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A value chain modeling approach for upscaling the production of fine flavor cocoa in Arauca (Colombia)

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Abstract

The fine flavor cocoa (FFC) market offers additional income for small farmers. Despite the potential of several Latin American countries to produce FFC, their lack of standardized postharvest processes hinders compliance with high-quality standards demanded by the FFC market, as these processes have a direct impact on cocoa's organoleptic characteristics. This work supports the design of a collective postharvest transformation model that coordinates the main steps in the cocoa agri-food chain: transport of the cocoa harvest, classification, fermentation, drying, storage, and commercialization. Our methodology includes a modeling scheme combining optimization and simulation models, considering variability in the processes, and covering operational (transport and resource allocation), tactical (design and sizing of the processing plant), and strategic (sales dynamics) decisions across the cocoa value chain. We illustrate this methodology in a case study in Arauca, Colombia. Our findings emphasize the importance of combining these operational and strategic models since their inputs and outputs are interconnected influencing the decision-making within the cocoa value chain. Our study also identifies key determinants for the postharvest design, highlighting the postharvest center capacity, FFC prices, and the market selling mode (export or local).

Keywords: cocoa agri-food chain; postharvest center; fine flavor cocoa; cooperative model; operational research; optimization; simulation

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1. Introduction

Cocoa (*Theobroma cacao* L.) is a native species from the tropical forests of South and Central America, mostly grown (90%) on small farms (Araujo et al., 2014). The market classifies cocoa beans into two main categories: fine flavor cocoa (FFC) and bulk. These two categories are different in their organoleptic characteristics, sensory profiles, origin, traceability of the production process, and price.

Recently, the demand for FFC has grown steadily due to new consumer trends in global markets that favor FFC over bulk cocoa to produce chocolate (ICCO, 2020). Additionally, the FFC market offers monetary benefits and development opportunities to local farmers. Prices in the FFC market are determined by a bargaining process that fluctuates above the price of bulk cocoa by more than 1000 USD per ton (Ríos et al., 2017; ICCO, 2020), making it a promising crop for economic and social growth in rural areas.

Even though genetics, climate, and soil play a significant role in the quality of FFC, the cocoa postharvest transformation is essential to the development of chocolate flavors. During fermentation, the endogenous components of cocoa seeds are transformed into simpler compounds that have been called flavor precursor metabolites. During roasting, these metabolites react and generate flavor molecules expressed in sensory attributes in chocolate (Kongor et al., 2016; Santander Muñoz et al., 2020). Figure 1 shows the main activities in the cocoa value chain: harvest, transformation of pods into dried beans, and beans distribution and commercialization.

Despite the potential of some countries to produce FFC, postharvest practices in farms frequently lack standardized protocols and processes, which may cause cocoa to lose its quality. Artisan fermentation and transformation processes at farms often mix genetic species, do not consider sensory profiles, and lack aseptic control. Hence, cocoa does not develop into FFC. In addition, most of the producers (about 80%–90%) grow cocoa in small farms that range between two and four hectares (0.5 hectares in Colombia) (Beg et al., 2017), making their production levels too low to negotiate with buyers. The FFC market demands high quality and consistency for each batch of cocoa bean produced and enough volume to supply long-haul containerized shipments (for instance, 20-foot shipping containers with 25 tons of cocoa), which is hard to achieve by small farmers. Consequently, a postharvest transformation model operating under consistent standards fosters a consistent throughput of high-quality FFC and would generate improved revenue for the cocoa producers.

Through a cooperative transformation model, it is possible to conduct postharvest operations collectively in a processing plant with standardized equipment, labor, and classification and production methods (Dongo et al., 2009). Different studies, such as Abbott et al. (2017), propose a business model that integrates small cocoa farmers into cooperatives. This operating structure, specifically in agri-food chains, requires farmers working through a jointly owned and democratically controlled organization (FAO, 2012), enhancing access to markets and prices, information sharing, and agriculture technologies.

This work presents the design of a cooperative model owned by smallholders for upscaling the production of cocoa beans with fine sensory attributes, supported by a three-stage operational research methodology. The study includes the transportation of cocoa pods from farms to the processing plant, the transformation processes at the plant (fermentation and drying), the storage

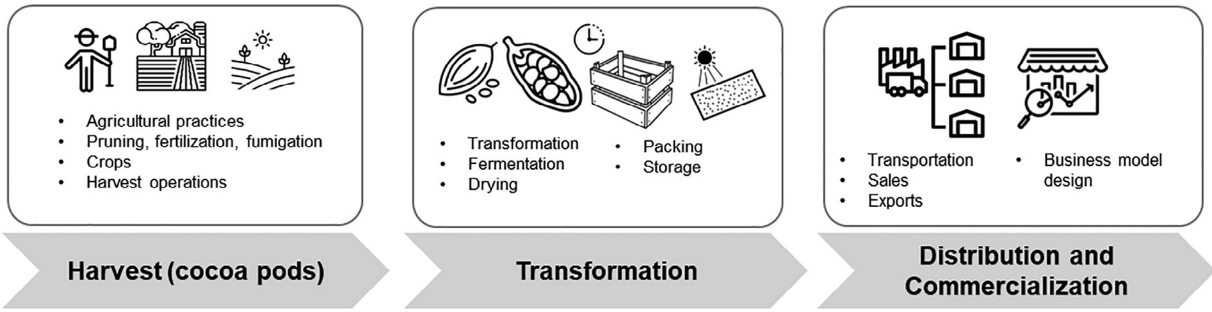

Fig. 1. Main activities in the cocoa value chain.

of cocoa beans at the production facility, and the sales planning and profit analysis for FFC and bulk cocoa.

We illustrate the methodology with a case study in Arauca (Colombia). Recently, cocoa crops in Colombia have increased their relevance, being labeled the *crop for peace*, since its family-based farms and long-term life cycle comprises a unique opportunity to re-energize remote areas where the internal conflict took place for decades. Furthermore, the Colombian government focused its efforts on increasing and promoting cocoa production, especially of FFC, with the aim of improving competitiveness of this agri-food chain and industry internationally (Abbott et al., 2017).

2. Related work

The inherent complexity of decisions in agriculture has attracted operational researchers and practitioners for several decades (Weintraub et al., 2007). The applications of operational research have focused on improving operational efficiency and efficacy and supporting decision-making in areas such as crop rotation, harvesting, processing, transportation and logistics, and access to markets, among others (Pla-Aragonnes, 2015; Gupta et al., 2023). Some methods used to model and improve productivity of agri-food chains are linear programming (LP), dynamic programming, stochastic programming, mixed integer programming (MIP), simulation, metaheuristics, and Markov chains, among others. Methods such as LP, MIP, and heuristics have been widely used in harvest planning, location models, and transport allocation (Weintraub & Romero, 2006; Ahumada & Villalobos, 2009). Other authors use stochastic methods to deal with uncertainties in agri-food chains and improve their performance. As an example, Albornoz and Vera (2023), use a stochastic bilevel program to coordinate the harvest planning and scheduling in agri-food supply chains; and Mateo-Fornés et al. (2023) explore the variability of the quality in processed agri-food products through a two-stage stochastic program model.

The application of combined operational research techniques to improve agri-food chains has been wide in scope. In the case of sugarcane, Teixeira et al. (2023) represent the main stages of the sugarcane supply chain through mathematical optimization models, emphasizing on the strength of the models and solution methods in the harvesting phase. For perishable agricultural products, several authors have employed descriptive and prescriptive analytics models to study their harvesting operations since these have different ripening rates. Escallón-Barrios et al. (2022) proposed an analytics solution involving simulation and optimization models to synchronize the use of resources (e.g., crews and a cable car transportation system) to solve the harvest cycle length problem in the palm oil supply chain. Aside from operational efficiency objectives, other authors have addressed other criteria while studying agri-food chains. For instance, Clavijo-Buritica et al. (2023) addressed the resilience of the coffee supply chain by using optimization and simulation; and Rönnqvist et al. (2023) described different levels of collaboration and sharing restrictions between farms through optimization models.

Focusing on cocoa, some authors have used operational research techniques to model parts of the cocoa agri-food chain. Sana et al. (2017) proposed an optimization model in a collaborative system between producers and traders to maximize profits from cocoa sales in Bolívar, Colombia. Similarly, our study aims to explore the dynamic of cocoa production, sales, and its profits. However, we do not plan to design a collaborative system between producers and traders but rather one of our goals is to increase the volume and quality of FFC production, which translates into larger profit margins for the farmers. Mujica Mota et al. (2019) proposed a discrete-event simulation (DES) model for the cocoa agri-food chain in Côte d'Ivoire. This model aims to identify inefficiencies and bottlenecks in cocoa transportation. In contrast, our model aims to standardize the cocoa production process; therefore, it considers not only the transportation of cocoa pods but also its postharvest processing and profit analysis. Alshekhli et al. (2011) proposed a computer-aided process simulation to analyze the production processes of industrial cocoa in Malaysia. This type of simulation allows for plant dimensioning and processing cost calculations. This model, unlike ours, solely focuses on cocoa processing to produce chocolate, thus avoiding decisions associated with cocoa seeds transportation and sales planning. Van Hoof et al. (2024) combined Monte-Carlo methods for simulating critical resource and production flows with multi-criteria decision-making to explore circular economy alternatives in cocoa farms in the state of Meta (Colombia), including feedback from farmers in a transdisciplinary-based research methodology.

Recently, the research landscape in agri-food chains has evolved to embrace a sustainability perspective. Studying agri-food chains through the sustainability viewpoint requires a more holistic approach that includes farmer welfare, technology innovation, circular economy practices, and financial metrics, among other criteria (Gupta et al., 2023). As highlighted by Higgins et al. (2010), the need for a systemic view to coordinate the agri-food chains demands the analysis of all the echelons in the supply chains to identify risk factors, uncertainties, and improvement opportunities. However, most of the time, there is a lack of a comprehensive design of these agri-food supply chains.

This work aims to fill an existing gap in the literature and promote sustainable production patterns aligned with the 12th Sustainable Development Goal (Responsible Consumption and Production) (United Nations-UN, 2024) by designing a comprehensive model of the cocoa agri-food chain, including harvest output, first-mile transportation, postharvest transformation, and commercialization. Our interconnected modeling covers: yield estimation; transport of the cocoa harvest from small farms to the processing plant; classification of pods into compatible varieties; fermentation, drying, and storage of cocoa beans; and sales and inventory planning to maximize profit. Our solution comprises interconnected operational research models that include optimization and simulation methods that account for certain degree of variability.

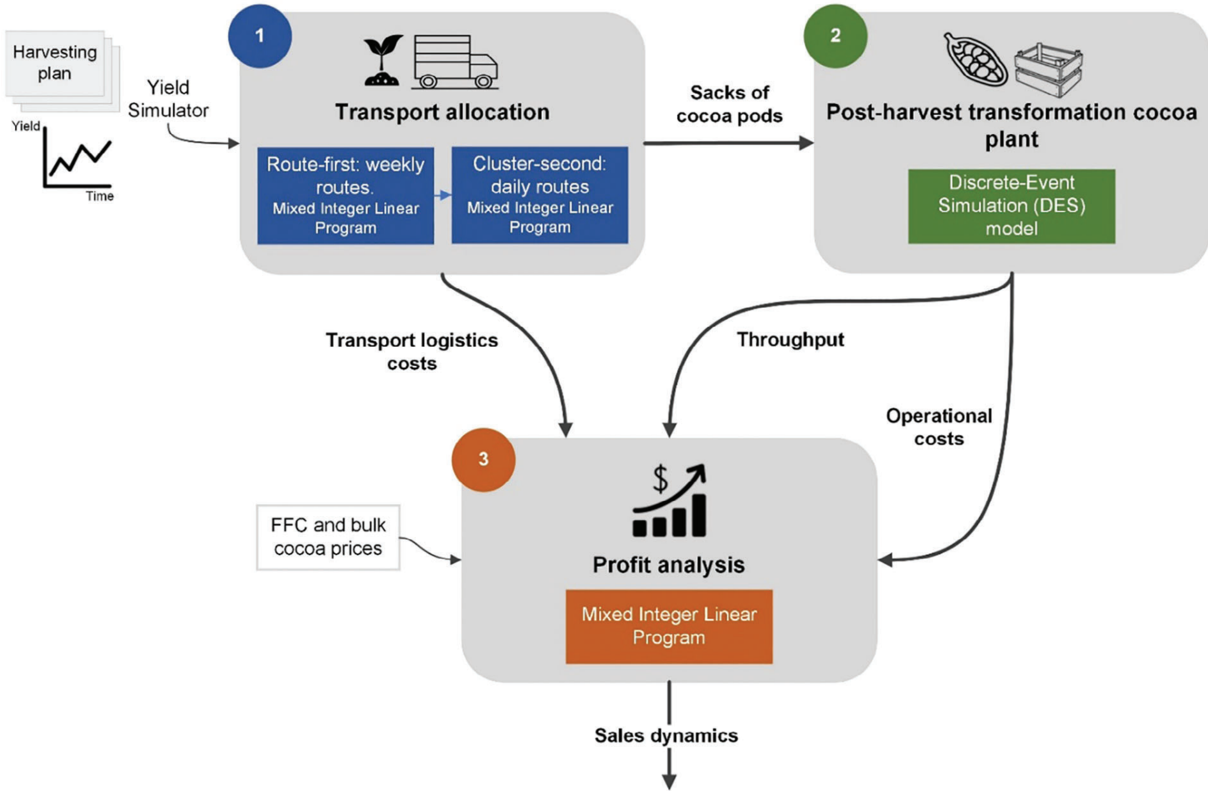

Fig. 2. A three-stage approach for the design of an interconnected cocoa agri-food chain modeling.

