The interrelationships between system components are critical to improving the performance of a complex supply chain system. Thus, any improvement or development can be carried out systemically and comprehensively. The complexity of coordination grows as the number of echelons in a supply chain increases. In practice, coordination becomes more difficult to implement in a supply chain with more echelons. Through demand information sharing, this research attempts to figure out how coordination can have implications for complex multi-echelon supply chains with a modeling approach. The Aggregate Andesite Stone Supply Chain is used as an empirical model with four echelons. Changes in dimensions and values per ton of product in each echelon displacement add complexity. Total holding cost is not the only consideration. The timely completion of projects downstream is also a priority. So the system's behavior that runs and changes over time also needs to be observed. To accommodate this complexity, a system dynamics modeling approach is used. This modeling technique could capture fluctuations in volatile conditions that change in time sequences. The pattern of model behavior shows that demand information sharing in the andesite aggregate supply chain is faint, and the "bullwhip effect" occurs. The demand information sharing can eliminate this effect, reduce up to 73.5 % of total supply chain holding costs, and increase the percentage of project completion on time downstream of the supply chain. These results provide a scientific and practical understanding that although there are many obstacles, demand information sharing can significantly improve performance in multi-echelon complex supply chains and be worthwhile applied

Keywords: downstream project completion, multi-echelon supply chain, demand information sharing, system dynamics, andesite aggregate stone

UDC 339
DOI: 10.15587/1729-4061.2023.269284

HIERARCHIC CHANGE SYSTEM DYNAMICS SUPPLY CHAIN MODEL: IMPACT OF DEMAND INFORMATION SHARING ON HOLDING COST AND DOWNSTREAM PROJECT COMPLETION

Ahmad Fatih Fudhla
Doctoral Student*, Assistant Professor
Departement of Industrial Engineering
Universitas Maarif Hasyim Latif
Raya Ngelom str., 30, Taman, Sidoarjo, East Java, Indonesia, 61257

Budisantoso Wirjodirdjo
Corresponding author
Doctor of Engineering, Professor*
E-mail: budisantoso.wirjodirdjo@gmail.com

*Departement of Industrial and Systems Engineering
Institut Teknologi Sepuluh Nopember
Kampus ITS Keputih, Sukolilo, Surabaya, East Java, Indonesia, 60111

Received date 22.11.2022
Accepted date 30.01.2022
Published date 28.02.2023

***How to Cite:** Fudhla, A. F., Wirjodirdjo, B. (2023). Hierarchic change system dynamics supply chain model: impact of demand information sharing on holding cost and downstream project completion. Eastern-European Journal of Enterprise Technologies, 1 (3 (121)), 25–37. doi: https://doi.org/10.15587/1729-4061.2023.269284*

1. Introduction

Good supply chain management has tremendous leverage on the sustainability of every business [1]. In Managing a Supply Chain, two challenges must be faced; structural challenges with many involved parties (multi-echelon and multi-actors) and uncertainty challenges [2, 3]. Both challenges drive complexity. Complexity grows as the supply chain's echelons increase, making Supply Chain Coordination essential [4, 5]. Supply Chain Management aims to manage chain interest trade-offs [6]. If a trade-off exists, then coordination can be a means to improve supply chain performance. The most commonly used approach to supply chain coordination is through information sharing [7]. Information sharing may include sharing point-of-sale, delivery schedules, inventory level, and demand information. Interactions and relationships between system components and their behavior are also essential in complex systems to improve performance [8] and gain a competitive advantage [9]. Thus, any improvement can be carried out systemically and thoroughly.

The echelons in previous research were mainly in two [10–13] and three layers [14–18]. Only a few have built four echelons or more in the supply chain coordination model [19, 20]. Even then, Mathematical Programming approaches such as Linear Mixed Integer Programming [21, 22], goal programming [23], differential modeling [24], heuristic approaches [25, 26], or a combination of optimization and heuristics [20], with many assumptions for modeling process simplifications. Making it somehow requires much effort to apply in the practical world and capture the complex system's actual behavior. However, there has never been comprehensive coordination modeling that captures causative relationships and the behavior between interconnected variables along the supply chain. Therefore, this study is devoted to developing a complex multi-echelon supply chain coordination model and capturing the behavior. Due to the complexity and many interactions between components in complex multiple echelons supply chain networks, a system dynamics approach is the most appropriate [27]. This modeling technique can accommodate fluctuations in uncertain conditions that run over time and capture the behavior [28]. Multiple echelon Aggregate Andesite Stone (AAS) Supply Chain is used as an empirical system with four echelons. Moreover, the demand information sharing as coordination.

Every Quarry could supply andesites to more than two stone crushers industry in the AAS supply chain. Each stone crusher serves various industries: the ready-mix, precast, asphalt mixing plants, paving-stone, and stockpilers/distributors. The flow of andesite aggregate is quite long, involving many factors influencing its flow, from open pit extraction quarry to the final infrastructure product. The shape and value per unit product change in every echelon shifting, making holding cost per unit in each echelon and each industry a divergent value. On the other hand, as the primary raw material for end users in the completion of infrastructure projects, supply delays mean poor supply chain performance. Not only causing fines for delays but business continuity in the future can be threatened. Therefore, studies that are devoted to examining the demand information sharing in the complex multi-echelon supply chain, such as The AAS, are scientifically relevant. It becomes even more critical if uncertainties exist (demand, weather, availability, workforce, pandemic, and timing). The result could be used as a solution or benchmark for supply chains or industries with similar complexity to improve their performances.

2. Literature review and problem statement

Integration and coordination from upstream to downstream in the supply chain can improve performance [29, 30]. Managing resources across company boundaries in manufacturing companies are becoming increasingly important [31]. They should be an essential element in the strategy to win the competition. However, supply chain coordination is also not always in the primary interest of the individual members of the supply chain components. As a result, an orderly coordination mechanism within the supply chain is needed to change the behavior of supply chain components to improve supply chain performance [32]. Information flow significantly affects the material flow's smooth behavior [33]. Traditionally, companies operate in environments with insufficient information. Partial and periodic purchase orders become the primary information channel for sharing among components. Strategic Decisions related to the supplies, such as production and storage, have been made based on local information at the activity site [34]. This results in operational inefficiencies in excess inventory, increased operating costs, and additional coordination costs. Therefore, inefficiencies in the supply chain must be eliminated [35]. The alignment and coordination of information between components are essential to balance supply and demand [36]. Coordination and collaboration are the fundamental issues of supply chain existence. Much research has discussed various forms of coordination with different supply chain echelons [37].

The paper [22] studies coordination in two-echelons supply chains. The first echelon is the manufacturer (single), and the second is the retailer (multi). Developed framework and linear mixed integer programming model show that decentralized coordination could improve efficiency with discount decisions for different pricing. The study suggests that as the overall demand for the product increases, the manufacturer should increase the frequency of discount periods and the magnitude of the discounts to spread out production over a more extended period. But some issues have not been accommodated; The study only considers time-changing demand at the retailer level but does not consider other factors that may affect demand, such as market conditions or competitors. How the coordination could impact supply chain performance or other influences is not discussed in depth. It would provide a better impact if these could be considered in the model comprehensively.

In the paper [38], even though each one is not discussed in depth, more echelons of the supply chain systems are discussed. It described that collaboration and coordination in a supply chain could lead to performance enhancements, risk management, and cost savings. The key to successful collaboration is that all parties share the costs and benefits. It identified three key processes; defining cost and benefit parameters through a cost-benefit analysis, classifying cost-benefit sharing characteristics into two, three, and multi-echelon categories, and categorizing collaboration levels into four categories (data, knowledge, information, and cost-benefit sharing). It presents cost-benefit sharing scenarios based on these processes using Analytical Hierarchical Process. It shows that collaboration can lower costs and generally increase responsiveness in health facility services. The study highlights the importance of fair allocation of costs and benefits for successful collaboration in the healthcare supply chain. This framework can be helpful for healthcare supply chain managers and stakeholders to understand the benefits and challenges of collaboration and to develop strategies for cost-benefit sharing that can improve supply chain performance. The study in this paper has some limitations; the proposed framework is based on a relatively small number of case studies, which may limit its generalizability to other healthcare supply chain contexts. Additionally, the framework is theoretical in nature and does not provide empirical evidence of its effectiveness in practice.

The paper [39] investigates the use of Kanban systems in a multi-echelon pharmaceutical supply chain (MEPSC). It suggests that these systems can improve inventory management and information sharing within MEPSCs, and provide a foundation for innovation in the pharmaceutical industry. It presents two main findings: that Kanban systems can provide strategic benefits and improve the quality and information sharing within a MEPSC. They can also allow organizations to shift away from traditional "push" delivery and logistics systems towards improved strategies. The research offers an in-depth examination of various Kanban systems developed to address the difficulties and obstacles encountered by the original Kanban system. The paper presents a compelling argument for how implementing a Kanban system can effectively manage inventory and enhance communication throughout a multi-echelon supply chain. However, it relies on a single case study to demonstrate the implementation and benefits of Kanban systems within a MEPSC, which may limit the generalizability of the findings to other contexts. Additionally, it does not present empirical data on the impact of Kanban systems on inventory management and supply chain performance, which would help evaluate the validity of the proposed benefits. The research only focuses on using Kanban systems to control inventory status in each component rather than considering other potential applications. The Kanban systems operate based on predetermined rules or patterns.

