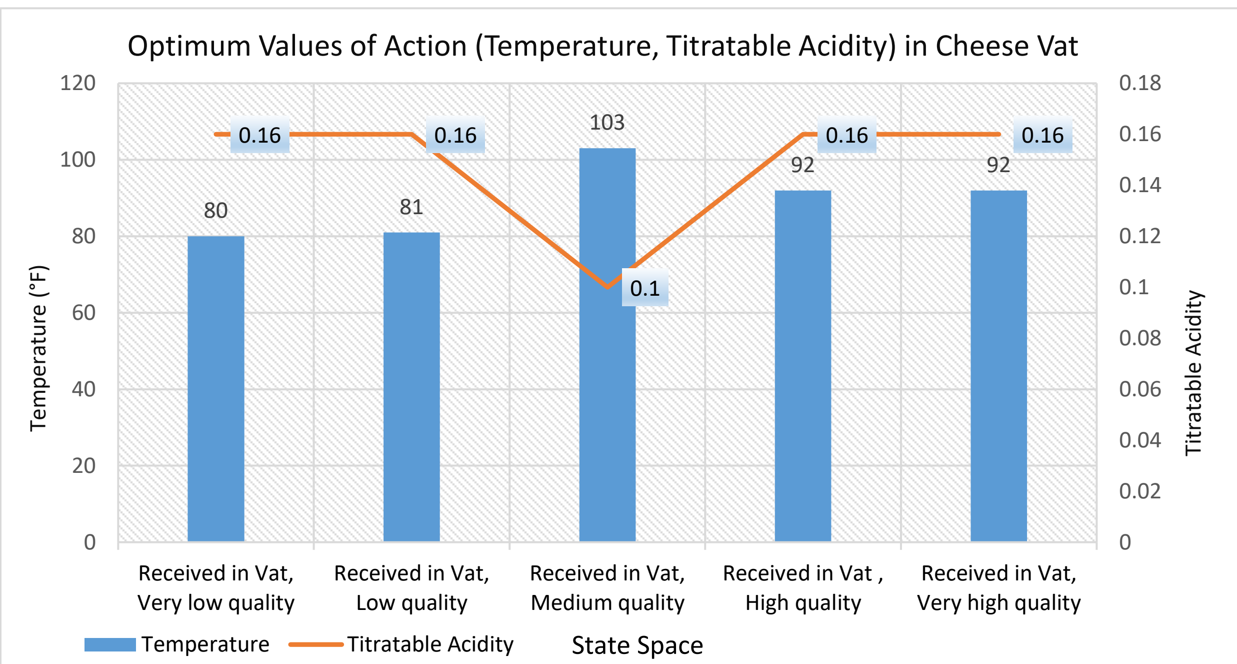

Figure 4.11 Optimal values of temperature and TA when raw milk is received in cheese vat

4.5 Conclusion

We consider a detailed wheat supply chain where temperature and humidity are the two main parameters responsible for bacterial contamination at any point in the network. Since obtaining transition probability is computationally expensive and practically impossible due to large number of states and choices of decisions, we implement a Q learning algorithm to learn the best course of action (choose values of parameters). This method determines the best values of temperature and humidity that is to be maintained to ensure good quality of wheat at every stage of the supply chain. A decision maker can have an idea what could his best and worst decision in determining the quality of wheat. The algorithm in our model is as good as the data. To validate our model, we collected realistic data from a cheese processing unit at Kansas State University and analyzed temperature and titratable acidity as parameters affecting cheese quality. The incorporation of real-time data into our validation process ensured that our model reflected reliability and practicality of its application for decision makers.