3. Methodology

The cocoa agri-food chain encompasses multiple stages, including production, harvesting, processing, distribution, and sales, among others. Our collective model concentrates on stages beyond production and harvesting. Specifically, we address crop transportation, cocoa transformation processes, and sales decisions, tackling them in an interconnected manner (see Fig. 2). We follow a bottom-up approach, starting with logistic and operational decisions, which allows us to progress to strategic decisions regarding sales timing while analyzing the plant's profitability.

For upscaling smallholders' production, first, we establish a transport allocation model that defines harvest collection routes from farms to the processing plant. Then, a simulation model prototypes the plant's transformation processes, providing outputs on cocoa bean throughput and guiding decisions on machinery and workforce requirements. Last, a profit analysis model uses the cocoa bean throughput and the operational costs, to optimize cocoa bean sales decisions aiming to maximize profitability. This methodology is replicable and extensible to other cooperative agri-food chains.

Considering that cocoa production varies due to factors like seasonality and yield fluctuations by cocoa variety, we first estimated the distribution of the monthly production. In Fig. 2, this component appears as *yield simulator*, and captures the inherent stochastic nature of the cocoa production by a farm. This (random) cocoa production is used as input for the first stage, namely, the *transport allocation model*, which establishes the postharvest collection routes that minimize transport logistics costs and balances the daily load to the processing plant. To build these routes, we followed a route-first cluster-second approach that is supported by mixed integer linear optimization models. With the optimal transport policy and the number of cocoa pods collected daily, the next stage receives the cocoa input amounts and models the postharvest transformation processes at the plant through a discrete-event simulation (DES). This DES model considers the variability of the cocoa input and resembles the complex transformation processes within the plant, along with their interactions and timing, which is challenging to represent with simpler queueing models. Through the execution of multiple scenarios, one of the DES model's aims is to identify productivity bottlenecks that help determine the necessary resources (e.g., workers, fermentation equipment, and dryers) required to achieve the desired system performance. The DES model also establishes the weekly throughput of processed cocoa and the operational costs associated with the weekly payroll. Finally, the third stage of our methodology defines the profit analysis model, which takes as input the transport logistics costs, the plant's operational costs, and the weekly throughput of processed cocoa to determine when and how much FFC and bulk cocoa to sell to maximize profit. This profit analysis is modeled via mixed integer linear optimization.

To emphasize how the three stages are connected, note that everything starts from the *yield simulator* that generates multiple realizations of the random yields per farm, capturing the seasonality of the crop. The yield realizations define multiple instances for the *transport allocation model*. The output of the multiple instances of the transport allocation model captures the variability of the daily routes that enter the processing plant modeled by the *DES model*. A single replicate of the DES model generates a weekly throughput of bulk and FFC cocoa over a year that feeds the *profit analysis model*. As the DES model has multiple replicates, it generates multiple instances for the profit analysis model.

This three-stage methodology provides a complete view of the postharvest cocoa value chain, including the transport of cocoa pods to the plant, the transformation processes at the plant, and sales and inventory management strategies to access high-value markets.

3.1. Transport allocation model

This model receives as input from the yield simulator the weekly number of cocoa pods to be harvested in the rural areas. As a result, this model finds the (near-) optimal daily harvesting routes that minimize the transport logistics costs associated with carrying the cocoa from the farms to the processing plant while keeping the daily load balanced. The routing model is based on the classical optimization problem known as the time-constrained capacitated vehicle routing problem (TCVRP) (Cokyasar et al. 2023), which is the time variant of the distance-constrained capacitated vehicle routing problem (DCVRP) (Toth & Vigo, 2002). The output of the routing model is the input of a clustering model that puts together routes to guarantee a daily balanced workload for the processing plant. To solve this problem, we used a route-first, cluster-second approach.

3.1.1. Route-first stage: finding the weekly routes

In this stage, we obtain the routes needed to collect the weekly harvest of cocoa from the rural areas to start its transformation process at the plant. We addressed this problem with a mixed integer linear programming (MILP) model, whose parameters description can be found in Table B1 in Appendix B.

To determine the whole set of weekly collection routes from the processing plant to the rural areas (and back), we let $\mathcal{N}$ be the set of nodes to visit including the depot (processing plant), which we denote as $\mathcal{N} = \{0, 1, \ldots, n, n+1\}$. Note that nodes 0 and $n+1$ represent the depot, and nodes $1, \ldots, n$ represent the rural areas. In terms of data, the parameter p_i corresponds to the amount of cocoa (pods) that each rural area $i \in \mathcal{N}\backslash\{0, n+1\}$ produces in a given week. The parameter b_i corresponds to the number of cocoa sacks (filled with pods) to be collected at each rural area $i \in \mathcal{N}\backslash\{0, n+1\}$. Parameters p_i and b_i are related by the conversion factor γ, which denotes the number of pods per sack. The parameters $\tau_{i,j}$ correspond to the travel time (in minutes) between nodes $i \in \mathcal{N}$ and $j \in \mathcal{N}$. The parameters c and $t^{\max}$ correspond to the load capacity (in pods) and the time limit or maximum route time (in minutes) of the vehicles, respectively. The parameter σ corresponds to the cost of the trip per minute used by each vehicle, and the parameter η corresponds to the number of vehicles available to collect the harvest. The parameter l corresponds to the estimated time for loading a cocoa sack into the vehicle. In terms of decisions, the binary variable $x_{i,j}$ takes the value of 1 if the rural areas $i \in \mathcal{N}$ and $j \in \mathcal{N}$ are visited in sequence; it takes the value of zero, otherwise. The variable y_i represents the cumulative amount of cocoa before arriving to node $i \in \mathcal{N}$. Finally, variable w_i corresponds to the arrival time to node $i \in \mathcal{N}$. The *weekly route MILP model* follows:

$$\min \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} x_{i,j} \cdot \left(\tau_{i,j} + l \cdot b_i\right) \cdot \sigma, \tag{1}$$

s. t.

$$\sum_{j\in\mathcal{N}\backslash\{0\}|i\neq j} x_{i,j} = 1 \qquad \forall i \in \mathcal{N}\backslash\{0,\ n+1\}, \tag{2}$$

$$\sum_{i\in\mathcal{N}\backslash\{n+1\}|i\neq j} x_{i,j} = 1 \qquad \forall j \in \mathcal{N}\backslash\{0,\ n+1\}, \tag{3}$$

$$\sum_{j\in\mathcal{N}\backslash\{0\}} x_{0,j} \leq \eta, \tag{4}$$

$$\sum_{i\in\mathcal{N}\backslash\{n+1\}} x_{i,n+1} \leq \eta, \tag{5}$$

$$\sum_{j\in\mathcal{N}\backslash\{0\}} x_{0,j} = \sum_{i\in\mathcal{N}\backslash\{n+1\}} x_{i,n+1}, \tag{6}$$

$$\sum_{j\in\mathcal{N}\setminus\{0\}} x_{0,j} \geq \left\lceil \frac{\sum_{i\in\mathcal{N}\setminus\{0,n+1\}} p_i}{c} \right\rceil, \tag{7}$$

$$w_i \leq t^{\max} \qquad \forall i \in \mathcal{N}, \tag{8}$$

$$w_j \geq w_i + \tau_{i,j} + l \cdot b_i - t^{\max}\left(1 - x_{i,j}\right) \qquad \forall i \in \mathcal{N}, \forall j \in \mathcal{N}, \tag{9}$$

$$y_i \leq c \qquad \forall i \in \mathcal{N}, \tag{10}$$

$$y_j \geq y_i + p_i - c\left(1 - x_{i,j}\right) \qquad \forall i \in \mathcal{N}, \forall j \in \mathcal{N}, \tag{11}$$

$$x_{i,j} \in \{0, 1\} \qquad \forall i \in \mathcal{N}, \forall j \in \mathcal{N}, \tag{12}$$

$$y_i \geq 0 \qquad \forall i \in \mathcal{N}, \tag{13}$$

$$w_i \geq 0 \qquad \forall i \in \mathcal{N}. \tag{14}$$

The objective function (1) minimizes the logistics cost associated with transporting the cocoa pods from each rural area to the processing plant. Note that it suffices to minimize $z = \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} \tau_{i,j} \cdot x_{i,j}$, which represents the total travel time, as it is necessary to visit every rural area to collect their pods. After the optimization process, the logistics cost can be computed by the expression $\sigma \cdot (z^* + l \cdot \sum_{i\in\mathcal{N}} b_i)$, adding to the total travel time, the loading service times and multiplying by the cost per time σ. The sets of constraints (2) and (3) require each rural area to be visited by only one route. Constraints (4) and (5) ensure that the number of routes departing from and arriving to the processing plant should be less than or equal to the maximum number of vehicles available. Constraint (6) guarantees that the number of routes departing from and arriving to the plant match. Constraint (7) sets a lower bound on the number of routes required to collect the weekly production. The set of constraints (8) ensures that the cumulative transport time does not exceed the maximum route duration. Constraints (9) impose time consistency by ensuring that if node *i* and *j* are connected, the time to reach node *j* should be at least the time required to reach node *i*, plus the time required to load the sacks at node *i*, plus the time required to move from node *i* to node *j*. More importantly, these subtour elimination constraints extend those proposed by Miller et al. (1960) for the Travelling Salesperson Problem (TSP) to the TCVRP and are known by the acronym MTZ. Likewise, the set of constraints (10) ensures that the capacity of the vehicles is not exceeded; while constraints (11) guarantee the load consistency in a route and also act as MTZ subtour elimination constraints. Finally, constraints (12)–(14) specify the nature of the decision variables. Note that variables y_0 and w_0 can be preprocessed and fixed to zero, possibly leading to a slight performance improvement in the optimization process.

The model defined in (1)–(14) is known to have a weak dual bound that causes a slow convergence under a branch and bound solution procedure, making it difficult to prove optimality. Even though the quality of the solution might be good within a reasonable amount of time, the optimality gap will not provide that assurance. As an alternative, one could use an exact vehicle routing optimizer based on branch-and-cut-and-price (Pessoa et al., 2020; Errami et al, 2023; Yamín et al., 2024) or derive a stronger dual bound (or a heuristic) using a column generation on a set covering formulation (Feillet, 2010). Last, but not least, a simple constructive heuristic based on savings could lead to a fast and scalable procedure in practice (Mendoza et al., 2009).