The paper [40] presents a well-defined research question and addresses it using a novel simulation method based on hierarchical colored Petri nets. It provides a clear and thorough explanation of the method and how it was used to model inventory management in multi-echelons serial supply chains. One strength of the paper is that it builds upon existing knowledge on the bullwhip effect and inventory inaccuracy and situates the research within this context. It also provides a comprehensive review of the literature on RFID technology and its potential to mitigate the bullwhip effect. Using a colored Petri nets base allows for modeling complex supply chain dynamics in the presence of inventory inaccuracy and RFID technology. But there are a few areas that could be improved. One limitation is that it only considers the impact of inventory inaccuracy on the bullwhip effect in RFID-enabled supply chains. It would be interesting to see how the results compare to supply chains without RFID or with different collaboration strategies. Additionally, the study does not present any real-world data, and it may not fully capture the complexity of real-world supply chains.

The paper [41] presents a three-echelon model in the closed-loop supply chain that optimizes the profits of each member: a manufacturer, retailer, and collector. It introduces models for remanufacturing by offering a certain level of physical and financial assistance to the collector. It utilizes optimization techniques to identify optimal solutions. The study finds that through coordination and shared responsibility, the collector's profit can be enhanced, the performance of the supply chain can improve over time and the profit of each member of the supply chain increases as the percentage of sharing increases up to a certain point. The study provides insight into how responsibility sharing can improve profitability and reduce an individual's workload. It can be helpful in supply chain industries where the coordination among the members of the supply chain is crucial for the overall performance of the supply chain. Nevertheless, the differences between manufactured and remanufactured products have not been accommodated in the model. The study only considers a single retailer; the model has not considered multiple retailers and stochastic demand patterns.

The paper [42] proposes and analyses some scenarios in which upstream (replenishment lead time) and downstream (demand) information are shared simultaneously in a two-echelon supply chain with multiple products. It minimizes the overall system cost, which includes holding, ordering, penalty, and transportation costs, using a centralized decision-making process in which the warehouse is the decision maker. The developed genetic algorithms successfully find the optimal inventory positions at the warehouse and allocate quantities for each product to each retailer to minimize the system cost. But it only considers centralized decision-making, where the warehouse is the decision maker and does not explore the potential impacts of decentralized decision-making on the value of information sharing. It would be helpful if it provided more details about the specific genetic algorithm used, such as the selection and crossover operators, as well as the specific optimization objectives and constraints.

The approach proposed in the paper [43] appears to be a promising solution for addressing the challenges of managing a decentralized supply chain where the entities are independent and do not fully cooperate. Using a bi-level model and Nash game strategies at the upper level allows for coordination and decision-making in a non-cooperative environment. In contrast, optimizing individual objectives at the lower level allows each entity to pursue its own goals. The numerical analysis and comparison with other approaches provide good support for the effectiveness of the proposed approach. Overall, the approach proposed in this paper represents a valuable contribution to the literature on decentralized supply chain management and has the potential to be applied in practice to improve coordination and sustainability in such environments. But this paper may still have shortcomings; it assumes an independent body at the upper level to coordinate the planning and decision-making process. It may not always be feasible in practice, and it is unclear how the approach would work without such a body. Additionally, the sensitivity analysis only considers a few select parameters, and it would be beneficial to see a more comprehensive analysis of the robustness of the approach to different variations in the model parameters.

The paper [44] addresses a case study to illustrate the use of sell-through data in forecasting and evaluates the performance of various methods using empirical data. It provides a practical example of how sell-through data can be used in practice and adds credibility to the conclusions drawn. The study suggests that incorporating sell-through data from intermediaries can improve the forecast accuracy of traditional univariate forecasting methods. It is a valuable insight for manufacturers as it can help them build a more agile supply chain by improving short-term forecast accuracy. One potential area for improvement could be to provide more detail on the specific methods used to evaluate the forecasting performance in the case study. While it describes the use of time series methods and machine learning techniques, it does not provide much detail on the specific algorithms or approaches employed. Additionally, it would be useful to have a more in-depth discussion of the potential limitations and considerations for using sell-through data in forecasting. It mentions that sell-through data may not always be available or subject to delay but does not delve into these issues in much detail.

The paper [20] presents a mathematical model for analyzing a sustainable and traceable fish closed-loop supply chain network, which includes consideration of carbon emissions from transportation, production, and warehousing activities. The inclusion of carbon emissions in the model is also a notable feature, as it aligns with current concerns about the environmental impact of supply chain activities. The consideration of multiple types of costs, including production and traceability, transport, inventory, and emission costs, is also a good feature of the model. The potential area for improvement could be to provide more detail on the specific assumptions and constraints used in the mathematical model. While it describes the various components of the supply chain and the cost factors considered, it does not provide much information on how these are incorporated into the model or how the model accounts for the complexities of the real-world system. Furthermore, it does not address the potential for variability or uncertainty in demand for fish products or the costs of production and transportation, which may impact the model results.

Extensive research has been carried out. From the reviews above, the echelon was studied primarily on two and three. Only a few in four echelons were developed for a single product without change in shape or value in every echelon. Mainly Systems are observed using the mathematical and algorithmic modeling approach (Linear Programming, goal programming, Genetic algorithm, Petri net graph, Nash game, differential model), which is rigid through assumptions. However, there has never been a study that develops the model for a multiple-echelon supply chain that captures the interrelationship and behavior between actors and factors in the product supply chain that changes over time and addresses supply chain coordination for differentiated products or changes in the type, size, or value in the middle of the flow.

This study builds the model based on the system dynamics modeling approach. System dynamics are effectively used for a system that requires a lot of data management [45]. The system dynamics (SD) approach for supply chain modeling is widely used. Paper [46] reviews that SD has been used as a modeling approach in the supply chain functions for distribution, logistics, planning, and sourcing. Paper [46] also reviews that based on the supply chain field, SD has been applied in Agri/aquaculture, daily tools, automotive, biofuels, electronic products, food and beverages, woodworking, mining, transportation, and utility. This method is not new in the construction sector's supply chain modeling approach; it is used to build a green strategy evaluation model [47–49], construction supply chain risk [50], circular issue [51, 52], and prefabricated construction supply chain product [53, 54]. As primary construction materials, Previous studies of the supply chain of aggregate andesite stone products and their derivatives are limited on analyzed the network design and production planning with linear mix integer programming. Where the primary outcome is location planning [55]. However, System Dynamics has never been used to model the supply chain of andesite aggregate stones as construction material and overview the coordination, especially demand information sharing.

3. The aim and objectives of the study

The aim of the study is to develop ways to reduce difficulties in a complex multi-echelon supply chain. It allows supply chains of the same complexity to use as benchmarks or strategic evaluation tools to improve performance.

To achieve this aim, the following objectives are accomplished:

– to identify and develop a system dynamics model that could accommodate complexity in multi-echelon AAS Supply Chain and system behavior that changes over time;

– to reveal how demand information sharing on multi-echelons of AAS Supply Chains affects total holding cost and project completion downstream.

4. Materials and Methods

The System Dynamics model captured the system behavior in management science [56]. While the definition of dynamic systems, according to JW Forrester [57], is a simulation methodology used to evaluate complex systems that evolve or change over time, primarily in management science and modern control theory, through computer simulations.

The stages for developing a system dynamics model are as follows [28, 58]:

1. Observation of the entire system observed and Variables Identification.

This first step seems the simplest, but it is the most crucial step in the system dynamics approach. A researcher's understanding of the observed system is the key to moving on to the next stage. Understanding the system's various components and behaviors that change over time stands at this stage. Moving on to the next stage is not easy when the observed system is not adequately understood.

In this study, observations were made starting in the stone crusher industry. The data obtained included production mechanisms, material supply patterns from quarries, and delivery mechanisms of stone crusher products, identifying any matters that affect production, product delivery, and material receipt. The search continues upstream and downstream. Upstream there is The Quarry. Observations were made to capture how the stone open pit mining process is carried out, what influences the quarry production rate and capacity, and how the process of receiving orders and andesite stone delivery is carried out. In the downstream direction, observations are made by tracing where the stone crusher products are sent to end users. The end users of this entity are the contractors of various infrastructure projects. At the downstream end of the supply chain, the most important data to obtain is the monthly demand of aggregate andesite or its derivative products, usage rate, and the deadline for each infrastructure project undertaken.

