Discovering and Analyzing Stochastic Processes to Reduce Waste in Food Retail*

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Abstract. This paper proposes a novel method for analyzing food retail processes with a focus on reducing food waste. The approach integrates object-centric process mining (OCPM) with stochastic process discovery and analysis. First, a stochastic process in the form of a continuous-time Markov chain is discovered from grocery store sales data. This model is then extended with supply activities. Finally, a *what-if* analysis is conducted to evaluate how the quantity of products in the store evolves over time. This enables the identification of an optimal balance between customer purchasing behavior and supply strategies, helping to prevent both food waste due to oversupply and product shortages.

Keywords: Food Waste Reduction · Grocery Store Sales Data · Object-Centric Process Mining · Stochastic Process Discovery

1 Introduction

Globally, it is estimated that roughly one-third of all food produced for human consumption goes to waste [11]. This staggering figure represents more than a billion tons of food lost every year, exposing the inefficiencies of our current food system. Such waste occurs at various stages along the food life cycle: during harvest (due to poor storage or transport), in processing (where food may not meet quality standards), and at the consumer level (where oversupply may lead to unnecessary disposal). *Food waste* is a significant sustainability challenge, contributing to the growing pressures on environmental and social systems.

Sustainability is achieved through the implementation of *circular economy* principles, which aim to minimize waste, reduce resource consumption, and promote regenerative systems. In [13], circular economy is defined as "*a regenerative system in which resource input and waste, emission, and energy leakage are minimized by slowing, closing, and narrowing material and energy loops*". While

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slowing and *closing* food retail loops refer to extending product use or enabling recycling and donations to charities, *narrowing* primarily involves optimizing logistics to purchase only the amount of food likely to be sold [6]. In this paper, we study models that support the optimization of food supply (narrowing).

Since data describing retail processes often comes as a collection of sales events with timestamps and additional contextual information, process mining [1] emerges as a promising tool for analyzing these processes. It provides a comprehensive set of techniques [16] to support sustainability initiatives by enabling data-driven insights and process analysis. Although food waste reduction has been discussed within the realm of process mining [23,29,39,41], no specific process mining technique for food waste reduction has been proposed.

In [12], a 5 phase approach for process mining research strategy in sustainability area was proposed. This paper focuses on the first three stages: modeling (discovery), analysis, and process improvement and optimization. We introduce methods for discovering stochastic processes that capture the dynamics of store capacity, specifically the amount of products on the shelves. We then provide analytical tools for performing what-if analysis on the discovered models, which can support process optimization and food waste reduction strategies.

The paper is organized as follows. Section 2 provides a literature review, including relevant research in process mining and, more broadly, in food waste analysis. The main event log and process model concepts are introduced in Section 3, followed by the presentation of process discovery and analysis techniques in Section 4. The analysis of real-world data is presented in Section 5. Finally, Section 6 concludes the paper.

2 Literature Review

This section provides an overview of relevant research on process mining, its applications in supply chain analysis, and existing methods for food waste analysis.

While no process mining techniques have been specifically developed for food waste analysis, several methods have been proposed for supply chain analysis more broadly. A comprehensive review of process mining techniques applicable to supply chains is presented in [30], and systematic literature reviews are available in [19,20]. The work in [25] bridges the gap between supply chain analysis and process mining by proposing concrete strategies for understanding and analyzing logistics processes. In [36], process mining is applied to evaluate supply chain resilience. An overview of successful practical applications is provided in [33], and a specific framework for analyzing food supply chains is introduced in [24].

A key area of process mining suited for analyzing complex scenarios, such as supply chains involving multiple objects, is the so-called *object-centric process mining (OCPM)* [2]. Within the realm of OCPM, a trace in an event log can represent a sequence of events associated not with a single process case but with a specific object, such as a customer, item, or order [3]. The OCEL standard for object-centric event logs was developed and introduced in [14]. More recently, the application of OCPM and the OCEL standard to sustainability analyses was explored in [15], where the authors propose a framework to support the reduction of negative impacts from companies' operations.

