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SIMULATION-BASED ORDER MANAGEMENT FOR THE ANIMAL FEED INDUSTRY

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ABSTRACT

Animal feed production constitutes a significant market in today's agricultural sector, with an annual turnover of 55 billion euros within the European Union in 2020. Nevertheless, feed logistics stills suffer from low digitization and manually coordinated supply chains. These factors lead to high transportation and product costs for customers and retailers by inducing short-term orders that often disregard current price developments. This article presents a simulation model for feed supply networks consisting of a number of customers, retailers, and manufacturers. It proposes a fuzzy-based decision strategy for customers to decide when to order specific products. Moreover, it describes a possible decision strategy for retailers to optimize their transport routes by selecting viable manufacturers. The evaluation shows that the proposed decision strategy can reduce costs for feed and, depending on the supply network structure, reduce delivery distances for feed retailers.

1 INTRODUCTION

As part of the agricultural market, feed production achieved a turnover of 52 billion Euro within the European Union in 2019, marking an increase of 28% since 2007 and amounting to approximately 1,112 Megatons of feed (FEFAC 2021). Nevertheless, animal feed constitutes one of the highest cost factors for livestock production, ranging between 11% for cattle to 57% for poultry (FEFAC 2021). The differences result from the diversity of animal feeds and the fact that farmers often produce parts of their own feed, e.g., grains or grasses. According to Leenstra (2013), poultry production only marginally profits from this option and generally relies on buying animal feed in full. In general, feed production combines many actors with an extensive range of product variants that require a high level of coordination across the supply chain.

The efficiency of this supply network highly relies on fast communication and predictable customer behavior. For example, Annosi et al. (2021) describe in their study that the food sector only shows a limited degree of digitization. This limited degree results, e.g., from a large number of small actors within the market, missing expertise, and capabilities to monitor and handle the necessary data, comparably high investment costs, and missing trust. For example, Böhmerle (2020) states that 237 different manufacturers for compound feed existed in Germany (2019) while, according to Germany's Ministry for Food and Agriculture, 168,833 companies/farms were registered to hold livestock in 2021. Moreover, approximately 2,700 agricultural retailers existed in Germany by 2018. These numbers indicate an extreme bandwidth of digitization and highlight that the barriers identified by Annosi et al. (2021) also hold for feed production. Similarly, Vennemann and Theuvsen (2004) describe a study where only 6% of the participants used online marketplaces to procure feed or other tools. Most participants ordered by phone as they conceived online alternatives as too complicated or time-consuming. Accordingly, feed production requires solutions with low entry costs and barriers to use modern technologies and methods to streamline its processes. The

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availability of fast and unproblematic access to such technologies for farmers, both as customers and raw material producers, constitutes a major factor in increasing the supply network's efficiency.

Together with the *avency GmbH*, the research project *XCeedFeed* aims to develop and provide an online platform for involved actors which allows better coordination with low entry barriers considering financial investments and expertise requirements. While other research projects mainly focus on the development of storage level sensors and inter-connectivity, e.g., Raba et al. (2020), this platform uses an agent-based simulation model, to estimate the actors' behavior and market developments to provide customers with order suggestions based on their inventory or silo levels and feed requirements. Ultimately, the platform aims to streamline processes to reduce costs and CO_2 emissions.

Consequently, this article contributes to the current literature by first providing a concise overview of feed-logistics supply chains, market characteristics, and available online tools by summarizing different sources from literature. Second, the article describes a new agent-based simulation model covering these characteristics and proposes a fuzzy-based decision strategy for customers considering this sector's highly dynamic price developments.

After presenting an introduction to the markets and targeted supply networks, the following section presents current solutions available in the feed market. Section 3 presents the simulation model used to evaluate different methods to derive order suggestions. Finally, section 4 evaluates the effect of these methods on the overall performance. The article closes with a conclusion and a preview of future works.

2 MARKET DESCRIPTION AND STATE OF THE ART

Figure 1 shows the main components and distribution channels for compound feed to the actual customers. Farmers mainly procure their animal feed through agricultural retailers and feed manufacturers. In addition, several farmers produce their own feedstuff. Manufacturers use raw materials like grains, mineral products, oils, or supplements to produce compound feed in various combinations, e.g., as pellets or crumbles. Therefore, they rely on imported materials like soybeans and, preferably, locally sourced materials from other farmers, the food industry, e.g., for oils or starch, and mineral or other supplements to be added to the compound feed.