2. Causal Loop Diagram (CLD).

Relations among observed variables are shown in this diagram. It is positively marked if it has a positive relationship and a negative mark for a negative relationship. This arrangement of relationships forms a Loop that can be both positive and negative. This Loop is necessary for the system dynamics because it reflects the natural system's behavior. When a condition continues to increase, there will be a mechanism that counters this condition and encourages a decrease, and vice versa.

3. Stock & Flow Diagram (SFD).

This diagram shows the system's structure with more detailed information than in the CLD. In this diagram, the identified variables are categorized into auxiliary, rate, and level/stock. Flow interaction is also more visible than CLD. There are two types of flow, namely, the flow of information and material. Material flow is accommodated in stock/level with control in and out of rate. In SFD, interactions among variables in CLD are transformed into equations inside each variable. SFD is The system dynamics model that runs over time. In this study, developed SFD is simulated for 3 years with monthly timestep.

4. Model Validation.

The simulation model can be validated by comparing the output of several parameters from the model with actual conditions. It can be done with a statistical approach by comparing the similarity of variance and mean of these parameters [59]; this is called a model behavior replication test [60, 61] added Model parameter tests. In the behavior tests, parameter values in the model can be tested in simple ways, for example, against historical behavior. The model parameters can be validated by examining two interrelated variables: comparing the actual logic with the simulation outcomes. The simulation results are considered accurate if the pattern matches the actual logic.

5. Analysis and Developing Alternative Scenarios in a valid model.

After obtaining a valid model, an analysis of the existing conditions of the model's behavior is carried out at this stage. Moreover, applying and analyzing some planned scenarios or the observed system changes tested at the model level is possible.

In this study, there is no coordination in the initial model. The alternative scenarios model is carried out by enhancing aspects of demand information sharing. The demand is made into transparent information among industries and echelons. The output of the two models is then calculated for the total holding cost and captures the completion time of the infrastructure project at end-users.

5. Result of System Dynamics Modeling Approach on the Aggregate Andesite Stone Multi-Echelons Supply Chain

5. 1. Developing system dynamics model

5. 1. 1. The aggregate andesite stone supply chain (observed system)

Most infrastructure projects include road construction, bridges, dams, irrigation, and housing, all of which require raw materials from aggregate stones supplied by the stone crusher plant. The product consists of coarse and fine aggregates derived from hard rocks (andesite). All concrete-based constructions require andesite aggregate stone as a material. For example, when building bridges and dams for homes, a mixture of sand (fine aggregate) and gravel (coarse aggregate) is needed [62]. Compacting layers on road construction projects require Stone ashes. Smoothing the road surface requires a mixture of asphalt, stone ashes, and gravel measuring 0.5 mm [63]. Thus, the availability of aggregate andesite stones (AAS) becomes vital in supporting infrastructure projects in developing countries.

In aggregate andesite and its derivatives, profit from sales may not be a priority. Nevertheless, construction projects that are completed on time downstream are necessary. It is useless at one time; the sales numbers are high. Still, the next time it could not be continuous because of the low service level of aggregate supply and unable to maintain inter-chain relationships. Low because it fails to predict downstream needs, but when overconfidence saves excess product. It causes high opportunity costs and holding costs. This is why this research examines how much and how demand information sharing affects the behavior of the andesite aggregate supply chain along the stream.

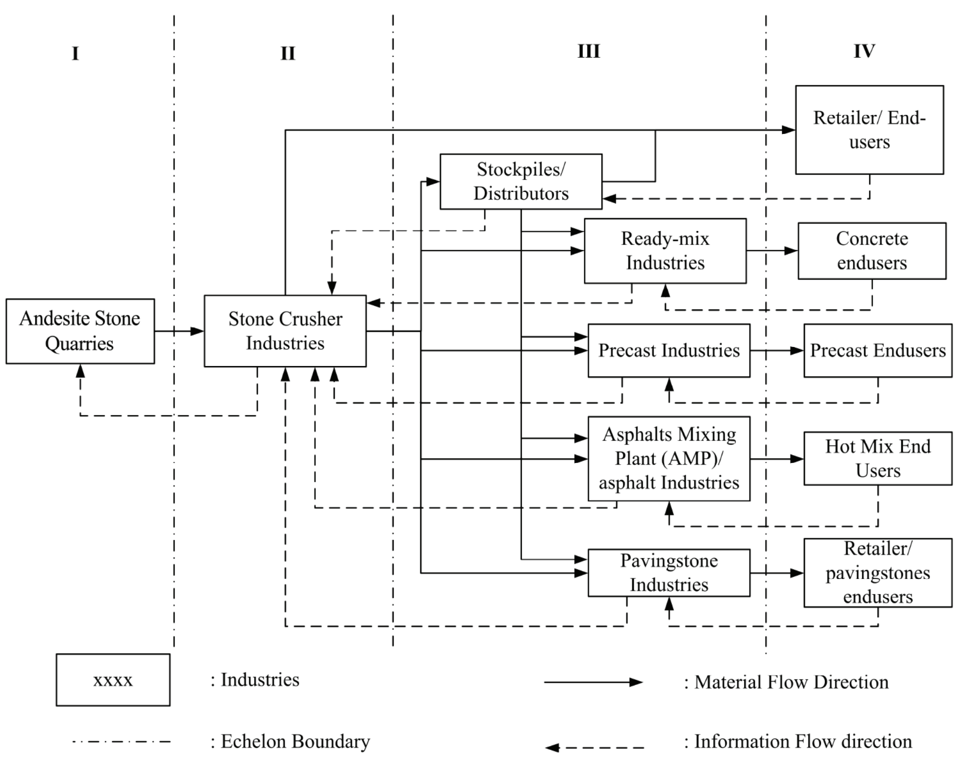

Fig. 1. Andesite aggregate stone supply chain

The gradual processing of non-renewable materials causes the guarantee of availability needs to be a priority. Suppose there is a delay in supply or low product quality, it could hamper the construction of infrastructure projects. As the main component, the stone crusher industry must provide raw materials on time and in good quality.

The supply chain of aggregate stone is quite complex. As shown in Fig. 1, the chains consist of four echelons, where the center is at echelon II, the stone crusher industry. The upline comes from the stone quarry at echelon I. Furthermore, the downline of the supply chain is spread from echelon III to echelon IV. Aggregate stone distributors supply to retailers and end-users directly. Ready-mix and precast industries use aggregate stone as bulk concrete dough mixtures. The asphalt mixing and paving stone industry is also located at Echelon III. The end-user of each sector is at echelon IV of the supply chain. The andesite aggregate stone end-users are not close to the possibility of getting the product directly to the stone Crusher industry.

The entity journey begins from an open pit quarry, boulders obtained from nature in massive size. The process of breaking with explosives and/or breakers is carried out so that they are of sufficient size to be loaded in the transporter and sent to the stone crushers industry. The boulders are then crushed by crusher machines until aggregate andesite of various sizes and value-added changes are produced. AMP Industry and paving-stone require types of stone ash and stone sizes of 5–10 mm; ready mix and precast require sizes 10–20 and 20–30 mm. All produce different new products with andesite aggregate as the primary raw material, which is then absorbed by the end market. So, entities change in shape and value throughout the supply chain stages.

Identified variables have a significant role in the flow of aggregated andesite stone product entities along the supply chain. The main of them in the model are:

1. Andesite production in the Quarry.
2. Andesite stone inventory.
4. Stone Crusher production rate.
5. Demands for stone crusher products.
6. End-user demand of each andesite derivative product.

5. 1. 2. Causal loop diagram

This diagram shows the relationships between variables identified as influential in the AAS supply chain from Quarry to end-user. There are at least 22 Loops generated with different Loop marks, both positive and negative, some of which are presented in Fig. 2. Since open pit, when rainfall increases, it could affect the decrease of production capacity in the Quarry and the stone crusher, so the nature of the relationship is negative. One stone crusher handles supply to all industries in echelon III.

