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ORIGINAL PAPER

A horizontal collaborative approach for planning the wine grape harvesting

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Abstract

Horizontal collaboration is a strategy that has increasingly been used for improving supply chain operations. In this paper, we analyze the benefits of using a collaborative approach when optimally planning the wine grape harvesting process. Particularly, we assess how labor and machinery collaborative planning impacts harvesting costs. We model cooperation among wineries as a coalitional game with transferable costs for which the characteristic function vector is computed by solving a new formulation for planning the wine grape harvesting. In order to obtain stable coalitions, we devise an optimization problem that incorporates both rationality and efficiency conditions and uses the Gini index as a fairness criterion. Focusing on an illustrative case, we develop several computational experiments that show the positive effect of collaboration in the harvesting process. Moreover, our computational results reveal that the results depend strongly on the fairness criteria used. The Gini index, for example, favors the formation of smaller coalitions compared to other fairness criteria such as entropy.

Keywords Wine industry · Harvesting planning · Horizontal collaboration · Cooperative game theory

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1 Introduction

Horizontal collaboration is a cooperative strategy that could enhance supply chain operations performance. This collaborative scheme occurs when two or more stakeholders operating at the same level of the supply chain agree to perform some operations coordinately. Literature shows that horizontal collaboration significantly impacts firms' performance by reducing costs, increasing service levels, and mitigating environmental damage. Successful applications at industry include: forestry (Frisk et al. 2010; Guajardo et al. 2018), furniture (Audy et al. 2011), energy (Flisberg et al. 2015), tourism (Falk 2017) and more recently, the wine industry (Basso et al. 2020).

The wine supply chain involves managing the flow of information, product, and funds between the following four stages: wine grape harvesting; wine production; bottling, labeling, and packaging; and wine distribution (Basso et al. 2020). To stay profitable in this low-margin industry, wine companies, especially export-focused ones, must design, plan, and operate their supply chain efficiently (Varas et al. 2020b). In this context, horizontal collaboration may be a promising alternative to improve operations efficiency. For instance, Basso et al. (2020) shows that a collaborative approach improves bottling performance. However, opportunities for collaboration arise at each stage of the wine supply chain. Examples are the following: joint planning of the harvesting season (reducing labor and machinery cost), joint procurement of dry products (increasing bargaining power), joint manufacturing and aging (reducing warehousing costs), joint bottling and labeling (increasing utilization rates and reducing delays) and joint transport of finished products (reducing Less-than-truckload shipping).

In this paper, we develop a collaborative approach for wine grape harvesting planning. This process involves several operational decisions, including when, where, how, and how much to harvest (Varas et al. 2020a). When planning, wineries could collaborate by sharing workers and machinery. Our objective, then, is to analyze the benefits of using a collaborative approach on harvesting costs. The research hypothesis is that joint capacity planning could reduce labor and machinery costs by better using these resources, which is a relevant issue due to labor scarcity and high equipment costs in this industry. We model cooperation among wineries as a coalitional game with transferable costs. In this case, the characteristic function vector is derived by solving a new mixed-integer programming formulation for supporting wine grape harvesting planning. We show that, due to a reduction in individual flexibility, the characteristic function may not fulfill the *subadditive* property. Therefore, it turns relevant to determine not only how to split the costs but also to find a suitable coalition structure. On this, we devise a novel optimization model that uses the Gini index as a fairness criterion. Focusing on an illustrative example, we develop several computational experiments that show the positive effect of collaboration in the harvesting process. Besides, we analyze how the fairness criteria used impact the coalitions formed and the sharing of costs in this context.

The contribution of this paper is threefold. First, we include capacity-building policies to the state-of-the-art mixed-integer programming formulations that tackle the wine grape harvesting process. This feature allows us to assess the benefits of collaboration under several hiring policies that reflect different legislative and cultural environments. Second, we tackle the collaborative wine grape harvesting planning problem and formulate it mathematically using cooperative game theory. Third, we devise a new coalition structure and cost allocation methodology that uses the Gini index as a cost-splitting driver. Employing the Gini index as a fairness criterion has several advantages. First, as opposed to other solution concepts (e.g., nucleolus, Schmeidler 1969; Guajardo and Jörnsten 2015,), the Gini index is widely-known and can be easily explained to decision-makers. This issue is critical since previous research argues that the employment of understandable allocation techniques is better accepted by practitioners (Leenders et al. 2017), increasing the likelihood of its adoption. This last is quite relevant in the old-fashioned wine industry that lags in adopting disruptive logistics practices. Second, the methodology we propose is characterized by a linear programming formulation. Consequently, it provides a more tractable approach compared to other non-linear formulations (e.g., entropy method, Shannon 1948a; Basso et al. 2020). Third, as our computational experiments show, the Gini method favors the formation of smaller coalitions, which may facilitate, in practice, the implementation of a collaborative scheme due to a low coordination level.

The rest of this paper is organized as follows. In Sect. 2, we provide a literature review. In Sect. 3, we develop a MIP formulation for the wine grape harvesting problem, and we state the collaborative game. In Sect. 4, we discuss two egalitarian models and introduce a new coalition formation and cost allocation model. In Sect. 5, we illustrate the performance of these methods on an illustrative example, and we push the analysis forward by developing several computational experiments. Finally, in Sect. 6, we provide some concluding remarks and directions for future research.

2 Literature review

2.1 Wine supply chain

The wine supply chain consists of four stages (Basso et al. 2020). First, the grape harvesting stage, which we focus on in this paper, corresponds to the agricultural task of grape planting and cropping. Second, the wine production stage corresponds to all the chemical processes needed to convert grape juice into wine using, among others, the cellar tank and piping network resources. Third, the packaging stage consists of bottling, labeling, and corking. Last, in the fourth stage, the wine is transported from the wineries to the customers using different distribution modes and sales channels.

Previous efforts have studied the wine supply chain holistically, focusing mainly on logistics performance indicators (Chandes et al. 2003; Garcia et al. 2012; Smit et al. 2017; Díaz-Reza et al. 2018; Varas et al. 2020b) and sustainability issues (Cholette and Venkat 2009; Rugani et al. 2013; Varsei and Polyakovskiy 2017; Ponstein et al. 2019; Fragoso and Figueira 2020). In all wine supply chain stages, operations research models and methodologies have been used to improve efficiency and reduce costs (Moccia 2013). Next, we review some contributions for the grape harvesting stage.

Ferrer et al. (2008) presents a novel optimization model for generating wine grape harvest schedules. Their formulation includes the allocation of labor, routing decisions, and a loss function used for representing the effects of an early or late harvest on the quality of the grapes. Building on this work, Arnaout and Maatouk (2010) generalizes this formulation by incorporating a new set of scheduling constraints. Furthermore, the authors develop an ad-hoc heuristic that outperforms the branch-and-bound algorithm for large instances of this problem. Bohle et al. (2010) extends the modeling approach of Ferrer et al. (2008) by incorporating uncertainty in harvesting productivity. Particularly, the authors apply the robust optimization approach of Bertsimas and Sim (2004) and devise a new robust method for tackling right-hand side uncertainties. Finally, Varas et al. (2020a) develops a multi-objective approach for supporting wine grape harvest operations. The proposed model studies the opposing interests of growers and planners, seeking to maximize grape quality and minimize logistics costs.

Although the works above capture the most relevant features of wine grape harvesting, all of them consider just one hiring/renting policy. A distinctive feature of our formulation is that we consider several hiring/renting policies, which allow us to assess the effects of different legislative and cultural settings.

2.2 Collaborative logistics

Collaborative logistics occur when two or more stakeholders coordinate processes to improve their performance. Particularly, this strategy usually leads to a reduction in operational/transportation costs (Vanovermeire et al. 2014), increase the service level (Wadhwa et al. 2006) or decrease environmental emissions (Pérez-Bernabeu et al. 2015), among others. There are two types of collaboration in logistics: vertical and horizontal. In the former, cooperation is developed between supply chain members of different stages (Simatupang and Sridharan 2002; Borodin et al. 2016). An example of vertical collaboration is the information sharing from a downstream to an upstream supply chain member to mitigate the bullwhip effect (Audy et al. 2012; Wang and Disney 2016). On the other hand, in horizontal collaboration, cooperation occurs between members at the same level of the supply chain, which are usually competitors. This imposes several practical difficulties to overcome, including high coordination costs and anti-trust problems (Bahinipati et al. 2009; Basso et al. 2019a).

Multiple logistics problems have been addressed using a horizontal collaboration approach, being the ones that belong to the transportation stage, the most studied (Guajardo and Rönnqvist 2016). This last happens because the transportation phase is relatively standard, and usually, it does not belong to the core business of production companies, even being outsourced in many cases. The seminal work of Göthe-Lundgren et al. (1996) proposes a collaborative vehicle routing problem (CVRP) in which customers share dispatching costs considering a homogeneous fleet. This last assumption is relaxed in Engevall et al. (2004), and the resulting model is applied for supporting a gas and oil products dispatching problem. Since then, CVRPs have gained attention among researchers. We refer the reader to Gansterer and Hartl (2018) for a comprehensive review.