3.1.2. Cluster-second stage: finding the daily routes

In this stage, a second model distributes the weekly routes over the six working days of the processing plant (Monday through Saturday). To this end, we see this problem as one of building daily route clusters to ensure that the processing plant has a daily stable inflow to avoid harsh variabilities that may cause congestion and excessive waiting and processing times. Conceptually, for each day, we define a cluster and assign routes found earlier (see Section 3.1.1) trying to minimize the absolute deviation between the collection load assigned to that day and the average daily load computed across the week. We model this clustering problem as a mathematical program. The model parameters with their description can be found in Table B1 in Appendix B. Let $\mathcal{R}$ be the set of weekly routes found in the first stage and $\mathcal{Q}$ the set of days. The parameter $\bar{z}$ denotes the average daily load, and it is defined by $\bar{z} \triangleq \sum_{r\in\mathcal{R}} p_r/|\mathcal{Q}|$, where p_r denotes the total load (pods) in route $r \in \mathcal{R}$. The binary variable y_{rd} takes the value of 1, if the whole load of route $r \in \mathcal{R}$ is sent to the plant in day $d \in \mathcal{Q}$; it takes the value of zero, otherwise. The decision variable z_d captures the total load (pods) sent to the plant in day $d \in \mathcal{Q}$. The *daily-route clustering model* follows:

$$\min \sum_{d\in\mathcal{Q}} |z_d - \bar{z}|, \tag{15}$$

s. t.

$$\sum_{d\in\mathcal{Q}} y_{rd} = 1 \qquad \forall r \in \mathcal{R}, \tag{16}$$

$$z_d = \sum_{r\in\mathcal{R}} p_r \cdot y_{rd} \qquad \forall d \in \mathcal{Q}, \tag{17}$$

$$y_{rd} \in \{0, 1\} \qquad \forall r \in \mathcal{R}, \forall d \in \mathcal{Q}, \tag{18}$$

$$z_d \geq 0 \qquad \forall d \in \mathcal{Q}. \tag{19}$$

The objective function (15) minimizes the absolute deviation between the daily load sent to the plant and the average daily load (across the week); that is, the objective balances the plant workload by making the daily input to the plant as close as possible to the daily average. Constraints (16) guarantee that all routes found in the previous stage are assigned to one (and only one) of the working days. The set of constraints (17) accounts for the total load of pods that enter the processing plant in any given day. Finally, the set of constraints (18) and (19) specify the nature of the decision variables.

To linearize the absolute value of the model's objective, we proceed as follows. As the terms $(z_d - \bar{z})$ in the objective (15) are *free* to take positive, negative, or zero values, we need to account for this variation between the daily load and the average daily load, using deviation variables. We define the deviation variables δ_d^+ and δ_d^- as the amount of load (pods) above or below the daily average (across the week) for day $d \in \mathcal{Q}$, respectively. For example, if the daily average (across the week) is 1000 pods/day and in any given day d the plant receives 1100 pods, then $\delta_d^+ = 100$ pods (and $\delta_d^- = 0$); on the contrary, if the plant receives 800 pods, then $\delta_d^- = 200$ pods (and $\delta_d^+ = 0$). As these deviation variables are non-negative, it is possible to linearize the absolute value in the objective and to capture the deviations with respect to the daily average in the equivalent mixed integer linear model of the (linear) daily-route clustering model:

$$\min \sum_{d \in \mathcal{Q}} \left(\delta_d^+ + \delta_d^- \right), \tag{20}$$

s. t.
(16)–(19),

$$\delta_d^+ - \delta_d^- = z_d - \bar{z} \qquad \forall d \in \mathcal{Q}, \tag{21}$$

$$\delta_d^+, \delta_d^- \geq 0 \qquad \forall d \in \mathcal{Q}, \tag{22}$$

where the objective function (20) minimizes the absolute deviation between the daily load sent to the plant and the average daily load (across the week). As only one of the two variables, either δ_d^+ or δ_d^-, account for the difference against the average daily load (i.e., the corresponding variable is always zero), and adding them leads to the same absolute deviation expressed in (15). Constraints (21) capture the (signed) difference between the daily load and the average daily load. Finally, constraints (22) define the non-negative nature of the deviation variables.

3.2. Postharvest cocoa plant DES model

The DES model receives the daily load of cocoa pods that randomly arrive at the processing plant. To generate this daily inflow of cocoa pods to the plant, we fit a normal distribution with mean and variance according to the output of the transport allocation model for every month. Additional model parameters include the percentage of pods from varieties with FFC potential that arrive at the plant, the seed weight per pod, and the number of workers in the processing plant. This stage presents the three main postharvest transformation processes that take place in the plant: pods classification and opening, fermentation, and drying. The production rate of bulk and FFC cocoa, along with the operational costs associated with the plant's weekly payroll can be calculated as model outputs.

Implementing the proper fermentation and drying practices with the right machines, materials, and timing is fundamental to the production of FFC and has a direct impact on cocoa quality (Schwan & Fleet, 2014). For instance, the maximum time between the extraction of cocoa seeds from pods and the start of fermentation should not exceed four hours (Afoakwa et al., 2013), and the maximum storage time for dry cocoa beans is around one year. With proper transformation processes, FFC will have the organoleptic characteristics of taste, color, and aroma that are typical of high-quality cocoa (ICCO, 2020). The DES model that follows accounts for such a level of detail to monitor key quality-related processes.

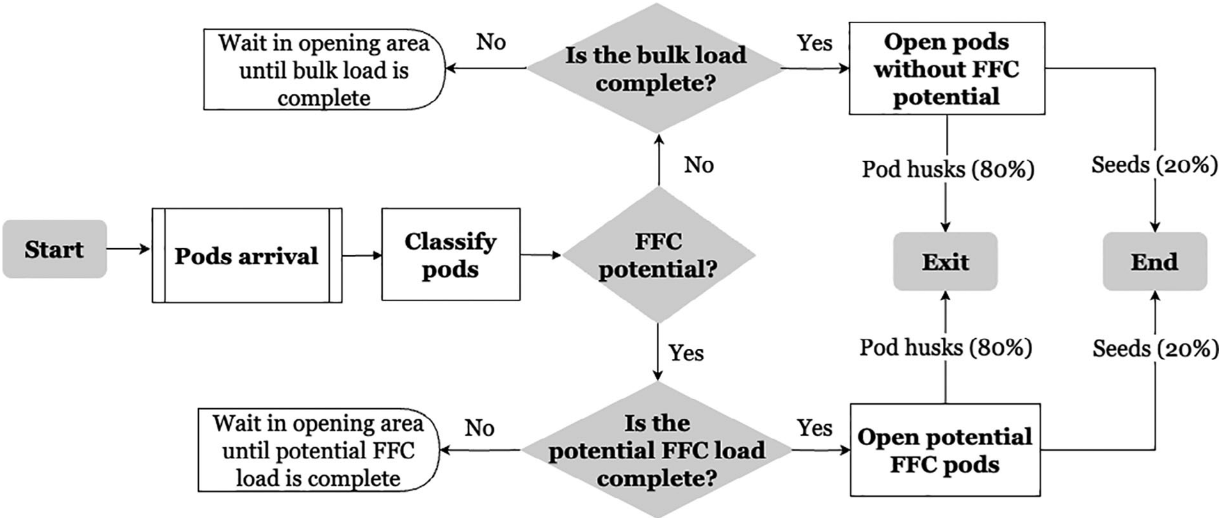

Fig. 3. Flow chart of the pods' classification and opening stage.

3.2.1. *Stage 1. Classifying and opening pods*

Cocoa pods (randomly) arrive to the processing plant, according to the distribution of daily load determined by the transport allocation model. The entities in the DES model are sacks of cocoa pods with a capacity of 40 kg each. Once the pods arrive, they are classified according to their genetic varieties, separating potential FFC and bulk pods. Then, they are opened to form batches of 400 kg of fresh seeds from compatible classifications (FFC or bulk). Fresh seeds represent just 20% of the original pods' mass (Schwan & Fleet, 2014); thus, the entity of the simulation model is transformed into packages of 8 kg of cocoa seeds. In the context of this study, the cocoa pod husks are discarded and excluded from consideration for any other processes.

It is worth mentioning that potential FFC pods cannot be opened until a determined number of sacks of FFC pod varieties have arrived at the plant. The rationale behind this batch-formation process is that fresh cocoa seeds should not wait more than four hours outside the pods before starting their fermentation process; otherwise; they jeopardize their quality. Since bioreactors for FFC fermentation have a given capacity, a determined number of cocoa sacks are required to fill them and start the fermentation process. We conduct the same procedure for the combination of pod varieties that become bulk cocoa since a determined number of sacks are required to fill the capacity of a wooden box for bulk cocoa fermentation. Figure 3 summarizes this process.

3.2.2. *Stage 2. Fermentation process*

The fermentation stage involves two chemical processes: (1) the induction of biochemical reactions inside the cocoa seeds and (2) the removal of the mucilaginous pulp that surrounds the seeds. These two processes are responsible for producing the flavor and aroma precursor metabolites (Albertini et al., 2015). The fermentation process for the FFC is carried out in a special fermentation equipment (SFE), a bioreactor powered by renewable energy, with no worker intervention. The seeds remain inside the bioreactor for two days without movement. Then, they are automatically mixed

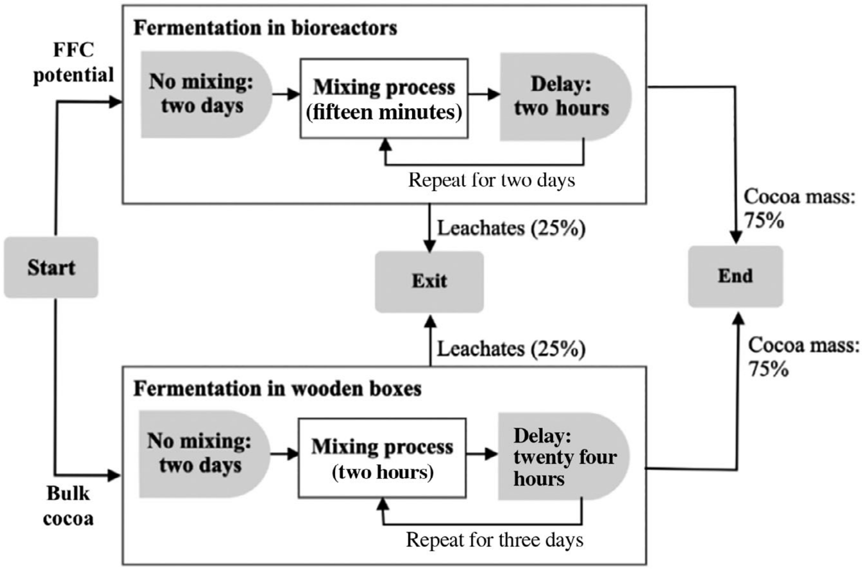

Fig. 4. Flow chart of the fermentation stage.

every two hours for 15 minutes during the next two days. On the other hand, bulk cocoa is fermented in wooden boxes. Similarly, cocoa seeds must remain inside the wooden boxes for a period of two days without mixing. Afterward, the seeds are manually mixed for two hours every 24 hours, during a period of three days.

In this stage, 25% of the seeds' mass is released as leachates (Schwan & Fleet, 2014); therefore, the DES *entity* changes from packages of 8 kg of fresh seeds to packages of approximately 6 kg of seeds. Figure 4 depicts the flow of the fermentation process.

3.2.3. Stage 3. Drying and storage

After fermentation, cocoa seeds begin their drying process, which involves changes in their features (color, flavor, and texture). Consequently, the development of precursor metabolites of flavor that started in the fermentation process continues in this stage (Rodriguez Campos et al., 2012). Cocoa seeds' humidity ranges between 40% and 50% after fermentation; however, it is reduced to 6%–7% after the drying process (Lutheran World Relief, n.d.). The humidity loss reduces the mass by approximately 60%. Again, the DES *entity* of the model changes from packages of 6 kg of seeds to packages of about 2.4 kg of dry beans. The drying process consists of three sequential stages. Initially, the seeds undergo a nine-hour drying period, followed by a four-hour resting period. Finally, they undergo an additional four-hour drying phase. Figure 5 presents the flow chart of the drying process.

3.3. Profit analysis model

Sales of FFC represent the main source of income, as it sells above the price of regular bulk cocoa (Ríos et al., 2017). Under the cooperative scheme, associated farmers process and store FFC until

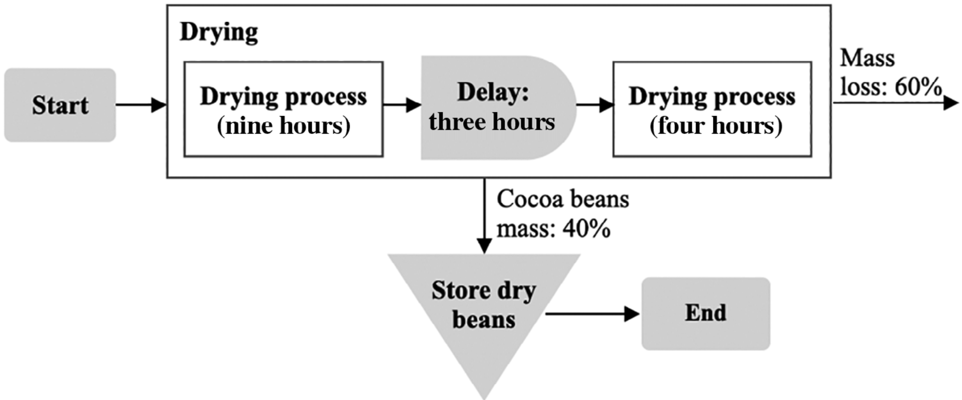

Fig. 5. Flow chart of the drying and storage process.

they can ship a container for export. Its price is agreed according to contracts between the buyer and the seller. In the meantime, bulk cocoa and FFC sales to the local market are responsible for generating profit and a stable cash flow for the plant.