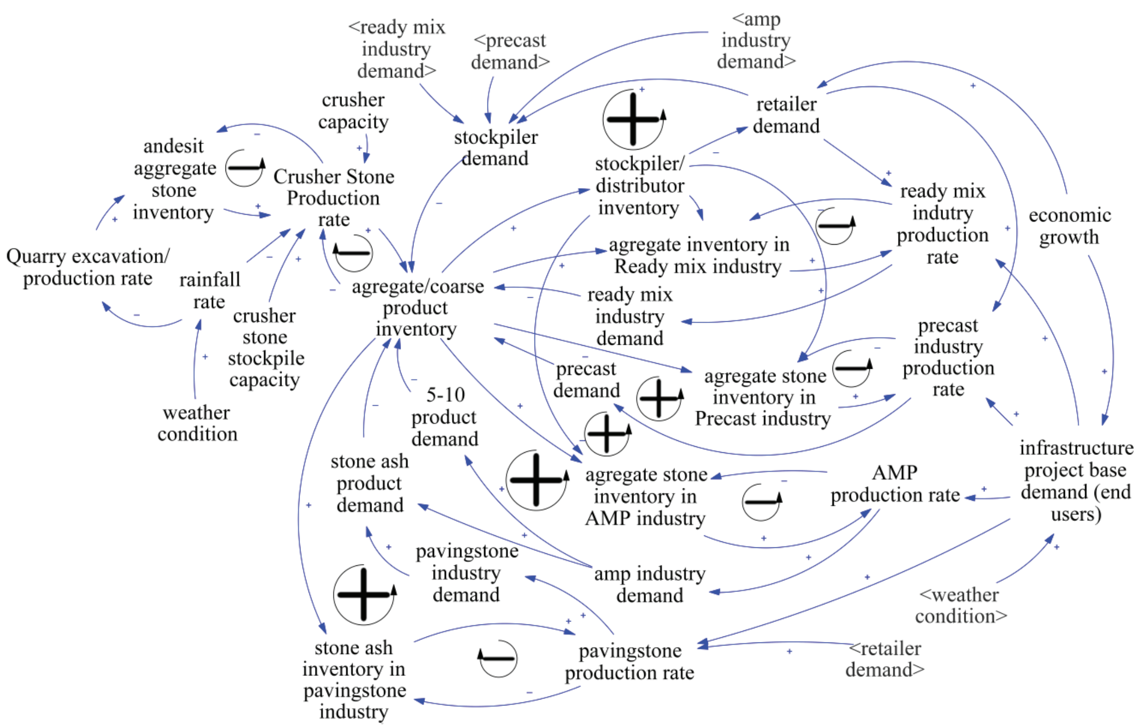

Fig. 2. Aggregate andesite stone supply chain causal loop diagram

As the stockpile of stone crusher products increases, it encourages the construction industries to fill their raw material storage because there are fears of material shortages at certain times, so the relationship is positive. Once the demand from the construction industry increases, it lowers the level of stone products storages. Everything is driven by demand from retailers and infrastructure projects-based end-users.

5. 1. 3. Stock and flow diagram

Interaction and feedback systems can be described by functions or equations that produce mathematical functions when integrated and sequenced. The equations used in modeling for some stocks are as follows.

The stock of "inventory of quarry andesite stone" with units of tons in the t-period (X_t) is influenced by the initial inventory in the null period (X_0) and the integral of the "quarry production" rate in the t-period (Y_t) reduced by the level of "raw materials deliveries" in the t period (Z_t). So mathematically described in the form:

$$X_t = X_0 + \int_{n=0}^{t} (Y_t - Z_t)\,\mathrm{d}t. \quad (1)$$

The stock of "crusher stone raw material" in period $t(A_t)$, influenced by the initial conditions (A_0) and integrals of the "raw materials deliveries" in period $t(Z_t)$, minus the production rate of each product type i at each period $t\left(B_t^i\right)$, where i consists of stone ash, aggregate 05–10, 10–20, 20–30, and waste. It can be written as follows:

$$A_t = A_0 + \int_{n=0}^{t} \left(Z_t - \int_{m=1}^{i} \left(B_t^i \mathrm{d}i\right) \right) \mathrm{d}t. \quad (2)$$

The stock of each product type piles i at each period $t\left(C_t^i\right)$ is affected by each initial inventory status $\left(C_0^i\right)$ and each production rate $\left(B_t^i\right)$ and reduced by total demand product i at period $t\left(D_t^i\right)$. The stock is expressed as:

$$C_t^i = C_0^i + \int_{n=0}^{t} \left(B_t^i - D_t^i\right) \mathrm{d}t, \quad (3)$$

$$E_t^i = E_0^i + \int_{n=0}^{t} \left(F_t^i - G_t^i\right) \mathrm{d}t, \quad (4)$$

describes mathematically that, at the third echelon, stocks are defined as the inventory level of material piles in the precast industry, distributors, ready mix industry, Asphalt Mixing Plant, and paving stone industry (E_t^i: stone aggregate inventory level industry i at period t). each affected by the total inbound of each i material at period $t\left(F_t^i\right)$ and the total usage rate for production in industry i at the same period $\left(G_t^i\right)$.

Capturing the flow of andesite stone material from the Quarry to the end-user in various product forms becomes the starting point of modeling. All equations (1)–(4) are inserted into each variable in the stock and flow diagram. Andesite stone sources are obtained from nature by open mining techniques. The stocks and flows model of the chain is shown in Fig. 3. Massive andesite stones are cleaved by two methods, mechanical breaker, and blasting. Since the Quarry is on the surface, each month's production results depend on weather conditions. In the rainy season, production is lower than the monthly average.

The Andesite stone is sent to the stockpiles of the stone crusher industry, which are processed into various sizes from 20–30 mm, 10–20 mm, 5–10 mm, and the most delicate is stone ash. The residual products of this process go into waste, which is usually a type of stone of low quality mixed with mud and soil. Each size of aggregate andesite stone has its market share. Dimensions of 20–30 mm are needed as a precast and ready-mix raw material, 10–20 mm are required by the precast industry and distributor stockpiler, 5–10 and stone ash are needed by the AMP and paving stone industries. Therefore, demand for each end-user of the processing industry is highly dependent on the weather and annual budget cycle of infrastructure projects. Moreover, end customers/users in the 4th echelon do not have any stockpile of products.

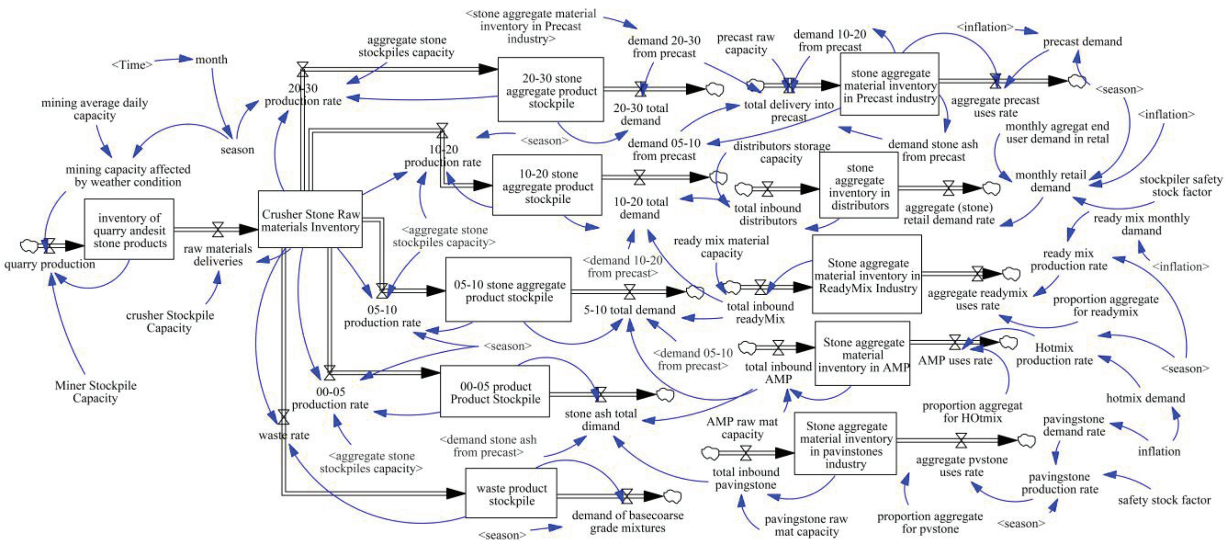

Fig. 3. Aggregate andesite stone supply chain system dynamics model

5. 1. 4. Model Validation

Validation of each model is a crucial process. This process test and ascertain whether the model built can represent the actual system. The better the model, the more similar to the actual condition of the modeled system. In this study, model parameter and Behaviour replication tests carry out for Validation.

In the Model Parameter Test, relationships between variables in the model are compared with the pattern of relationships in actual conditions. For example, the precast demands and aggregate precast uses rate relationship in the existing system is positive and in the model; as shown in Fig. 4 above, when demand rises, the use of precast aggregate stone also increases. Conversely, aggregate stones in the precast industry also fall when demand for precast products falls.

The tests were a variance similarity test and an average similarity test. Using the 2-variance test (Bonett and Levene method) for the variance. With hypotheses:

– H_0: $\sigma_i / \sigma_i^* = 1$ {Ratio of actual data variance of variables i (σ_i) with the variance of simulation data of variable $i(\sigma_i^*)$ is equal to 1};

– H_1: $\sigma_i / \sigma_i^* \neq 1$ {Ratio of actual data variance of variables i (σ_i) with the variance of simulation data of variable i (σ_i^*) is unequal to 1}.

