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Simulating a Global Dynamic Supply Chain as a Market of Agents with Adaptive Bidding Strategies

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The use of modular plants in the chemical industry is expected to make the structure of supply chains more dynamic. The models currently used to get insight in supply chains assume a predefined supply chain structure, as orders are exogenously defined. Consequently, those models cannot grasp the dynamic nature of supply chains with modular plants. In this paper a market conceptualization based on agent-based computational economics is presented that includes transport costs in the negotiations and enables the modeling of supply chains as structures that emerge from market dynamics. It is shown that this conceptualization can capture the market dynamics that are needed to simulate a dynamic supply chain.

Keywords: Agent-based modeling, Dynamic supply chains, Many-to-many negotiation, Market simulation, Modular plants

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1 Introduction

In recent years, due to developments in process intensification and modularization of process equipment, the functioning of modular plants has been demonstrated in projects like CoPIRIDE [1] and F^3 Factory [2]. One of the main distinguishing characteristics of modular plants is that they can easily be relocated to follow demand. Consequently, if those modular plants start to constitute a considerable part of the installed capacity in the chemical industry, the industry may change significantly. No longer will plants be situated at a fixed location and ship products to their customers, but modular plants will be relocated to a customer's site and produce there. This will make the supply chain's structure more dynamic. For example, if a modular plant relocates, it might buy its feedstock from another supplier and might sell its products to another customer, thereby creating new supply relations and changing the supply structure. Those changes have a direct and possibly indirect effect on the relocated plant, so they have to be considered if one wants to study the economics and policies of modular plants throughout their entire life cycle. Since those changes are largely market-driven, the market dynamics will be more relevant for understanding the behavior and performance of modular plants.

As the performance and behavior of dynamic supply chains is expected to differ from existing supply chains, new insights need to be obtained into how companies should operate in such a dynamic environment. Before modular plants will be used on a significant scale, a number of issues need to be addressed, like the economics of modules (e.g., what is the value of being able to relocate a module?), the placement of modules (e.g., how should it be decided when to relocate a module?), and modular network configuration (what types of modules should be brought together to maximize the profit?). However, also companies that do not use modular plants are affected by the more dynamic nature of a supply chain in which there are modular plants. Their environment – of suppliers, competitors, and customers – becomes more dynamic, which will have an effect on their operations. For example, with the introduction of modular plants in an industry, incumbents have to compete with plants that have a very short lead time and, thus, can be more flexible. The incumbents will have to reassess their policies to compete successfully with those newcomers.

The performance and behavior of companies in a supply chain has extensively been studied using supply chain models [3, 4]. The modeling paradigms predominantly used to study supply chains assume a predefined supply chain structure with a focal company and a set of suppliers and

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customers. The dynamic nature of the supply chain structure and market dynamics are not taken into account as, e.g., orders are exogenously specified [5 – 8]. Due to this restriction the existing supply chain models are of limited use for obtaining insights into the performance and behavior of dynamic supply chains that comprise modular plants. Hence, there is a need for new supply chain models that let supply chain relations emerge from market interactions, so that the supply chain structure in the model is dynamic and the performance of a company – operating modular plants in a dynamic supply chain – can be studied.

In recent years, first steps towards the development of a dynamic supply chain model have been made, e.g., [9, 10]. In those models a supply chain has been conceptualized as a network of markets. The supply relations in a market materialize as outcome of the negotiations between sellers and buyers. Since companies are active in multiple markets (e.g., in one market to buy feedstock and in another market to sell their product) different markets are connected and a network of supply relations emerges, i.e., a supply chain [11]. The structure of this supply chain is dynamic, because if the market conditions change (e.g., a modular plant relocates) the market outcomes – and subsequently the supply chain structure – will change accordingly. As those models are mainly concerned with the price dynamics of connected markets, they do not consider transport costs in their negotiations. However, logistic costs represent 10 % of total turnover in the chemical industry and, thus, are an important factor in the formation of a supply chain [12]. So, for a dynamic supply chain model to be useful for a global supply chain, the transport costs need to be considered in the negotiations that are driving the supply chain structure. Including those costs is not straightforward, because it requires a fundamentally different market conceptualization than the double-sided auctions [13] or detailed negotiations [14] generally used. Therefore, a new market conceptualization needs to be developed that can simulate a market with multiple buyers and sellers and allows them to consider the transport costs in their negotiations.

In this paper a market conceptualization is presented that uses a set of interconnected auctions to simulate a market of multiple simultaneously negotiating buyers and sellers. The buyers and sellers can adjust their bidding strategy to the opposing party so that they can include transport costs in the negotiation. Sect. 2 gives an overview of previous work on simulating markets and their applicability to simulating a market for the purpose of studying a dynamic supply chain. Hereafter, in Sect. 3, the market conceptualization in the form of a negotiation framework is presented and its implementation is discussed. In Sect. 4 the framework is verified by performing two experiments in order to show that the framework is capable of considering the transport costs in negotiations between multiple buyers and sellers and, thus, can represent a global dynamic supply chain. Finally, applications of the framework and possible extensions to it are discussed.