Chapter 5 - Multi-level Decomposition Based Approach for Route Optimization in Bulk Transportation with Order Compatibility Constraints

5.1 Introduction

In this research, we analyze a large-scale rich tanker trailer routing problem with stochastic transit times and product incompatibility (Section 1.4.3) for perishable bulk orders. Unlike classical transportation problems, bulk transportation falls under the umbrella of rich vehicle routing problems that involve several intermingled decisions. From an operational perspective, additional complexity arises in determining the best dispatching strategies for tanker trailers to transport perishable food. Typically, the customer orders represent requests to freight products that are characterized by a set of attributes consisting of an origin-destination location pair, pickup and delivery time windows, an order specification, restrictions based on prior orders compatibility matrix, and possibly special equipment (washed and prepped) or handling instructions. The execution of each task requires several inter-dependent sourcing decisions that determine an appropriate tanker trailer and (usually) several drivers to complete execution of the order. The trailer choice decision is comprised of several steps: (1) determine a collection of suitably cleaned, prepped, and configured tanker trailers that are compatible with order requirements, (2) further reduce this trailer set by checking whether previous contents of the trailer meet compatibility rules for the new order, (3) select among sourcing locations (tank wash facilities) where such trailers are available, (4) select another tank wash facility (post-wash location) where the trailer will be washed and prepped for the subsequent order(Delli & Sinha, 2019). Considering the effect of traffic congestion and highly uncertain weather delays, we assume our transit times to be stochastic (gamma distributed). We also assume that the processing times to get the trailers cleaned at wash locations are negligible.

The primary objective of the trailer route optimization is to determine optimal trailer-order-wash combinations from the large number of all feasible solutions. The decisions for pre-wash choices are important because they take into consideration both the travel costs and inventory costs (i.e., trailers left at these locations after the end of time period). Post-wash choice decisions play a key role in future order selections and are bound by the wash capacity constraints. The optimization model will select the route with the shortest possible distance which in turn means less cost incurred. It is to be noted that while making the order covering decisions, product compatibility constraints could be of major concern. The unique demands of each customer influence the pre-order compatibility rules, which, in conjunction with the physical attributes of the trailers (such as lining material, heaters, pumps, etc.), define the specific set of tanker trailers suitable for a given order Note that the selection of post wash location could strategically position the tanker trailer to serve the subsequent order. However, the interaction properties of these orders must be accounted for which limits the feasibility and selection of next order in the route. For every trailer, we define a restricted prior orders matrix which stores the information of up to three prior orders that should not be included in the route. This means the trailer should not cover any of the restricted prior orders corresponding to a current customer order.

Typically, over the course of a year, around 10,000 orders could be transported, and an expedited decision-making process is needed in route planning. To address large-scale nature of this problem and address order-compatibility constraints, we develop a novel multi-level decomposition-based approach that decomposes the original network into multiple sub-networks to account for compatibility constraints and determine the optimal trailer-order-wash combinations. The proposed approach also utilizes novel pruning strategies to efficiently find the solution. We also theoretically prove that the proposed decomposition approach gives the optimal solution. The first step in our solution approach is to generate all feasible routes with single orders and tank wash locations. Then we solve the LP relaxation of Restricted Master Problem which takes into account only a subset of the decision variables. Here, we employ the concept of shortest path to determine the routes with the minimum distance and cost. Then, we use these single order routes and the dual values generated from the LP relaxation to generate the second order routes with post tank wash locations. This is achieved by utilizing the concept of shortest path coupled with efficient graph decomposition. It is to be noted that in the process of generating routes with two orders, we ensure that the orders are compatible by looking at the restricted set of prior orders. When a situation is encountered where two orders are incompatible, we decompose the problem and develop an upper bound on the solution. The decomposed problems are solved or decomposed further until the optimal solution is achieved. Using numerical experiments, we can illustrate the performance of our approach under different scenarios with varying number of trailers, orders and tank-wash locations. We also can compare the proposed approach with brute force based on parallel computation. Additionally, we can analyze the impact of wash constraints (capacity, location, etc.) on the order coverage. The results of the numerical investigation can be expected to reveal that the order coverage is limited by the number of trailers as well as wash capacity. Less wash capacity leads to single order trailer routes in the optimal solution to reduce the number of trips to the wash locations.

The rest of the chapter is comprised of three sections. Section 5.2 presents bulk transportation problem under study. Section 5.3 provides the mathematical formulation of the VRP model. Section 5.4 provides solution approach for Stochastic VRP with order compatibility constraints.