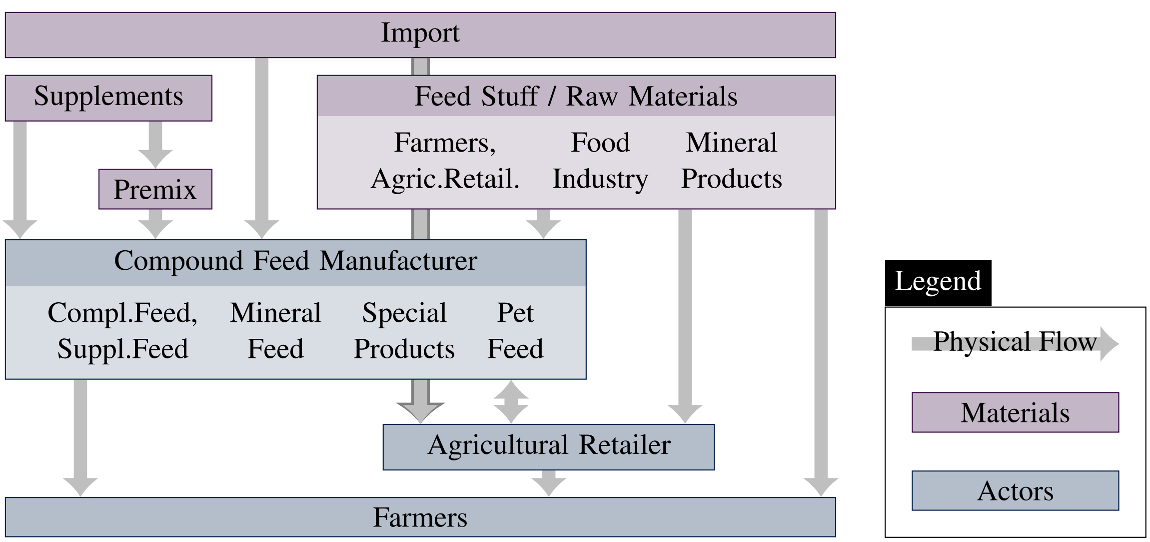


Figure 1: Compound Feed Supply Chain, modeled after DVT (2022).

Agrarheute (2014) describes a survey conducted across 591 farmers in Germany to characterize their buying behavior. In summary, 49% of the farms procure their feed from private agricultural retailers, 41%

buy from cooperative agricultural retailers, and only 10% obtain their feeds directly from manufacturers. Moreover, the study shows that about 22% of farmers produce their own feed.

These numbers show that agricultural retailers take on the role of intermediaries between farmers and manufacturers. In consequence, most manufacturers produce in a make-to-order mode (Rippel et al. 2017). Therefore, retailers usually supply the raw materials as part of their order. Similarly, current statistics from Germany's Federal Office for Agriculture and Food show that manufacturers only hold a minimum inventory of raw materials apart from additives (Böhmerle 2020). According to this report, most of the stored inventory of raw materials and finished feed remains with the farmers themselves. Consequently the compound feed market mainly relies on just-in-time concepts (Böhmerle 2020).

2.1 Market Characteristics

Wajszczuk (2016) reviews unique characteristics that differentiate agri-food supply chains from supply chains in other manufacturing areas. While focusing on food supply chains, most of these characteristics hold for feed manufacturing. Among others, he highlights the dependence of processes and products on climatic conditions, the need for fast transport and processing to retain quality, and the high diversification in products. The article states that these characteristics lead to shifts in logistic costs. For example, physical flow costs (transport) make up approximately 86.5% of logistics costs, compared to 31.5% in other sectors. In contrast, inventory costs only amount to 12.2% compared to an average of 39.7% in other domains.

Consequently, feed production constitutes a highly customer-driven market with high product variety. For example, Rippel et al. (2017) describe the use case of a manufacturer who manufactured feed using 119 recipes across 60 different ingredients at the time of the process analysis. The manufacturer could replace several ingredients within a recipe with others, as the products usually need to satisfy specific characteristics, e.g., protein or fat levels, instead of including specific ingredients. Similarly, Böhmerle (2020) states that many ingredients could be substituted, e.g., most grains could be interchanged. Moreover, this contract manufacturer received orders short-term, usually for the current or next day.

This example demonstrates the importance of order management and supply chain coordination within feed production supply networks. In most cases, the actual process begins with a customer realizing its need to (re-)order feed and placing the order with the respective retailer. The retailer then procures the raw materials (stored or from other sources), places the manufacturing order, and arranges the materials and final product transport. Depending on the materials' sources and the manufacturer's timetable, the retailer can arrange direct delivery of the materials to the manufacturer or provide short-term storage to collect the materials before delivery. Once produced, the retailer usually arranges transport from the manufacturer to the customer directly. In some cases, the retailer might hold some inventory of commonly requested products, simplifying and separating the manufacturing from the customer. Nevertheless, the high variability and perishable nature of feeds combined with the volatile demand, depending, e.g., on regional-, climate-, or seasonal factors, only allows for a small subset of stored products.