2 Market Simulation

Simulating the behavior and performance of dynamic supply chains requires simulation of the market dynamics that shape those supply chains. A variety of paradigms for simulating markets has been developed, but agent-based computation economics (ACE) is deemed the most appropriate as it allows the most realistic behavior [15]. ACE is "the computational study of economies modeled as evolving systems of autonomous interacting agents" [16]. Instead of determining at what price supply and demand are in equilibrium, ACE models let autonomous agents negotiate with each other to determine a price at which they agree to trade a product [15]. Depending on the way those negotiations are conceptualized, the agents may be able to adapt their bidding strategy to the opposing party in order to consider transport costs in their bid. The market outcomes (prices and order volumes) emerge as a result of those negotiations and form the supply relations between the agents. Hence, a network of ACE markets can be used to simulate a global dynamic supply chain if the conceptualization of the negotiations between agents enables them to consider the transport costs in their bids. Therefore, this section discusses what conceptualization of negotiations is best suited to simulate the market dynamics that drive the structure of a global dynamic supply chain.

2.1 Negotiation Classification

In the ACE field a multitude of agent-based negotiation frameworks have been developed and applied, ranging from simple bilateral negotiations to double-sided auctions (cf. [17]). Many of those frameworks have been developed for an application in e-commerce [18, 19], but also for the simulation of systems that comprise a market and negotiations, such as supply chain coordination [20], an electricity market [21], or an urban land market [22].

Negotiations occur in a variety of forms, from negotiations between two parties to negotiations between numerous parties in a centralized marketplace like a stock exchange. Negotiation frameworks are often only (best) suited for a particular type of negotiation. So, in order to determine which framework to use to simulate a particular negotiation one has to be able to identify the type of negotiation. Multiple classification structures have been developed to identify the negotiation types based on a certain set of dimensions (cf. [23, 24]). The dimensions most relevant for a market simulation are the protocol category and the interaction type. On the basis of those dimensions one can determine the type of negotiation and what type of framework is best suited to simulate that negotiation.

With regard to the protocol category there is typically a distinction between two categories: auctions and bilateral negotiations [23]. Auctions are structured negotiation protocols that are used to sell or buy a certain product. By their nature auction make coordination of interactions with multiple opposing parties inexpensive, since the coordination is an integrated part of the auction [25]. However, the disadvantage of an auction is that it typically only allows the negotiation about the price, which requires any other attributes to be monetized [24]. Bilateral negotiations describe the process of the negotiation between two parties [14]. The disadvantage is that bilateral negotiation protocols do not integrate the coordination of multiple negotiation threads, and thus, do not allow a market player to negotiate with multiple opposing parties. In order to enable the coordination of multiple negotiation threads a separate mechanism is required. The type of mechanism can be categorized into two groups: sequential, i.e., conducting one negotiation after another, and concurrently, i.e., conducting all negotiations at the same time [24].

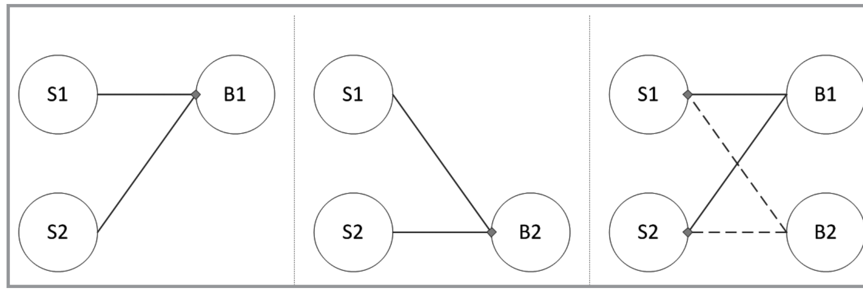

Figure 1. Coordinating multiple single-sided auctions (left and center) to model a many-to many negotiation (right).

With respect to the interaction type of a negotiation, there are three types: one-to-one, one-to-many (many-to-one), and many-to-many [26].

1) One-to-one: In a one-to-one negotiation one buyer negotiates with one seller. Typically one-to-one negotiations are modeled as bilateral negotiations, using a heuristic protocol [27]. This type of negotiation only contains one negotiation thread; from the one seller to the one buyer.
2) One-to-many: In a one-to-many negotiation one party negotiates with multiple opposing parties. Both auctions and multiple bilateral negotiations are being used to model one-to-many negotiations. This type of negotiation contains negotiation threads between the one (seller or buyer) and each of the many (buyers or sellers).
3) Many-to-many: In a many-to-many negotiation multiple buyers negotiate with multiple sellers. Because many-to-many negotiations require the most coordination of negotiation threads, the double-sided auction is the most used action protocol for this type of negotiation [13]. In this type of negotiation each of the many (sellers or buyers) has a negotiation thread to every other many (buyers or sellers). In a double-sided auction the number of threads is reduced significantly by the introduction of a third party auctioneer that has a thread to each of the buyers and each of the sellers. Consequently, there is no direct interaction between buyers and sellers.