Another promising direction of OCPM that can advance sustainability analysis is *stochastic OCPM*, which was introduced in [10]. This position paper emphasizes the importance of analyzing stochastic properties of object-centric models, which can enable the derivation of frequent process patterns. Although methods for discovering stochastic process models from event logs have been proposed in [35,9,26,5], the research presented in this paper introduces a novel approach that integrates OCPM with stochastic process discovery and analysis.

A systematic literature review of approaches for (1) improving supply chain *resilience*, i.e., the capacity of the supply chain to respond to interruptions, and (2) *reducing food waste*, is presented in [37]. For example, an optimization problem aiming to maximize profit and minimize total supply chain lead time was addressed in [7]. A simulation method for analyzing supply chains under disruption was proposed in [42]. Furthermore, a technique for analyzing supplier disruptions, which combines Markov chains to model supplier capacity and dynamic Bayesian networks to examine the propagation impact of a disruption, was presented in [18].

An optimization problem that ensures food donations are proportional to each country's demand while minimizing the amount of undistributed food was studied in [31]. An optimal packaging problem that minimizes both transportation costs and food waste was proposed and applied to simulated data in [17]. An optimization model incorporating dynamic shelf life (early discounting of products) was studied and demonstrated its effectiveness in real-world settings in [8].

Other food waste reduction approaches based on mathematical optimization techniques were proposed in [21,32]. [28] suggests simulation techniques to model and analyze waste in food supply chains. In [40], a non-linear regression model relating temperature and maximum shelf life was introduced. A comprehensive analysis of various machine learning techniques for short-term demand forecasting in food catering services was proposed in [34]. An approach based on game theory that develops and investigates optimal food decision-making strategies between a retailer and a supplier was proposed in [27]. Research utilizing grey causal modeling to identify and analyze the main factors contributing to food waste was presented in [4,38].

In contrast to the above techniques, the approach presented in this paper leverages process mining and OCPM concepts to build *stochastic process models* from event logs, enabling the modeling and analysis of food waste based on the temporal aspects of customer behavior.

3 Background

In this section, we define object-centric event logs and stochastic processes for application in food retail process discovery and analysis.

In retail, event logs capture various types of information, including transaction and product identifiers, timestamps, quantities of purchased products, payment methods, and customer types. This data can be represented in a form

Table 1: An event log of a grocery sales system.

	Objects	*Quantity*	*Total price*	*Timestamp*
e_1	{orange, client 1}	10	12.0	2025-07-19 08:23:42
e_2	{apple, client 1}	15	10.3	2025-07-19 08:24:03
e_3	{orange, client 2}	5	6.0	2025-07-19 08:24:22
e_4	{mango, client 2}	2	8.0	2025-07-19 08:24:49
e_5	{watermelon, client 2}	1	6.3	2025-07-19 08:25:05

of an object-centric event log that also contains timestamps of transactions. We will adapt the definitions provided in [3] and [22] to represent the retail processes event data.

Definition 1 (Event log). *Let $\mathcal{E}$ be a universe of event identifiers, $\mathcal{O}$ a universe of objects, and $\mathcal{A}$, $\mathcal{V}$, and $\mathcal{T}$ the universes of attributes, values, and timestamps, respectively. An* event log *$L = (E, O, f_o, f_a, f_t)$ is a tuple, where:*

- *$E \subseteq \mathcal{E}$ is a set of events;*
- *$O \subseteq \mathcal{O}$ is a set of objects;*
- *$f_o : E \to \mathcal{P}(O)$ is a function that maps events to subsets of objects[1];*
- *$f_a : E \times \mathcal{A} \rightharpoonup \mathcal{V}$ is a partial function that assigns values to some event attributes;*
- *$f_t : E \to \mathcal{T}$ defines the occurrence times of events.*

An example of such an event log is presented in Table 1. Each event from the set $E = \{e_1, e_2, e_3, e_4, e_5\}$ represents a transaction in which a client buys fruits in the grocery store. Objects are represented by fruits and clients: $O = \{orange, apple, mango, watermelon, client\ 1, client\ 2\}$.