While the average similarity test uses a 2t-sample test with hypotheses:

– H_0: $\mu_i - \mu_i^* = \delta_0$ {difference between average actual data of variable i (μ_i) with average simulation data of variable $i(\mu_i^*)$ is equal to null (δ_0)};

– H_1: $\mu_i - \mu_i^* \neq \delta_0$ {difference between average actual data of variable i (μ_i) with average simulation data of variable $i(\mu_i^*)$ is unequal to null (δ_0)}.

Both tests use Minitab, obtained recapitulation of p-value results as shown in Table 2.

In Behaviour Replication Test, Some parameters in the model statistically compare to the parameter data at actual conditions. The variables compared are shown in Table 1. The table presented 36 data (36 months) simulation results and actual data for the variable inventory of quarry stone products, crusher stone raw materials inventory, stone aggregate material inventory in the precast industry, stone aggregate inventory in distributors, stone aggregate material inventory in AMP and stone aggregate material inventory in paving stones industry.

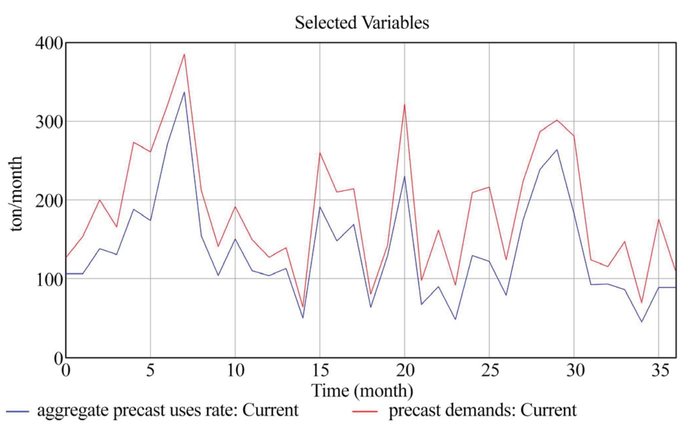

Fig. 4. Model output graph of "precast demands" and "aggregate precast uses rate"

Table 1

Data Recapitulation of Model Parameter

No.	Monthly Echelons Inventory (in tons)											
	Inventory of quarry stone products		Crusher Stone Raw materials Inventory		Stone aggregate material inventory in the Precast industry		Stone aggregate inventory in distributors		Stone aggregate material inventory in AMP		Stone aggregate material inventory in the paving stones industry	
	Actual Condition	Simulation output	Actual Condition	Simulation output	Actual Condition	Simulation output	Actual Condition	Simulation output	Actual Condition	Simulation output	Actual Condition	Simulation output
1	2	3	4	5	6	7	8	9	10	11	12	13
1	502.0	500.0	286.5	298.6	36.6	38.7	64.8	73.1	73.3	8.4	9.5	19.7
2	570.0	455.3	294.9	361.8	42.1	53.2	16.6	34.4	36.2	41.2	54.8	104.6

Continuation of Table 1

1	2	3	4	5	6	7	8	9	10	11	12	13
3	572.4	533.0	264.0	346.9	14.2	27.1	3.1	60.7	36.9	13.6	2.6	58.7
4	757.1	807.6	641.7	436.7	138.1	82.2	25.8	28.2	144.3	69.0	144.3	69.0
5	692.2	701.0	689.0	482.6	93.2	87.7	6.5	88.9	57.9	75.7	57.9	75.7
6	709.1	860.6	345.1	590.1	72.0	124.0	73.7	13.7	60.5	18.5	60.5	18.5
7	806.4	732.0	572.7	760.4	76.6	126.5	123.7	123.6	77.8	63.5	77.8	63.5
8	603.3	785.9	439.3	714.2	40.6	8.8	98.0	66.1	89.7	50.5	89.7	50.5
9	845.9	731.7	711.8	393.1	91.3	39.0	64.0	142.4	49.2	123.9	49.2	123.9
10	480.1	840.4	321.2	328.2	34.8	46.5	24.5	9.2	49.8	61.8	0.2	82.2
11	484.4	640.8	307.4	350.7	20.9	27.6	24.1	6.9	48.0	13.8	19.9	60.9
12	552.8	721.7	296.1	305.3	35.4	63.8	18.5	63.6	40.3	35.0	14.9	–12.7
13	496.9	578.2	225.2	408.4	18.0	22.2	15.2	43.9	92.8	5.6	13.8	41.1
14	311.9	550.9	294.6	365.1	24.7	5.9	37.4	2.4	55.6	58.7	19.8	71.8
15	565.6	805.6	328.3	297.4	44.1	2.7	34.4	42.5	96.9	47.9	11.8	88.7
16	629.6	873.5	815.8	627.6	104.2	48.6	87.0	76.8	110.1	124.2	110.1	124.2
17	633.2	872.8	689.9	772.0	104.8	128.0	96.7	35.1	51.9	81.5	51.9	81.5
18	651.1	456.0	732.7	495.3	127.1	85.5	71.0	112.6	143.3	115.9	143.3	115.9
19	747.9	673.0	863.2	794.7	46.7	87.1	90.9	81.1	48.1	46.8	48.1	46.8
20	834.3	563.7	376.2	554.4	42.0	113.6	154.0	111.8	73.7	86.0	73.7	86.0
21	754.9	674.1	327.9	565.9	116.4	105.3	121.2	85.0	80.5	54.3	80.5	54.3
22	570.1	486.1	261.9	340.3	23.8	48.5	32.8	100.4	60.6	30.0	25.5	68.6
23	502.4	490.4	322.4	265.2	17.1	16.5	20.5	93.3	84.7	50.8	29.5	6.8
24	559.7	502.5	292.0	328.3	36.8	37.0	32.2	26.9	27.6	38.5	19.5	28.7
25	338.3	375.6	254.6	296.1	34.2	48.9	14.7	85.8	16.9	52.6	21.4	63.7
26	477.3	284.5	257.9	376.7	40.4	17.5	23.3	36.9	96.8	11.0	44.9	20.6
27	464.8	249.8	340.3	325.7	28.6	45.0	81.5	88.7	83.5	20.0	7.4	34.3
28	642.4	334.7	188.7	455.1	47.3	127.6	73.4	99.0	58.3	41.6	58.3	41.6
29	704.3	867.3	485.4	198.1	115.0	109.0	69.7	76.8	63.7	67.2	63.7	67.2
30	542.2	730.1	507.9	298.9	66.7	93.2	57.3	52.6	86.7	113.9	86.7	113.9
31	752.3	662.1	556.6	789.3	97.8	71.7	35.0	121.7	53.1	78.2	53.1	78.2
32	698.0	743.3	757.4	513.7	65.6	140.5	85.4	103.9	90.0	65.5	90.0	65.5
33	850.5	583.2	570.9	578.0	181.0	96.7	89.9	30.1	60.0	108.2	60.0	108.2
34	476.0	542.1	283.4	201.7	35.4	27.2	21.7	46.2	65.0	53.1	22.1	76.8
35	464.2	409.9	263.7	414.8	19.7	53.7	16.2	2.3	31.6	27.3	27.2	13.6
36	570.9	412.4	284.3	226.5	38.1	28.8	4.0	64.5	17.3	46.1	34.4	41.9

Of the six variables tested, with α=0.05, all test results showed a failure to reject the null hypothesis. There is not enough evidence for the similarity of variance to claim that the two populations of pairs have different variances. Moreover, there is no evidence of an average difference between all variables in actual conditions and the average simulation results for the average similarity test. Based on all the tests conducted, the model is valid. Furthermore, it is statistically the same as the actual system conditions.

Table 2

P-value recapitulation of similarity tests

No	Variables	Similarity Test of Variances (σ)			Similarity Test of Means (μ)	
		P-Value		Result (α:0.05)	P-Value	Result (α:0.05)
		Bonett Method	Levene Method			
1	Inventory of quarry stone products	0.069	0.052	Fail to reject the null hypothesis	0.871	Fail to reject the null hypothesis
2	Crusher Stone Raw materials Inventory	0.438	0.636	Fail to reject the null hypothesis	0.794	Fail to reject the null hypothesis
3	Stone aggregate material inventory in the Precast industry	0.955	0.614	Fail to reject the null hypothesis	0.74	Fail to reject the null hypothesis
4	Stone aggregate inventory in distributors	0.859	0.842	Fail to reject the null hypothesis	0.196	Fail to reject the null hypothesis
5	Stone aggregate material inventory in AMP	0.578	0.599	Fail to reject the null hypothesis	0.126	Fail to reject the null hypothesis
6	Stone aggregate material inventory in the paving-stones industry	0.674	0.649	Fail to reject the null hypothesis	0.116	Fail to reject the null hypothesis

5. 2. Total holding cost and downstream project completion in demand information sharing of aggregate andesite stone supply chain

Time step of the model in "month." It simulates for 36 months. The total inventory level recapitulation of each echelon at the end of the month is shown in Fig. 5. The initial model simulates the AAS Supply chain with no coordination. Each echelon and its member forecast each demand separately. When analyzed at each echelon component of the AAS Supply Chain, the higher upstream inventory level is available at the end of each month. At Echelon 3, the average inventory was 246 thousand tons. Echelon 2 averaged up to 194 thousand tons. At the most upstream echelon rose again to 171 thousand tons. The standard deviation is also higher upstream. End users take no material stock strategy at their sites. There is no inventory in the 4th echelon.