This cooperative scheme, in which cocoa producers collaborate to organize functions and activities among themselves, brings additional benefits to the existing decentralized postharvest transformation system. Currently, each producer independently handles the cocoa processing and sales to the local market. However, by adopting a collective approach, producers gain access to high-value markets and can negotiate favorably better FFC prices, leading to a significant increase in their profits. Furthermore, operating as a cooperative allows farmers to gain access to financial markets, ensuring working capital to cover essential costs, such as payments to producers for cocoa pods. Ultimately, the main goal is to enhance profitability through this collective model, creating a scenario where the cooperative can even afford to provide quality premiums to its affiliated producers.

For this third stage, we propose a MILP, whose parameters summary is presented in Table B2 in Appendix B, to establish a sales plan for FFC and bulk cocoa that maximizes profit. This model also determines the optimal inventory policy for the cocoa beans storage over the time horizon of interest. It receives as input the transport logistics costs, operational costs, and random throughput of the processing plant, which are determined by the previous models.

For the problem formulation, let $\mathcal{T}$ be the set of weeks along the time horizon, that is, $\mathcal{T} = \{1, \ldots \tau\}$. Let n_t^B and n_t^F be the tons of bulk and FFC cocoa beans produced during week $t \in \mathcal{T}$ in the plant, respectively. Note that these throughputs are the random output of the simulation model. For a given replicate of the simulation, these parameters are specific realizations of the random variables. We define p_t^B as the selling price in USD per ton during week $t \in \mathcal{T}$ for bulk cocoa. The parameters $p_t^{F,\,E}$ and $p_t^{F,\,L}$ correspond to the export and local selling prices in USD per ton during week $t \in \mathcal{T}$ for FFC, respectively. Let c^P be the weekly amount to pay to the producers for a ton of cocoa pods, α the capacity in tons of the export container, c^E the export costs associated with the container, c^{FC} the weekly fixed total costs for the plant operation (workforce, storage, pods transportation, energy and equipment maintenance, and the costs related to the loan amortization for the initial capital investment), β the weekly cost of capital (interest rate), and parameter s the maximum storage capacity in tons of cocoa. The conversion factor from tons of dry beans to tons of cocoa pods is denoted by θ. Finally, let i_0^B and i_0^F be the parameters that represent the tons of bulk cocoa and FFC in storage at the beginning of the operation, respectively.

The model decisions account for selling positions and inventory levels. The variable z_t denotes the tons of bulk cocoa to sell in week $t \in \mathcal{T}$, f_t^E represents the number of 25-ton containers of FFC to export in week $t \in \mathcal{T}$, and f_t^L indicates the tons of FFC to sell locally. In addition, let i_t^B and i_t^F be the inventory in tons at the end of week $t \in \mathcal{T}$ of bulk cocoa and FFC, respectively. As for the financial structure of the model, u_t denotes the profit of the operation in week $t \in T$.

The profit analysis optimization model is defined as follows:

$$\max \sum_{t \in \mathcal{T}} \frac{u_t}{(1+\beta)^t}, \tag{23}$$

s. t.

$$i_t^B = i_{t-1}^B + n_t^B - z_t \qquad \forall t \in \mathcal{T}, \tag{24}$$

$$i_t^F = i_{t-1}^F + n_t^F - \left(\alpha \cdot f_t^E\right) - f_t^L \qquad \forall t \in \mathcal{T}, \tag{25}$$

$$i_t^B + i_t^F \leq s \qquad \forall t \in \mathcal{T}, \tag{26}$$

$$u_t = \left(z_t \cdot p_t^B + \left(\alpha \cdot f_t^E \cdot p_t^{F,\,E}\right) + f_t^L \cdot p_t^{F,\,L}\right) - \left(c^E \cdot f_t^E\right) - \left(\left(\frac{n_t^B + n_t^F}{\theta}\right) \cdot c^P\right) - c^{FC} \qquad \forall\, t \in \mathcal{T}, \tag{27}$$

$$f_t^E \in \mathbb{Z}_+^1 \qquad \forall t \in \mathcal{T}, \tag{28}$$

$$z_t, f_t^L,\; i_t^B, i_t^F \geq 0 \qquad \forall t \in \mathcal{T}, \tag{29}$$

$$u_t \in \mathbb{R}^1 \qquad \forall t \in \mathcal{T}, \tag{30}$$

where objective (23) maximizes the net present value by discounting the profit cash flows by the interest rate β. Constraints (24) and (25) model the inventory level of bulk cocoa and FFC, respectively, by setting the inventory level at the end of the week equal to the inventory carried from the previous week, plus the weekly production, minus the weekly sales. Constraints (26) keep the total inventory under the maximum storage capacity of the processing plant over the time horizon. Constraints (27) accounts for the weekly profit by adding sales of bulk cocoa and FFC; and subtracting the costs of cocoa pods and their transportation from the farmers to the plant, inventory costs, export costs of FFC, and variable and fixed weekly costs. Finally, constraints (28)–(30) specify the nature of the decision variables.

4. Case study: results and discussion

To illustrate our methodology, we consider the design of a large-scale processing plant of cocoa beans in the state of Arauca in Colombia. This region is identified as a key development zone

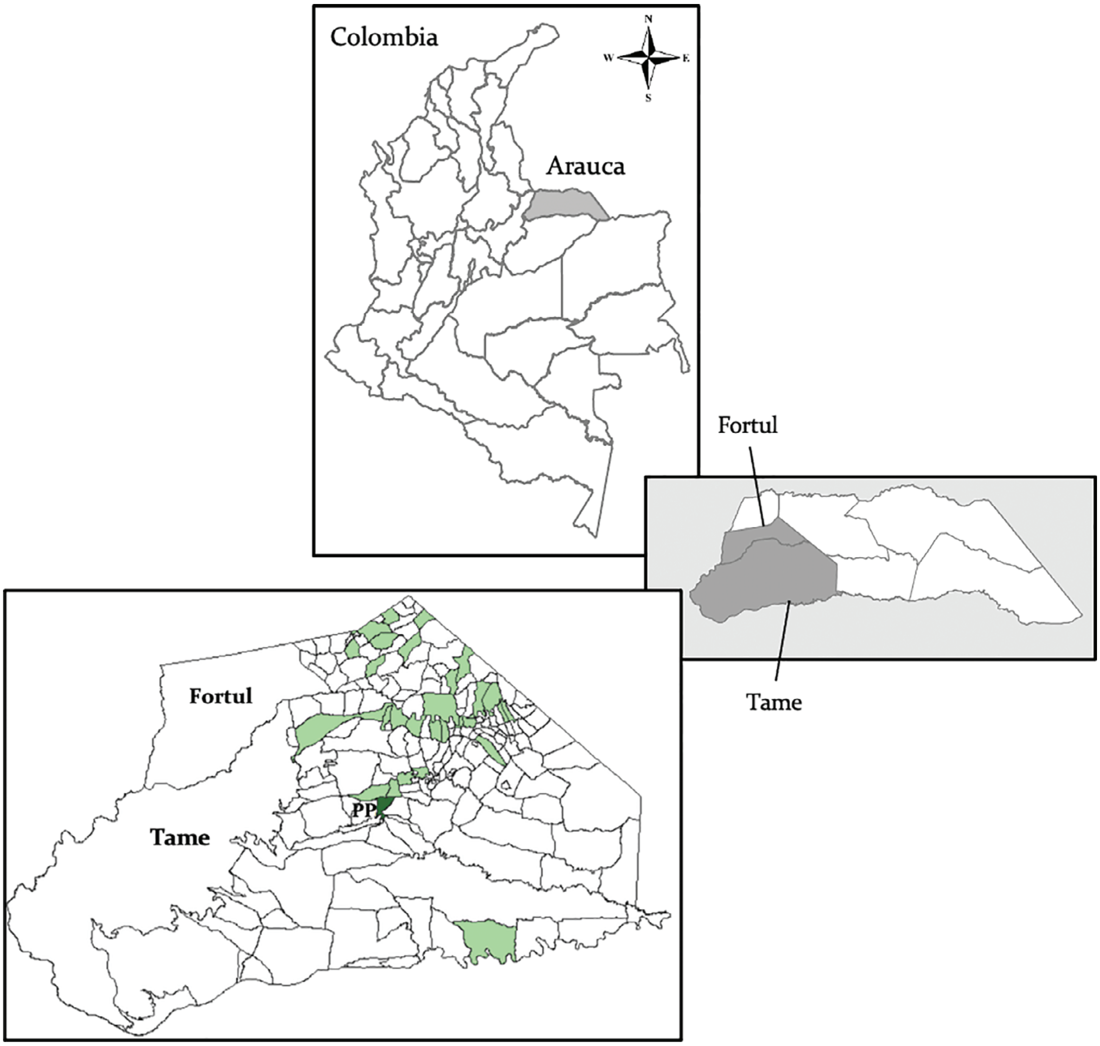

Fig. 6. Rural areas (in green) in Fortul and Tame (Arauca) covered by the collective processing plant. Adapted from (OCHA, 2014)

for agricultural projects that foster cocoa production in the country. Indeed, cocoa from Arauca has been recognized twice for its high quality at the "International Cocoa Awards" of the Salon Du Chocolat in Paris (Colombia CO, n.d.). Moreover, Arauca reported one of the largest cocoa productions in Colombia: 8.94% of the total Colombian production (Agronet, 2022). For its high-quality potential, Arauca is an ideal context for the design of an interconnected and cooperative production model. This implementation also serves as a pilot model to be applied to other regions and crops.

In this setting, cocoa pods are collected from small farms distributed throughout 29 rural areas in the municipalities of Tame and Fortul (Arauca) as shown in Fig. 6. Green areas represent the rural settlements where farms are located. The processing plant is denoted by PP in Fig. 6 and was conceived to process and produce a maximum of six tons of cocoa per week. Fermentation of FFC and bulk cocoa takes place in five SFE and 10 wooden boxes, respectively. Each of these units has a capacity of fermenting 400 kg of seeds. The plant also includes two dryers, with a 1000-kg capacity each. For quality standards required to access high-value markets of FFC, the entire postharvest process takes place within the plant, which includes opening the cocoa pods, fermenting, drying the seeds, and storing the cocoa beans.

In the upcoming sections, we describe the results of the methodology shown in Section 3. The transport allocation and profit analysis optimization models were built using Python and Gurobi (Gurobi Optimization LLC, 2024) as the optimization engine. The transport allocation model experiments were conducted on an Intel Xeon Gold 6230R CPU running at 2.10GHz with two processors with 64GB of RAM on a Windows 10 64-bit environment. For the postharvest cocoa plant DES model, we used Simio (Smith & Sturrock, 2023), an object-oriented simulation modeling framework. The DES model and profit analysis model experiments were conducted on an Intel Core i5-1135G7 running at 2.40GHz with four cores with 8GB of RAM on a Windows 11- Pro 64-bit environment.

4.1. *Yield simulator*

The production estimates of cocoa pods in the farms are perhaps the most critical inputs for the methodology. These estimates initially feed the transport allocation model, push cocoa into the agri-food system, and introduce sources of variability.

The logic of the yield simulator follows. First, we determined the number of cocoa trees for each cocoa variety in each municipality (Tame and Fortul). This estimation considers the annual cultivated hectares and the cocoa planting density in Arauca. Next, considering the annual cocoa pods per trees, we estimated the minimum, maximum, and average total of pods per year for each municipality. This is the first source of variability with the total pods following a triangular probability distribution. As a second source of variability, the yield simulator includes the monthly fluctuation of cocoa production in Arauca according to historic records. Combining these sources, the simulator calculates the production of cocoa pods per municipality in a typical week of each month. Due to the postharvest center capacity, only a fraction of the weekly production is considered for collection. Last, we allocate the weekly production to the rural areas of Tame and Fortul, based on the number of productive units (farms) in the municipalities. Based on this logic, the yield simulator randomly generates data of the cocoa pods to be collected in each rural area (of Tame and Fortul) in a typical week of each month considering the seasonality of the crop. Figure 7 summarizes the data generated for the case study, where two harvest peaks occur in May (fifth month) and December (12th month). This output assumes that 1% of the total production of Tame and Fortul is collected and sent to the processing plant.