Events are mapped to sets of objects, as presented in Table 1. For example, $f_o(e_1) = \{orange, client\ 1\}$. Attributes such as *Quantity* and *Total price* are assigned to all the events in the event log; for instance, $f_a(e_1, \mathit{Quantity}) = 10$. Each event is also associated with a timestamp, e.g., $f_t(e_1) = $ 2025-07-19 08:23:42. Although this event log includes both products and clients to ensure applicability across different types of process analysis, including user behavior, the approach presented in the following sections focuses exclusively on products as objects.

The main type of process model used in our analysis is the so-called *finite-state continuous-time Markov chain*, which we will refer to simply as a *continuous-time Markov chain*.

Definition 2 (Continuous-time Markov chain). *Let $S = \{0, 1, \ldots, k\}$ be a finite set of model states. A continuous-time Markov chain is defined as a pair: $CTMC = (\lambda, Q)$, where:*

- *$\lambda = (p_0, p_1, \ldots, p_k)$ is a probability vector on S that defines the* initial state probability*, such that $\sum_{i \in S} p_i = 1$.*

[1] $\mathcal{P}(O)$ denotes the powerset of O, i.e., the set of all subsets of O.

- $Q = (q_{i,j})_{i,j \in S}$ *is a* rate matrix *on* S*, such that: 1)* $\forall i, j \in S, i \neq j, q_{i,j} \geq 0$*; 2)* $\forall i \in S$ *it holds that* $\sum_{j \in S} q_{i,j} = 0$.

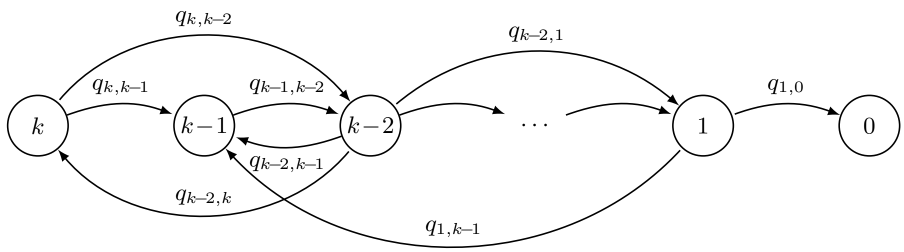


Figure 1: A continuous-time Markov chain with states $S = \{0, 1, \ldots, k\}$.

At each moment in time, the stochastic process defined by a continuous-time Markov chain is in one of the states from the set S. Initial state of the process is selected randomly according to the vector λ. When the process enters a state $i \in S$, the next state is determined based on the outgoing transition rates $q_{i,j}$. For each transition rate $q_{i,j} > 0$, the transition time is drawn from the exponential distribution with rate $q_{i,j}$ with the probability density function $q_{i,j}e^{-q_{i,j}t}$. The process then transitions to the state j with the minimal transition time, after waiting for that time delay.

A continuous-time Markov chain, presented in Figure 1, consists of states and transitions between these states with positive rates. Notice that continuous-time Markov chains do not have self-loops (transitions connecting the state to itself), because the holding time in state i is exponentially distributed with the rate $\sum_{j, j \neq i} q_{i,j}$.

In this paper, we use the concept of irreducible continuous-time Markov chains, defined below.

Definition 3 (Irreducible continuous-time Markov chain). *Let* S *be a set of states, and let* $CTMC = (\lambda, Q)$ *be a continuous-time Markov chain defined on this set. The chain* $CTMC$ *is called* irreducible *if, for every pair of distinct states* $i, j \in S$*, there exists a sequence of transitions with positive rates that leads from* i *to* j*.*

Formally, $CTMC$ *is irreducible if:* $\forall i, j \in S,\ i \neq j,\ \exists\, s_1, \ldots, s_m \in S$*, such that* $s_1 = i,\ s_m = j,$ *and* $q_{s_l, s_{l+1}}$ *is positive for all* $1 \leq l < m$.

4 Discovery and Analysis of Stochastic Processes

This section presents an approach for the discovery and analysis of continuous-time Markov chains to model and analyze grocery store processes.