2.2 Availability of Online Marketplaces

Schulze Schwering and Kunz (2020) present a recent review of online marketplaces for animal feed. The article highlights that there exist several online marketplaces, e.g., *agrando*, *agrar2b*, *agrarconnect*, or *Agrora*, or online shops, e.g, *ag.supply*. While most of these shops and marketplaces offer a variety of resources, e.g., workwear or tools, only very few of them offer animal feed. Those shops offering feed only offer a very limited product range of standardized feed, e.g., so-called starter diets or feed for poultry. Nevertheless, these standardized products only cover a minimal range of feeds. Furthermore, the authors describe a literature review on factors influencing feed availability in online marketplaces. Besides a deep-rooted traditionalism within this sector, resulting in a hesitancy to adopt new business models and technologies, the authors highlight that the extreme number of product variants, volatile price developments, high transportation efforts, and the sectors demographics impede online availability of feed.

While online shops and marketplaces show high potential to offer and procure standardized products, they are not suitable for configurable products, consisting of hundreds of substitutable ingredients whose prices change daily. Consequently, most companies offering online ordering for feed rely on nonautomated channels, e.g., online forms, quick phone contacts, or a limited product range in online shops. Moreover, features like product finders or configurators, common to online shops targeting pets or horses, have not yet been established in the agricultural feed sector (Schulze Schwering and Kunz 2020).

Consequently, animal feed requires a dedicated solution for online marketing that reaches beyond a simple online shop or marketplace. On the one hand, it needs to handle the extensive product variety and customize the feed to the customer's needs. On the other hand, it needs to simplify and streamline to overall process chain, from the customer over the retailers and manufacturers to the transport companies, to achieve tangible benefits for all involved parties.

3 SIMULATION MODEL AND ORDER STRATEGIES

On the one hand, the platform aims to provide an easy-to-use online portal to configure feed and manage orders for customers, retailers and manufacturers. Therefore, it consists of a specifically tailored database for feeds and ingredients to allow customer-specific recipes. On the other hand, it aims to streamline ordering itself. Therefore, the platform allows connecting silo level sensors to monitor the customers' silo levels. The platform uses a simulation model to connect these data with the current feeds' recipes and market conditions to offer the customers suggestions on when to order which feeds in what quantity. Overall, integrating such sensors already reduces late or rush orders by creating transparency on the current levels. Moreover, it allows more intelligent decision methods to determine optimal order characteristics. Finally, if the customer desires, information on current silo levels allows retailers to place targeted offers, enhancing the efficiency of transports or production plans. In contrast to other strategies evaluated in the literature, e.g., retailer-centric fixed-batch or variable-batch strategies (Raba et al. 2017), this setup allows a higher level of integration between the costs of retailers, manufacturers and customers.

3.1 Simulation Model

The logistics system has been implemented in AnyLogic 8.7 and includes the main agent types of customers (farms), retailers, manufacturers, and transport vehicles, as shown in Figure 2.

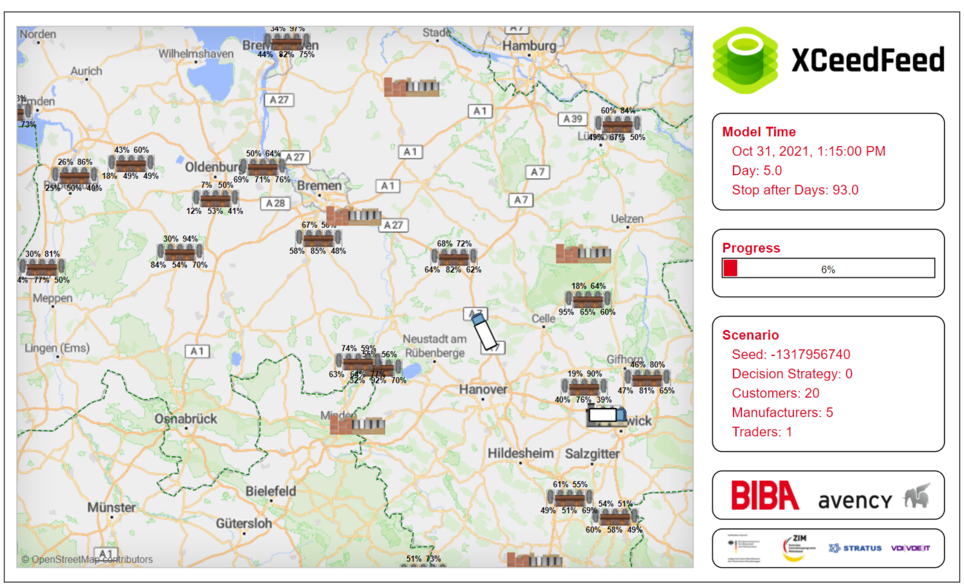


Figure 2: Screenshot of the simulation model.