5.2 Problem Description

Unlike conventional bulk transportation problems, the proposed bulk transportation problem with compatibility constraints is very complex because of the sheer scale of decisions to be made while selecting trailers and tank wash locations for each order. To reiterate, a typical route of a tanker trailer involves: sourcing a clean trailer from a pre-wash location, pick-up and drop-off of a perishable product, then cleaning the dirty trailer at a post-wash location and getting ready to process the next order as shown in figure 5.1. The bold lines of figure 5.1 indicate one possible trailer route to process a single order during a certain time period (W1-P1-C1-W4). In this route, the order needs to be picked up at the pick-up location P1 and dropped o at the consignee location C1. First, a clean and prepped trailer has to be located at pre-wash location W1 and then it should be moved to the pick-up location P1 for loading. Then, the trailer moves the order assignment to a consignee location C1. After order drop-off, the trailer needs to be cleaned at the post-wash location W4 to make it ready for the next order assignment. The Safety Data Sheet (SDS) provides crucial information about a product's compatibility with other substances, whether it pertains to the compatibility between current and previous cargo or when transporting a mixed load. Its importance lies in preventing contamination and ensuring the product's integrity remains intact during transportation. Given the number of distinct options that are often available for each decision based on the number of products and the number of tanker trailer available, the overall number of trailer route combinations can be counted in billions.

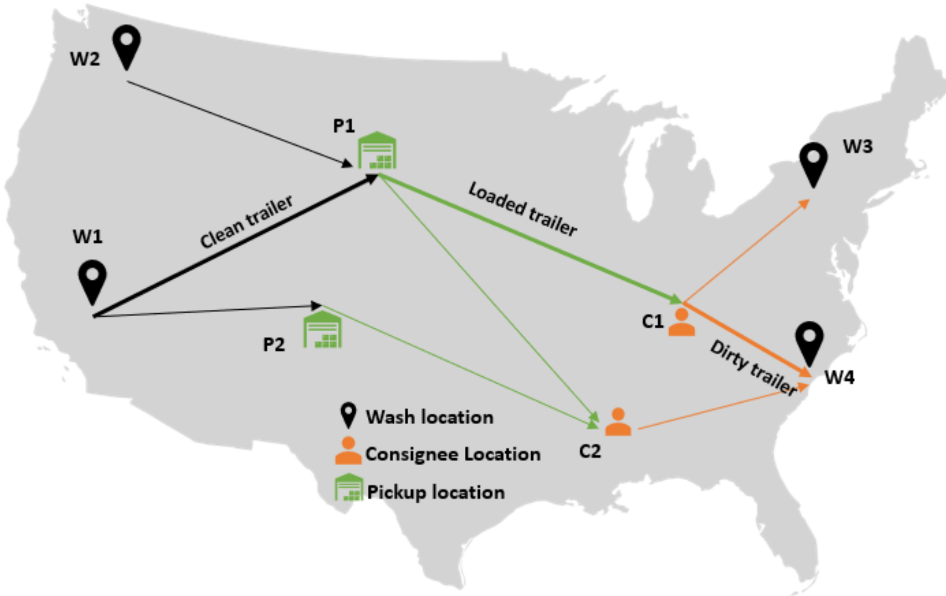

Figure 5.1 A typical trailer route (W1-P1-C1-W4)

5.2 Bulk Dispatch Optimization Model for Perishable Item

In this section, we discuss the optimization model that has been developed to solve our proposed bulk transportation problem. For a given customer order $o_i \in \Theta$ we define an upper bound and lower bound for pickup time window $(l_{o,p}, u_{o,p})$ and delivery time window $(l_{o,d}, u_{o,d})$. We consider stochastic transit times (follows gamma distribution), due to traffic congestion and weather delays. We can then define expected earliness at pickup location and expected delay at consignee location as parameters $\mathbb{E}_{r_t}, \mathbb{L}_{r_t}$ respectively, where r_t is trailer route for trailer t. The trailer t belongs to a set of tanker trailers τ.