Resource sharing in horizontal collaborative manufacturing processes has gained the attention of scholars during the last years. Seok and Nof (2014) studies capacity sharing between manufacturers to minimize lost sales and maximize their production capacity utilization in the long-term, considering an uncertain lumpy demand. uit het Broek et al. (2019) proposes a collaborative purchasing and resource sharing of jack-up vessels for offshore wind farm maintenance. Results show that a cost reduction of 45% can be achieved when comparing to a leasing policy. Basso et al. (2020) studies the benefits of sharing bottling lines to diminish job delay costs in the wine industry. Numerical experiments show that collaboration decrease delays by up to 56.9%. Similarly, in this paper, we study the advantages of sharing workers and machines in the wine grape harvesting stage. At the cost of some $200,000 apiece, mechanical harvesters are expensive, so they are typically shared by several wineries (Zhang and Wilhelm 2011).

2.3 Cost allocation and coalition structure models

When firms collaborate, a common issue is to determine a split benefits plan between partners (Young 19875). Literature shows several allocation methods that satisfy different fairness criteria (Guajardo and Rönnqvist 2016). These methods try to produce allocations that benefit all firms in a *fair way* while avoiding incentives to deviate from the collaboration (Basso et al. 2020).

In cooperative game theory, a common assumption for coalition formation is stability, which implies that any player has no incentives to leave the coalition (Chalkiadakis et al. 2012). A widely-known concept formalizing this idea is the *core* (Gillies 1959). A payoff vector belongs to the core of a game if it satisfies both *rationality* and *efficiency*. Rationality states that each coalition's payoff must be at least as good as the cost of the coalition for avoiding some players to have incentives to break the grand coalition. On the other hand, efficiency assures that the entire grand coalition cost is split among its members. The core stability concept has been widely used in collaborative logistics (Frisk et al. 2010; Guajardo and Rönnqvist 2015a; Basso et al. 2020). Even though Bondareva (1963) and Shapley (1967) proved the necessary and sufficient condition for the core's non-emptiness, in general terms, the core could be empty.

When firms collaborate, the cost of each coalition (group of players) is stored in the so-called *characteristic function*. When this function does not fulfill the subadditive property, it becomes relevant not only to compute a cost allocation but also to find the *best* partition of the player set. This coalition formation problem relates to the well-known complete set partitioning problem in the Operations Research literature (Contreras et al. 2020).

Several authors have tackled coalition structure and cost allocation problems jointly. For example, Elomri et al. (2012) devises a procedure to form a coalition structure, assuming that players share cost according to a proportional method. This procedure iteratively finds the coalition that guarantees the highest profits over the remaining set of players. The authors show that the proposed structure is weakly stable. Guajardo and Rönnqvist (2015b) model this problem as a set partitioning problem considering stability constraints. The authors analyze both core stability and strong stability concepts. They test the models in two applications: one in collaborative forest transportation and the other in inventory pooling of spare parts for oil and gas operations. Jouida et al. (2017) studies the coalition formation problem for cooperative replenishment with one supplier. The authors propose an exact solution method to find profitable and stable coalitions structures.

As we have seen in this literature review, despite the numerous collaborative opportunities, to the best of our knowledge, only the work developed in Basso et al. (2020) studies horizontal collaboration in the wine supply chain. Our paper seeks to contribute to the literature by expanding horizontal logistics to the grape harvesting process.

3 Collaborative wine grape harvesting

3.1 A new MIP formulation for the wine grape harvesting problem

The grape harvesting is defined for a set of *blocks* that corresponds to a specific land area with similar ground composition, grape variety, and grape quality. For illustrative purposes, Fig. 1 depicts an instance of harvesting blocks. The wine grape harvesting problem involves deciding which blocks to harvest and when subject to several operational constraints, including feasibility time windows, labor allocation, reception capacity, and routing decisions.

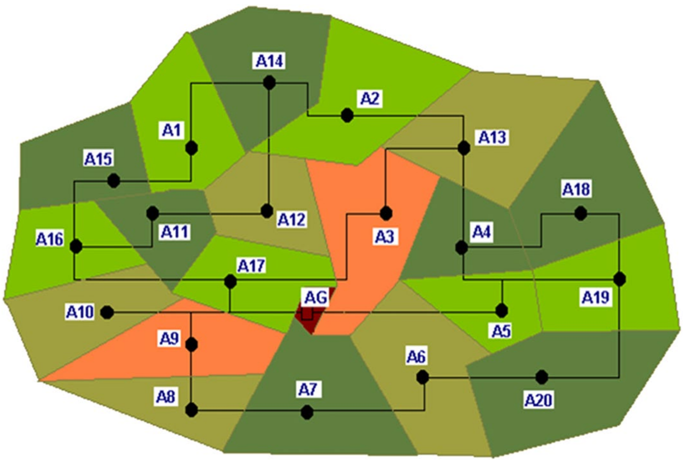


Fig. 1 Harvesting blocks. *Source*: Ferrer et al. (2008)

Since the seminal work of Ferrer et al. (2008), several authors have developed models and methods for supporting wine grape harvesting operations (Arnaout and Maatouk 2010; Bohle et al. 2010; Varas et al. 2020a). Building on these efforts, we develop a brief but comprehensive mixed-integer programming formulation for tackling the wine grape harvesting problem in this paper. Although we include both operational and tactical decisions, we keep our model as simple as possible to focus on collaboration opportunities. A distinctive feature of our formulation is that we consider several hiring/renting policies that allow considering the effects of different legislative and cultural environments.

Consider the following sets, parameters, variables, objective function, and constraints.

3.2 Sets

J : set of blocks (indexed by i, j).

$\{1, \dots, T\}$: planning horizon (indexed by t). We also consider two auxiliary periods, 0 and $T+1$.

R : set of resource types (indexed by r). We consider two types of resources, workers and harvesting machines.

3.3 Parameters

$T \in \mathbb{Z}_+$: horizon length (periods).

$W_{jt} \in \{0,1\}$: takes value 1 if it is possible to harvest block $j \in J$ in period $t \in T$, 0 otherwise.

$Q_{jt} \in \mathbb{R}_+$: quality loss cost for block $j \in J$ in period $t \in T$. This parameter is equal to zero for the optimal harvesting day and increases with deviations from this day (\$/kg).

$G_j \in \mathbb{R}_+$: grapes availability in block $j \in J$ (kg).

$N_j \in \mathbb{R}_+$: lower bound for grapes harvested in block $j \in J$ in any period (kg).

$K \in \mathbb{R}_+$: reception capacity in any period (kg/period).

$P_r \in \mathbb{R}_+$: cost of resource r in any period (\$/unit of resource).

$H_r \in \mathbb{R}_+$: productivity of resource r in any period (kg/unit of resource).

$M \in \mathbb{R}_+$: constant large enough.

$\epsilon \in \mathbb{R}_+$: constant small enough.

$A_r \in \{1, ..., T\}$: number of times the winery can hire or rent the resource $r \in R$. It depends on the policy of the winery and the country's law.

$B_r \in \{1, ..., T\}$: number of times the winery can lay-off or return the resource $r \in R$. It depends on the policy of the winery and the country's law.

3.4 Variables

$x_{jt} \in \mathbb{R}_+$: quantity of harvested grapes from block j in period t (kg).

$y_{jt} \in \{0, 1\}$: takes value 1 if harvesting of block j starts in period t, 0 otherwise.

$v_{jt} \in \{0, 1\}$: takes value 1 if harvesting of block $j \in J$ takes place in period $t \in T$, 0 otherwise.

$z_{rt} \in \mathbb{Z}_+$: quantity of resource r available in period t (unit of resource).

$u_{rjt} \in \mathbb{Z}_+$: quantity of resource r allocated to block j in period t (unit of resource).

$p_{rt} \in \mathbb{Z}_+$: quantity of resource r added (rented or hired) at the beginning of period t (unit of resource).

$q_{rt} \in \mathbb{Z}_+$: quantity of resource r removed (returned or laid-off) at the end of period t (unit of resource).

$a_{rt} \in \{0, 1\}$: takes value 1 if quantity of resource r increases in period t, 0 otherwise.

$b_{rt} \in \{0, 1\}$: takes value 1 if quantity of resource r decreases in period t, 0 otherwise.