As the overall platform is still in development, this article initializes the logistics network randomly using a predefined seed, product range and some fixed assumptions regarding silo and vehicle characteristics. Consequently, the model places a defined number of agents randomly scattered around a given region (Lower-Saxony, Germany) with random characteristics.

Customer agents consist of a given number of silos, each containing 10 tons of a single product. The current implementation specifies the number of dairy cattle and laying hens. Afterward, the model selects the required products for each type of animal and allocates the corresponding number of silos with a randomly chosen initial inventory level. Nevertheless, the model allows replacing products in silos and, if available, allocates additional silos to products with higher consumption. Moreover, the agent specifies if the customer always purchases a product from a specific retailer or if they compare prices between different retailers. Every day, the customer agent consumes an amount of each product that correlates with the number of animals. Therefore, common feed suggestions indicate consumption of about 20 kg of grass silage, 15 kg corn silage, 1.5 kg hay, 0.25 kg mineral feed, and additionally about 9 kg of dry feed manufactured from ray, corn, and rapeseeds, per dairy cattle. Similarly, they indicate consumption of about 125 g of cornmeal per laying hen.

During the spring and summer months, cattle usually graze, effectively reducing feed consumption of some products depending on the current grass growth as depicted in Figure 3. The simulation estimates the growth using a regression function derived from averaged values within the literature and accordingly reduces the consumption of affected products and ingredients (Josera Agrar 2022). After consuming products, the customer checks their silo levels and decides whether to reorder a specific product. In such cases, they request offers from one or more retailers for chosen dates and accept the best offer.

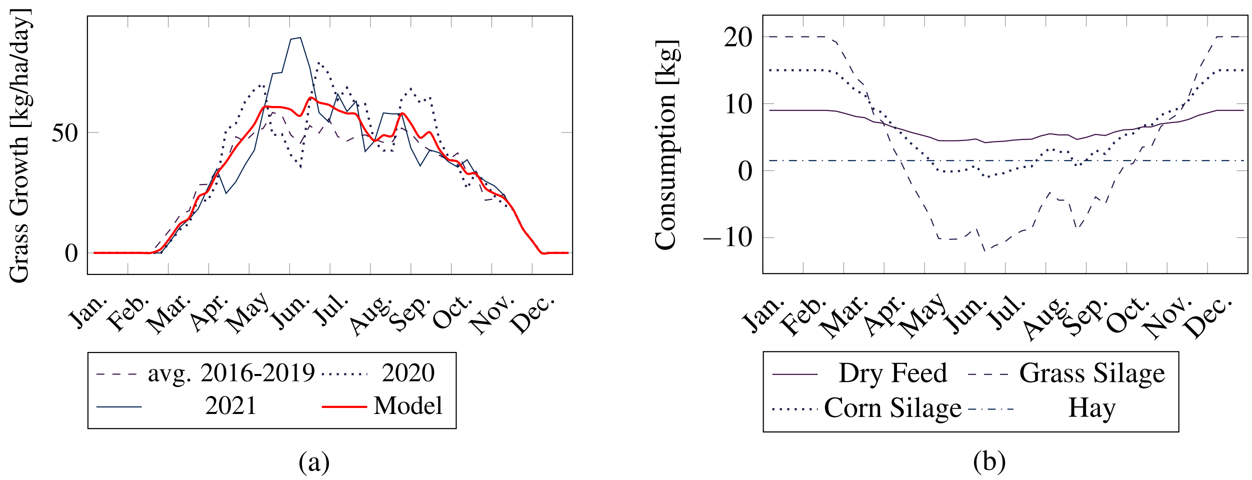
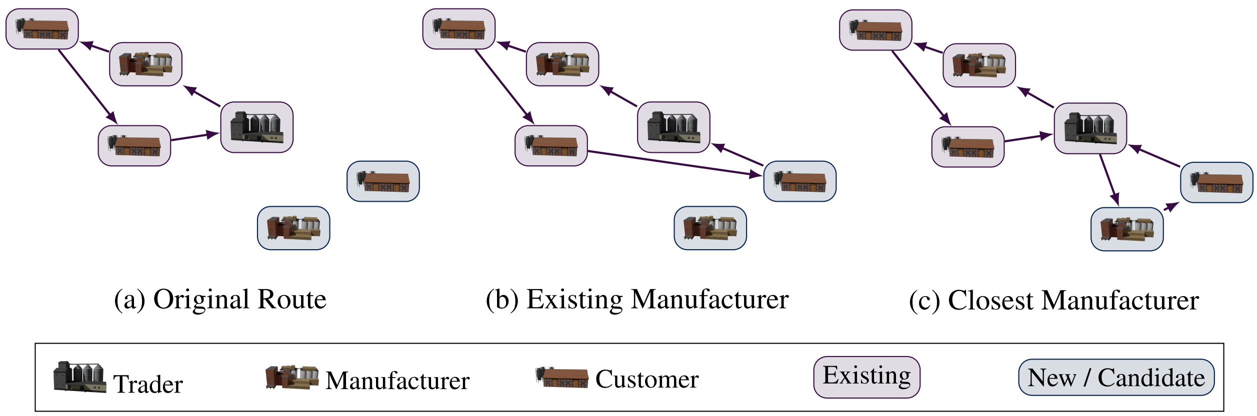