2.2 Negotiations for a Global Dynamic Supply Chain Model

In most markets there are multiple sellers and buyers negotiating with each other over a particular product, which therefore can be conceptualized as a many-to-many negotiation.[1)] However, the double-sided auction – usually applied to model many-to-many negotiations – is not suited to model those markets, as the agents cannot adjust their bidding strategy to the opposing party as they assume they sell to the auctioneer and, thus, are unaware of whom the opposing party is [24]. Consequently, they cannot incorporate the transport costs (which differ per opposing party) in their bid, and a different negotiation framework is needed.

Instead of modeling a many-to-many negotiation as a double-sided auction, we model a many-to-many negotiation as multiple connected single-sided auctions. Like multiple bilateral negotiations can be coordinated by a market player (to form a one-to-many negotiation), multiple single-sided auctions, i.e., one-to-many negotiations, can be coordinated to form a many-to-many negotiation (see Fig. 1, representing how two one-to-many negotiations are combined into a single many-to-many negotiation). Using a single-sided auction to model the one-to-many auctions ensures that market players are aware of whom they are negotiating with, as single-sided auctions have no third-party auctioneer. As the coordination of multiple negotiation threads is integrated in the auction, the (computational) complexity of the auction is limited. Hence, a market driving the structure of a dynamic supply chain can be conceptualized as a set of agents that negotiate with each other; and those negotiations can be framed as a set of connected single-sided auctions.

3 Framework

The framework presented in this section conceptualizes the market as a set of negotiating agents. The negotiations are modeled as multiple coordinated single-sided auctions. As discussed in the previous section, single-sided auctions enable the transport costs to be included in the negotiations, so

1) We are aware of market structures different than one with multiple sellers and multiple buyers, like monopolistic markets. However, markets that are truly monopolistic on a global scale are very rare and, thus, are not considered for this framework.

that geographical differences among plants are considered in the formation of the supply chain structure.

3.1 Overview

The agents in the market are either buyers or sellers. The buyers are trying to purchase their entire demand for the lowest price possible, while the sellers strive to maximize the revenue they obtain from selling their entire supply. To reach those objectives the buyers order products from the sellers. An order specifies what quantity will be supplied by what seller to what buyer, what gross price is paid and what net price is obtained. The difference between the gross and net price of an order is the cost of shipping the product from the seller to the buyer. Each seller has a certain quantity (supply) that he is willing to supply at a price higher than his willingness to accept. Each buyer, on the other hand, has a certain quantity (demand) that he wants to procure at a price lower than his willingness to pay. This information results for each seller in a simple supply curve and for each buyer in a demand curve (as illustrated by Fig. 2).

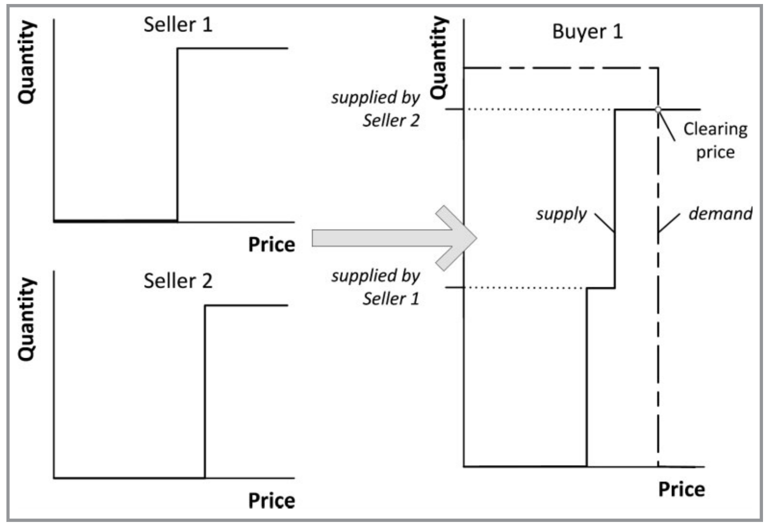

Figure 3. A single-sided auction.

To facilitate the trade of goods between the buyers and sellers, each buyer conducts an auction in which the sellers participate. The buyer has a negotiation thread with each of the sellers that participate in the auction. The coordination of those threads is an integral part of the auction's design. The auctions are conceptualized as clock auctions, which are particularly suited when auctioning (the demand for) multiple products [27]. The objective of the buyer is to assess what the lowest price is at which he can fulfil his demand (i.e., clearing price) and which sellers are willing to supply goods at that price. Fig. 3 illustrates an auction in which buyer 1 explores the clearing price and what quantity seller 1 and 2 are willing to supply for that price.