3.5 Objective function

Expression (1) shows the objective function. In this case, the aim is to balance: (a) the workforce and machinery costs and (b) the quality loss cost, which is incurred by not harvesting the grapes at their optimal maturity. The last term (c), together with constraints (8) and (9), ensures that a_{rt} and b_{rt} take value 1 if and only if the quantity or resource r increases or decreases during period t, respectively.

$$\min \overbrace{\sum_{t=1}^{T}\sum_{r\in R} P_r \cdot z_{rt}}^{(a)} + \overbrace{\sum_{t=1}^{T}\sum_{j\in J} Q_{jt} \cdot x_{jt}}^{(b)} + \overbrace{\epsilon \cdot \sum_{t=1}^{T}\sum_{r\in R}(a_{rt} + b_{rt})}^{(c)} \tag{1}$$

3.6 Constraints

We group the constraint into five types: harvest operation, capacity, hiring/renting policies, scheduling, and nature of decision variables.

3.7 Harvest operation constraints

$$\sum_{t=1}^{T} x_{jt} = G_j \quad \forall j \in J \tag{2}$$

$$\sum_{j\in J} x_{jt} \leq K \quad \forall t \in \{1, \dots, T\} \tag{3}$$

3.8 Capacity constraints

$$x_{jt} \leq \sum_{r\in R} H_r \cdot u_{rjt} \quad \forall j \in J, t \in \{1, \dots, T\} \tag{4}$$

$$\sum_{j\in J} u_{rjt} \leq z_{rt} \quad \forall r \in R, t \in \{1, \dots, T\} \tag{5}$$

$$z_{rt} = z_{rt-1} + p_{rt} - q_{rt-1} \quad \forall r \in R, t \in \{1, \dots, T+1\} \tag{6}$$

$$z_{rt} \geq q_{rt} \quad \forall r \in R, t \in \{0, \dots, T+1\} \tag{7}$$

$$p_{rt} \leq M \cdot a_{rt} \quad \forall r \in R, t \in \{1, \dots, T\} \tag{8}$$

$$q_{rt} \leq M \cdot b_{rt} \quad \forall r \in R, t \in \{1, \dots, T\} \tag{9}$$

3.9 Hiring/renting policy constraints

$$\sum_{t=1}^{T} a_{rt} \leq A_r \quad \forall r \in R \tag{10}$$

$$\sum_{t=1}^{T} b_{rt} \leq B_r \quad \forall r \in R \tag{11}$$

$$a_{rt} \leq \sum_{l=t}^{T} b_{rl} \quad \forall r \in R, t \in \{1, \dots, T\} \tag{12}$$

$$z_{rt}, p_{rt}, q_{rt} = 0 \quad \forall r \in R, t \in \{0, T+1\} \tag{13}$$

3.10 Scheduling constraints

$$x_{jt} \leq G_j \cdot v_{jt} \quad \forall j \in J, t \in \{1, \dots, T\} \tag{14}$$

$$N_j \cdot v_{jt} \leq x_{jt} \quad \forall j \in J, t \in \{1, \dots, T\} \tag{15}$$

$$v_{jt} \leq W_{jt} \quad \forall j \in J, t \in \{1, \dots, T\} \tag{16}$$

$$y_{jt} \leq v_{jt} \quad \forall j \in J, t \in \{1, \dots, T\} \tag{17}$$

$$v_{jt} \leq \sum_{s \leq t} y_{js} \quad \forall j \in J, t \in \{1, \dots, T\} : W_{jt} = 1 \tag{18}$$

$$y_{jt} \leq \sum_{s \geq t} v_{js} \quad \forall j \in J, t \in \{1, \dots, T\} : W_{jt} = 1 \tag{19}$$

$$\sum_{t=1}^{T} y_{jt} = 1 \quad \forall j \in J \tag{20}$$

$$v_{jt+1} - v_{jt} \leq y_{jt+1} \quad \forall j \in J, t \in \{1, \dots, T-1\} \tag{21}$$

3.11 Nature of decision variables

$$x_{jt} \in \mathbb{R}_+ \quad \forall j \in J, t \in \{1, \dots, T\} \tag{22}$$

$$z_{rt}, u_{rjt}, p_{rt}, q_{rt} \in \mathbb{Z}_+ \quad \forall j \in J, r \in R, t \in \{1, \dots, T\} \tag{23}$$

$$y_{jt}, v_{jt}, a_{rt}, b_{rt} \in \{0, 1\} \quad \forall j \in J, r \in R, t \in \{1, \dots, T\} \tag{24}$$

Constraint (2) imposes that, for each block, all the grapes must be harvested during the planning horizon. Constraint (3) represents the winery reception capacity. Constraint (4) states that the number of grapes harvested cannot exceed the available harvesting capacity. Constraint (5) bound the total amount of machines and workers to be allocated for harvesting. Constraint (6) establishes a balance for the number of workers and machines available for harvesting at the beginning of each period. Constraint (7) bounds the number of resources to be removed. Constraints (8) and (9) are big-M constraints. Constraints (10) and (11) impose the maximum number of times that the winery is allowed to increase and decrease the amount of each resource, respectively. The values of A_r, B_r reflect the country's labor legislation or the company's policy itself. Constraint (12) is a valid inequality that reflects the non-anticipative of firing decisions. Constraint (13) is a boundary condition. Constraint (14) relates the harvesting decision with the number of grapes harvested (big-M constraint). Constraint (15) establishes a lower bound on the quantity harvested. Constraint (16) imposes that harvesting occurs within the harvesting window. Constraints (17)–(19) relate the scheduling variables. Particularly, a block can be harvested if and only if this process has started in that period or before. Constraint (20) establishes that harvesting starts once. Constraint (21) ensures no interruptions once the harvest starts. Finally, constraints (22)–(24) establish the nature of decision variables.

3.12 Some cooperative game theory concepts and the wine grape harvesting game

In what follows, we state some general definitions in cooperative game theory and apply them to the wine grape harvesting game that we introduce in this subsection. Let $\mathcal{F}$ be the set of all players. We denote by S any non-empty subset of $\mathcal{F}$. In this context, $S \subseteq \mathcal{F}$ is called a *coalition*. Let $\mathcal{K}$ be the set of all coalitions. The set $\mathcal{F} \in \mathcal{K}$ is called the grand coalition. We denote by $C : \mathcal{K} \rightarrow \mathbb{R}_+$ the so-called *characteristic function*, which stores the cost of each coalition $S \in \mathcal{K}$ (by convention $C(\emptyset) = 0$). The pair $(\mathcal{F}, C)$ is called *a transferable cost game*, that is, a cooperative game that is possible to transfer costs among players in the same coalition.

We model the cooperation among wineries as a transferable cost game adopting a centralized approach in which all data is available for a central planner that computes the collaborative solution (Smirnov and Sheremetov 2012). Let $\mathcal{F}$ be the set of wineries. We define J_f and K_f as the set of blocks and the reception capacity of winery $f \in \mathcal{F}$, respectively. Let $S \subseteq \mathcal{F}$ be a subset of wineries that agreed to cooperate in the wine grape harvesting process. Here, we focus on the case where wineries can share only workforce or machinery, excluding the sharing of reception capacities, as in Jouida et al. (2020). In other words, we assume that wineries can use workforce or machinery from another winery of the same coalition, but grapes must be moved to their own warehouses. For each coalition S, we denote by $J_S = \bigcup_{f \in S} J_f$ the set of blocks to harvest. Let β_{jf} be a parameter that takes value 1 if block j belongs to winery f, and 0 otherwise. Then, the cost of each coalition S, $C(S)$, is computed by solving the integer programming model of Sect. 3.1 considering $J = J_S$ and replacing constraint (3) by (25). We denote this problem by P_S. Thus, by solving this problem for all coalitions, the pair $(\mathcal{F}, C)$ is completely defined.

$$\sum_{j \in J_S} \beta_{jf} \cdot x_{jt} \leq K_f \quad \forall f \in S, t \in T \tag{25}$$

If the corresponding optimal solutions for any pair of coalitions are feasible for the union of those coalitions, then, the characteristic function fulfills the subadditive property (Basso et al. 2020), thus, the grand coalition forms. However, some cooperative games may violate this property, so it turns relevant finding a partition of the player set. This paper deals with such a game. When wineries cooperate following less flexible hiring/renting policies and operate as a single firm, the problem's optimal solution might not be feasible for the collaborative problem. For the sake of the explanation, consider the following example. When $A_r = 1$ and wineries do not cooperate, each winery $f \in S$ can hire/rent a single time, so $|S|$ hiring/renting instances exists. In contrast, when $A_r = 1$ and wineries cooperate, a single hiring/renting instance occurs.

Supposing that coalitions operate as a single firm allows us to analyze the most restrictive case and compare it with the most flexible case in which coalitions can hire/rent and fire/return multiple times. Furthermore, supposing that firms can hire/rent and fire/return once may help model some strict labor legislation. Besides, laid-off workers might not be available at a later time when the high season resumes. This issue is quite relevant in the Chilean wine industry, as wineries face increasing difficulties finding seasonal workers. In this matter, evidence from other industries shows that when the size of the labor market is small, as in the case of the wine industry, companies tend to avoid hiring and firing multiple times, finding it preferable to retain their surplus workers in the slow season (see, e.g., Krakover 2000).