We assume $x_{r_t} \in x$ to be a binary variable that takes the value 1 if for trailer t, route r_t is selected, and 0 otherwise. Then, different sets of routes that include the set of routes for trailer t is denoted by R^t where $R^t \in R$ the set of routes that cover order o denoted by R^o where $R^o \in R$ and the set of routes using tank wash w denoted by R^w where $R^w \in R$. Each trailer route r_t incurs a cost Ψ_{r_t} that includes travel costs, empty mile costs, bonuses and penalties. Empty mile cost is the cost incurred by a trailer t for every mile traveled without covering/processing any orders. A bonus may be gained in form of a benefit in some situations like a certain wash location offering some discounts for any trailer t during a festive season. A penalty cost will be incurred when a trailer t either delivers an order o outside of the delivery time windows or does not cover that order at all. We use a set partitioning formulation with side constraints to best describe our proposed bulk dispatch problem which is interpreted in model P below:

$$P: Z = min \sum_{r_t \in R} \Psi_{r_t} x_{r_t} - \sum_{r_t \in R} \left(\mathbb{E}_{r_t} + \mathbb{L}_{r_t}\right) - \sum_{o \in \Theta} \mathrm{F}_o \Upsilon_o \tag{5.1}$$

Subject to:

$$\sum_{r_t \in R^t} x_{r_t} + \Upsilon_t = 1, \forall t \in \tau \tag{5.2}$$

$$\sum_{r_o \in R^o} x_{r_o} + \Upsilon_o = 1, \forall o \in \Theta \tag{5.3}$$

$$\sum_{r_w \in R^w} x_{r_w} \leq \mathrm{K}_w, \forall w \in \omega \tag{5.4}$$

In the above formulation the objective function defined by equation (5.1) minimizes the cost that includes three cost terms , total cost of the route $\sum_{r_t \in R} \Psi_{r_t} x_{r_t}$, total penalty cost for delivering the order late by any trailer route, $\sum_{r_t \in R}(\mathbb{E}_{r_t} + \mathbb{L}_{r_t})$, and $\sum_{o \in \Theta} \mathrm{F}_o \Upsilon_o$ where F_o and Υ_o are the corresponding penalty cost and slack variable associated with not covering order o with any trailer route. There are three main constraints to this problem which include, equation(5.2) which ensures that for any given trailer t, we can only have one route scheduled in the optimal solution and Υ_t is the slack variable for not using the truck, equation (5.3) which ensures that each order o can be assigned to a route or it can be unscheduled, equation (5.4) which ensures that the number of trailers at a tank wash location will not be more than the capacity K_w at tank wash w.

Taking into consideration the number of combinations of trailers and tank wash locations possible for each order, the total route combinations for trailer-order-tank wash could be in billions. This kind of large-scale problem cannot be effectively solved using the conventional branch-and-bound approach. Instead, we propose an efficient approach that decomposes the problem into multiple sub-problems and then aggregate the solution from the sub-problems to reach the optimal solution for the original problem. Next section discusses the proposed decomposition-based approach.

5.2 Solution Approach

The main objective posed by the large-scale nature of this problem is determining the optimal trailer-order-wash combinations while meeting the order compatibility requirements and expected service level. Column generation technique (Ceselli et al., 2009; Feillet, 2010b) is the most commonly applied approach to solve classical dispatch problems where we solve LP relaxation of the problem and consider only a subset of all the decision variables (R1 2 R) which transforms the Master Problem (Equations (5.2-5.5)) into a Restricted Master Problem. However, the presence of compatibility constraints adds additional complexity in determining the next batch of routes to include at each iteration of column generation. To overcome this deficit, we propose an integrated approach that makes best use of graph decomposition and column generation. Note that the presence of incompatibility could mean that the two orders are not reachable from each other. Lemma 1 highlights the shortest cost path for two unreachable nodes.