4.1 Mining customer purchasing behavior from event data

Consider an event log of a grocery store system (Table 1). First, this event log $L = (E, O, f_o, f_a, f_t)$ is filtered, and a sublog for each product is extracted. For example, for the product *orange*, the sublog L' will contain only events that have *orange* as an associated object. More formally, $L' = (E', O, f'_o, f'_a, f'_t)$, where $E' = \{e \in E | orange \in f_o(e)\}$, and f'_o,f'_a,f'_t are the restrictions of functions f_o,f_a,f_t to E', respectively. After the event log L' for a particular product has been derived, the corresponding continuous-time Markov chain will be discovered by applying Algorithm 1. Note that, in real-world store event data, each product typically corresponds to a single transaction (i.e., one event), and thus attributes such as quantity usually refer to only one product.

Algorithm 1 Discovery of a continuous-time Markov chain from event log $L' = (E', O, f'_o, f'_a, f'_t)$

Input: Event log L' for a specific product, maximum quantity of the product k (capacity), and initial quantity of the product i.
Output: Continuous-time Markov chain $CTMC = (\lambda, Q)$ on a set of states S.

- Define the set of states as $S = \{0, \ldots, k\}$.
- Set the initial state probability vector as $\lambda = (0, \ldots, 0, 1, 0, \ldots, 0)$, such that $p_j = 0$ if $j \neq i$, and $p_i = 1$.
- Collect all the purchased product quantities: $\mathcal{Q} = \{f'_a(e', Quantity) \mid e' \in E'\}$.
- For each $\mathscr{Q} \in \mathcal{Q}$:
  – Filter the event log L' to retrieve events with the corresponding quantity $\mathscr{Q}$, $E'_{\mathscr{Q}} = \{e' \in E' \mid f'_a(e', Quantity) = \mathscr{Q}\}$.
  – If the size of the set $E'_{\mathscr{Q}}$ is 1 or all events have identical timestamps defined by the function f'_a, continue with the next quantity $\mathscr{Q}$ from $\mathcal{Q}$.
  – Order the events from $E'_{\mathscr{Q}}$ into a sequence $l'_{\mathscr{Q}} = \langle e'_1, e'_2, \ldots, e'_m \rangle$ according to their timestamps, as defined by the function f'_t. Events with identical timestamps can be placed in any order.
  – Calculate the time intervals for the sequence $l'_{\mathscr{Q}}$ as a multiset[2]of numbers: $\Delta'_{\mathscr{Q}} = [f'_t(e'_{i+1}) - f'_t(e'_i) \mid 1 \leq i < m]$.
  – Calculate the mean interval value $\mu'_{\mathscr{Q}}$ for the multiset $\Delta'_{\mathscr{Q}}$.
  – For each state i, such that[3], $\mathscr{Q} \leq i \leq k$, set the $q_{i,i-\mathscr{Q}} = \frac{1}{\mu'_{\mathscr{Q}}}$.
- Set all undefined non-diagonal entries of the matrix Q to 0 and define all diagonal entries as $q_{i,i} = -\sum_{j,j \neq i} q_{i,j}$.
- Return $CTMC = (\lambda, Q)$.

This algorithm illustrates how to construct a model of clients' purchasing behavior for each product available in the store. A fragment of a purchasing

[2] Note that the same time interval may appear multiple times.
[3] We assume that k is large enough and larger than any value of $\mathscr{Q}$ presented in the data.

behavior model, in which clients buy either one or two units of the product, is presented in Figure 2. Notice that in this model $q_{k,k\text{–}1} = q_{k\text{–}1,k\text{–}2} = q_{k\text{–}2,k\text{–}3}$, and $q_{k,k\text{–}2} = q_{k\text{–}1,k\text{–}3}$. The models discovered from event data using Algorithm 1 represent only the purchasing behavior. The following subsection discusses the enhancement of these models with supply transitions and their further analysis.

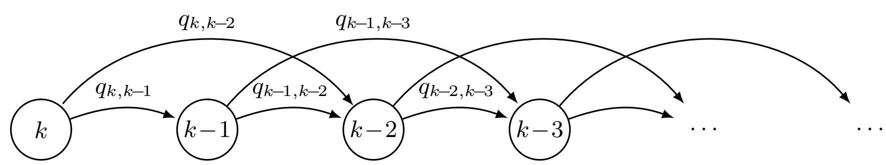


Figure 2: A fragment of a continuous-time Markov chain modeling clients' purchasing behavior when clients buy either 1 or 2 units of the given product.