4 Coalition structure and cost allocation models

This section reviews several models that address how to form coalitions and split the potential savings. First, we discuss the Entropy Method developed in Basso et al. (2020). Then, we state a generalized version of the Equal Profit Method originally proposed by Frisk et al. (2010), and finally, we devise a new methodology that uses the Gini index as a driver for sharing operational costs.

4.1 The entropy method

Basso et al. (2020) develops a new methodology, called the Entropy Method that simultaneously tackles both coalition formation and cost allocation problems. The authors include Shannon's measure of entropy (Shannon 1948b) in the objective function to foster equity in cost allocations. We review their approach next. Consider the following sets, parameters, variables, objective function, and constraints.

4.2 Sets

$\mathcal{F}$: set of players.

$\mathcal{K}$: set of all possible coalitions.

$\mathcal{F}_k$: set of players belonging to coalition $k \in \mathcal{K}$.

4.3 Parameters

$C(k) \in \mathbb{R}_+$: cost of coalition $k \in \mathcal{K}$.

$\alpha_{fk} \in \{0, 1\}$: it takes value 1 if player $f \in \mathcal{F}$ belongs to coalition $k \in \mathcal{K}$, 0 otherwise.

4.4 Variables

$x_k \in \{0, 1\}$: it takes value 1 if coalition $k \in \mathcal{K}$ is formed, and 0 otherwise.

$y_{fk} \in \mathbb{R}_+$: cost allocated to player $f \in \mathcal{F}_k$ in coalition $k \in \mathcal{K}$.

$\rho_{fk} \in [0, 1]$: proportion of cost allocated to player $f \in \mathcal{F}_k$ in coalition $k \in \mathcal{K}$.

4.5 Objective function

$$\text{minimize} \sum_{k \in \mathcal{K}} \sum_{f \in \mathcal{F}_k} \rho_{fk} \ln(\rho_{fk}) \tag{26}$$

4.6 Constraints

$$\sum_{k' \in K} \sum_{f \in \mathcal{F}_k \cap \mathcal{F}_{k'}} y_{fk'} \leq C(k) \quad \forall k \in \mathcal{K} \tag{27}$$

$$\sum_{f\in\mathcal{F}_k} y_{fk} = C(k)\cdot x_k \quad \forall k\in\mathcal{K} \tag{28}$$

$$\sum_{k\in\mathcal{K}} \alpha_{fk}\cdot x_k = 1 \quad \forall f\in\mathcal{F} \tag{29}$$

$$y_{fk} = \rho_{fk}\cdot C(k) \quad \forall k\in\mathcal{K}, f\in\mathcal{F}_k \tag{30}$$

$$\sum_{f\in\mathcal{F}_k} \rho_{fk} \le x_k \quad \forall k\in\mathcal{K} \tag{31}$$

$$y_{fk} \ge 0 \forall k\in\mathcal{K}, f\in\mathcal{F}_k \tag{32}$$

$$\rho_{fk} \in [0,1] \forall k\in\mathcal{K}, f\in\mathcal{F}_k \tag{33}$$

$$x_k \in \{0,1\} \forall k\in\mathcal{K} \tag{34}$$

Constraint (27) ensures strong rationality; that is, no subset of players, neither from the same or different coalitions, have the incentive to break their coalitions. Constraint (28) ensures efficiency; that is, for all formed coalitions, the coalition cost must be split among its members. Constraint (29) states that each player must be assigned to exactly one coalition. Constraint (30) defines ρ_{fk} as the proportion of the coalition cost allocated to the corresponding player. Constraint (31) imposes that if a coalition does not form, then the proportion allocated to each player within this coalition must be zero. Finally, constraints (32)–(34) establish the nature of decision variables.

4.7 The equal profit method

Frisk et al. (2010) proposes a novel cost allocation methodology, called Equal Profit Method. This methodology assumes that the grand coalition forms and aims to find an allocation in the core of the game, such that the maximum difference in pairwise relative savings is minimized. In what follows, we generalize this approach by allowing that any coalition structure could be formed. This alternative formulation is suitable for tackling non-subadditive characteristic functions, such as those considered in our paper. Consider the following sets, parameters, variables, objective function, and constraints.

4.8 Sets

$\mathcal{F}$: set of players.

$\mathcal{K}$: set of all possible coalitions.

$\mathcal{F}_k$: set of players belonging to coalition $k \in \mathcal{K}$.

4.9 Parameters

$C(k) \in \mathbb{R}_+$: cost of coalition $k \in \mathcal{K}$.

$\alpha_{fk} \in \{0, 1\}$: it takes value 1 if player $f \in \mathcal{F}$ belongs to coalition $k \in \mathcal{K}$, 0 otherwise.

4.10 Variables

$x_k \in \{0, 1\}$: it takes value 1 if coalition $k \in \mathcal{K}$ is formed, and 0 otherwise.

$y_{fk} \in \mathbb{R}_+$: cost allocated to player $f \in \mathcal{F}_k$ in coalition $k \in \mathcal{K}$.

$z_k \in \mathbb{R}_+$: maximum difference in pairwise relative savings within coalition $k \in \mathcal{K}$.

4.11 Objective function

$$\text{minimize} \sum_{k \in \mathcal{K}} z_k \tag{35}$$

4.12 Constraints

$$z_k \geq \frac{y_{fk}}{C(\{f\})} - \frac{y_{f'k}}{C(\{f'\})} \quad \forall k \in \mathcal{K}, f, f' \in \mathcal{F}_k \tag{36}$$

$$\sum_{k' \in K} \sum_{f \in \mathcal{F}_k \cap \mathcal{F}_{k'}} y_{fk'} \leq C(k) \quad \forall k \in \mathcal{K} \tag{37}$$

$$\sum_{f \in \mathcal{F}_k} y_{fk} = C(k) \cdot x_k \quad \forall k \in \mathcal{K} \tag{38}$$

$$\sum_{k \in \mathcal{K}} \alpha_{fk} \cdot x_k = 1 \quad \forall f \in \mathcal{F} \tag{39}$$

$$y_{fk} \geq 0 \quad \forall f \in \mathcal{F}, k \in \mathcal{K} \tag{40}$$

$$z_k \geq 0 \forall k \in \mathcal{K} \tag{41}$$

$$x_k \in \{0, 1\} \forall k \in \mathcal{K} \tag{42}$$

Together with the objective function (35), constraint (36) defines z_k as the maximum difference in pairwise relative savings. Constraint (37) ensures strong rationality. Constraint (38) ensures efficiency. Constraint (39) states that each player must be assigned to exactly one coalition. Finally, constraints (40)--(42) establish the nature of decision variables.

4.13 The gini index method

This paper proposes a novel methodology for tackling the coalition structure and cost allocation problem, which we call the Gini Index Method, that uses the Gini index to drive the optimization process towards more equitable solutions. The Gini coefficient represents an income inequity level of a particular population. This coefficient takes value zero in the perfectly equitable case and a value of one for the maximal inequality case (Gini 1912). Formally, the Gini coefficient is the area between the curves of perfect equity and the Lorenz curve. In order to compute the Gini index, it is necessary to sort the population's income in non-decreasing order, which is done endogenously by the model we discuss next. Consider the following sets, parameters, variables, objective function, and constraints.

4.14 Sets

$\mathcal{F}$: set of players.

$\mathcal{K}$: set of all possible coalitions.

$\mathcal{F}_k$: set of players belonging to coalition $k \in \mathcal{K}$.

$\mathcal{N}_k = \{1, ...|\mathcal{F}_k|\}$: set of positions for the players within coalition $k \in \mathcal{K}$.

4.15 Parameters

$C(k) \in \mathbb{R}_+$: cost of coalition $k \in \mathcal{K}$.

$\alpha_{fk} \in \{0, 1\}$: it takes value 1 if player $f \in \mathcal{F}$ belongs to coalition $k \in \mathcal{K}$, 0 otherwise.

$\beta_k \in \mathbb{Z}_+$: number of players in coalition $k \in \mathcal{K}$.

$M \in \mathbb{R}_+$: large enough constant.

4.16 Variables

$x_k \in \{0, 1\}$: it takes value 1 if coalition $k \in \mathcal{K}$ is formed, and 0 otherwise.

$g_k \in [0, 1]$: Gini index for coalition $k \in \mathcal{K}$.

$z_k \in [0, 1]$: Gini index for coalition $k \in \mathcal{K}$ if it forms, and 0 otherwise.

$y_{fk} \in \mathbb{R}_+$: cost allocated to player $f \in \mathcal{F}_k$ in coalition $k \in \mathcal{K}$.

$u_{nk} \in \mathbb{R}_+$: cost allocated to the player with the n-th smallest cost ($n \in \{0\} \cup \mathcal{N}_k$) in coalition $k \in \mathcal{K}$. u_{0k} allows to define a boundary condition.