$\boldsymbol{Lemma\ 1}: For\ a\ network\ G = (N, A), N$

$$= \{n_0, n_1, \dots n_m\}, where\ the\ node\ pair\ (n_{i_1}, n_{i_2}), 0 < i_1, i_2$$
$$< m, is\ not\ reachable\ from\ node\ pair\ (n_{i_3}, n_{i_4}), 0 < i_3, i_4$$
$$< m, the\ lowest\ cost\ path\ from\ n_0\ to\ n_m\ in\ network\ G, \chi^*_{G,n_0,n_m}$$
$$\in \{\chi^*_{G_1,n_0,n_m}, \chi^*_{G_2,n_0,n_m}\}\ where\ G_1 = (N_1, A_1), N_1 = N/\{n_{i_1}, n_{i_2}\}\ and\ G_2$$
$$= (N_2, A_2), N_2 = N/\{n_{i_3}, n_{i_4}\}$$

We prove this Lemma by aggregating results from three cases. In case 1, we remove one of the unreachable nodes and solve of shortest path in the reduced graph. In case 2, we remove the other unreachable nodes. Finally, in case 3, we remove both unreachable nodes. At each column generation iteration, we solve the Restricted Master Problem and search for new columns (or potential solutions) with the minimum negative reduced cost. The negative reduced cost at any column generation iteration for route rt could be given by:

$$\delta^{-r_t} = \delta_{r_t} - \sum_{t \in \tau} a_{r_t,t} \emptyset_t - \sum_{o \in \Theta} a_{r_t,o} \sigma_o - \sum_{w \in \omega} a_{r_t,w} \mu_w \tag{5.5}$$

where $\emptyset_t$ is the non-negative dual variable associated with the $'t'$th constraint of the set (5), $a_{r_t,t}$ is 1 if route r_t contains trailer t or 0 otherwise, σ_o is the non-negative dual variable associated with the $'o'$th constraint of the set (6), $a_{r_t,o}$ is 1 if route r_t covers order o or 0 otherwise, μ_w is the non-negative dual variable associated with the $'w'$th constraint of the set (7) and $a_{r_t,w}$ is 1 if route r_t contains tank wash w or 0 otherwise.

Proof of Lemma 1**:** Let $G = (N, A)$ be a network where $N = \{n_0, n_1, \dots n_m\}$ denotes the set of nodes in which n_0 is the origin and n_m is the sink node , and A is the set of arcs A cost C_{ij} is associated with each arc $(n_i, n_j) \in A$. Let $\chi_{G,n_0,n_i} = \{n_0, \dots, n_j, \dots, n_i\}$, $0 < i, j < m$ be a path from n_0 to n_i. Consider a case where a node pair (n_{i_1}, n_{i_2}), $0 < i_1, i_2 < m$ is not reachable from node pair (n_{i_3}, n_{i_4}),$0 < i_3, i_4 < m$. Then the lowest cost path χ^*_{G,n_0,n_m} from n_0 to n_m in the network G can be exhaustively determined using three cases.

Case 1: $(n_{i_1}, n_{i_2}) \notin \chi^*_{G,n_0,n_m}$: Let $G_1 = (N_1, A_1)$ be a network where $N_1 = N/(\{n_{i_1}, n_{i_2}\})$, and A_1 denotes the set of arcs in the network G_1 .Then the lowest cost path for network G_1 is denoted by $\chi^*_{G_1,n_0,n_m}$

Case 2: $(n_{i_3}, n_{i_4}) \notin \chi^*_{G,n_0,n_m}$: Let $G_2 = (N_2, A_2)$ be a network where $N_2 = N/(\{n_{i_3}, n_{i_4}\})$, and A_2 denotes the set of arcs in the network G_2 .Then the lowest cost path for network G_2 is denoted by $\chi^*_{G_2,n_0,n_m}$.

Case 3: $(n_{i_1}, n_{i_2}) \notin \chi^*_{G,n_0,n_m}$ and $(n_{i_3}, n_{i_4}) \notin \chi^*_{G,n_0,n_m}$: Let $G_3 = (N_3, A_3)$ be a network where $N_3 = N/(\{n_{i_1}, n_{i_2}, n_{i_3}, n_{i_4}\})$, and A_3 denotes the set of arcs in the network G_3. Let $\chi^*_{G_3,n_0,n_m}$ be the lowest cost path for network G_3 since, all paths in $G_3 \subseteq G_1, G_2$. So, $\chi^*_{G_1,n_0,n_m} \leq \chi^*_{G_3,n_0,n_m}$ and $\chi^*_{G_2,n_0,n_m} \leq \chi^*_{G_3,n_0,n_m}$.