4.2 Enhancement and analysis of the discovered continuous-time Markov chain

Once the clients' behavior process is discovered, it can be enhanced with backward transitions that model the store's supply strategies. For example, the store may choose to supply all products at the same rate, approximately once a week, with deliveries made in large batches to replenish the stock. This enhancement updates all models corresponding to different products by adding backward transitions with a specified supply rate q_s, connecting states based on the quantity of supplied products. For example, if a product is supplied in batches of $\mathscr{Q}$ units, each state $0 \leq i \leq k - \mathscr{Q}$, where k is the store's capacity for the product, is connected to the state $j = i + \mathscr{Q}$. The model assumes that no supply occurs if the resulting quantity would exceed the capacity k.

The enhanced continuous-time Markov chain will contain both forward and backward transitions (as illustrated in Figure 1) and should be checked for irreducibility. As will be demonstrated later, in real-life processes, almost all products can be sold in quantities of 1. Consequently, the resulting continuous-time Markov chain will contain forward transitions connecting neighboring states, such as i and $i + 1$. We will show that, in this case, any supply strategy will result in an irreducible model.

Theorem 1 (Irreducibility). *Let CTMC be a continuous-time Markov chain defined on a set of states* $S = \{0, 1, \dots, k\}$ *and discovered by Algorithm 1 from store event data, where products are sold in quantities that include 1. Then, for any supply strategy that adds backward transitions between reachable states without exceeding the capacity, the resulting enhanced model is irreducible.*

Proof. To prove irreducibility, we need to demonstrate that every state $i \in S$ is reachable from any other state $j \in S$. It suffices to show that the state corresponding to the maximum capacity k is reachable from j, and that every state

i is reachable from k via a sequence of forward transitions through the states $k, k-1, \ldots, i$.

Let $\mathscr{Q}$ be the supply batch size. Starting in state j, we can apply a sequence of backward transitions (representing supply events) to reach some state j' such that $k-\mathscr{Q} < j' \leq k$.

If $j' = k$, we have reached the maximum capacity. Otherwise, we apply forward transitions from j' to $k-\mathscr{Q}$, followed by a single backward transition to reach state k. $\square$

Once an irreducible continuous-time Markov chain has been constructed, it can be used to analyze the model and determine the distribution over states, i.e., the probabilities of being in each state during a sufficiently long system run. These probabilities are called *steady-state probabilities* and can be computed using the global balance equation: $\pi Q = 0$, where $\pi = (\pi_1, \ldots, \pi_k)$ is the vector of steady-state probabilities, subject to the normalization condition $\sum_{1 \leq i \leq k} \pi_i = 1$.

Knowing the probability of being in each state, that is, the probability of having a given number of product units in the store, allows for the assessment of food waste in relation to product oversupply. This analytical approach will be discussed and applied to real-world event data in the following section.

5 Case Study

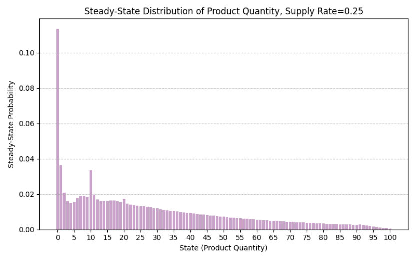
The proposed approach was implemented[4] and tested on real-world grocery store data[5]. The dataset contains grocery store transactions, including information on which product was purchased, in what quantity, and at what time. Overall, the dataset contains information on 300 unique product identifiers and 7,829 transactions. This dataset can be considered as an event log (Definition 1) to which Algorithm 1 can be applied. Because nearly all products had at least one transaction with a quantity of 1 (with only 8 exceptions), irreducible continuous-time Markov chains were able to be constructed and analyzed.