$p_{nk} \in [0, 1]$: proportion of cost allocated to the player with the n-th smallest cost ($n \in \mathcal{N}_k$) in coalition k.

$w_{fnk} \in \{0, 1\}$: it takes value 1 if the cost of player $f \in \mathcal{F}_k$ is the n-th smallest cost ($n \in \mathcal{N}_k$) in coalition $k \in \mathcal{K}$, 0 otherwise.

4.17 Objective function

$$\text{minimize} \sum_{k \in \mathcal{K}} z_k \tag{43}$$

4.18 Constraints

$$\sum_{k' \in K} \sum_{f \in \mathcal{F}_k \cap \mathcal{F}_{k'}} y_{fk'} \leq C(k) \quad \forall k \in \mathcal{K} \tag{44}$$

$$\sum_{f \in \mathcal{F}_k} y_{fk} = C(k) \cdot x_k \quad \forall k \in \mathcal{K} \tag{45}$$

$$\sum_{k \in \mathcal{K}} \alpha_{fk} \cdot x_k = 1 \quad \forall f \in \mathcal{F} \tag{46}$$

$$u_{0k} = 0 \quad \forall k \in \mathcal{K} \tag{47}$$

$$u_{(n-1)k} \leq u_{nk} \quad \forall k \in \mathcal{K}, n \in \mathcal{N}_k \tag{48}$$

$$w_{fnk} \leq x_k \quad \forall k \in \mathcal{K}, f \in \mathcal{F}_k, n \in \mathcal{N}_k \tag{49}$$

$$u_{nk} \leq y_{fk} + M \cdot (1 - w_{fnk}) \quad \forall k \in \mathcal{K}, f \in \mathcal{F}_k, n \in \mathcal{N}_k \tag{50}$$

$$y_{fk} \leq u_{nk} + M \cdot (1 - w_{fnk}) \quad \forall k \in \mathcal{K}, f \in \mathcal{F}_k, n \in \mathcal{N}_k \tag{51}$$

$$\sum_{k \in \mathcal{K}, n \in \mathcal{N}_k, f \in \mathcal{F}_k} w_{fnk} = 1 \quad \forall f \in \mathcal{F} \tag{52}$$

$$\sum_{f \in \mathcal{F}_k} y_{fk} = \sum_{n \in \mathcal{N}_k} u_{nk} \quad \forall k \in \mathcal{K} \tag{53}$$

$$u_{nk} = p_{nk} \cdot C(k) \quad \forall k \in \mathcal{K}, n \in \mathcal{N}_k \tag{54}$$

$$g_k = 1 - 2 \sum_{n \in \mathcal{N}_k} \left[\frac{p_{nk}}{2\beta_k} + (\beta_k - n) \frac{p_{nk}}{\beta_k} \right] \forall k \in \mathcal{K} \tag{55}$$

$$z_k \leq x_k \forall k \in \mathcal{K} \tag{56}$$

$$z_k \leq g_k \forall k \in \mathcal{K} \tag{57}$$

$$z_k \geq g_k + x_k - 1 \forall k \in \mathcal{K} \tag{58}$$

$$y_{fk}, u_{nk} \geq 0 \quad \forall k \in \mathcal{K}, f \in \mathcal{F}, n \in \mathcal{N}_k \tag{59}$$

$$p_{nk}, g_k, z_k \in [0, 1] \quad \forall k \in \mathcal{K}, n \in N_k \tag{60}$$

$$x_k, w_{fnk} \in \{0, 1\} \quad \forall k \in \mathcal{K}, f \in \mathcal{F}, n \in \mathcal{N}_k \tag{61}$$

For a partition of the players set, the Gini Index Method generates a cost allocation that minimizes the sum of the Gini indexes for each coalition of the selected structure. On the other hand, constraint (44) ensures strong rationality. Constraint (45) ensures efficiency. Constraint (46) states that each player must be assigned to exactly one coalition. Constraints (47)–(53) define the non-decreasing ordering u_{nk} for the allocated costs y_{fk} within each coalition $k \in \mathcal{K}$. Constraint (54) defines the ordered proportion of the allocated cost within each coalition. Constraint (55) computes the Gini index for each coalition (see Appendix A for details). Constraints (56)–(58) linealize the product $g_k \cdot x_k$, which is equal to z_k, and it is used in the objective function (43). Finally, constraints (59)–(61) establish the nature of decision variables.

5 Numerical analysis

In this section, we perform several numerical experiments applying all the models defined in Sect. 4. Particularly, in Sect. 5.1, we present an illustrative example gathered from Ferrer et al. (2008), and we compute the cost for all possible coalitions for the wine grape harvesting game defined in Sect. 3.2. Then, we solve the three cost allocation and coalition structure models. Next, we show the resulting schedules and resource usages for two cases: all the wineries work together or work separately. In Sect. 5.2, on the other hand, we develop an experimental design that takes the illustrative example as a starting point. By generating multiple instances by permuting blocks between the wineries, these experiments seek to draw further managerial insights, including quantifying collaboration's benefits and determining which cost allocation method favors large coalitions.

All mathematical programming models are coded in AMPL. The linear formulations are solved using CPLEX 12.10.0, whereas the non-linear models are solved using Artelis Knitro 12.3.0. The runs are performed on a PC with an AMD Ryzen 5 CPU@ 2.00 GHz processor and 8 GB RAM, each of them finishing in less than 60 s.

5.1 An illustrative example

The illustrative example consists of 20 blocks, two harvest modes (machinery and human) with a planning horizon of 13 periods. The data for this illustrative example is gathered from Ferrer et al. (2008) where, since no collaboration is studied, only one winery is considered. However, we assume that four different wineries own five of these 20 blocks each to include collaboration. A detailed description of the data is shown in Appendix B. We run the model described in Sect. 3.2 for every possible coalition and four hiring policies. Consider Table 1. In this table, A_r represents the maximum number of times wineries can hire or rent the resource r, while B_r represents the maximum number of times wineries can lay-off or return the resource r, as described in Sect. 3.1. Consequently, we are studying two extreme cases: wineries can hire/rent and lay-off/return only once ($A_r = 1$, $B_r = 1$) or they can hire/rent and lay-off/return in every period ($A_r = T$, $B_r = T$). These policies allow us to analyze the benefits of collaboration in the most restrictive case (−−) and compare it with the most flexible case (++), in which coalitions can both hire/rent and fire/return multiple times. Table 2 shows the characteristic functions for all hiring/renting policies considered, and Fig. 2

Table 1 Hiring/renting policies considered

A_{worker}	B_{worker}	A_{machine}	B_{machine}	Notation
1	1	1	1	(−−)
1	1	T	T	(−+)
T	T	1	1	(+−)
T	T	T	T	(++)

shows the resulting schedules for both the grand coalition and stand-alone cases for the hiring policy (−−).

For each day and block, the total planned volume to be harvested is depicted in Fig. 2. The green area indicates when is possible to develop harvesting, and a darker cell indicates the estimated optimal harvest date. As expected, the harvesting occurs in the neighborhood of the dates that minimize the quality loss function. However, in some cases, the harvest period departs from the optimal date. This is explained due to both some capacity constraints bind or a decrease in logistics cost compensates the increase in quality loss cost. From Table 2, on the other hand, it follows that the grand coalition is not always the best outcome. For example, for the hiring policy, (−−), the grand coalition cost is greater than the sum of the stand-alone costs (11,980,015 > 10,961,439), which means that the grand coalition is not stable. For this illustrative example, this result holds for all the hiring policies.

To get a sense of why the grand coalition is not profitable in some cases, let us consider the resources' usage for the hiring policy (−−). Table 3 shows that 31 harvesting machines are employed from period 2–11 (310 periods-machines), while 196 workers are used in period 8. For the stand-alone situation, Table 4 shows that a total of 133 periods-workers and 302 periods-machines are used. Recall that the hiring policy (−−) implies that each firm can hire/rent once. Thus, in the stand-alone situation, it is possible to hire/rent four times (one for each winery), providing more flexibility to decision-makers than the collaborative case where hiring/renting occurs once.

Thus, it turns relevant not only to find a proper cost allocation scheme but also to decide which wineries should collaborate. For example, for the hiring policy (++), all coalition structures but the grand coalition minimize the overall costs.