4.2. *Transport allocation model*

The transport allocation model assembles the weekly routes that collect the harvest from the rural areas and deliver the cocoa pods to the processing plant balancing the daily inflow by clustering

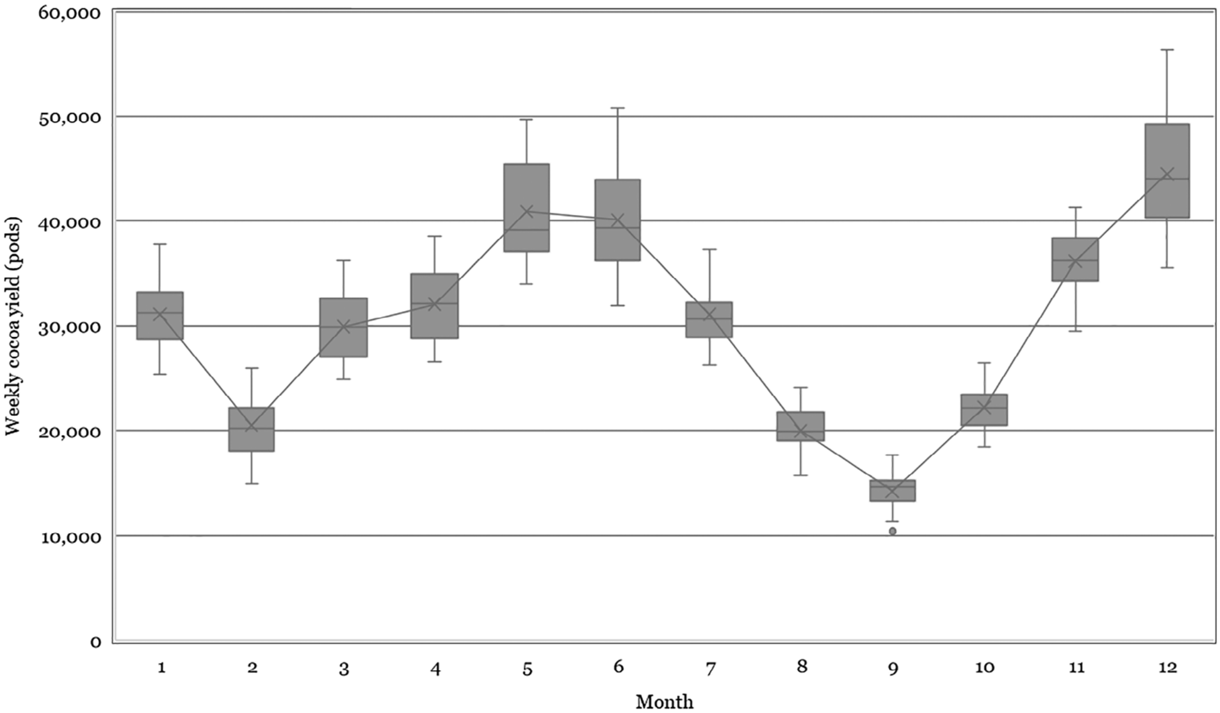

Fig. 7. Sample output of the yield simulator. Weekly production for each month to be collected in the rural areas of Tame and Fortul.

the routes by days. Using the yield simulator, we generated data for the 29 rural areas in Fortul and Tame, capturing the seasonality and variability of every month. For every month, we generated 20 random weekly productions for every rural area. One of the parameters of the yield simulator is the fraction of the cocoa production of the two municipalities sent to the processing plant. As this plant is a pilot with limited capacity, we explored three scenarios for the transport allocation model, allowing its capacity to capture 0.5%, 1.0%, and 2.5% of the production of Tame and Fortul.

Between the two optimization components within the transport allocation model, the MILP that finds the weekly routes (see Section 3.1.1) is computationally harder to solve than the MILP that finds the daily routes (see Section 3.1.2). For this reason, we focused on calibrating the routing model to obtain a good-quality solution within a reasonable amount of time. We took the scenario with the production of 1% and focused on a month where the production is high (viz., December). Figure 8 shows a typical execution of the routing model.

Figure 8 shows how the solution quality (primal bound) improves dramatically in just a few seconds. In less than five seconds, the optimization model reaches the optimal solution with an objective value (logistics costs) of 930,440. At that time, the dual bound promises an objective that could be as low as 735,048 with an optimality gap of 21.0%. For this reason, the solver continues improving the dual bound slowly until it proves optimality after 3990 seconds. As it is known that the model defined in Section 3.1.1, Equations (1)–(14), has a weak dual bound, we derived a stronger one with a column generation approach on a set covering formulation (Feillet, 2010). This

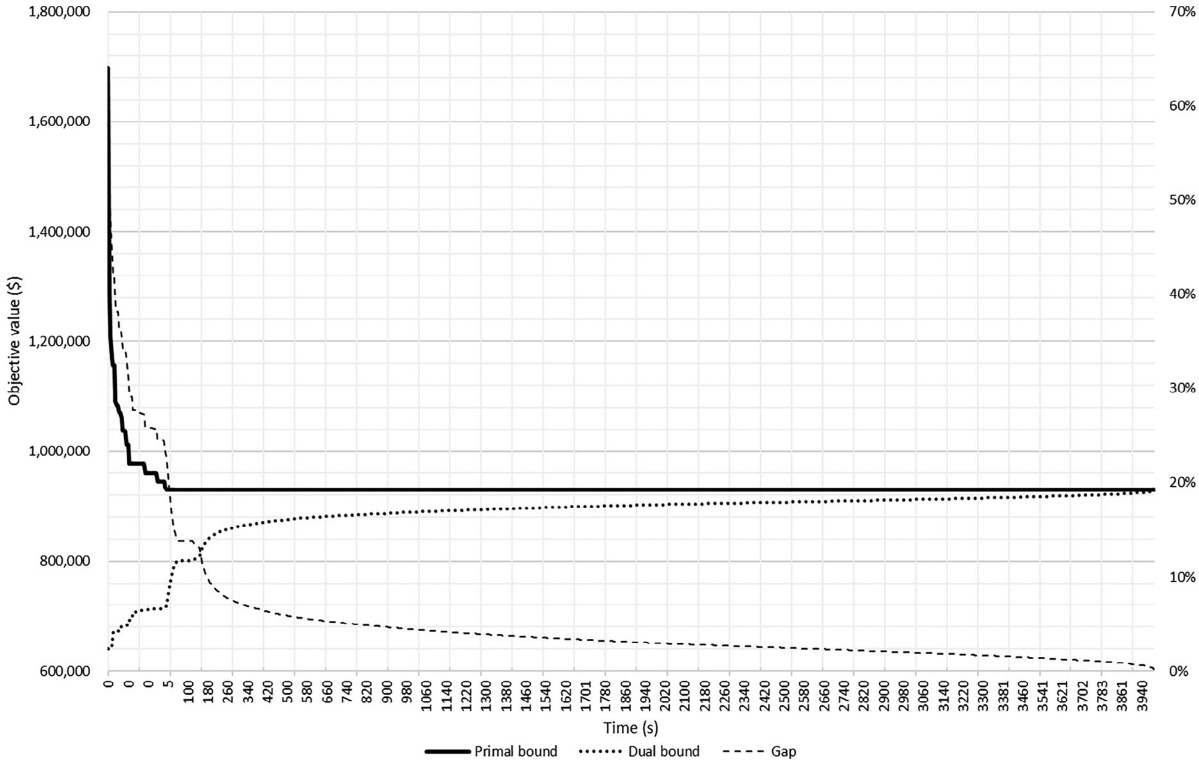

Fig. 8. Typical quality progress of the solution of the routing model. Instance for the scenario of 1% (instance # 14)

dual bound of 927,574 would have proven that the solution obtained by the proposed routing model in just five seconds is at most 0.3% away from the optimal solution. Based on these observations, we decided to set a time limit of 600 seconds for the routing model.

The MILP that finds the daily routes (see Section 3.1.2) is significantly easier to solve than the routing model. This model takes the routes generated from the routing model and assigns them to days while balancing the daily load. Figure 9 shows the computational time required for the instances of the production scenarios of 0.5%, 1.0%, and 2.5%, which took less than eight seconds to solve (about 92.5% of the 720 instances). All 720 instances were solved to optimality (or within 1% of the optimality gap) and 85% were solved in less than one second. The results show that for the scenarios with less cocoa to collect (0.5% and 1%), the routing model generates less routes, and it is easier to pack them into days. As more cocoa is available (scenario of 2.5%), the routing model generates more routes, and there are more options to explore to pack them with a balanced daily load.

Finally, to illustrate the output of the transport allocation model, Fig. 10 shows the load, in pods, of the daily routes for 20 random instances of a typical week of December for the production scenario of 2.5%, which corresponds to some of the hardest instances represented by the rightmost box and whisker plot in Fig. 9. As the yield simulator generates a random weekly production, the size of the tiled bar representing the weekly collection load varies from instance to instance. After sorting them in increasing order, it is easy to see that regardless of the weekly load, the clustering

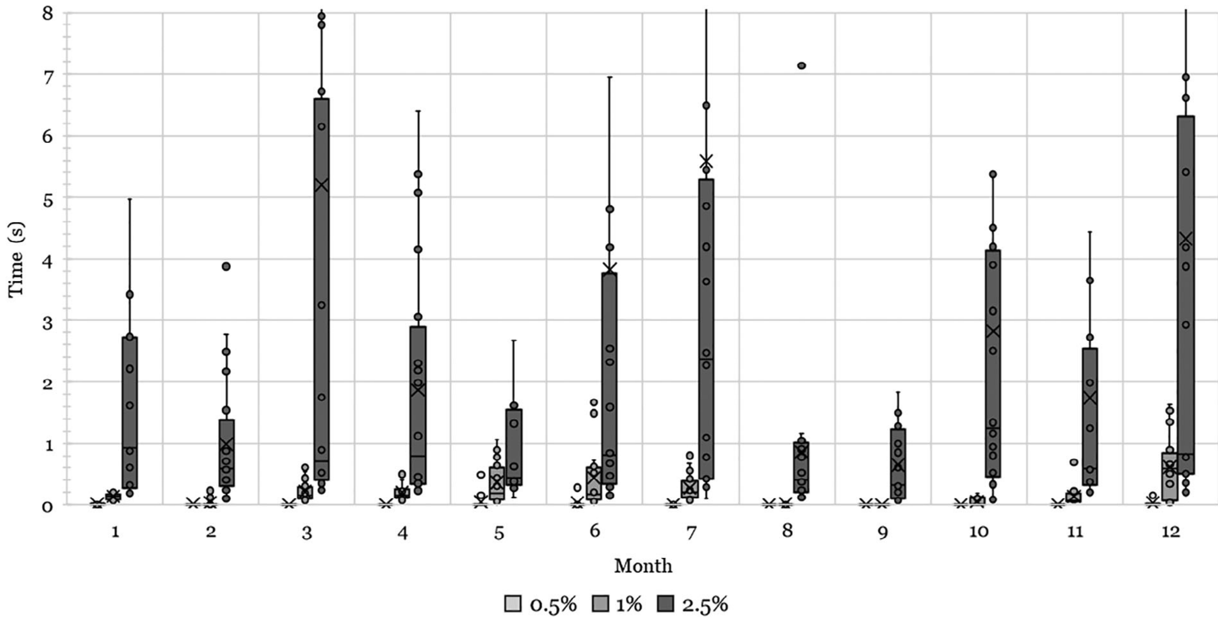

Fig. 9. Solution time for the clustering model (daily routes). Comparison of production scenarios (0.5%, 1%, and 2.5%).