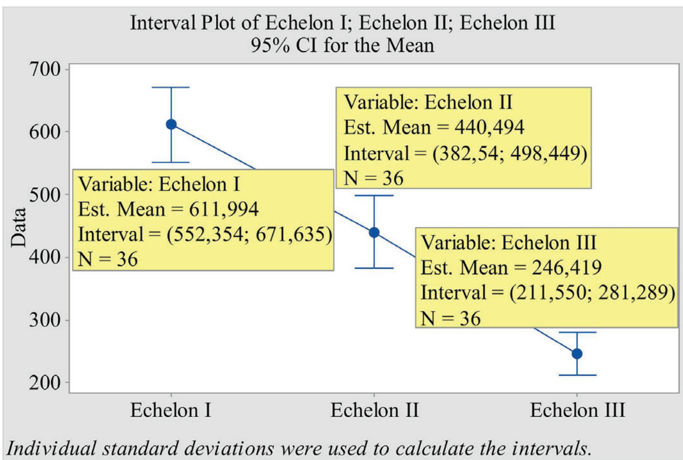

Fig. 5. Level of Andesite Aggregate Supply Chain Interval Plot Inventory (36 months simulation report)

For cost calculation, if the holding cost per ton of products at each supply chain echelon is 2 % per year from the product's price. The average price of items at echelons 1, 2, and 3, respectively, is $100.00, $130.00, and $160.00. Thus, based on the simulation results of no demand information sharing between aggregate andesite supply chain echelons, as shown in Table 3, the total holding cost for 36 months amounted to $ 9,473.45.

If coordination exists, decentralized coordination with applied demand information sharing, there must still be a safety stock of 5 % at echelon 2 and 3 % for echelon 1 to serve the end-user that can pick directly up to each echelon. That is why holding costs still must be allocated at echelon 1 and 2 as shown in Table 3. Then there is the potential to reduce the cost of saving the supply chain to $ 2,506.09. For industries in echelon 4, critical performance is measured by the completion of projects on time. The existence of demand for information sharing increased the percentage of projects completed on time to 91.92 %. The remaining 8.08 % is likely due to other factors beyond AAS supply chain coordination.

6. Discussion of coordination in aggregate andesite stone supply chain results

Fig. 3 shows the system dynamics model of the multi-echelon AAS Supply Chain. There are up to 69 variables connected by information and material flow. They are divided into three categories; first is "stock/level", such as "inventory of quarry andesite stone products," "Crusher Stone Raw materials Inventory", variable inventory of stone crush products, and variable stockpile material of the processing industry in echelon 3. The second is "rate," such as "quarry production", "raw material delivery", and production rate. The third is free variable or "auxiliary". This model is then validated to see the similarity of the model's behavior pattern with the existing system. a model is good when it is more similar to the actual conditions. As shown in Table 2, the model passed the parameter validation test statistically. Fig. 4 shows the pattern output of two variables that appear to be volatile over three years (36 months) – inventory levels up high on the 5th to 8th of each year. Inventory levels were lower in the 9th to 4th month of the following year. It happened due to an increase of end of year demand. Moreover, the rainy season from September until March decreases the production rate in Quarry and Stone crusher.

The model output in Fig. 5 indicates the bullwhip effect phenomenon. This condition occurs because supply chain components run independently between echelons and within the echelon. There is no intense communication and coordination regarding product demand. Echelon 3 predicts demand from end-users. Based on historical data and forecast results, echelon 2 indicates customer demand across echelon 3. At the same time, the Quarry in Echelon 1 of the supply chain also forecasts the stone crusher line-up at echelon 2. Each echelon guessed the real needs of the echelons below. Because historical demand is highly volatile, forcing them to use a safety stock strategy with a high inventory level. The bottleneck in Information processing occurs when the information journey of demand is distorted as it moves between echelons leading to increased order variability in the supply chain. Forecasting is based on the number of orders and does not direct consumer demand. Due to the absence of direct access to consumers, producers tend to receive distortions of information from the echelons below them. Information or data flowing at this supply chain echelon is prone to distortion, resulting in decisions that trigger fluctuations. Thus, transparency or disclosure of information between one echelon and another of the supply chain is essential and deserves careful attention. As a result, information distortion occurs, which leads to an increase in variance from downstream to upstream.

From the model's output in Table 3, it can be understood that the bullwhip effect causes multiplying holding costs in the upstream direction of the supply chain when there is no coordination. One solution to minimize the occurrence of this phenomenon is to improve coordination between supply chain echelons, such as demand information sharing. In this AAS Supply Chain model, Demand

Table 3

AAS supply chain performance comparison

Condition	Holding cost (HC)				% Projects completed on time at echelon 4
	Echelon 1	Echelon 2	Echelon 3	Total HC	
No demand information sharing	$ 3,671.97	$ 3,435.86	$ 2,365.63	$ 9,473.45	67.32 %
Demand information sharing	$ 44.36	$ 96.10	$ 2,365.63	$ 2,506.09	91.92 %

information sharing could reduce up to 73.5 % total supply chain holding cost. Holding costs at echelon 3 remain the same because they capture demand fluctuations from scattered end-users and are very difficult to coordinate. Coordination emerged between echelon 3 to echelon 2 and echelon 2 to echelon 1, reducing holding costs. When inventory is zero, holding costs can reach zero. Due to the emergence of safety stock, there is still storage cost at echelons 1 and 2, but the value is minimal according to the allocation.

Table 3 also shows that project completion in 4th echelon could increase with coordination. It is because AAS is the primary material in infrastructure projects. The main end-users of this material supply chain are infrastructure project contractors, who have a deadline for each work/project. When the supply of AAS material is hampered, it is also hampered by completion, which leads to late fines that are not small in value. When there is no coordination, often when demand increases, the goods at the supplier are empty. End-users eventually had to delay work or switch to other alternative sources of supply. These conditions are not very good for the AAS supply chain in business continuity. So this parameter becomes essential to consider as the performance of the AAS supply chain. The model's output shows that with coordination, demand information sharing from echelon 4 to echelon 1 can increase the number of projects completed on time from 67.32 % to 91.92 % in 36 months. The remaining 8.08 % of delays could be due to other factors besides AAS, such as extreme weather, Lack of other non-construction materials, workforce problems, etc.

While coordination is essential in achieving success and smooth flow within the supply chain, it is not always easy to do without a hitch. In reality, in the supply chain, various obstacles hinder coordination itself. These constraints lead to distortions, information delays, and supply chain variability [64]. Therefore, it is necessary to have complete accuracy and awareness to make it easier to identify obstacles. Among these is the behavior of the supply chain itself. The behavior of supply chain actors is also a problem that significantly influences the distortion of information. These problems are related to the structure and communication established between stages or echelons in the supply chain. The attitudinal barriers that frequently enhance supply chain coordination constraints are [65]; Each echelon of the supply chain only sees the results of their actions locally and cannot see the impact that occurs in later stages. There is a tendency to react to their local situation rather than trying to identify the root cause of the problems that occur in supply chain flows. Different stages of the supply chain blame each other for the fluctuations. No echelon of the supply chain learns from its actions over time. As a result, they are trapped in a similar cycle, where actions taken by one stage create a problem, triggering mutual blame. Lack of trust between supply chain partners causes actors to be willing to sacrifice the overall performance of the supply chain, for example, when information available at different stages is no longer shared or even ignored due to a lack of trust between one another.

Nevertheless, there are still some limitations in this study. Andesite Stone is a natural resource that does not come fast in renewability. The Quarry is only opened if the results of geological studies state that the andesite reserves are sufficient for at least ten years. Since the model was simulated for 36 months, the availability of massive andesite material stone of the Quarry in the model is considered unlimited. The resource limitation could be examined for the future model. Agility evaluation and responsive strategy design of the aggregate stone supply chain or other complex multi-echelon supply chains can also be future discussion topics.

7. Conclusions

1. Marked passed parameter test and behavior replication test, a valid system dynamics model has been developed that could accommodate complexity in multi-echelon AAS Supply Chain and system behavior that changes over time. This supply chain model provides an overview of how the system behaviors could help AAS supply chain components evaluate strategies at the model level. This model could be a benchmark or evaluation tool for multi-echelon supply chains in other parts of the world and provides additional insight into how demand information sharing could improve supply chain performance. Not only measured through profit or cost but through the on-time infrastructure finishing on the downstream industry.