The sellers are participating in multiple auctions, in order to determine to what buyer(s) they can sell their supply at the highest price. This implies that a seller has negotiation threads with each of the buyers he is negotiating with, i.e., in whose auction it participates. The sellers need to coordinate those different threads to ensure that they sell their products at the auction(s) with the highest price. In this framework the coordination is achieved by letting sellers discard accepted orders of other buyers in favor of a more profitable new order. As a consequence competition for the supply is created, as the buyers have to outbid each other. This automatically causes the seller to sell his supply to the highest paying buyer and, thus, coordinates the seller's negotiation threads. By having all sellers negotiate with all buyers, and vice versa, perfect information in the market is assumed here.

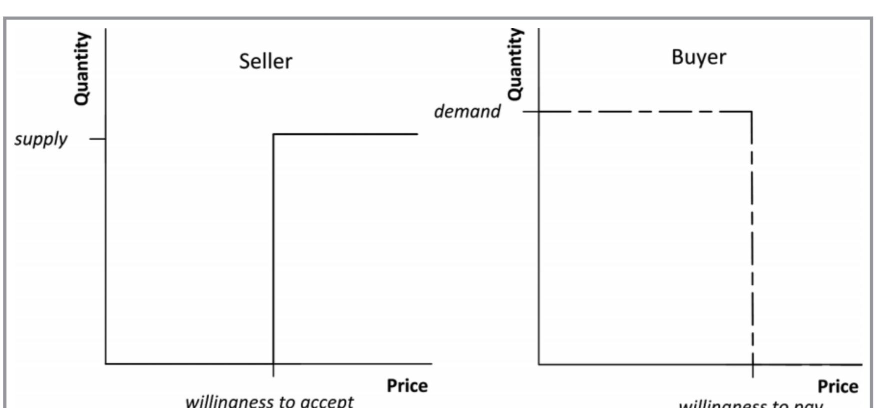

Figure 2. Supply curve (left) and demand curve (right).

3.2 Implementation

The negotiation consists of multiple rounds. In each round the buyers and sellers communicate offers and bids and determine whether they can agree with each other on the negotiation outcomes. While there are buyers and sellers that want to continue negotiating a new round will start. Each round consists of four actions that are performed by either the sellers or the buyers: communicate bids, communicate offers, process offers, and process final bids.

3.2.1 Communicate Bids

In each round of the auction the buyers first communicate their auction's clock price in a bid to the sellers they negotiate with. The price at the clock represents the price the buyer is willing to pay in that particular round, and is determined in the previous round on basis of the balance between supply and demand. The purpose of communicating bids is that the sellers can indicate what quantity they can supply for that price and the buyer can determine whether this supply is in line with its demand.

3.2.2 Communicate Offers

Subsequently, the sellers that have received bids determine for each bid what quantity they are willing to supply for the communicated bid price. For that purpose the sellers first determine the net price they obtain at that gross price, by subtracting the transport costs from the bid's gross price. Then they determine whether that net price is higher than their willingness to accept. If that is the case they will offer their supply that has not been sold yet, otherwise they will offer nothing. Regarding the supply that has already been sold, the seller determines for each accepted order whether the net price of the bid is higher than the net price of that order. If that turns out to be true, the quantity of that order is added to the quantity that the seller is willing to supply (see Appendix A.1 for a more elaborate discussion of how the offered quantity is determined).

Considering accepted orders in the assessment of the quantity that can be supplied implies that the seller's supply curve is dynamic as a result of developments at other auctions. Fig. 4 indicates how the supply curves of seller 1 and seller 2 (from Fig. 3) change as a result of accepting orders (for quantity *b* and *d*) from other buyers. Instead of willing to supply quantity ($a+b$) and ($c+d$) for any net price above their willingness to accept, they will only supply quantity *a* and *c* above that net price. To procure quantity *b* and *d* the buyer 1 will have to offer a net price that is above the net price of the accepted orders. This leads to changes in their supply curve. In the auction with buyer 1 this decreases the quantity he can procure from sellers 1 and 2 significantly, while the clearing price remains the same.

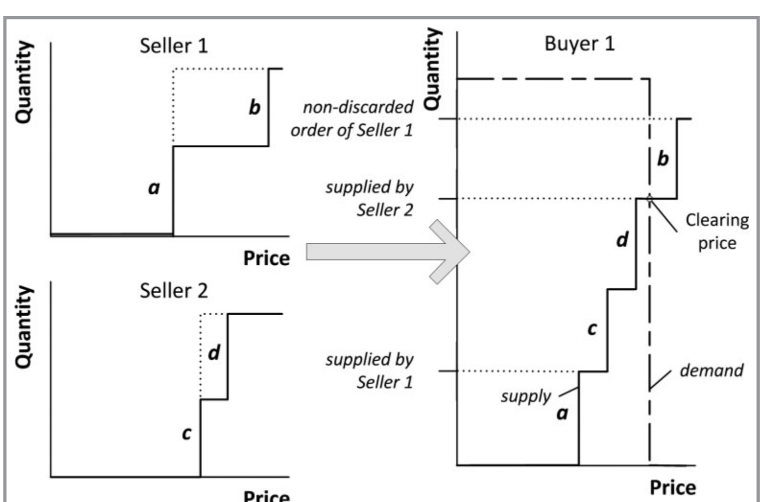

Figure 4. One auction influenced by the developments at another auction.