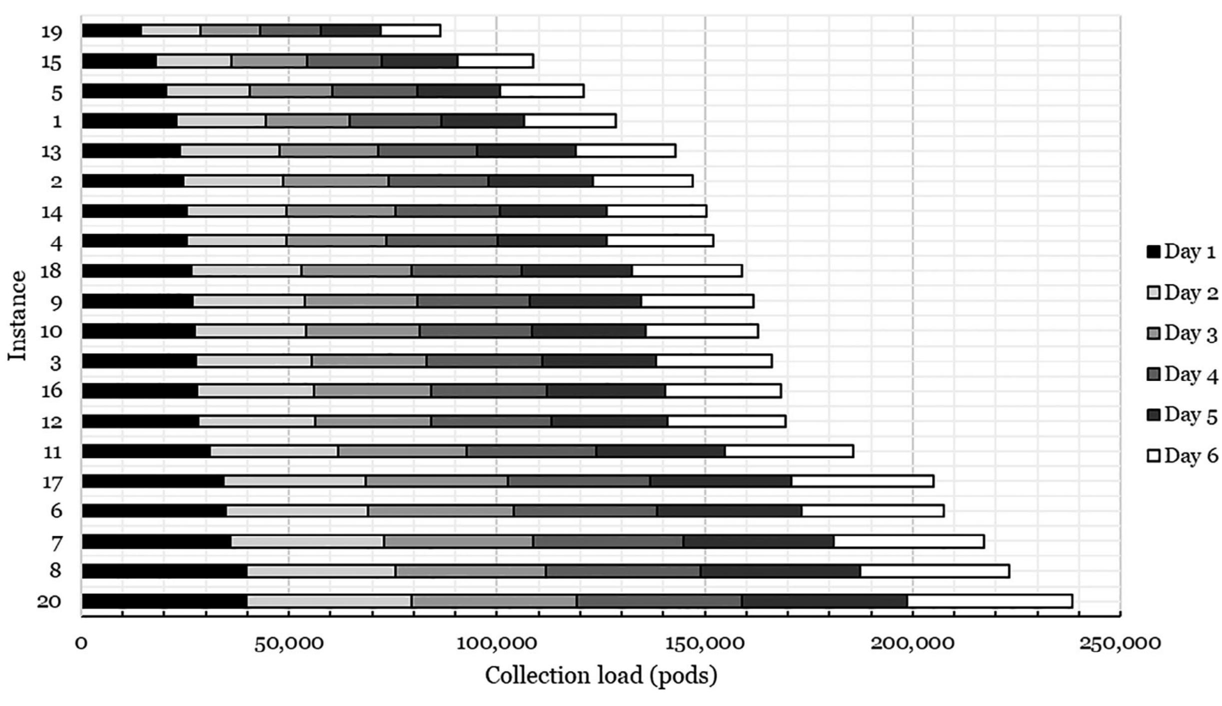

Fig. 10. Output of the transport allocation model (daily routes) for 20 random instances of a typical week of December for the production scenario of 2.5%.

model balances the inflow to the plant by assigning routes to each day with a similar daily load over the week. This balancing effort pays off in the processing plant, as it regulates the cocoa pods inflow, avoiding unnecessary congestion and uses more efficiently the plant's resources throughout the week.

In the forthcoming sections, for the DES model and the profit analysis model, we focus on the scenario that collects 0.5% of the production of Tame and Fortul, as it is a conservative scenario that requires a small-scale cooperative, and it meets the planned capacity of the pilot processing plant currently under construction. The DES model that follows allows us to size the resources for this scenario, while the profit analysis model explores market conditions that could make this production scenario viable.

4.3. DES model of the cocoa processing plant

The DES model receives as input for each month the number of cocoa pods that arrive daily at the processing plant, according to the mean value in a typical week reported by the transport allocation model. Pod arrivals for each month follow a normal distribution, which was derived from the daily pod collection data provided by the transport allocation model for each month. Specifically, we utilized data from the 0.5% production scenario, encompassing 20 weekly instances per month. Furthermore, several cocoa transformation processes are subject to uncertainty. For instance, pods must be classified according to their genetic variety using visual inspection and opened to remove the fresh cocoa seeds. This process must be done by workers with pruning hook tools. We estimated the distribution of the time to perform this procedure with data from the pod-opening competition held in Arauca (see Appendix A). Additional stochastic factors include the time required to unload a sack that arrives at the plant, the time to empty the contents of the boxes and bioreactors, and the time to unload the contents of dryers (see Appendix A). Figure 11 presents the main data and processes at the postharvest facility.

The processing plant needs workers to classify and open the pods, introduce the fresh seeds into the fermentation devices, mix the cocoa seeds in the fermentation wooden boxes, empty the contents of the boxes and bioreactors, load and unload the contents of the dryers, and transport cocoa among the different transformation stages. Thus, it is critical to determine the right number of workers to ensure the stability of the system and to guarantee that the time that cocoa seeds remain outside the pods before controlled fermentation starts does not exceed four hours. We defined three scenarios with different numbers of available workers during weekdays (Monday through Saturday) and weekends (Sunday) as shown in Table 1. Despite no cocoa arrivals on Sundays, workers are still necessary on this day due to the extended duration of processes like fermentation and drying.

We ran 74 replications of our simulation model with a 56-week (392-day) run length and a seven-day warm-up period. The number of replications was determined considering a target error of one cocoa entity in the system. We established the duration of the warm-up period from the time that it takes for the number of cocoa entities in the system to reach a steady state, which is approximately seven days. Figure 12 shows the average utilization of weekday and weekend workers for each scenario, at a 5% significance level. Note that the largest utilization for scenario 1 (low number of workers) is bounded by 85.20% and 62.48% for workweek and Sunday shifts, respectively.

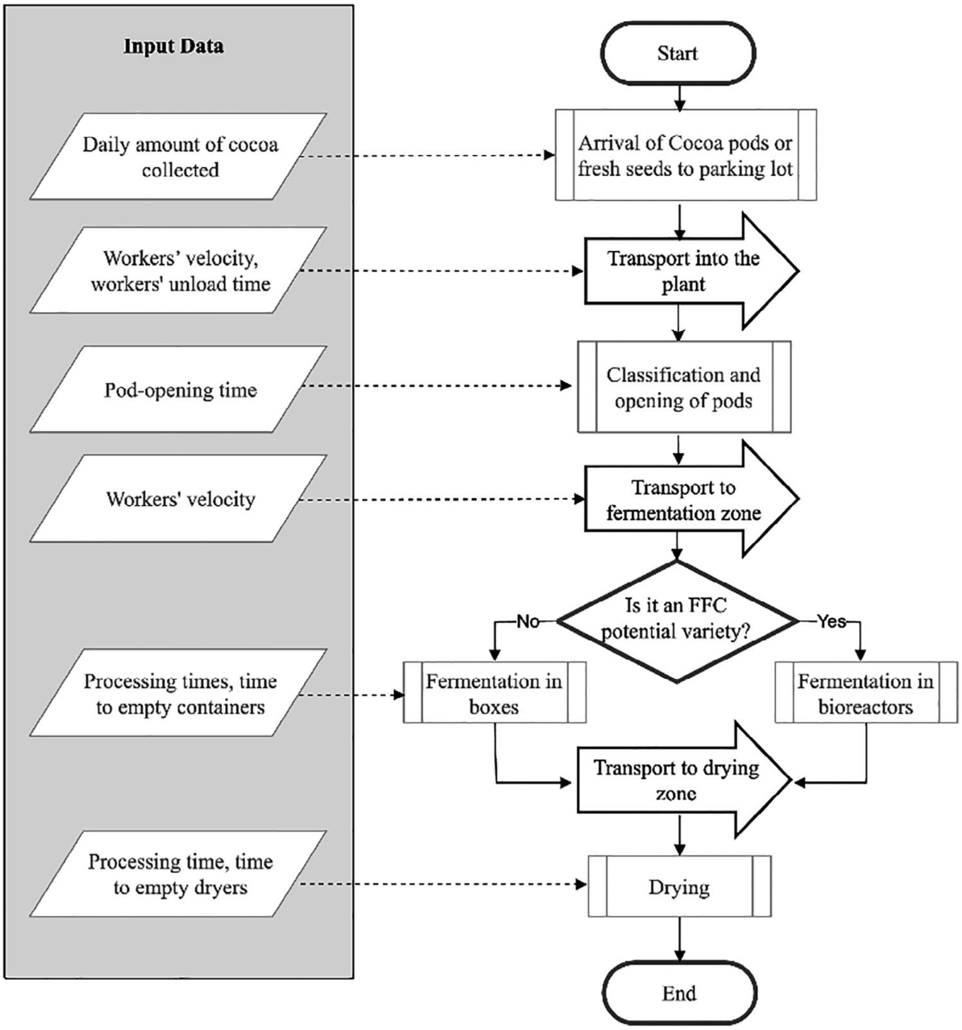

Fig. 11. Input data and processes at the postharvest center.

Table 1
Scenarios for the number of workers in the processing plant

Scenario	Type of shift	
	Monday–Saturday (workweek)	Sunday
1: low number of workers	2	1
2: medium number of workers	3	1
3: high number of workers	4	2

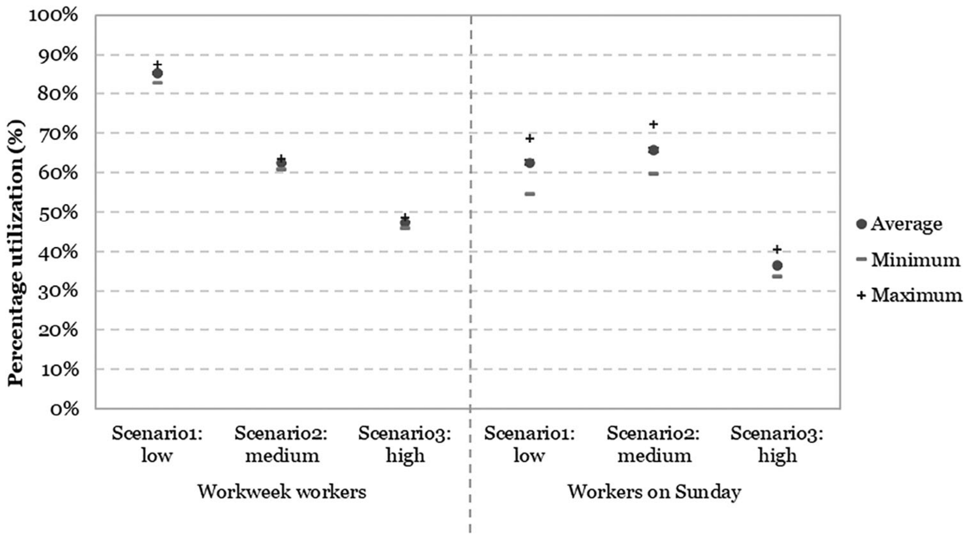

Fig. 12. Workers' utilization in the processing plant.

Table 2
Resource utilization in Scenario 1

Resource	Utilization (%)
Boxes	81.81 ± 0.35
SFE	73.28 ± 0.31
Dryers	24.88 ± 0.09

Abbreviation: SFE, special fermentation equipment.

Scenarios 2 and 3 result in lower utilizations for workweek workers. Thus, Scenario 1 is preferred, as it provides a reasonably high utilization, yet it saves some spare capacity if a peak situation emerges.

Table 2 shows the Scenario 1 (low number of workers) maximum utilization of the fermentation resources –boxes for bulk cocoa and SFE for FFC– and the dryers, at a significance level of 5%. Note that fermentation resources, particularly fermentation boxes, reach a maximum utilization of about 82%, yet leaving a margin of 18% to use as spare capacity. SFEs are in use approximately 73% of the time, aligning with practical expectations due to the occasional need for preventive maintenance. Dryers are underutilized (25%); nevertheless, due to the space, setup, and daily handling required for these resources, it makes practical sense to have the capacity to spare.

For quality purposes and to preserve the sensory attributes of cocoa, it is critical to validate that the workforce and resources are enough to ensure that seeds are processed within a proper timeframe. Thus, one of the key performance metrics of the DES model is the waiting time, which measures the time between the opening of the pods until the fermentation process begins. Table 3 presents the average waiting time and the average time in the system (i.e., the time between arrival to the plant until cocoa beans are dry and ready to exit to the market). We observe that seeds remain less than 2.5 hours waiting for the start of the fermentation process, which meets the recommended time limit of four hours.