The question of which coalitions should form and how to divide the costs among the participants can be simultaneously tackled by the models presented in Sect. 4. Table 5 shows, for the three methods and the four hiring policies, the coalition structures, the coalition costs (CC), the allocated costs (AC), and the objective function value (FO). First, note that, for the policies (−−) and (−+), the resulting coalition structures are identical and equal to $\{1, 2, 34\}$. For the policy (+−), the

Table 2 Characteristic function for the hiring/renting policies considered

S	{1}	{2}	{3}	{4}	{1,2}	{1,3}	{1,4}	{2,3}
(−−)	$1,555,824	$2,588,212	$3,040,827	$3,776,576	$4,822,873	$ 6,683,707	$ 7,243,021	$6,646,191
(−+)	$1,555,824	$2,588,212	$3,040,827	$3,772,266	$4,795,086	$ 6,670,287	$ 6,924,000	$6,646,191
(+−)	$1,376,200	$1,696,800	$2,351,800	$1,932,600	$3,095,400	$ 3,750,400	$ 3,325,000	$4,048,600
(++)	$1,376,200	$1,696,800	$2,351,800	$1,926,400	$3,073,000	$ 3,728,000	$ 3,302,600	$4,048,600
S	{2,4}	{3,4}	{1,2,3}	{1,2,4}	{1,3,4}	{2,3,4}	{1,2,3,4}	
(−−)	$6,392,709	$6,791,518	$8,296,215	$8,691,973	$9,814,484	$10,688,991	$11,980,015	
(−+)	$6,365,169	$6,752,492	$8,296,215	$8,614,596	$9,736,518	$10,595,334	$11,844,546	
(+−)	$3,635,600	$4,290,600	$5,453,400	$5,028,000	$5,683,000	$ 5,993,600	$ 7,386,000	
(++)	$3,623,200	$4,278,200	$5,424,800	$4,999,400	$5,654,400	$ 5,975,000	$ 7,355,000	

Collaborative Case			Planning Horizon													Grand Coalition
Winery	Block ID	kg	1	2	3	4	5	6	7	8	9	10	11	12	13	Cost
1	1	40,000	0	0	27,000	13,000	0	0	0	0	0	0	0	0	0	11,980,015
	2	84,860	0	84,860	0	0	0	0	0	0	0	0	0	0	0	
	3	84,550	0	84,550	0	0	0	0	0	0	0	0	0	0	0	
	4	40,000	0	0	27,000	13,000	0	0	0	0	0	0	0	0	0	
	5	40,000	0	0	27,000	13,000	0	0	0	0	0	0	0	0	0	
2	6	82,280	0	0	0	82,280	0	0	0	0	0	0	0	0	0	
	7	60,050	0	0	0	0	60,050	0	0	0	0	0	0	0	0	
	8	74,240	0	0	0	0	0	74,240	0	0	0	0	0	0	0	
	9	91,790	0	0	0	0	0	0	16,915	74,875	0	0	0	0	0	
	10	43,000	0	0	0	0	0	0	16,801	26,199	0	0	0	0	0	
3	11	68,632	0	0	0	0	0	0	68,632	0	0	0	0	0	0	
	12	126,287	0	0	0	0	0	0	22,548	75,514	28,225	0	0	0	0	
	13	99,920	0	0	0	0	0	0	0	0	99,920	0	0	0	0	
	14	43,000	0	0	0	0	0	0	22,552	20,448	0	0	0	0	0	
	15	157,520	0	0	0	0	0	0	0	0	0	157,520	0	0	0	
4	16	57,390	0	0	0	0	0	0	0	0	44,390	13,000	0	0	0	
	17	125,610	0	0	0	0	0	0	22,407	103,203	0	0	0	0	0	
	18	40,000	0	0	40,000	0	0	0	0	0	0	0	0	0	0	
	19	40,000	0	0	40,000	0	0	0	0	0	0	0	0	0	0	
	20	138,380	0	0	0	0	0	0	0	0	0	0	138,380	0	0	

(a) Collaborative solution.

Non-Collaborative Case			Planning Horizon													Stand Alone
Winery	Block ID	kg	1	2	3	4	5	6	7	8	9	10	11	12	13	Costs
1	1	40,000	0	0	40,000	0	0	0	0	0	0	0	0	0	0	1,555,824
	2	84,860	0	68,379	16,481	0	0	0	0	0	0	0	0	0	0	
	3	84,550	0	84,550	0	0	0	0	0	0	0	0	0	0	0	
	4	40,000	0	0	40,000	0	0	0	0	0	0	0	0	0	0	
	5	40,000	0	0	40,000	0	0	0	0	0	0	0	0	0	0	
2	6	82,280	0	0	0	82,280	0	0	0	0	0	0	0	0	0	2,588,212
	7	60,050	0	0	0	0	60,050	0	0	0	0	0	0	0	0	
	8	74,240	0	0	0	0	0	74,240	0	0	0	0	0	0	0	
	9	91,790	0	0	0	0	0	0	40,985	50,805	0	0	0	0	0	
	10	43,000	0	0	0	0	0	0	14,775	28,225	0	0	0	0	0	
3	11	68,632	0	0	0	0	0	0	68,632	0	0	0	0	0	0	3,040,827
	12	126,287	0	0	0	0	0	0	0	112,900	13,387	0	0	0	0	
	13	99,920	0	0	0	0	0	0	0	0	99,920	0	0	0	0	
	14	43,000	0	0	0	0	0	0	0	43,000	0	0	0	0	0	
	15	157,520	0	0	0	0	0	0	0	0	0	157,520	0	0	0	
4	16	57,390	0	0	0	0	0	0	0	0	57,390	0	0	0	0	3,776,576
	17	125,610	0	0	0	0	0	0	0	112,610	13,000	0	0	0	0	
	18	40,000	0	0	40,000	0	0	0	0	0	0	0	0	0	0	
	19	40,000	0	0	40,000	0	0	0	0	0	0	0	0	0	0	
	20	138,380	0	0	0	0	0	0	0	0	0	25,480	112,900	0	0	

(b) Stand-alone solutions.

Fig. 2 Harvest schedules

Table 3 Resource usage for the collaborative solution

Winery	Resource	Planning horizon												
		1	2	3	4	5	6	7	8	9	10	11	12	13
1 2 3 4	Workers								196					
	Machinery		31	31	31	31	31	31	31	31	31	31		

EPM and Gini coalition structures coincide ($\{1, 2, 3, 4\}$), while the Entropy solution differs ($\{1, 23, 4\}$). For the policy (++), all the methods lead to different coalition structures: $\{1, 234\}$ for the EPM, $\{12, 34\}$ for the Entropy method and $\{1, 2, 3, 4\}$ for the Gini method. On the other hand, the cost allocated by the three methods differs marginally when it is possible to share some resources, that is, for (−+), (+−), and (++). However, for (−−), the most restrictive policy, the costs allocated by the methods present non-negligible differences. Particularly, the absolute difference between Gini and Entropy methods for the wineries belonging to the coalition $\{34\}$ is 1297, while between the Gini method and EPM is 11,548. This last occurs because the Gini and Entropy methods work with equity measures which

Table 4 Resource usage for the stand-alone solutions

Winery	Resource	Planning Horizon												
		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Workers		1											
	Machinery		27	27										
2	Workers				6									
	Machinery				14	14	14	14	14					
3	Workers													
	Machinery							28	28	28	28			
4	Workers			126										
	Machinery								20	20	20	20		

aim to provide cost allocations as equal as possible to each coalition's members, while the EPM compares only against the stand-alone situation. It is important to point out that, when a winery remains as a singleton coalition, the outcomes of the three studied methods are identical. These results are not surprising since all three methods consider the individual rationality stability constraint, implying that the firms receive their own exact cost for the stand-alone case.

5.2 Further experimental analysis

In this subsection, we push the analysis forward. The aim is to determine if the previous results hold in a more general setting. To do so, we perturb the illustrative example data by making $\mathcal{Q}$ permutations between blocks of different wineries. Figure 3 depicts an example for $\mathcal{Q} = 3$. The idea is simple: to explore the neighborhood of the illustrative example instance, keeping a tabu list to avoid duplicity. Note that the greater the value of $\mathcal{Q}$, the farther the perturbed instance is from the base case. For each $\mathcal{Q} \in \{1, 2, 3, 4\}$, we randomly generate 100 new instances. For each of these 400 instances, we compute the coalition structure and the allocated costs, considering, on the one hand, the three methods discussed in Sect. 4, and on the other hand, the four hiring policies stated in the previous Sect. 5.1. We also compute the grand coalition's relative cost variation compared to the stand-alone case, which is established in Eq. (62).

$$\Delta C = \frac{C(\{1234\}) - \sum_{i=1}^{4} C(\{i\})}{C(\{1234\})} \tag{62}$$

Table 6 shows the average, maximum, and minimum relative cost variations and the number of instances in which this measure is positive (cost reduction) or negative (cost increase). We observe that averages increase as $\mathcal{Q}$ increases, achieving a cost reduction of 13.86% for $\mathcal{Q} = 4$ and policy (−−). This fact shows that the illustrative