The ability to discard accepted orders in favor of more profitable orders causes the seller to coordinate its negotiation threads. This coordination is not active, in a sense that the seller uses an algorithm to determine what buyer gets allocated what part of the supply in order to maximize its profits [17, 18], but is passive. As a result of discarding accepted orders that are less profitable than a new order, the seller automatically sells its supply to the buyer(s) that can pay the highest price. Therefore, there is no need for the seller to use an algorithm to determine what buyer can pay the highest price and what part of its supply should be sold to that buyer.

3.2.3 Process Offers

On basis of the communicated offers each buyer assesses its follow-up action. For this assessment the buyer first sums the quantity offered by the sellers to determine how much of the good can be supplied to it (see Appendix A.2 for a more elaborate discussion of how this is determined). On basis of how this quantity relates to its demand (see Appendix A.2), the buyer selects one of the four possible follow-up actions (a flowchart of this decision is provided in Appendix A.2.3). If the quantity that can be supplied is higher than the demand, the clock price is higher than the clearing price and the buyer decreases the clock price in order to decrease supply and/or increase demand. On the other hand, if the supply is lower than the demand, the buyer increases the clock price in order to increase supply and/or decrease demand. However, if the quantity that can be supplied equals the demand, the clock price is the clearing price of the market. If the quantity at which the market clears is positive, the buyer sends final bids to the sellers. If the market clears 0 goods, the sellers and buyer will not be able to agree on the terms of trade and the buyer will end the negotiation.

3.2.4 Process Final Bids

The sellers that have received a final bid determine whether this bid is profitable enough to be accepted. For this purpose a seller first accepts that part of the final bid that can be supplied with the unsold supply. If that quantity is not enough to cover the entire final bid, the seller determines whether the net price of the final bid is higher than that of the accepted order with the lowest net price. If this turns out to be true the seller discards that accepted order to the extent that is needed to accept the entire final bid. It keeps discarding accepted orders until the entire final bid is accepted or there are no accepted orders left with a lower net price than that of the final bid. The buyers of the discarded orders are informed about the discarding of their order, so they can start a new round of auctions and bid a higher price.

4 Verification

In order to simulate a global dynamic supply chain, the negotiation framework used in the market conceptualization has to be able to: 1) lead to market outcomes (prices and order volumes) that are representative of the ratio between demand and supply, and 2) has to consider the transport costs in the negotiations so that the geographical differences between agents are reflected in the market outcomes. In this section two experiments are performed in order to assess whether the framework meets the two requirements.

Table 2. Expected and observed prices of experiment 1.

Scenario	Expected price [$ kg^{-1}]	Observed price [$ kg^{-1}]
1	4	4
2	4	4
3	20	20
4	6	6
5	10	10
6	18	18

4.1 Experiment 1: Materialization of Prices

In this experiment it is assessed whether the prices that emerge from the negotiation are a good representation of the ratio of demand and supply. For this purpose a market is considered that consists of five buyers and five sellers that all are situated at the same location, thereby effectively forming a centralized marketplace.

In this experiment six different scenarios are considered. The scenarios differ according to two different parameters: the distribution of willingness to accept and willingness to pay between the sellers and buyer, and the ratio of supply to demand. Tab. 1 shows for each scenario how the willingness to accept and willingness to pay are distributed over the sellers and buyers. Also, it indicates what supply each seller and what demand each buyer has in each of the six scenarios. This data forms the input parameters of the experiment.

Tab. 2 indicates what prices are expected to materialize on basis of the input parameters. On basis of the ratio of demand and supply different prices are expected to materialize:

- In the scenarios in which supply is larger than demand (scenario 1 and 4) the expected price is equal to willingness to accept of seller 3, as it only requires the supply of the 2.5 cheapest sellers to meet the demand.
- In the scenarios in which supply equals demand (scenarios 2 and 5), the price can be anywhere in the range between the highest willingness to accept and the lowest willingness to pay, as demand and supply are equal in that entire range. However, as the sellers offer their full capacity to each of the buyers, the supply (in the offers) is overestimated which drives the price down to the low end of the possible range. If supply is not equal to demand this has no effect on the price. In a situation in which supply is larger than demand the price is actually supposed to go down, and in a situation in which supply is smaller than demand the competition between buyers for supply eventually drives the price back up to the expected price. However, in a situation in which supply equals demand the buyers are not competing with each other over supply and, thus, they will not drive the price up. Therefore the price is expected to be at the low end of the possible range.
- In the scenarios in which demand is higher than supply (scenarios 3 and 6) the price is expected to equal the willingness to pay of buyer 3, because there is only sufficient supply to meet the demands of the 2.5 most paying buyers.