Table 3
Cocoa quality related metrics for Scenario 1

Cocoa category	Waiting time (hours)	Time in system (days)
Bulk	2.49 ± 0.02	9.62 ± 0.024
Fine flavor	1.72 ± 0.02	8.32 ± 0.02

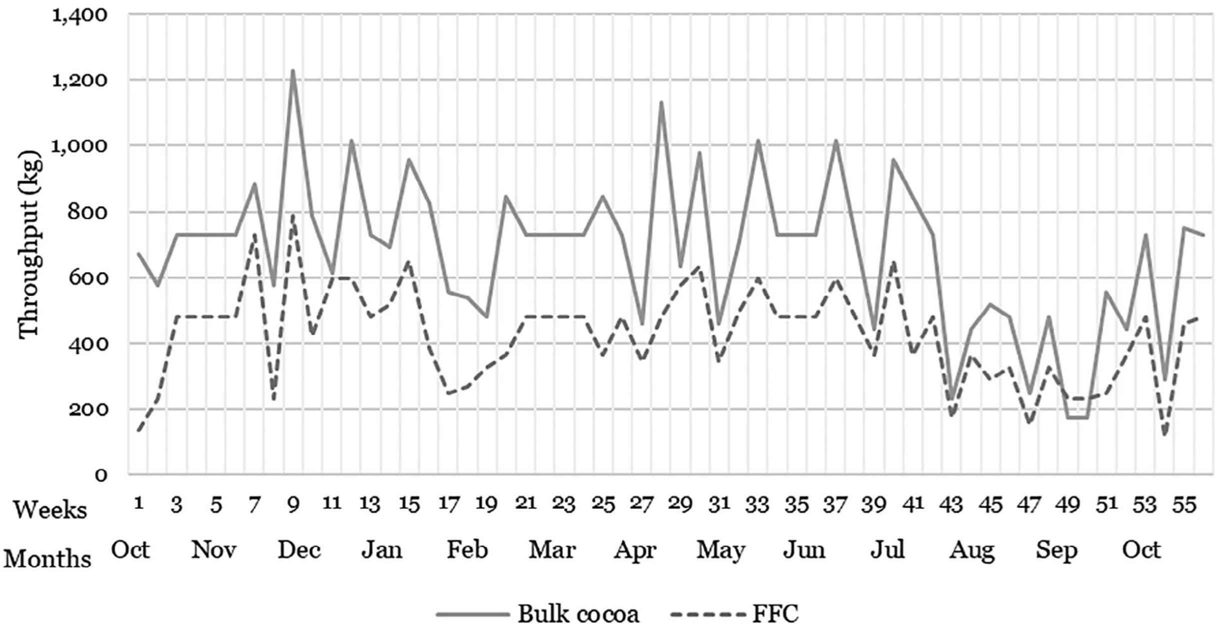

Fig. 13. Bulk cocoa and fine flavor cocoa (FFC) throughput per week for Replicate 1.

Figure 13 presents the weekly kilograms of bulk cocoa and FFC throughput for a sample replication, under Scenario 1 (low number of workers). About 40% of the cocoa throughput in the plant corresponds to FFC, and the throughput changes throughout the simulation according to the cocoa pods' fluctuation, introduced by the yield simulator. For instance, in Week 7 of the simulation (December) when the cocoa pods input is starting one of its peaks, the total throughput is about 1612.8 kg of dry cocoa, which translates into a processing capacity of 5760 kg of cocoa seeds at the plant. This means that the six-ton capacity of the processing plant is almost reached.

4.4. *Profit analysis model*

The profit analysis model receives input from the transport allocation and DES models. The transport allocation model provides input on the transportation costs and the average tons of cocoa pods that are collected from farmers every week. The DES model estimates the weekly throughput of FFC and bulk cocoa produced in the postharvest facility, and the operational (labor) costs. The profit analysis model determines the sales and inventory decisions that optimize the profit of the

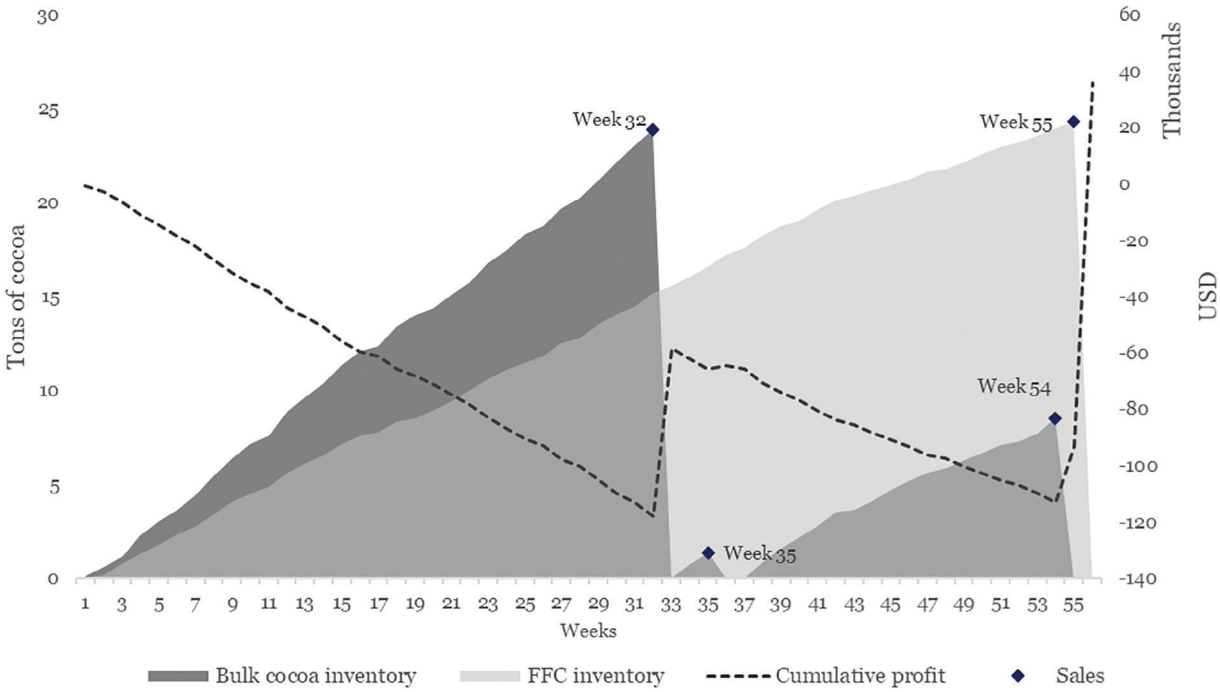

Fig. 14. Bulk cocoa inventory, fine cocoa inventory, selling positions and cumulative profit per week for a single run of the profit analysis model.

plant, over a 56-week horizon, aligned with the planning horizon of the DES (October as the first month in the simulation).

Each replication of the simulation model generates data to run one instance of the profit analysis model. To illustrate the output of a single run of the profit analysis model, Fig. 14 shows the suggested inventory levels of bulk cocoa (dark gray) and FFC (light gray), along with the cumulative total profit. In this single run, to generate enough cash flow over the horizon, the model proposes selling bulk cocoa in weeks 32, 35, and 54, when the price estimation peaks (information on the bulk cocoa price estimates is presented in Appendix A). Additionally, FFC is accumulated until there is enough cocoa to fill a 25-ton container for export, which occurs in Week 55. Commercialization of FFC is mostly done through export; however, local selling represents a potential alternative to increase the cash flow. Indeed, local sales of FFC occur in the first two weeks (about 0.46 tons). Losses are accumulated for several periods due to the preference for selling FFC until there is enough inventory to complete a container for export. Nevertheless, for this illustrative run, the plant generates profits at the end of the horizon.

We ran 74 instances of the profit analysis model matching the replications of the DES. We analyzed the profit variability to devise robust policies to negotiate prices or options in the future. The capacity of the processing plant determines the ability to commit to high-value customers who demand FFC and are willing to pay a premium price for higher quality. We conducted a sensitivity analysis to explore the impact on profit due to changes in FFC prices and the export container capacity (25-ton vs. 12.5-ton/half container), considering optimistic, most likely, and pessimistic

Table 4
Fine flavor cocoa (FFC) export and local market prices per scenarios

Scenario	FFC export price per kg (USD)	FFC local market price per kg (USD)	Container capacity. Export selling mode (tons)
1: High prices, 25 ton	5.2	4.0	25.0
2: Likely prices, 25 ton	4.6	3.8	25.0
3: Low prices, 25 ton	3.6	3.0	25.0
4: High prices, 12.5 ton	5.2	4.0	12.5
5: Likely prices, 12.5 ton	4.6	3.8	12.5
6: Low prices, 12.5 ton	3.6	3.0	12.5

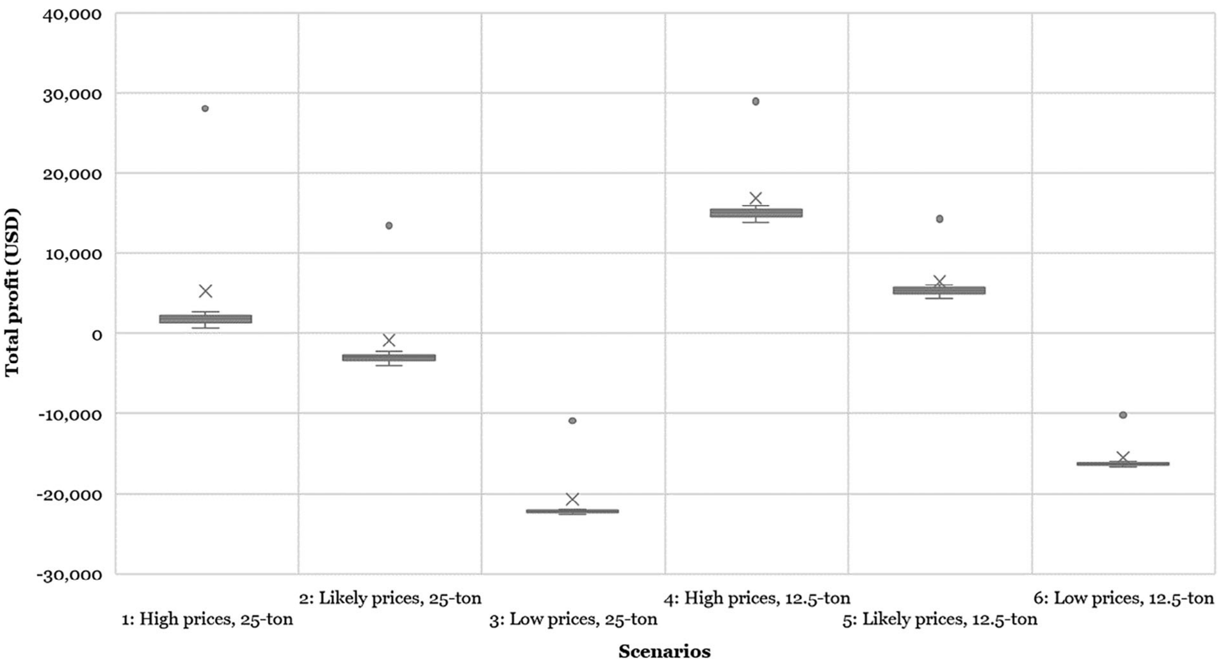

Fig. 15. Total profit varying the FFC's price and the container export load.

values for the FFC local market price and the FFC export price. Table 4 shows the parameters for the six scenarios (= 2 × 3), combining the two container loads and the three price estimates. Figure 15 shows these changes in profits.

Figure 15 considers the six scenarios combining FFC prices and container export load capacity. In the more optimistic scenarios with FFC prices (Scenario 1 and Scenario 4 with 25-ton and 12.5-ton containers, respectively) we observe that profits are positive for all 74 instances; however, in Scenario 1, where the center accumulates enough cocoa to fill a 25-ton container for export, the average total profit is about 5000 USD, lower than the one presented in Scenario 4 where half-container is exported (16,827 USD). In the latter scenario, although the plant exports only half of a 25-ton container and receives less profit per export than when exporting a full container, the total and cumulative profit over time is larger. This is because the plant does not have to wait to fill a 25-ton container; instead, it regularly exports half containers (in partnership with a third party) and supplements its revenue by selling FFC in the local market. This flexibility pays off, especially considering that in the first scenario, the plant's throughput might not be sufficient to fill the 25-ton container within the planning horizon. As for costs, when the plant exports a 12.5-ton half container, the fixed costs are divided, and the cumulative profit remains relatively stable, as it primarily depends on the total FFC sales achieved. Note that the average profit of the first scenario is pulled up because of extreme instances when the plant's throughput fills the 25-ton containers (i.e., profits of nearly 30,000 USD), which are simply outliers. The negative effect of the strategy of filling 25-ton containers for export shows when we compare Scenario 5 (likely FFC prices, 12.5-ton containers) and Scenario 2 (likely FFC prices, 25-ton containers). While Scenario 5 shows positive profits for all 74 instances (with an average total profit of 6400 USD), most instances of Scenario 2 present losses. Last, the pessimistic Scenarios 3 and 6, with lower FFC prices, show negative profits throughout the planning horizon. Under these scenarios, FFC prices do not allow farmers to cover the processing facility costs. Using the profit analysis model, farmers working collectively, could negotiate FFC prices in the future (e.g., financial options) and negotiate partnering with other actors/cooperatives to commit to fill half-containers for export throughout the planning horizon, such as the strategy presented in the fourth scenario suggests.

In summary, the profit analysis model can be used as an initial tool to devise a commercialization strategy to sell bulk and FFC supported by a collaborative transformation process. To avoid the end-of-period effect of time-indexed inventory models, it would be advisable to embed it in a rolling horizon solution scheme that considers that the system continues its life cycle beyond the end of the planning horizon of the optimization model (Solano-Blanco et al., 2023). Last, as highlighted before, the cooperative approach not only improves the farmers' ability to produce on a larger scale but also boosts their overall income by incorporating premium payments for high-quality cocoa, in addition to the payment (at a market price) for their cocoa pods.