Figure 3 presents the steady-state distributions for continuous-time Markov chains constructed for a specific product from the fruit category. This fruit was purchased in quantities ranging from 1 to 4. The store capacity for this type of product was set to 100, and the batch size for the supply strategies was defined as 10. The supply rates considered included 0.25 (i.e., one supply every 4 hours), 0.30, 0.35, and 0.40. The probabilities of being in a state from 0 to 3 (indicating undersupply) are 0.1867, 0.0642, 0.0153, and 0.0031 for supply rates of 0.25, 0.30, 0.35, and 0.40, respectively. State 0 exhibits a relatively high steady-state probability. This is due to the fact that it only has backward transitions associated with supply, and no further purchases can occur from this state.

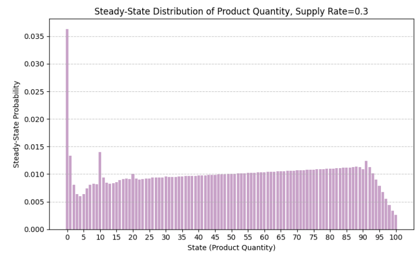
Using the steady-state distributions, the expected product quantities corresponding to supply rates of 0.25, 0.30, 0.35, and 0.40 are calculated as 27.77,

[4] The code is available at `https://github.com/akalenkova/foodwaste`.

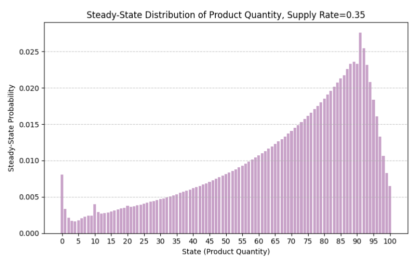
[5] `https://www.kaggle.com/datasets/abhinayasaravanan/grocery-supply-chain-isuue`.



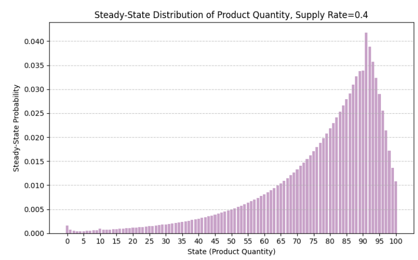
(a) Steady-state distribution for a supply rate of 0.25 per hour.



(b) Steady-state distribution for a supply rate of 0.30 per hour.



(c) Steady-state distribution for a supply rate of 0.35 per hour.



(d) Steady-state distribution for a supply rate of 0.40 per hour.

Figure 3: Comparison of steady-state distributions across different supply strategies for a fruit product.

49.35, 67.34, and 77.31, respectively. One may also observe that state 91 has a relatively high probability, which can be explained by the fact that it has no outgoing supply transitions due to the batch size of 10.

Assuming that any quantity exceeding a certain threshold (e.g., 70 units) results in food waste, the expected surplus can be calculated for each model. Using 70 as the threshold for the given product, the expected surplus, potentially indicating food waste, is 1.0239, 4.1024, 8.4592, and 12.1044 for supply rates of 0.25, 0.30, 0.35, and 0.40, respectively. The stochastic models highlight a trade-off: as the supply rate grows, undersupply diminishes, whereas oversupply intensifies.

We consider this framework as a foundation for future developments in food waste analysis. First, we plan to develop methods for optimizing supply processes across all products in the store, recognizing that while supply batch sizes may vary, supply rates are often similar due to simultaneous delivery. Second, we aim to extend the continuous-time Markov chain model by explicitly incorporating food waste and linking it to product quantity and shelf time. Finally, we intend to study transition times and generalize the model to accommodate non-exponential time distributions, while also incorporating additional parameters such as financial factors and sustainable supply strategies.

6 Conclusion

This paper combines object-centric process mining and stochastic process discovery to propose a novel approach for analyzing food retail processes. The proposed *what-if* analysis enables the evaluation of different supply strategies by assessing the trade-off between food waste and product availability. By modeling customer purchase behavior with continuous-time Markov chains and enhancing these models with supply dynamics, we provide a quantitative basis for assessing and improving inventory management in grocery stores.

The approach was implemented and tested on real-world grocery store data, demonstrating its practical applicability. Through steady-state analysis, we were able to derive insights into stock levels, undersupply, and potential food waste under varying supply scenarios. Our results show that the method can effectively identify critical supply thresholds and offer guidance for decision-making in retail logistics.

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