Table 5 Coalition structure and cost allocation for the illustrative example

EPM					Entropy					Gini				
Policies	Coalition	CC	AC	FO	Policies	Coalition	CC	AC	FO	Policies	Coalition	CC	AC	FO
−−	1	$1,555,824	$1,555,824	0	−−	1	$1,555,824	$1,555,824	− 0.688	−−	1	$1,555,824	$1,555,824	0.052
	2	$2,588,212	$2,588,212			2	$2,588,212	$2,588,212			2	$2,588,212	$2,588,212	
	34	$6,791,520	$3,029,280			34	$6,791,520	$3,039,531			34	$6,791,520	$3,040,828	
			$3,762,240					$3,751,989					$3,750,692	
−+	1	$1,555,824	$1,555,824	0	−+	1	$1,555,824	$1,555,824	− 0.689	−+	1	$1,555,824	$1,555,824	0.050
	2	$2,588,212	$2,588,212			2	$2,588,212	$2,588,212			2	$2,588,212	$2,588,212	
	34	$6,752,490	$3,013,780			34	$6,752,490	$3,039,073			34	$6,752,490	$3,040,829	
			$3,738,710					$3,713,417					$3,711,661	
+−	1	$1,376,200	$1,376,200	0	+−	1	$1,376,200	$1,376,200	− 0.681	+−	1	$1,376,200	$1,376,200	0
	2	$1,696,800	$1,696,800			23	$4,048,600	$1,696,801			2	$1,696,800	$1,696,800	
	3	$2,351,800	$2,351,800					$2,351,799			3	$2,351,800	$2,351,800	
	4	$1,932,600	$1,932,600			4	$1,932,600	$1,932,600			4	$1,932,600	$1,932,600	
++	1	$1,376,200	$1,376,200	0	++	12	$3,073,000	$1,376,200	− 1.377	++	1	$1,376,200	$1,376,200	0
	234	$5,975,000	$1,696,800					$1,696,800			2	$1,696,800	$1,696,800	
			$2,351,800			34	$4,278,200	$2,351,799			3	$2,351,800	$2,351,800	
			$1,926,400					$1,926,401			4	$1,926,400	$1,926,400	

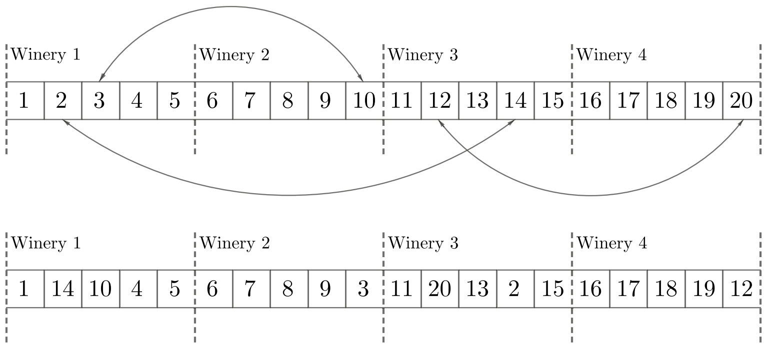


Fig. 3 An instance of a $\mathcal{Q} = 3$ permutation

example instance is very particular: as long as we get farther from it, collaboration becomes more relevant. We also note that, as more hiring flexibility is allowed, the benefits of collaboration decrease, so there is a negative effect of flexibility over collaboration. In fact, for the (++) policy, the benefits of collaboration vanishes.

Table 7 shows the number of coalitions formed. First, note that some instances are infeasible. This phenomenon occurs because the three methods include the constraint that the selected payoff vector should belong to the core, which may be empty. For the policy (−−), the number of instances in which the grand coalition forms increases with $\mathcal{Q}$ for the three methods, which implies that when departing from the illustrative example, collaboration increases. The same happens for instances with two coalitions, which supports the statement that, for policy (−−), the illustrative instance is unfavorable for developing a collaborative scheme. For the policy (++), when comparing the three coalitions structure and cost allocation methods, we observe that, on the one hand, the Gini model diminishes the likelihood of the grand coalition's formation. On the other hand, the EPM has the maximum number of instances where the grand coalition form, while the Entropy method leads the number of cases where two coalitions form.

Finally, Table 8 compares the Gini, Entropy and EPM average objective function values, for $\mathcal{Q} \in \{1, 4\}$ and the (−−) policy, through a *payoff table* commonly used in a multi-objective framework. That is to say, in each row, we compute the optimal solution of the corresponding model, and we evaluate the performance of that solution in the other two models. For each metric (column), we show in parenthesis the ranking position when using the three models. As expected, each metric obtains the best results when optimizing its corresponding objective function. However, the entropy method's solutions show, on average, a more equitable behavior when evaluated on the other two fairness criteria.

Table 6 Relative cost variations

	$\mathcal{Q} = 1$				$\mathcal{Q} = 2$				$\mathcal{Q} = 3$				$\mathcal{Q} = 4$			
	−−	−+	+−	++	−−	−+	+−	++	−−	−+	+−	++	−−	−+	+−	++
Average (%)	− 1.98	− 1.19	− 0.23	0.00	5.52	5.78	− 0.27	0.00	10.07	9.92	− 0.25	− 0.01	13.68	13.40	− 0.24	0.00
Maximum (%)	12.08	12.24	− 0.08	0.00	20.32	18.62	0.00	0.00	23.06	20.55	0.00	0.00	23.84	21.87	− 0.08	0.00
Minimum (%)	− 19.60	− 18.18	− 0.39	− 0.05	− 20.84	− 19.55	− 0.47	− 0.05	− 12.46	− 11.12	− 0.39	− 0.05	− 10.12	− 9.08	− 0.39	− 0.05
>0	42	46	0	0	75	78	0	0	90	93	0	0	95	94	0	0
<0	58	54	100	5	25	21	99	4	10	7	98	11	5	6	100	5
=0	0	0	0	95	0	1	1	96	0	0	2	89	0	0	0	95

Table 7 Number of coalitions formed

	(−−)					(−+)					(+−)					(++)					
# coalitions	1	2	3	4	inf	1	2	3	4	inf	1	2	3	4	inf	1	2	3	4	inf	
$\mathcal{Q}$																					
1	2	30	58	10	0	0	2	69	29	0	0	0	93	7	0	0	0	38	62	0	Gini
2	7	41	46	2	4	0	8	57	35	0	0	10	86	1	3	1	3	72	24	0	
3	9	56	26	1	8	0	16	52	32	0	0	9	89	0	2	0	0	86	14	0	
4	11	58	19	0	12	0	32	46	22	0	0	13	79	0	8	0	0	88	12	0	
1	2	30	58	10	0	0	2	69	29	0	0	5	95	0	0	21	79	0	0	0	Entropy
2	7	45	46	2	4	0	8	57	35	0	0	11	85	1	3	14	86	0	0	0	
3	9	62	26	1	8	0	16	52	32	0	0	9	89	0	2	10	90	0	0	0	
4	11	69	19	0	12	0	32	46	22	0	0	15	77	0	8	9	91	0	0	0	
1	2	30	58	10	0	0	2	69	29	0	0	5	93	2	0	32	2	38	28	0	EPM
2	7	41	46	2	4	0	8	57	35	0	0	3	93	1	3	16	4	74	6	0	
3	9	56	26	1	8	0	16	52	32	0	0	6	92	0	2	11	3	86	0	0	
4	11	58	19	0	12	0	32	46	22	0	0	11	81	0	8	9	2	89	0	0	

Table 8 Gini, Entropy and EPM average objective function values for $\mathcal{Q} \in \{1, 4\}$ and the $(--)$ policy

Metric			
OF	Gini	Entropy	EPM
$\mathcal{Q} = 1\,(--)$			
Gini	0.0679064 (1st)	– 0.7445929 (3rd)	0.1315235 (3rd)
Entropy	0.0758889 (2nd)	– 0.8965567 (1st)	0.1287054 (2nd)
EPM	0.1042889 (3rd)	– 0.8881164 (2nd)	0.0428887 (1st)
$\mathcal{Q} = 4\,(--)$			
Gini	0.0887985 (1st)	– 1.1126436 (2nd)	0.2595562 (3rd)
Entropy	0.0887985 (2nd)	– 1.1965807 (1st)	0.2548440 (2nd)
EPM	0.1282386 (3rd)	– 1.0947972 (3rd)	0.1766500 (1st)

6 Concluding remarks

This paper analyzes the benefits of using a collaborative approach for the wine grape harvesting process. This last consists of deciding when and which blocks to harvest during the harvesting season, considering several operational constraints. We assess how joint planning of labor and machinery capacity impacts harvesting costs. We also consider several hiring policies that allow us to analyze the benefits of collaboration depending on the number of times firms can hire workers or rent machinery during the season. Using a cooperative game theory approach, we propose a novel coalition structure and cost allocation model based on the Gini index. Our method simultaneously determines which wineries should collaborate and how the costs must be split among them.

We use an illustrative example to show how the proposed procedure works. Additional experiments are performed on perturbed data to push the analysis forward. We find that the flexibility level of the hiring policies impacts the benefits of collaboration significantly. Particularly, when firms can hire/rent and fire/return multiple times, the collaborations' impact diminishes. Conversely, less flexible hiring policies make collaboration an appealing option to reduce costs. Besides, our results show that the fairness criteria used strongly affect the coalitions formed and the sharing of costs, which is in line with recent findings (Guajardo et al. 2016; Basso et al. 2020; Le Cadre et al. 2019; Jouida et al. 2020).