5. Concluding remarks and future work

This paper presents a comprehensive methodology to design a cooperative model for large-scale cocoa postharvest processing and sales planning. The proposed methodology integrates three stages of the cocoa postharvest operations through the design of a processing center fed by a yield simulator that embeds variability sources inherent in the cocoa crop (i.e., seasonality and productivity). The methodology is applied in the state of Arauca (Colombia), where a pilot processing plant is currently under construction. In the first stage, a *transport allocation model* collects the harvest, which is estimated through a yield simulator, and transports cocoa pods from small farms located in rural areas to the processing plant. This model also feeds the cocoa pods with a balanced daily inflow to make cocoa processing smoother in the plant. At the second stage, a *DES model* mimics the transformation process of bulk and FFC cocoa into dry seeds that takes place in the processing plant. This model allows to dimension and size the plant's resources and estimates the bulk cocoa and FFC throughputs. Finally, in the third stage, a *profit analysis model* takes as input the transport logistics costs, operational costs, and the weekly throughput of cocoa to determine when and how much FFC and bulk cocoa to sell, in order to keep the processing plant running over the planning horizon. The methodology, supported by combining simulation and optimization models, allows to explore and evaluate different what-if scenarios while designing a collective postharvest transformation scheme.

This study also identifies key determinants for a supply chain postharvest design. At an operational and tactical decision level, a key factor is the postharvest center's capacity. This not only determines the number of cocoa pods to be weekly collected and the routes of the transport allocation model but also the resources that the center needs. Also, having more capacity allows the collective model to produce on a larger scale and compete in high-volume cocoa markets. Alternatively, at a strategic decision level, FFC market prices negotiation and the chosen selling mode—export (half- vs. full- container loads) or local sales—are the key factors affecting the farmers' profit. Thus, it is crucial to have a tool that allows small farmers working collectively to obtain a high-quality (standardized) product and find the best commercialization strategies that improve their income.

Compared to other approaches applied to cocoa crops, the proposed methodology integrates multiple echelons of the cocoa agri-food chain. This is crucial since to design a better cocoa supply chain, we need to observe, analyze, and solve problems at several echelons, from the transport of cocoa pods to the design of the processing center and the design of the commercialization strategy for the cocoa beans. This new perspective of cocoa supply chain management, in which small farmers transform their harvest in a collective and controlled way, will impact the farmers' performance and profits, as a larger fraction of cocoa beans will be sold as FFC and not as bulk. This leads to better prices, quality of life, and cocoa reputation for the region. The proposed collaborative and interconnected model is applicable to other regions and other agri-food chains.

There are several limitations to the current study. First, we did not consider preventive maintenance operations at the processing plant, which are required to avoid failures, impurities, and internal damage. Since maintenance operations should be periodically conducted by workers in bioreactors, fermentation boxes, and dryers, this should be considered when deciding the number of required workers. Second, regarding the profit analysis model, it would be appropriate to consider possible delays in payment due to negotiations or export administrative procedures since this affects the cash flow of the processing center and consequently the farmer's profits.

Future research should explore a more comprehensive systemic and organizational analysis of the methodology. Given its collective nature, it is crucial to investigate the governance of cooperative organizations and the incentives that drive actors to participate in the system. As part of the profit analysis modeling, it would be desirable to include a rolling horizon scheme to consider, as part of the selling decisions, forthcoming periods past the end of the planning horizon. In terms of pricing, the model should incorporate a forecasting component to anticipate the approximate behavior of FFC prices over time and mitigate market uncertainty. Last, the profit analysis model could explore the possibility of considering potential additional income from carbon sequestration in this long-cycle crop and the monetization of byproducts arising from circular economy practices.

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Appendix A: Parameter estimation

This section describes the input parameters estimation of the three interconnected models.

- Transport allocation model

The average annual production of dry cocoa beans for the municipalities of Fortul and Tame in 2022 was 2102.08 and 1319 tons, respectively (Agronet, 2022). To determine the weekly production of cocoa pods in these municipalities, we elaborated the yield simulator (Section 4.1), considering a fraction of 0.5% for the collection of cocoa pods.

- Discrete event simulation: postharvest cocoa plant

The varieties of FFC that are considered for this project are FEAR-5, Tame-2, and FSA-13, which are considered of high quality and high yield, as they have received several prizes at the "International Cocoa Awards" at the Paris Chocolate Fair (Fedecacao, 2021). These varieties are known as the "Modelo Araucano," which produces mostly FFC. We estimate a travel speed for workers within the processing plant that is evenly distributed between 0.5 and 1 m/s (International Organization for Standardization, 2021). Then, based on interviews, we estimated the time required to unload a sack of pods from the vehicles, as uniformly distributed, between 11.03 and 13.48 seconds. Additionally, we estimate the time required to open the pods and extract the seeds. We took data from the "Concurso de Apertura de Mazorcas" (a pod opening contest) organized in Arauca, and we performed a Kolmogorov–Smirnof goodness-of-fit test and found that it follows a continuous uniform distribution between 5.19 and 15.87 seconds to open a cocoa pod. Hence, according to the central limit theorem, the time to open a whole package follows a normal distribution, with parameters that depend on the group of genetic varieties for, as explained before, the packages of distinct group varieties contain different amounts of pods. Finally, according to Agrosavia specialists, the mean time that a worker takes to mix a fermentation box is about two hours. The time to empty the contents of the boxes and bioreactors is uniformly distributed between 9.20 and 11.23 minutes, and the time to unload the contents of dryers follows a uniform distribution between 6.17 and 7.55 minutes, based on our interviews with cocoa farmers.

- Profit analysis

The main parameters in this model are the administrative and operational costs of the processing center and the prices of the bulk cocoa and FFC. First, the minimal capital investment needed for the processing plant to operate is about 130,000 USD, according to market studies made by Agrosavia. For this reason, the weekly amortization of the loan acquired to pay this initial investment is about 234.5 USD, which was estimated considering the payment conditions of a loan, with a seven-year repayment period, for collective agricultural models by Finagro. Second, the weekly plant operating fixed costs correspond to 599.47 USD (including workforce, transporting the cocoa pods, amortization of a loan, and plant operations). The cost for each ton of cocoa pods collected from the farmers is about 154 USD. These values were estimated from surveys conducted on cocoa producers in the region and estimations from Agrosavia. Third, the costs of exporting a 25-ton container correspond to 2500 USD. This value was estimated considering freight rates for containers and the destination of the cocoa, which according to ProColombia is mainly Mexico in recent years. The interest rate, which corresponds to 0.05% (weekly) was calculated considering the rates of the Central Bank of Colombia and those estimated by Finagro for their loans. Last, the inventory costs are negligible since the cooperative has enough space to store cocoa beans, which can last for about six months once dried. For this reason, in the model, the inventory costs were set to zero. Also, the initial inventory of FFC and bulk cocoa stored at the beginning of the operation was assumed to be zero.

Regarding prices, the price of regular cocoa is determined by the international market. Specifically, in Colombia, the selling price considers the value of the cocoa commodity at the New York Stock Exchange and the London Stock Exchange. Information on the price of bulk cocoa per

Fig. A1. Prices of bulk cocoa. Agronet. Fedecacao.

kilogram is taken from reports of Fedecacao through the Agronet database. Figure A1 shows the weekly prices of bulk cocoa from July of 2013 to March of 2022.

For the profit analysis model, it was necessary to estimate the future prices. Our approach considers a random forest regression considering 24 historical periods. Moreover, the price of FFC is determined by bargaining, which makes it a somewhat unpredictable parameter for conventional forecasting methods. In the current market conditions of a worldwide cacao shortage, the export price value of FFC could begin at 3 USD per kg. However, under a more optimistic scenario, this value could potentially increase to 5 USD per kg.

Appendix B: Notation tables

Table B1
Summary of the notation used in the Transport Allocation Model. Dimensions in square brackets [·]

Route-first stage: weekly routes—Section 3.1.1	
Sets	
$\mathcal{N} = \{0, 1, \ldots, n, n+1\}$	Set of nodes (rural areas) to visit, including the depot (processing plant). Nodes 0 and $n+1$ represent the depot and nodes $1, \ldots, n$ represent the rural areas.
Parameters	
p_i	Amount of weekly cocoa pods that each rural area $i \in \mathcal{N}\backslash\{0, n+1\}$ produces [pods].
γ	Number of pods per sack [pods/sack]. For the case study, there are approximately 58 pods per sack.
b_i	Number of weekly cocoa sacks (with pods) to be collected at each rural area $i \in \mathcal{N} \backslash\{0, n+1\}$ [sacks/week]. It is defined as follows: $b_i \triangleq \lceil \frac{p_i}{\gamma} \rceil$.
$\tau_{i,j}$	Travel time between nodes $i \in \mathcal{N}$ and $j \in \mathcal{N}$ [min].
c	Load capacity of the vehicles [pods].
t^{max}	Maximum time for a route [min].
σ	Cost of the trip per minute used by each vehicle [USD/min].
η	Number of vehicles available to collect the harvest [dimensionless].
l	Time for loading a cocoa sack into the vehicle [min/sack].
Decision variables	
$x_{i,j}$	1 if the rural areas $i \in \mathcal{N}$ and $j \in \mathcal{N}$ are visited in sequence; 0, otherwise [dimensionless].
y_i	Cumulative amount of cocoa transported up to (before arriving at) node $i \in \mathcal{N}$ [pods].
w_i	Arrival time to node $i \in \mathcal{N}$ [min].
Cluster-second stage: routes-to-days assignment—Section 3.1.2	
Sets	
$\mathcal{R}$	Set of weekly routes found in the first stage.
$\mathcal{Q}$	Set of days. Working days of the processing plant (Monday through Saturday).
Parameters	
p_r	Total amount of cocoa pods collected in route $r \in \mathcal{R}$ [pods].
$\bar{z}$	Average daily load computed over the days of the week [pods].
Decision variables	
y_{rd}	Takes the value of 1, if the load of route $r \in \mathcal{R}$ is sent to the plant in day $d \in \mathcal{Q}$; takes the value of 0, otherwise [dimensionless].
z_d	Total load sent to the plant in day $d \in \mathcal{Q}$ [pods].
δ_d^+	Amount of load above the daily average $\bar{z}$ for day $d \in \mathcal{Q}$ [pods].
δ_d^-	Amount of load below the daily average $\bar{z}$ for day $d \in \mathcal{Q}$ [pods].

Table B2
Summary of the notation used in the profit analysis model. Dimensions in square brackets [•]

Profit analysis model—Section 4.3	
Sets	
$\mathcal{T} = \{1, 2, 3 \ldots, 52\}$	Set of weeks along the time horizon.
Parameters	
p_t^B	Selling price during week t $\in \mathcal{T}$ for bulk cocoa [USD/ton].
$p_t^{F,E}$	Selling price during week t $\in \mathcal{T}$ for FFC to export [USD/ton].
$p_t^{F,L}$	Selling price during week t $\in \mathcal{T}$ for FFC locally [USD/ton].
n_t^B	Bulk cocoa beans produced in the plant during week t $\in \mathcal{T}$ [tons].
n_t^F	FFC beans produced in the plant during week t $\in \mathcal{T}$ [tons].
c^{FC}	Weekly fixed expenses for the plant operation [USD/week].
c^E	Export costs associated with selling a 25-ton container [USD/week].
c^P	Weekly payment of cocoa pods to the producers [USD/ton].
β	Weekly cost of capital (interest rate) [dimensionless].
θ	Conversion factor from tons of dry beans to tons of cocoa pods [dimensionless].
α	Capacity of the export container [tons].
s	Maximum storage capacity of cocoa [tons].
i_0^B	Total amount of bulk cocoa stored at the beginning of the operation [tons].
i_0^F	Total amount of FFC cocoa stored at the beginning of the operation [tons].
Decision variables	
z_t	Amount of bulk cocoa to be sold in week $t \in \mathcal{T}$ [tons].
f_t^L	Amount of FFC to be sold locally in week $t \in \mathcal{T}$ [tons].
f_t^E	Containers of FFC to be sold by exporting in week $t \in \mathcal{T}$ [dimensionless].
i_t^B	Inventory in tons at the end of week $t \in \mathcal{T}$ of bulk cocoa [tons].
i_t^F	Inventory in tons at the end of week $t \in \mathcal{T}$ of FFC cocoa [tons].
u_t	Profit of the operation in week $t \in \mathcal{T}$ [USD/week].