The prices that are observed when we let the agents negotiate in each of the scenarios are presented in Tab. 2, as well. The observed prices are exactly in line with the expected prices and, hence, it can be conclude that the negotiation framework is capable of determining the clearing price, given all possible ratios of supply and demand. The framework is also capable of considering differences in willingness to

Table 1. Input parameters of experiment 1.

	Willingness to accept (sellers) [$ kg^{-1}]					Willingness to pay (buyers) [$ kg^{-1}]						
Scenario	1	2	3	4	5	1	2	3	4	5	Supply [kg]	Demand [kg]
1	4	4	4	4	4	20	20	20	20	20	1000	500
2	4	4	4	4	4	20	20	20	20	20	1000	1000
3	4	4	4	4	4	20	20	20	20	20	500	1000
4	2	4	6	8	10	14	16	18	20	22	1000	500
5	2	4	6	8	10	14	16	18	20	22	1000	1000
6	2	4	6	8	10	14	16	18	20	22	500	1000

accept and willingness to pay, as the cheapest sellers are preferred suppliers and the most paying buyers are preferred customers. However, caution is needed with the outcomes that emerge from a market where supply and demand are equal to each other, since the price that materializes is at the low end of possible range of prices.

4.2 Experiment 2: Transport between Sites

The second requirement of the negotiation framework is that it can include transport costs in the negotiation. To verify this ability a market with two sites is considered: one site has oversupply, while the other has undersupply. The transport costs of shipping one unit of the product from one site to the other are 4.0. The input parameters of the experiment, specifying the supply and demand curves of the sellers and buyers, are presented in Tab. 3.

As there is an oversupply of 1000 at site 1 and a shortage of 1000 at site 2, the sellers at site 1 are expected to supply the superfluous 1000 to the buyers at site 2. It costs 4.0 to ship one unit of the good from site 1 to site 2 and the sellers at site 1 will not supply to site 2 at a lower net price than at site 1. Therefore, the price at site 2 is expected to be 4.0 higher than at site 1. Due to the shortage at site 2, the buyers at that site are not in a position to drive the price down and, therefore, have no alternative but to accept the higher price. As the supply and demand in the total market are balanced, the algorithm is expected to drive the price down to the lower end of the possible range, i.e., 4.0. Hence, the price at site 1 is anticipated to be 4.0 and at site 2 8.0.

The simulated market outcomes are presented in Tab. 4. As expected, the buyers at site 1 are exclusively supplied by the sellers at site 1. Also, the superfluous goods are shipped from site 1 to buyer 4 at site 2. Buyer 3 is supplied by the sellers at site 2. Like economic logic dictates, the price at site 2 is 4.0 higher than at site 1, as the shipment need to be paid for and the sellers at site 1 will not supply if it is less profitable than supplying to site 1. Based on those outcomes it can be concluded that the negotiation framework is capable of considering the transport costs in the negotiation.

With these experiments it has been verified that the negotiation framework used in this market conceptualization lets prices emerge that are in line with the expectations on basis of supply and demand, and that the framework is capable of considering transport costs in the negotiations. The simulation of a global dynamic supply chain requires that the negotiation framework includes those aspects in the negotiation as expected. Hence, our negotiation framework is verified in that regard and is suited to study the behavior and performance of global dynamic supply chains.

5 Conclusions and Recommendations

To study dynamic supply chains of modular plants, one has to consider the market dynamics that have a significant influence on the supply chain behavior and performance.

Table 3. Input parameters of experiment 2.

	Site 1				Site 2			
	Sellers		Buyers		Sellers		Buyers	
	1	2	1	2	3	4	3	4
Supply [kg]	1000	1000	–	–	500	500	–	–
Demand [kg]	–	–	500	500	–	–	1000	1000
Willingness to accept [$ kg^{-1}]	4	4	–	–	4	4	–	–
Willingness to pay [$ kg^{-1}]	–	–	20	20	–	–	20	20

Table 4. Observed orders (quantity (price)) of experiment 2.

		Site 1		Site 2	
		Buyer 1	Buyer 2	Buyer 3	Buyer 4
Site 1	Seller 1	0 (0.0)	500 (4.0)	0 (0.0)	500 (8.0)
	Seller 2	500 (4.0)	0 (0.0)	0 (0.0)	500 (8.0)
Site 2	Seller 3	0 (0.0)	0 (0.0)	500 (8.0)	0 (0.0)
	Seller 4	0 (0.0)	0 (0.0)	500 (8.0)	0 (0.0)

The current market conceptualizations are not capable of simulating a market in which multiple buyers and sellers negotiate simultaneously, while considering the transport costs in the negotiations. Those transport costs need to be considered as they are an important factor in the formation of a supply chain. Therefore, this paper presents a market conceptualization that frames the negotiations between market parties as multiple coordinated single-sided auctions. The single-sided auction enables the market parties to be aware of whom they are negotiating with (so they can include the transport costs in their bid), while the coordination connects the different auctions with each other so that a single market emerges. The experiments that have been performed indicate that the market conceptualization meets the requirements to simulate a global dynamic supply chain.