We compare the Gini method performance against two other models previously used in the literature, namely, the Entropy and the Equal Profit Method. We draw two main conclusions that shed light on different aspects of the problem, showing that different methods might be more adequate depending on the decision-makers' preferences. First, we find that the entropy method's solutions show, on average, a more equitable behavior when studying the payoff table of the three studied fairness metrics in the spirit of a multi-objective optimization framework. Second, we show that the Gini method favors the formation of smaller coalitions. This result might be relevant for the practical implementation of collaboration since some authors have mentioned that larger coalitions make collaboration more difficult (Flisberg et al. 2015) due to coordination issues (Basso et al. 2019).

Although we focus on the grape harvesting problem, the contributions of this paper are relevant in a broader scope. The wine grape harvesting problem can be seen as a lot-sizing and scheduling problem that arises in other industries. Thus, as our collaborative framework builds on this formulation, we think the proposed cooperative methodology can be expanded to other crop industries straightforwardly. The broader applicability of our methods is explained because several harvesting decisions considered in our modeling approach are similar between crops. Specifically, as stated in Ahumada and Villalobos (2009), the typical harvesting decisions include the timing for collecting the crops from the fields, resource utilization, labor and machinery scheduling, and routing. Likewise, the Gini index can be used as a fairness criteria in any cooperative game theory application, even beyond logistics. Indeed, note that the formulation we propose does not consider any wine supply chain's specific constraint, and only requires to be able to compute the characteristic function for any possible coalition. That is to say, the Gini index can be employed in any characteristic function game.

Future work should address how coalition structure and cost allocation models could incorporate uncertainty in the characteristic function vector. Particularly, we expect to develop a two-stage stochastic programming formulation (Birge and Louveaux 2011), in which coalition structure is a first stage decision, and cost allocation is a recourse action. Another interesting avenue for future research is studying the interaction between equity and stability in horizontal collaboration. Coalition structure and cost allocation models usually incorporate equity as the objective function, while stability is considered a constraint. This approach assumes that stability must always be satisfied. Thus, unstable coalitions are set apart, but they could be much more equitable. Then, a trade-off appears straightforwardly. How much inequity would the decision-maker accept in order to keep the coalition stable? Conversely, how much instability would the decision-maker allow in order to keep the coalition equitable?

Appendix A

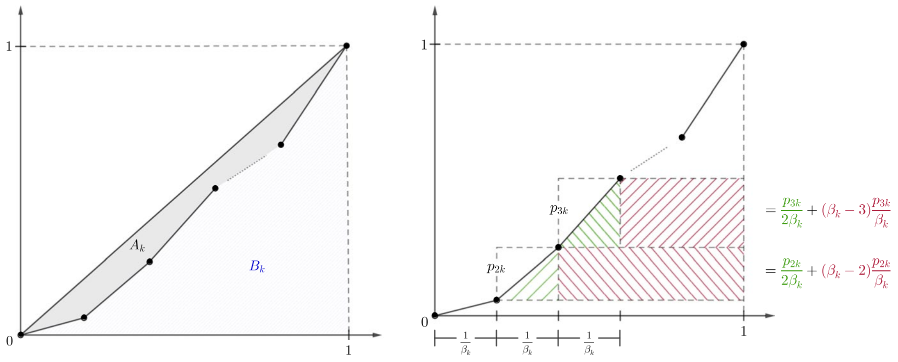
The Gini Index for coalition $k \in \mathcal{K}$ is defined as $\frac{A_k}{A_k+B_k}$ where A_k and B_k are the areas depicted in Fig. 4a.

As shown in Fig. 4b, the Gini Index for coalition $k \in \mathcal{K}$ can be computed according to Eq. (66).

$$g_k = \frac{A_k}{A_k + B_k} \tag{63}$$

$$= \frac{0.5 - B_k}{(0.5 - B_k) + B_k} \tag{64}$$

$$= 1 - 2B_k \tag{65}$$



(a) Examples of A_k and B_k areas. **(b)** Computing B_k.

Fig. 4 Gini Index computation example

$$= 1 - 2 \sum_{n \in \mathcal{N}_k} \left[\frac{p_{nk}}{2\beta_k} + (\beta_k - n) \frac{p_{nk}}{\beta_k} \right] \tag{66}$$

Appendix B

The data used in the illustrative example (see Sect. 5.1) are shown in the following tables.

See Tables 9, 10, 11, 12, 13 and 14

Table 9 Coalition sets

Sets	Cardinality
F	4
J_f	5 $\forall f$
R	2

Table 10 Parameters

Parameter	Value
T	13
K	16,000,000
M	100,000

Table 11 Cost and productivity of the resources

r	P_r	H_r
1	26,200	5645
2	10,000	639

Table 12 Harvesting blocks features

	j	G_j	N_j
J_1	1	40,000	13,000
	2	84,860	13,000
	3	84,550	13,000
	4	40,000	13,000
	5	40,000	13,000
J_2	6	82,280	13,000
	7	60,050	13,000
	8	74,240	13,000
	9	91,790	13,000
	10	43,000	13,000
J_3	11	68,632	13,000
	12	126,287	13,000
	13	99,920	13,000
	14	43,000	13,000
	15	157,520	13,000
J_4	16	57,390	13,000
	17	125,610	13,000
	18	40,000	13,000
	19	40,000	13,000
	20	138,380	13,000

Table 13 Harvesting windows

W_{jt}	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0	1	1	1	0	0	0	0	0	0	0	0	0
2	1	1	1	1	1	1	0	0	0	0	0	0	0
3	1	1	1	1	1	1	0	0	0	0	0	0	0
4	0	1	1	1	0	0	0	0	0	0	0	0	0
5	0	1	1	1	0	0	0	0	0	0	0	0	0
6	0	0	1	1	1	1	1	0	0	0	0	0	0
7	1	1	1	1	1	1	1	1	1	1	0	0	0
8	0	0	0	0	1	1	1	1	1	0	0	0	0
9	0	0	0	0	0	0	1	1	1	1	1	0	0
10	0	0	0	0	0	0	1	1	1	1	1	0	0
11	0	0	0	0	0	1	1	1	1	1	0	0	0
12	0	0	0	0	0	0	1	1	1	1	1	0	0
13	0	0	0	0	0	0	0	1	1	1	1	1	0
14	0	0	0	0	0	0	1	1	1	1	1	0	0
15	0	0	0	0	0	0	0	0	1	1	1	1	1
16	0	0	0	0	0	0	0	1	1	1	1	1	1
17	0	0	0	0	0	0	1	1	1	1	1	0	0
18	0	1	1	1	0	0	0	0	0	0	0	0	0
19	0	1	1	1	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	1	1	1	1
W_{jt}	1	2	3	4	5	6	7	8	9	10	11	12	13

Table 14 Quality factor costs

Q_{jt}	1	2	3	4	5	6	7	8	9	10	11	12	13
1	–	12.45	0	7.95	–	–	–	–	–	–	–	–	–
2	12.45	0	7.95	12.15	18.10	29.75	–	–	–	–	–	–	–
3	12.45	0	7.95	12.15	18.10	29.75	–	–	–	–	–	–	–
4	–	12.45	0	7.95	–	–	–	–	–	–	–	–	–
5	–	12.45	0	7.95	–	–	–	–	–	–	–	–	–
6	–	–	12.45	0	7.95	12.15	18.10	–	–	–	–	–	–
7	49.75	36.60	21.15	12.45	0	7.95	12.15	18.10	29.75	46.95	–	–	–
8	–	–	–	–	12.45	0	7.95	12.15	18.10	–	–	–	–
9	–	–	–	–	–	–	12.45	0	7.95	12.15	18.10	–	–
10	–	–	–	–	–	–	12.45	0	7.95	12.15	18.10	–	–
11	–	–	–	–	–	12.45	0	7.95	12.15	18.10	–	–	–
12	–	–	–	–	–	–	12.45	0	7.95	12.15	18.10	–	–
13	–	–	–	–	–	–	–	12.45	0	7.95	12.15	18.10	–
14	–	–	–	–	–	–	12.45	0	7.95	12.15	18.10	–	–
15	–	–	–	–	–	–	–	–	12.45	0	7.95	12.15	18.10
16	–	–	–	–	–	–	–	12.45	0	7.95	12.15	18.10	–
17	–	–	–	–	–	–	12.45	0	7.95	12.15	18.10	–	–
18	–	12.45	0	7.95	–	–	–	–	–	–	–	–	–
19	–	12.45	0	7.95	–	-	–	–	–	–	–	–	–
20	–	–	–	–	–	–	–	–	–	12.45	0	7.95	12.15

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