Figure 3: Grass-growth model (a) and resulting feed consumption (b).

Retailer agents consist of several transport vehicles and associate with a given number of manufacturers. Currently, the simulation assumes that each retailer has a fleet of five silo vehicles, each providing a maximum payload of 26 tons across three compartments. Retailer agents have two tasks: offering prices and organizing the transport of manufactured or stored goods to the customers. Once retailers receive a pricing request, they first obtain a list of already existing orders for the requested delivery date. Afterward, they solve several pickup and delivery vehicle routing problems with time windows (PD-VRPTW) (Dumas et al. 1991) using the grasshopper JSPRIT Java library, which can be imported to the AnyLogic model directly. These problems include all existing jobs and assign the new order to either one of the manufacturers already visited that day or the manufacturer with the lowest round-trip distance between themselves, the manufacturer, and the customer. Please see Figure 4 for an example.



(a) Original Route (b) Existing Manufacturer (c) Closest Manufacturer

Figure 4: Example for possible routes extending the original network (a) by choosing an existing (b) or the closest (c) manufacturers.

The retailer assumes that they can pick up and deliver finished products between 12:00 and 22:00. After comparing the results of each route, the retailer selects the best manufacturer for an offer and denotes the corresponding (additional) transportation costs for each request and replies to the customer. In this simulation, the transportation costs describe the additional distance vehicles would need to travel that day by incorporating the new order with the optimized routing. Every day, the retailer solves the same PD-VRPTW using all orders posted for a given day and forwards the resulting routes to their transport vehicle agents. The simulation additionally allows retailers to rent additional transports if the PD-VRPTW results in unassigned jobs. In such cases, the retailer increases the number of transports by one until the problem can solve completely.

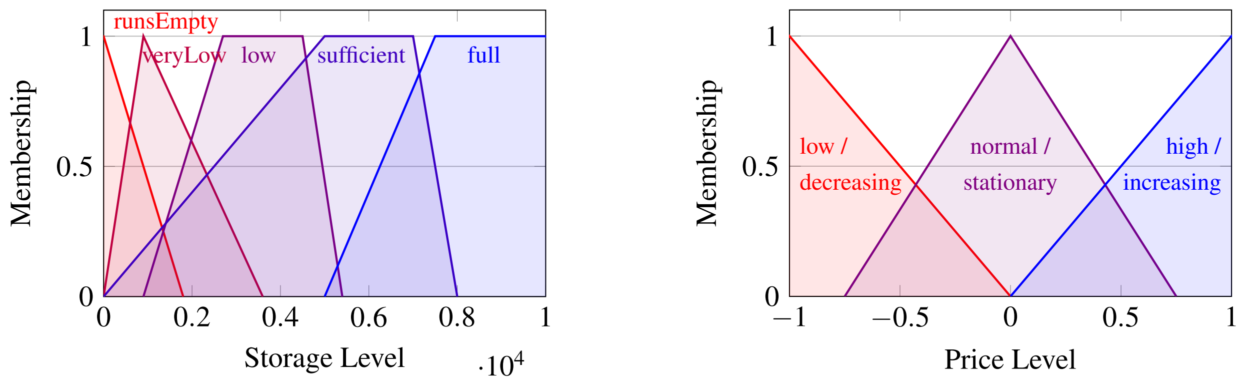
Finally, transport vehicle agents currently only follow their assigned routes and return to their retailer once finished. The assigned routes include all stops (pickup and delivery) and the corresponding processing times. Once a delivery job completes, the vehicle agent notifies the customer and proceeds to the next task. In contrast, manufacturer agents currently have no active tasks but mainly act as locations for the transport planning.