Using Case 1, Case 2 and Case 3, the lowest cost path of network $G, \chi^*_{G,n_0,n_m} \in \{\chi^*_{G_1,n_0,n_m}, \chi^*_{G_2,n_0,n_m}\}$.

This concludes the proof.

In order to address this issue, we propose we use breadth first approach coupled with graph decomposition to calculate the negative reduced cost of all the variables of the problem. If an optimal solution is found during any column generation iteration, we keep that subset of variables in the final solution. If not, we generate and evaluate another subset of variables and repeat the process until we generate an optimal integer solution. Considering the size of this problem, the column generation method could substantially decrease the total run-time.

The first step in our solution approach is to generate all feasible routes with single orders and tank wash locations. Then we solve the LP relaxation of Restricted Master Problem which takes into account only a subset of the decision variables. Here, we employ the concept of shortest path to determine the routes with the minimum distance and cost. Then, we use these single order routes and the dual values generated from the LP relaxation to generate the second order routes with post tank wash locations. This is achieved by utilizing the concept of shortest path coupled with efficient graph decomposition. It is to be noted that in the process of generating routes with two orders, we ensure that the orders are compatible by looking at the restricted set of prior orders. When a situation is encountered where two orders are incompatible, we solve the problem with the help of Lemma 1 and Theorem 1. Then the set of routes that are generated with single order and two orders will be fed into the main optimization model. This process continues until we generate an optimal integral solution.

$\boldsymbol{Theorem\ 1}$: $For\ a\ network\ G = (N, A), N = \{n_0, n_1, \ldots\ n_m\}\ with\ p\ prior\ order\ Incompatibilities, where\ prior\ order\ incompatibility$: $o_i \in P(o_j), o_i, o_j \in O, the\ lowest\ cost\ path\ from\ n_0\ to\ n_m\ in\ network\ G, \chi^*_{G,n_0,n_m} \in \{\chi^*_{G_1,n_0,n_m}, \chi^*_{G_2,n_0,n_m}\}\ where\ G_1 = (N_1, A_1), N_1 = N/\left(\{n_{i_1}, n_{i_2}\}, \ldots \ldots \ldots \left\{n_{i_{p1}}, n_{\,i_{p2}}\right\}\right)\ and\ G_2 = (N_2, A_2), N_2 = N/\left(\{n_{i_3}, n_{\,i_4}\} \ldots \ldots \ldots \left\{n_{i_{p3}}, n_{\,i_4}\right\}\right)$.

Proof of Theorem 1: Let $G = (N, A)$ be a network where $N = \{n_0, n_1, \ldots\ n_m\}$ denotes the set of nodes in which n_0 is the origin and n_m is the sink node , and A is the set of arcs A cost C_{ij} is associated with each arc $(n_i, n_j) \in A$. Let $\chi_{G,n_0,n_i} = \{n_0, \ldots, n_j, \ldots, n_i\}, 0 < i, j < m$ be a path from n_0 to n_i. Consider a case where a node pair $(n_{i_1}, n_{i_2}), 0 < i_1, i_2 < m$ is not reachable from node pair $(n_{i_3}, n_{\,i_4})$,$0 <\ i_3, i_4 < m$ because of prior order compatibility: order $o_i \in P(o_j), o_i, o_j \in O$ and there are 'p' such prior order incompatibilities. Then the lowest cost path χ^*_{G,n_0,n_m} from n_0 ton_m in the network G can be iteratively determined using two cases (similar to Lemma 1)

Case 1: $\left(n_{i_1}, n_{i_2}, \ldots \ldots, n_{i_{p1}}, n_{\,i_{p2}}\right) \notin\ \chi^*_{G,n_0,n_m}$: Let $G_1 = (N_1, A_1)$ be a network where $N_1 = N/\left(\{n_{i_1}, n_{i_2}\}, \ldots \ldots \ldots \left\{n_{i_{p1}}, n_{\,i_{p2}}\right\}\right)$, and A_1 denotes the set of arcs in the network G_1 .Then the lowest cost path for network G_1 is denoted by $\chi^*_{G_1,n_0,n_m}$