Applying this framework for the simulation of a global dynamic supply chain requires that multiple markets are connected to form a network of markets. This is done by letting agents participate in multiple markets (e.g., one in which they buy feedstock and another in which they sell their product), like discussed by Moyaux, et al. [9]. This connects the supply relations that emerge from each of the markets, so that a network of supply relations emerge, i.e., a supply chain [28]. The supply relations that emerge from the market simulation are dynamic and, hence, the supply chain is dynamic as well.

Such a simulation can be used to study a variety of issues related to modular plants. For example an assessment of the value of being able to relocate a module and follow demand. A dynamic supply chain structure needs to be considered for this issue, because at the new location the module will likely have to enter into new supply relations with suppliers and customers. Not considering those new relations would disregard the reason the module relocated in the first place, i.e., the (expected) higher profits at the new location. However, a simulation of a global dynamic supply chain can also be used for conventional plants. For example, to assess the extra revenues that can be obtained from a different inventory replenishment policy. This issue requires that a dynamic supply chain structure is considered, because a fixed structure – through exogenously specified orders – would specify the revenues (through prices and order volumes) beforehand.

The conceptualization presented in this paper has some characteristics that limit its use to simulate certain types of markets. First, all negotiations in a simulated market are connected with each other, which means that all agents have perfect information. Second, none of the agents can demonstrate strategic behavior. And third, the market is always cleared completely, so that the price that emerges is the equilibrium price. As a consequence of these characteristics, the conceptualization is suited to simulate markets with perfect completion, but has limited use for simulating markets in which the conditions of perfect competition do not apply. Therefore, if one wants to study a dynamic supply chain that is situated in a market with non-perfect competition, another negotiation framework may be necessary. A viable candidate for this is the use of reinforcement learning to let agents learn pricing strategies that maximize their profit. Those agents would have imperfect information, could demonstrate strategic behavior, and other prices than the equilibrium price could emerge. So far reinforcement learning to represent market dynamics in a supply chain context has only been used for simple cases [28]. Being able to represent a market with multiple sellers and multiple buyers that negotiate simultaneously requires further research.

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Appendix A: Equations

A.1 Communicating Offers

If seller i receives a bid bid_{ijx} from buyer j for product x, seller i first determines the net price r_{ijx} he obtains from selling to buyer j by subtracting the transport costs tc_{ijx} from the gross price p_{ijx} of the bid. In his offer the seller communicates both the minimum ($q^{-}_{ijx,r}$) and the maximum ($q^{+}_{ijx,r}$) quantity that he is willing to supply at that net price, so that the vertical sections of the supply curve can be accounted for.

Determining Minimum and Maximum Quantity to Supply

Eq. (A.1a) shows that the minimum quantity is calculated by subtracting the quantity of the as least as profitable accepted orders (Eq. (A.1c)) from the capacity that the seller has available at the bid's net price (Eq. (A.1b), with wta indicating the willingness to accept). The quantity of the as least as profitable accepted orders is subtracted from the capacity, because the seller will not discard those orders in favor of the bid.

$$q^{-}_{ijx,r} = \begin{cases} c_{ix,r} - \sum\limits_{ao \in AO} q_{ao,r}, & q^{-}_{ijx,r} > 0 \\ 0, & \text{else} \end{cases} \tag{A.1a}$$

$$c_{ix,r} = \begin{cases} c_{ix}, & r_{ijx} > \text{wta} \\ 0, & \text{else} \end{cases} \tag{A.1b}$$

$$q_{ao,r} = \begin{cases} q_{ao}, & r_{ao} \geq r_{ijx} \\ 0, & \text{else} \end{cases} \tag{A.1c}$$

Eq. (A.2a) shows that the maximum quantity is calculated by subtracting the quantity of more profitable accepted orders (Eq. (A.2c)) from the capacity that the seller has available at the bid's net price (Eq. (A.2b)).The quantity of the more profitable accepted orders is subtracted from the capacity, because the seller will not discard those orders in favor of the bid.

$$q^{+}_{\mathrm{ijx,r}} = \begin{cases} c_{\mathrm{ix,r}} - \sum\limits_{\mathrm{ao}\in \mathrm{AO}} q_{\mathrm{ao,r}}, & q^{+}_{\mathrm{ijx,r}} > 0 \\ 0, & \text{else} \end{cases} \quad \text{(A.2a)}$$

$$c_{\mathrm{ix,r}} = \begin{cases} c_{\mathrm{ix}}, & r_{\mathrm{ijx}} \geq \mathrm{wta} \\ 0, & \text{else} \end{cases} \quad \text{(A.2b)}$$

$$q_{\mathrm{ao,r}} = \begin{cases} q_{\mathrm{ao}}, & r_{\mathrm{ao}} > r_{\mathrm{ijx}} \\ 0, & \text{else} \end{cases} \quad \text{(A.2c)}$$