3.2 Ordering Strategies

While retailer agents use a fixed decision strategy in choosing viable manufacturers to minimize their traveling distance, customer agents currently possess two strategies to decide when to order which product. Generally, both options use a look-ahead strategy and usually obtain several offers. Each day and for each product, the customer first obtains their current inventory level and predicts their demand and remaining inventory for the next ten days as described later in this section. Based on these values, they apply either the order point or the fuzzy-based strategy to decide whether to post a pricing request for delivery on those days or not. After obtaining the prices for each option, the customer decides which offer to choose based on the (normalized) product price and the transportation costs.

The order point strategy evaluates when the current inventory should be used up and requests delivery for that day or the day before. While this strategy guarantees sufficient feed and, more or less, corresponds to today's practice, it does not consider daily price changes or allows the retailers much freedom to optimize their transports. In contrast, the fuzzy controller uses a set of rules to allow customers to decide whether to order or not using additional information. Moreover, this strategy tries to wait with actually posting pricing requests until its evaluation offers several advantageous delivery dates to the retailer(s).

Generally, fuzzy controllers operate in three stages. First, they fuzzify their inputs by turning numeric input values into memberships to so-called literal terms. Second, they apply a set of rules to determine the membership of the output variable. Finally, they defuzzify the output literals to a numeric value. As output, the proposed controller uses two values: *0/Do Nothing* or *1/Do Order*. The controller used in the simulation model has been implemented using the Java library JFuzzyLogic. The library offers the option to define controllers using strings, i.e., textual descriptions. Consequently, the following tables show code that has actually been used to define the controller.



(a) Silo Level for $drain = 900kg$ and $max = 10,000kg$

(b) Membership Functions for (expected) Price Levels

Figure 5: Membership functions used by the fuzzy controller: Example of the storage level (a) and functions for the price level and development variable (b).

The proposed controller uses four input variables: the predicted inventory at the day after the (possible) delivery, the current price level, and the predicted price levels at three and seven days into the future for the current day. Figure 5 shows the membership functions used in this article. In terms of the input values, price levels are normalized values between -1 (cheap or declining) to +1 (expensive or increasing), while the silo level is in kg. In addition to these inputs, the controller takes the maximum capacity (*max*) and the expected product consumption (*drain*) to adjust the membership functions for the silo level depending on the product's consumption. Accordingly, these membership functions are currently defined as triangular or trapezoid functions over these parameters, as given in Table 1.

Table 1: Definition of the "Storage Level" variable.

```
FUZZIFY storage
  runsEmpty  := (-1.5*drain, 1)  (0,1)         (2*drain, 0)
  veryLow    := (0, 0)           (drain,1)     (4*drain, 0)
  low        := (drain, 0)       (3*drain, 1)  (5*drain, 1)  (6*drain, 0)
  sufficient := (0, 0)           (0.5*max, 1)  (0.7*max, 1)  (0.8*max, 0)
  full       := (0.5*max, 0)     (0.75*max,1)  (max, 1)      (1.5*max, 0)
```

After obtaining the membership of the input values for each literal, the controller applies a set of weighted rules given in Table 2 to decide on whether or not to buy under the given circumstances. The code shows that the controller first checks the current storage level and, afterward, relies on the pricing data to render its decision. Moreover, the code demonstrates one of the main advantages of fuzzy controllers: Users can specify their behavior using close to natural language, which renders such controllers easy to adapt and configure in practical environments.

The controller uses estimations of the current price level and future price developments as input. While the platform will rely on pricing databases and include a prediction component in the future, the current implementation relies on datasets of historical price developments. The simulation uses averaged daily prices for different agricultural products, e.g., soybeans, between 2007 and 2021 and normalizes these prices as a baseline. The simulation randomly determines a shift within this data stream for each product