Case 2: $\left(n_{i_3}, n_{i_4}, \ldots\ldots, n_{i_{p3}}, n_{\,i_{p4}}\right) \notin \chi^*_{G,n_0,n_m}$: Let $G_2 = (N_2, A_2)$ be a network where $N_2 = N/\left(\{n_{i_3}, n_{i_4}\}, \ldots\ldots\ldots \{n_{i_{p3}}, n_{\,i_{p4}}\}\right)$, and A_2 denotes the set of arcs in the network G_2 .Then the lowest cost path for network G_2 is denoted by $\chi^*_{G_2,n_0,n_m}$

Using Case 1 and Case 2 the lowest cost path of network $G, \chi^*_{G,n_0,n_m} \in \{\chi^*_{G_1,n_0,n_m}, \chi^*_{G_2,n_0,n_m}\}$.

This concludes the proof.

The logic behind our solution approach can be explained using a simple example as in figure 5.2. Let us consider four orders O1, O2, O3, O4 and four tank washes W1, W2, W3, W4 (see figure 5.2). If there is no order compatibility issue, then the shortest path will be the optimal route.

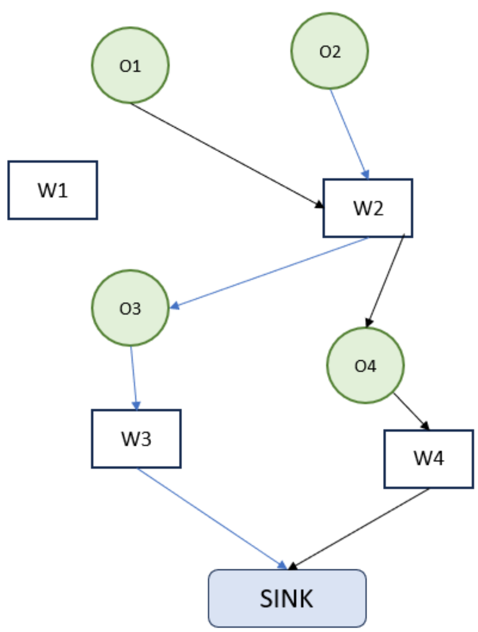

Figure 5.2 Route with no order incompatibility

Now, let us assume that orders O1 and O3 are incompatible. In this scenario, we solve the problem using graph decomposition. As defined in the Lemma 1 above, the optimal solution can be found by solving either Case 1 (in which order O3 is removed and routes are re-generated) or Case 2 (order O1 is removed) If we come across any more compatibility issues, then we solve the problem using Theorem 1 above. It is to be noted here that the incompatibility guides the graph decomposition.

Chapter 6 - Conclusion and Future Scope

In this chapter, we discuss model summaries in the past chapters, insights, conclusions, and research directions on handling unprecedented scenarios in perishable supply chains. Supply chain management becomes efficient and easier by having an insight into the transparency and traceability factors. During a crisis condition, say contamination of food, uncertain spike in demand or natural disasters, every member involved in the supply chain can be aware of the disruption and take appropriate decisions based on entire knowledge of the situation because the data is openly and securely accessible in the blockchain network. Blockchain technology is increasing being explored to be applied in FSCs due to its unique characteristics like, end-to-end tracing and tracking potential that can help in food recall management and identify the source of disruption, data authenticity where every relevant event data associated with the commodity is recorded and stored securely in a decentralized ledger, and fair-trade promotion of perishable items because of better visibility. Although adoption of this technology is still in infancy, in the domain of perishable food supply chains, many companies like Walmart, Nestle have already piloted and implemented blockchains in their food supply chains. We develop a blockchain UI as a part of our contribution to transparency in perishable FSCs. We stored data related to wheat and cheese supply chains where additional information was added in consecutive blocks and the same was notified to the servers involved. We also integrate our optimization model to the UI so that optimum decisions could be taken in real-time while monitoring the supply chains.