2. The simulation result indicates that if demand information sharing between supply chain echelons was robust, the AAS Supply Chain total holding cost could be reduced. Moreover, the delay in completing downstream infrastructure projects can be reduced. Disruptions that occur at the downstream echelon have more impact on Supply Chain performance than disruptions at the upstream echelon, especially from the total holding cost of the supply chain. Therefore, disruption reduction policies for downstream echelons and strengthening coordination along the supply chain should be prioritized.

Conflict of Interest

The authors declare that they have no conflict of interest concerning this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

The manuscript has data included as electronic supplementary material.

References

1. Gronwald, K.-D. (2020). SCM – Supply-Chain-Management. Integrierte Business-Informationssysteme, 25–69. doi: https://doi.org/10.1007/978-3-662-59815-3_3
2. Pujawan, I. N., Mahendrawathi, E. (2017). Supply Chain Management (Edisi 3). Yogyakarta, 374.

3. Kharsun, L., Kavun-Moshkovska, O., Kotova, M., Nechyporuk, A. (2022). Adaptation of risk management in the supply chains of e-commerce enterprises under the conditions of political instability. Eastern-European Journal of Enterprise Technologies, 5 (13 (119)), 6–20. doi: https://doi.org/10.15587/1729-4061.2022.265649
4. Wankmüller, C., Reiner, G. (2021). Identifying Challenges and Improvement Approaches for More Efficient Procurement Coordination in Relief Supply Chains. Sustainability, 13 (4), 2204. doi: https://doi.org/10.3390/su13042204
5. Li, S., Zhao, X., Huo, B. (2018). Supply chain coordination and innovativeness: A social contagion and learning perspective. International Journal of Production Economics, 205, 47–61. doi: https://doi.org/10.1016/j.ijpe.2018.07.033
6. Nguyen, W. P. V., Dusadeerungsikul, P. O., Nof, S. Y. (2022). Collaborative Control, Task Administration, and Fault Tolerance for Supply Chain Network-Dynamics. Springer Series in Supply Chain Management, 43–78. doi: https://doi.org/10.1007/978-3-031-09179-7_3
7. Arshinder, Kanda, A., Deshmukh, S. G. (2008). Supply chain coordination: Perspectives, empirical studies and research directions. International Journal of Production Economics, 115 (2), 316–335. doi: https://doi.org/10.1016/j.ijpe.2008.05.011
8. Feizabadi, J., Gligor, D., Alibakhshi, S. (2021). Strategic supply chains: a configurational perspective. The International Journal of Logistics Management, 32 (4), 1093–1123. doi: https://doi.org/10.1108/ijlm-09-2020-0383
9. Kurudzhy, Y., Mayorova, I., Moskvichenko, I. (2022). Building a model of supply chains duopoly taking into account the marketing and innovative activities of manufacturing enterprises. Eastern-European Journal of Enterprise Technologies, 2 (3 (116)), 15–21. doi: https://doi.org/10.15587/1729-4061.2022.253821
10. Ren, J., Hao, Y., Liu, Y. (2010). Two-Echelon Supply Chain Coordination with Uncertain Demand. 2010 Third International Conference on Intelligent Networks and Intelligent Systems. doi: https://doi.org/10.1109/icinis.2010.79
11. Du, R., Banerjee, A., Kim, S.-L. (2013). Coordination of two-echelon supply chains using wholesale price discount and credit option. International Journal of Production Economics, 143 (2), 327–334. doi: https://doi.org/10.1016/j.ijpe.2011.12.017
12. Xu, Y., Wei, W. (2010). Coordinative of one-shot cooperation in two-echelon supply chain. 2010 IEEE International Conference on Software Engineering and Service Sciences. doi: https://doi.org/10.1109/icsess.2010.5552270
13. Ren, J. Y., Liu, Y. X., Hao, Y. P. (2009). Two-Echelon Supply Chain Coordination with Vendor Managed Inventory. Applied Mechanics and Materials, 16-19, 1048–1052. doi: https://doi.org/10.4028/www.scientific.net/amm.16-19.1048
14. Giri, B. C., Bardhan, S. (2017). Sub-supply chain coordination in a three-layer chain under demand uncertainty and random yield in production. International Journal of Production Economics, 191, 66–73. doi: https://doi.org/10.1016/j.ijpe.2017.04.012
15. Seifert, R. W., Zequeira, R. I., Liao, S. (2012). A three-echelon supply chain with price-only contracts and sub-supply chain coordination. International Journal of Production Economics, 138 (2), 345–353. doi: https://doi.org/10.1016/j.ijpe.2012.04.006
16. Yu, Z., Zu, S. (2011). Three-echelon supply chain coordination model based on option-buyback contract. 2011 International Conference on E-Business and E-Government (ICEE). doi: https://doi.org/10.1109/icebeg.2011.5887240
17. Shaban, A., Costantino, F., Di Gravio, G., Tronci, M. (2020). Coordinating of multi-echelon supply chains through the generalized (R, S) policy. SIMULATION, 96 (9), 767–778. doi: https://doi.org/10.1177/0037549720920708
18. Abdelsalam, H. M., Elassal, M. M. (2014). Joint economic lot sizing problem for a three – Layer supply chain with stochastic demand. International Journal of Production Economics, 155, 272–283. doi: https://doi.org/10.1016/j.ijpe.2014.01.015
19. Hu, J., Zhang, J., Mei, M., Yang, W. min, Shen, Q. (2019). Quality control of a four-echelon agri-food supply chain with multiple strategies. Information Processing in Agriculture, 6(4), 425–437. doi: https://doi.org/10.1016/j.inpa.2019.05.002
20. Purnomo, M. R. A., Wangsa, I. D., Rizky, N., Jauhari, W. A., Zahria, I. (2022). A multi-echelon fish closed-loop supply chain network problem with carbon emission and traceability. Expert Systems with Applications, 210, 118416. doi: https://doi.org/10.1016/j.eswa.2022.118416
21. Khorshidvand, B., Soleimani, H., Sibdari, S., Seyyed Esfahani, M. M. (2021). Developing a two-stage model for a sustainable closed-loop supply chain with pricing and advertising decisions. Journal of Cleaner Production, 309, 127165. doi: https://doi.org/10.1016/j.jclepro.2021.127165
22. Tantiwattanakul, P., Dumrongsiri, A. (2019). Supply chain coordination using wholesale prices with multiple products, multiple periods, and multiple retailers: Bi-level optimization approach. Computers & Industrial Engineering, 131, 391–407. doi: https://doi.org/10.1016/j.cie.2019.03.050
23. Haque, M., Paul, S. K., Sarker, R., Essam, D. (2021). A combined approach for modeling multi-echelon multi-period decentralized supply chain. Annals of Operations Research, 315 (2), 1665–1702. doi: https://doi.org/10.1007/s10479-021-04121-0
24. Marchi, B., Zavanella, L. E., Zanoni, S. (2020). Joint economic lot size models with warehouse financing and financial contracts for hedging stocks under different coordination policies. Journal of Business Economics, 90 (8), 1147–1169. doi: https://doi.org/10.1007/s11573-020-00975-1
25. Liao, C.-J., Shyu, C.-C., Tseng, C.-T. (2009). A least flexibility first heuristic to coordinate setups in a two- or three-stage supply chain. International Journal of Production Economics, 117 (1), 127–135. doi: https://doi.org/10.1016/j.ijpe.2008.10.002
26. Buhayenko, V., Ho, S. C., Thorstenson, A. (2018). A variable neighborhood search heuristic for supply chain coordination using dynamic price discounts. EURO Journal on Transportation and Logistics, 7 (4), 363–385. doi: https://doi.org/10.1007/s13676-018-0122-2