Table 2: Rules used by the controller.

```
IF storage IS runsEmpty                                     THEN action IS restock WITH 2.0
IF storage IS veryLow AND current_price IS low              THEN action IS restock
IF storage IS veryLow AND current_price IS normal           THEN action IS restock WITH 0.75
IF storage IS veryLow AND current_price IS high             THEN action IS nothing
IF storage IS veryLow AND future_price_short IS increasing  THEN action IS restock
IF storage IS low AND future_price_short IS increasing      THEN action IS restock
IF storage IS low AND current_price IS low                  THEN action IS restock WITH 0.25
IF storage IS low AND current_price IS normal AND future_price_short IS increasing
                                                            THEN action IS restock
IF storage IS low AND current_price IS normal AND future_price_short IS stationary
                                                            THEN action IS nothing WITH 0.5
IF storage IS low AND current_price IS normal AND future_price_short IS decreasing
                                                            THEN action IS nothing
IF storage IS low AND current_price IS high THEN action IS nothing
IF storage IS sufficient                                    THEN action IS nothing WITH 0.1
IF storage IS sufficient AND current_price IS low AND future_price_long IS increasing
                                                            THEN action IS restock
IF storage IS sufficient AND current_price IS normal AND future_price_long IS increasing
                                                            THEN action IS restock WITH 0.5
IF storage IS full                                          THEN action IS nothing
```

as a starting point. Accordingly, the simulation uses realistic price developments and ensures that the developments are not similar for all products even if the current product does not have a data stream attached to it. The prediction currently looks up the future price, normalizes the difference to [-1; 1], and applies a slight random variance as prediction.

4 EVALUATION

This article aims to compare the two described order strategies for supply networks within the feed industry. Therefore, the article describes several simulation runs that use either control strategy in randomly generated networks. The experiments run each scenario, determined by a random seed, once for each decision strategy to ensure comparability. The experiment covers 20 randomly generated scenarios to provide a sufficient variety of settings. As most customers rely on a single retailer to procure their feed, the simulation scenario only includes a single retailer plus their network of five possible manufacturers and twenty customers. The experiments choose a random starting month due to the variance in feed consumption. Table 3 shows the parametrization for the scenarios. The left compartment shows parameters selected for this experiment, while the right compartment shows the distribution of random values based on the scenario's seed.

Table 3: Scenario parameters and domain.

Parameter	**Unit**	**Domain**	**Parameter**	**Unit**	**Domain**
Scenarios	Number of	20	Seed	Integer	Random by Scenario
Decision Strategy	OP, F	0, 1	Sim. Start	Date	Random Month
Simulation Time	Days	93	Locations	Per Agent	Random in Lower-Saxony
Manufacturers	Number of	5	Dairy Cattle	Number of	uniform(20, 60)
Retailers	Number of	1	Laying Hens	Number of	uniform(75, 200)
Customers	Number of	20	Silo Cur. Level	Percent	uniform(50, 100)
Silo Max. Level	kg	10,000	Product Price Shift	Days	uniform(50,2000)

This experiment compares the decision strategies using the difference in the delivery distance required to satisfy all orders, each customer's costs, and the number of orders completed in the scenario. These prices consist of the current, daily product price plus 0.70€ per additional kilometer the retailer's transports need to drive to penalize selecting inefficient routes for the customer. The simulation calculates the product prices using the normalized price variances stored within the model and the daily product prices obtained online on March 25$^{\text{th}}$ 2022 to obtain realistic prices for each product.

Table 4 summarizes the main results of all twenty scenarios. The table shows that the fuzzy-based decision strategy reduces the number of placed orders by an average of 1.6 orders per scenario with a total of 32 fewer orders. Moreover, it reduces the total distance required to satisfy all orders within the three months across all scenarios by 15,906 km, or on average by 795.35 km per scenario. Besides this reduction in distance, the fuzzy-based strategy achieved cost reductions for the customers of over 102,209 € in sum, with an average of 5,110 € within the three months of each scenario.

Table 4: Detailed simulation results separated by order point (O) and fuzzy (F) decision strategies.

Scenario ID	**Distance (O)** in km	**Distance (F)** in km	**Cost (O)** in €	**Cost (F)** in €	**Orders (O)** amount	**Orders (F)** amount
1	81,290	79,555	709,485	704,396	354	354
2	73,048	71,028	640,237	638,259	320	318
3	66,304	67,214	630,297	629,459	334	334
4	63,343	62,962	626,040	618,969	333	331
5	65,447	65,037	561,545	556,885	297	296
6	120,607	117,501	757,716	741,277	395	389
7	83,794	82,819	743,172	733,533	346	345
8	69,330	69,742	705,128	702,790	319	318
9	89,650	87,770	651,177	646,674	317	315
10	95,277	97,051	629,111	624,357	333	331
11	61,259	60,263	600,265	597,748	295	294
12	100,109	98,779	658,373	654,491	334	332
13	80,307	79,248	681,719	675,350	328	326
14	70,699	70,661	650,585	648,621	343	342
15	81,262	80,990	662,671	655,730	335	332
16	66,684	66,737	650,994	644,967	311	308
17	69,694	70,579	652,770	652,564	344	345
18	104,880	100,461	844,862	841,376	393	391
19	81,027	80,764	688,813	686,468	349	348
20	80,631	79,574	802,867	791,701	378	377

Evaluating the results given in Table 4 using a t-test in Matlab shows significant differences ($\alpha = 0.05$) with P-Values of 0.021765 for the distance, 0.000011 considering the costs and 0.000078 regarding the number of orders, discarding MatLab's base hypothesis that the data in *x*–*y* (OrderPoint - Fuzzy) comes from a normal distribution with mean equal to zero and unknown variance, using the paired-sample t-test.