In **chapter 3** of our thesis, we consider a batch dispersion model of a sausage manufacturing company experiencing stochastic demand of sausages. Raw materials are procured from several animal farms in the form of ham, belly, trimmings, etc., then mixed and minced according to bill of materials requirement to manufacture intermediary stages and finally produce packaged batches of sausages. The company can decide to outsource final products in case of uncertainty. In case of an exposure to bacterial contamination, batches are recalled from the market which incur huge loss in terms of food and cost. The batch dispersion model under our study is a 5-level disassembling bill of materials structure similar to Gozinto graphs. It is capable of tracking back contaminated batches at every intermediate level until its origin i.e., raw materials procured stage. We apply L-shaped method, a unique application in perishable FSCs, to minimize the mixing and mincing of materials to reduce the number of arcs i.e., the 'spread' of the graph or the batch size and satisfying random customer demand of final packaged products. Due to a reduced dispersion, in the advent of bacterial contamination, a more targeted and reduced number of efficient recalls could be made thus enhancing traceability because batches with high dispersion, calls for more challenges to monitor and control the quality and attributes of each individual batch, hindering effective traceability.

In **chapter 4**, we study wheat supply chain and cheese processing in detail and choose relevant parameters that could result in degradation of the products quality. For wheat, maximum chance of degradation occurs at the storage areas like silos or country elevators. Temperature and humidity are the most significant parameters in the contribution of bacterial growth. Our aim is to optimize the values of these relevant factors that lead to bacterial contamination at every stage of wheat supply chain and dynamically monitor and store the relevant data as a holistic approach to make perishable FSCs resilient In the blockchain UI, we add, validate, and send data related to detailed wheat supply chain from farmers growing crops to harvesting, storing in the silos or elevators, then processors for milling and sifting to develop end products (bread, biscuit, buns, tortillas, etc.) and distribute to retailers who finally sell them to consumers. Next, we implement a data driven reinforcement learning algorithm, Q-learning to dynamically optimize values of temperature and humidity with simulated data. MDP is an efficient framework for dynamic optimization problems that are designed for decision making when the value of a certain probability known as 'Transition probability' is available and cardinality of the problem considered is small. Obtaining transition probabilities can be challenging and, in some cases, infeasible in practicality, especially in complex large size problems , lack of historical data, and uncertain environments. MDPs often assume a fully know model, but RL algorithms like Q-Learning can learn in interaction with the real process by trial-and-error method to know the best course of action, which motivated us in implementing it. Our model worked as good as the simulated data. To check the credibility of our model, we collected real-time data from the cheese producing unit at Kansas State University and applied to obtain consistent results. We chose optimizing values of temperature and titratable acidity as these parameters were found to be most significantly affecting the texture, taste and quality of cheese.

In **Chapter 5**, of this thesis, we consider a large tanker-trailer routing problem for bulk transport of liquid perishable items like dairy products, liquid eggs, fruit juices, vegetable oils ,honey etc. These products when in transit experience several stochastic scenarios like, spoilage rates , traffic congestion, unfavorable weather conditions etc., resulting in stochastic transit times or expected earliness and delays at pickup or delivery locations. Transit times in our model follow a gamma distribution function. To protect the product's integrity throughout transit, certain guidelines are followed. For example, guidelines for all hired carriers with procedures addressing prior loads and the cleaning of bulk vehicles when a carrier commits to a shipper to use dedicated bulk containers or compatible raw ingredients and products. We take into account this complexity while modelling our routing problem or in other words for a route to be feasible, it should comply with the prior order compatibility relationships, along with stochasticity in transit times Typically, over the course of a year, around 10,000 orders could be transported and expedited decision-making process is needed in route planning. To address the large-scale nature of this problem, we develop an integrated framework that combines parallel computation with column generation technique and specialized set of mathematical models to determine the optimal trailer-order-wash combinations.

In the sausage supply chain, we didn't take into consideration the amount of material waste at every level (since bill of material can vary from 0% to 100% while manufacturing the next stage). Food waste significantly impacts the environment, aggravates world hunger and food security. So, in future, we propose exploring strategies to minimize food loss and waste at different stages of the supply chain. We can also integrate stochastic food quality degradation or spoilage rate from suppliers and compare methods like L-shape and heuristics to do a performance analysis. Studying interactions between several parameters impacting food quality other than temperature , humidity and acidity throughout the supply chain and analyzing the correlation between them can help achieve a more sustainable and resilient perishable supply chain.

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