27. Seeler, K. A. (2014). Introduction to System Dynamics. System Dynamics, 1–44. doi: https://doi.org/10.1007/978-1-4614-9152-1_1
28. Dangerfield, B. (2020). System Dynamics: Introduction. System Dynamics, 3–7. doi: https://doi.org/10.1007/978-1-4939-8790-0_538
29. Breitling, T. (2019). Inter-functional coordination of purchasing and logistics: impact on supply chain performance. Supply Chain Forum: An International Journal, 20 (2), 71–88. doi: https://doi.org/10.1080/16258312.2019.1612226
30. Wirjodirdjo, B., Ghiffary Budianto, A., Widjanarka, A., Pujawan, I. N., Maflahah, I. (2021). Carrier and Freight Forwarders Strategies to Utilize the Immobile Shipping Capacity of Freight Forwarders and Maximize Profits. International Journal of Technology, 12 (4), 876. doi: https://doi.org/10.14716/ijtech.v12i4.4413
31. Dogan, M., Cerci, H. S., Koyluoglu, A. S. (2022). The effect of green supply chain practices on the firm performance: an empirical research. Eastern-European Journal of Enterprise Technologies, 4 (13 (118)), 61–67. doi: https://doi.org/10.15587/1729-4061.2022.263634
32. Large, R. O., Merminod, N. (2019). Special Dossier: inter-functional coordination in the supply chain: myth or reality? Supply Chain Forum: An International Journal, 20 (2), 69–70. doi: https://doi.org/10.1080/16258312.2019.1609276
33. Qrunfleh, S., Tarafdar, M. (2014). Supply chain information systems strategy: Impacts on supply chain performance and firm performance. International Journal of Production Economics, 147, 340–350. doi: https://doi.org/10.1016/j.ijpe.2012.09.018
34. Cokins, G., Pohlen, T., Klammer, T. (2021). Why Supply Chain Cost Systems Differ from Traditional Cost Systems. Supply Chain Costing and Performance Management, 59–74. doi: https://doi.org/10.1002/9781119793663.ch5
35. Iida, T. (2012). Coordination of cooperative cost-reduction efforts in a supply chain partnership. European Journal of Operational Research, 222 (2), 180–190. doi: https://doi.org/10.1016/j.ejor.2012.03.029
36. Kim, M., Chai, S. (2017). The impact of supplier innovativeness, information sharing and strategic sourcing on improving supply chain agility: Global supply chain perspective. International Journal of Production Economics, 187, 42–52. doi: https://doi.org/10.1016/j.ijpe.2017.02.007
37. Huang, R., Yao, X. (2021). An analysis of sustainability and channel coordination in a three-echelon supply chain. Journal of Enterprise Information Management, 34 (1), 490–505. doi: https://doi.org/10.1108/jeim-12-2019-0413
38. Niemsakul, J., Islam, S. M. N., Singkarin, D., Somboonwiwat, T. (2018). Cost-benefit sharing in healthcare supply chain collaboration. International Journal of Logistics Systems and Management, 30 (3), 406. doi: https://doi.org/10.1504/ijlsm.2018.092624
39. Mouaky, M., Berrado, A., Benabbou, L. (2019). Using a kanban system for multi-echelon inventory management: the case of pharmaceutical supply chains. International Journal of Logistics Systems and Management, 32 (3/4), 496. doi: https://doi.org/10.1504/ijlsm.2019.098333
40. Drakaki, M., Tzionas, P. (2019). Investigating the impact of inventory inaccuracy on the bullwhip effect in RFID-enabled supply chains using colored petri nets. Journal of Modelling in Management, 14 (2), 360–384. doi: https://doi.org/10.1108/jm2-08-2017-0081
41. Khedlekar, U. K., Singh, P. (2019). Three-layer supply chain policy under sharing recycling responsibility. Journal of Advances in Management Research, 16 (5), 734–762. doi: https://doi.org/10.1108/jamr-01-2019-0002
42. Rached, M. (2020). Genetic Algorithm to Evaluate Downstream and Upstream Information Sharing. Current Signal Transduction Therapy, 15 (1), 24–33. doi: https://doi.org/10.2174/1574362413666180830105740
43. Haque, M., Paul, S. K., Sarker, R., Essam, D. (2020). Managing decentralized supply chain using bilevel with Nash game approach. Journal of Cleaner Production, 266, 121865. doi: https://doi.org/10.1016/j.jclepro.2020.121865
44. Van Belle, J., Guns, T., Verbeke, W. (2021). Using shared sell-through data to forecast wholesaler demand in multi-echelon supply chains. European Journal of Operational Research, 288 (2), 466–479. doi: https://doi.org/10.1016/j.ejor.2020.05.059
45. Ibrahim, A., Daniyal, H., Asmawaty, T., Kamaludin, A. (2021). Potential Data Collections Methods for System Dynamics Modelling: A Brief Overview. International Journal of Advanced Computer Science and Applications, 12 (3). doi: https://doi.org/10.14569/ijacsa.2021.0120332
46. Rebs, T., Brandenburg, M., Seuring, S. (2019). System dynamics modeling for sustainable supply chain management: A literature review and systems thinking approach. Journal of Cleaner Production, 208, 1265–1280. doi: https://doi.org/10.1016/j.jclepro.2018.10.100
47. Liu, J., Teng, Y., Wang, D., Gong, E. (2019). System dynamic analysis of construction waste recycling industry chain in China. Environmental Science and Pollution Research, 27 (30), 37260–37277. doi: https://doi.org/10.1007/s11356-019-06739-x
48. Sundarakani, B., Sikdar, A., Balasubramanian, S. (2014). System dynamics-based modelling and analysis of greening the construction industry supply chain. International Journal of Logistics Systems and Management, 18 (4), 517. doi: https://doi.org/10.1504/ijlsm.2014.063983
49. Wang, J., Li, Z., Tam, V. W. Y. (2015). Identifying best design strategies for construction waste minimization. Journal of Cleaner Production, 92, 237–247. doi: https://doi.org/10.1016/j.jclepro.2014.12.076
50. Malik, A., Khan, K. I. A., Qayyum, S., Ullah, F., Maqsoom, A. (2022). Resilient Capabilities to Tackle Supply Chain Risks: Managing Integration Complexities in Construction Projects. Buildings, 12 (9), 1322. doi: https://doi.org/10.3390/buildings12091322
51. Ghufran, M., Khan, K. I. A., Ullah, F., Nasir, A. R., Al Alahmadi, A. A., Alzaed, A. N., Alwetaishi, M. (2022). Circular Economy in the Construction Industry: A Step towards Sustainable Development. Buildings, 12 (7), 1004. doi: https://doi.org/10.3390/buildings12071004

52. Nasir, M. H. A., Genovese, A., Acquaye, A. A., Koh, S. C. L., Yamoah, F. (2017). Comparing linear and circular supply chains: A case study from the construction industry. International Journal of Production Economics, 183, 443–457. doi: https://doi.org/10.1016/j.ijpe.2016.06.008
53. Wang, X., Du, Q., Lu, C., Li, J. (2022). Exploration in carbon emission reduction effect of low-carbon practices in prefabricated building supply chain. Journal of Cleaner Production, 368, 133153. doi: https://doi.org/10.1016/j.jclepro.2022.133153
54. Yin, Y., Zhang, Y., Jin, K. (2021). System Dynamics Modeling of the Supply Chain Performance of Prefabricated Construction Based on the Stakeholder Analysis. Journal of Physics: Conference Series, 1827 (1), 012109. doi: https://doi.org/10.1088/1742-6596/1827/1/012109
55. Vanteddu, G., Nicholls, G. (2020). Supply Chain Network Design and Tactical Planning in the Dimension Stone Industry. Operations and Supply Chain Management: An International Journal, 13 (4), 320–335. doi: https://doi.org/10.31387/oscm0430273
56. Forrester, J. W., Collins, F. (1972). World Dynamics. Journal of Dynamic Systems, Measurement, and Control, 94 (4), 339–339. doi: https://doi.org/10.1115/1.3426619
57. Forrester, J. W. (2016). Learning through System Dynamics as Preparation for the 21st Century. System Dynamics Review, 32 (3-4), 187–203. doi: https://doi.org/10.1002/sdr.1571
58. Fudhlaa, A. F., Rachmawati, W., Retnowati, D. (2021). Analysis of sugar import policy effects on sugar cane farmer's income in East Java: A system dynamic approach. IOP Conference Series: Materials Science and Engineering, 1072 (1), 012023. doi: https://doi.org/10.1088/1757-899x/1072/1/012023
59. Barlas, Y. (1989). Multiple tests for validation of system dynamics type of simulation models. European Journal of Operational Research, 42 (1), 59–87. doi: https://doi.org/10.1016/0377-2217(89)90059-3
60. Shreckengost, R. C. (1985). Dynamic simulation models: how valid are they? PsycEXTRA Dataset. doi: https://doi.org/10.1037/e496952006-007
61. Olaya, C. (2020). System Dynamics: Engineering Roots of Model Validation. System Dynamics, 109–117. doi: https://doi.org/10.1007/978-1-4939-8790-0_544
62. Ghali, A., Favre, R., Elbadry, M. (2020). Concrete Structures. CRC Press, 672. doi: https://doi.org/10.1201/9781003061274
63. Nihad, Z., Sarsam, S. I. (2020). Variation of Asphalt Requirement and Strength Properties among Hot Mix (HMA) and Warm Mix (WMA) Asphalt Concrete. Association of Arab Universities Journal of Engineering Sciences, 27 (2), 24–33. doi: https://doi.org/10.33261/jaaru.2020.27.2.003
64. Amin, F., Khan, K. I. A., Ullah, F., Alqurashi, M., Alsulami, B. T. (2022). Key Adoption Factors for Collaborative Technologies and Barriers to Information Management in Construction Supply Chains: A System Dynamics Approach. Buildings, 12 (6), 766. doi: https://doi.org/10.3390/buildings12060766
65. Chopra, S. (2018). Supply Chain Management: Strategy, Planning, and Operation (What's New in Operations Management). Pearson, 528.