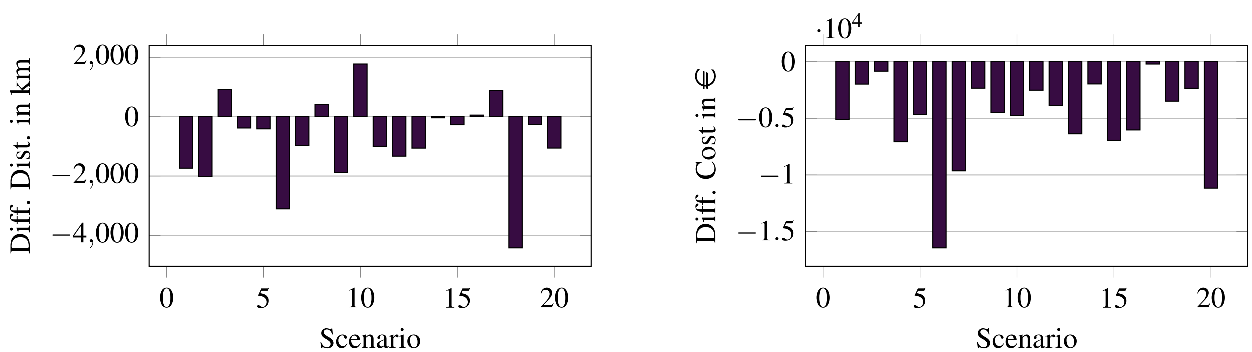


Figure 6: Relative results between the strategies by scenario as (Fuzzy - Order Point).

Figure 6 shows the difference in the retailer's travel distance and customers' product costs between the decision strategies. In all scenarios, the fuzzy-based strategy results in cost reductions for the customers. Additionally, most scenarios also show a reduction in the retailer's delivery distance. Depending on the network's characteristics, i.e., the placement of the retailer and the manufacturers, some scenarios benefit more from this decision strategy while a few scenarios show an increase in the delivery distance.

5 CONCLUSION AND FUTURE WORK

This article presents an agent-based simulation model that provides two different decision strategies for customer order generation in feed-supply networks. While the simulation model has yet to be integrated with the surrounding platform to receive real-world inputs, e.g., positions and characteristics of actors or product- and pricing data, this simulation study already shows the model's high viability to provide order suggestions to customers. Moreover, the agent-based design allows setting up different optimization strategies for each type of agent separately. The article demonstrates this extensibility by including two decision strategies for customers on when to place an order for feed. Retailers, in contrast, currently only have a single decision strategy on how to incorporate new requests or orders into their planning.

The comparison between the default order point strategy and the proposed fuzzy-based strategy shows high potential for cost savings throughout the network. On average, the new strategy could reduce the average delivery distance by 795 km for retailers, and the product costs by an average of 5,110 € for customers over a simulation horizon of three months. In all of the twenty randomly selected scenarios, the fuzzy-based strategy achieved cost reductions for the customers. Additionally, it also decreased delivery distances for retailers in all but four scenarios.

Future work will focus on integrating real-world data and developing viable demand, capacity, and price prediction algorithms. The current implementation uses a simple linear regression to predict upcoming feed consumption from the last n data points. Nevertheless, feed consumption can vary quickly, e.g., depending on seasonal effects, animal health, or other external influences, rendering a simple linear regression inappropriate for real-world applications. Considering the price development estimations, the model at hand looks up the future development from its database. While viable to compare the (possible) efficiency of new ordering strategies by providing a "best-case" estimate, future prices cannot be known or looked up in real-world applications. Therefore, future work will focus on integrating or developing prediction algorithms that operate on actual historical data for a given product.

Moreover, future work will focus on refining the simulation model, e.g., by incorporating the selection and delivery of raw materials to manufacturers in the early morning and by evaluating additional decision strategies. The modular setup of the simulation allows, e.g., to try other heuristics or optimizations. Furthermore, the simulation model will be used as a training platform for reinforcement-learning policies, which could offer a powerful alternative to manually designed decision strategies.

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