A.2 Processing Offers

A.2.1 Determining Minimum and Maximum Quantity that can be Supplied

For the minimum quantity that can be supplied by the sellers ($s^{-}_{\mathrm{jx,p}}$), the buyer j sums the minimum quantity communicated by the sellers (I) in their offers ($q^{-}_{\mathrm{ijx,r}}$), as indicated by Eq. (A.3).

$$s^{-}_{\mathrm{jx,p}} = \sum_{\mathrm{i}\in \mathrm{I}} q^{-}_{\mathrm{ijx,r}} \quad \text{(A.3)}$$

For the maximum quantity that can be supplied by the sellers ($s^{+}_{\mathrm{jx,p}}$), the buyer j sums the maximum quantity communicated by the sellers (I) in their offers ($q^{+}_{\mathrm{ijx,r}}$), as indicated by Eq. (A.4).

$$s^{+}_{\mathrm{jx,p}} = \sum_{\mathrm{i}\in \mathrm{I}} q^{+}_{\mathrm{ijx,r}} \quad \text{(A.4)}$$

A.2.2 Determining Minimum and Maximum Demand

The buyer's minimum demand $d^{-}_{\mathrm{jx,p}}$ is calculated by subtracting the quantity of the already accepted orders AO (q_{ao}) from the total demand the buyer has at the current price ($\mathrm{td}_{\mathrm{jx,p}}$), as indicated by Eq. (A.5a). The total demand at the current price is calculated in Eq. (A.5b), and is determined by assessing whether the price (p_{jx}) is lower than the buyer's willingness to pay (wtp). If that is the case, the buyer has a demand of $\mathrm{td}_{\mathrm{jx}}$. As the buyer does not have the opportunity to discard accepted orders, he does not differentiate between more and less profitable orders.

$$d^{-}_{\mathrm{jx,p}} = \begin{cases} \mathrm{td}_{\mathrm{jx,p}} - \sum\limits_{\mathrm{ao}\in \mathrm{AO}} q_{\mathrm{ao}}, & d^{-}_{\mathrm{jx,p}} > 0 \\ 0, & \text{else} \end{cases} \quad \text{(A.5a)}$$

$$\mathrm{td}_{\mathrm{jx,p}} = \begin{cases} \mathrm{td}_{\mathrm{jx}}, & p_{\mathrm{jx}} < \mathrm{wtp} \\ x, & \text{else} \end{cases} \quad \text{(A.5b)}$$

The maximum demand that the buyer j has ($d^{+}_{\mathrm{jx,p}}$) is calculated by subtracting the quantity of the already accepted orders AO (q_{ao}) from the total demand the buyer has at the current price ($\mathrm{td}_{\mathrm{jx,p}}$), as indicated by Eq. (A.6a). The total demand at the current price is calculated in Eq. (A.6b), and is determined by assessing whether the price (p_{jx}) is lower than or equal to the buyer's willingness to pay. If that is the case, the buyer has a demand of $\mathrm{td}_{\mathrm{jx}}$. As the buyer does not have the opportunity to discard accepted orders, he does not differentiate between more and less profitable orders.

$$d^{+}_{\mathrm{jx,p}} = \begin{cases} \mathrm{td}_{\mathrm{jx,p}} - \sum\limits_{\mathrm{ao}\in \mathrm{AO}} q_{\mathrm{ao}}, & d^{+}_{\mathrm{jx,p}} > 0 \\ 0, & \text{else} \end{cases} \quad \text{(A.6a)}$$

$$\mathrm{td}_{\mathrm{jx,p}} = \begin{cases} \mathrm{td}_{\mathrm{jx}}, & p_{\mathrm{jx}} \leq \mathrm{wtp} \\ x, & \text{else} \end{cases} \quad \text{(A.6b)}$$

A.2.3 Follow-Up Action

Fig. A1 shows a flowchart of how an agent decides upon its follow-up action. It actually goes through a maximum of three consecutive decisions in order to assess whether he will decrease its price, increase its price, send final bids to potential sellers, or end the negotiation.

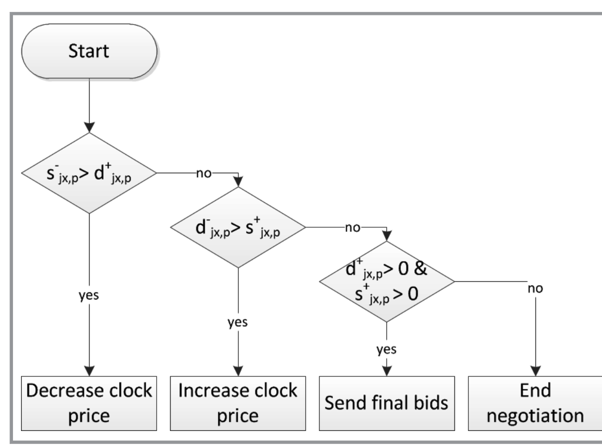

Figure A1. Decision logic for the follow-up action of a buyer.

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