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# An optimization approach for scheduling wine grape harvest operations

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## Abstract

This article presents a practical tool for optimally scheduling wine grape harvesting operations taking into account both operational costs and grape quality. We solve a mixed-integer linear programming model to support harvest scheduling, labor allocation, and routing decisions. A quality loss function is used to represent wine quality reduction at each vineyard block due to premature or deferred harvest with respect to an optimal date. We present computational results which show that the proposed tool could be used to support grape harvest planning in a large vineyard, at both a tactical and operational level.

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*Keywords:* Wine production; Grape harvesting; Operations scheduling; Optimization.

## 1. Introduction

Decision Support Systems for the agricultural sector have become a very attractive area of development, given the high complexity of decisions involved in different problems (Altieri and Faeth, 1994). This complexity is inherent to the biological aspects of the agricultural problems, which introduce uncertainty and variability. In addition, some cultural characteristics of the agricultural sector have delayed massive adoption of computational support tools, in comparison to other sectors, like services and manufacturing. This has been particu-

larly true in the recent development of the Chilean economy.

Several agricultural and related management problems can be stated as mathematical models that can be solved through the use of computational techniques. This has helped several industries to improve their productivity and solve many operational problems. In Chile the forest industry has been an icon of these developments; however, the wine industry has also modernized its operations. In fact, thanks to important investments in more modern equipment for winemaking and bottling, wine production has improved, both in efficiency and in quality assurance, a central aspect of this business. Harvesting operations, however, are falling behind in terms of adopting some technologies, particularly decision support tools. In most cases

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these operations currently depend mainly on the intuition and good criterion of the decision makers.

In Chile, although there are some computational systems that help wineries to monitor and trace their production processes, no planning or scheduling tools are used to support harvesting decisions of vineyard administrators and enologists. As a result of this lack of planning tools, grapes are not necessarily harvested at their optimal maturity or, if they are, the reception capacity of the winery sometimes is not taken into account, implying long delays, with the corresponding potential damage (Bordeu et al., 2002). This impacts profits as wines which should have been of good quality need to be *degraded* to inferior ones.

Harvesting is usually defined for basic units called *blocks*, which correspond to specific areas of land with similar characteristics in ground composition, grape variety, and quality. Planning consists on deciding for a planning horizon of a few weeks, which blocks must be harvested and when taking into account feasibility time windows (outside that interval, the grape is not harvested). It is also important to determine the allocation of labor and the number of harvesting machines needed to carry out that program. The problem becomes more complex when alternative wineries are available as destination.

In a typical winemaking operation, harvesting decisions require much interaction between the enologist and the vineyard manager, which have different priorities. The enologist is mostly concerned about wine quality, while the vineyard manager considers more specific agricultural variables, including operational costs. The vineyard manager seeks to minimize harvesting cost through the optimal allocation of resources (optimal allocation of labor and machinery), as well as providing the winery with the required grapes. The objective of the enologist, on the other hand, is to maximize wine quality.

To avoid subordinating one objective to the other, we developed an optimization model which balances the operating costs of the harvesting process with the quality loss effects of the schedule. That is, the model attempts to assign harvesting resources to the blocks with the highest quality grapes to harvest them on time, but without disregarding the economic impact of the decision. The quality effect of the schedule is represented in this work by a *quality loss function*, which is a way of measuring the potential reduction in the quality

of the wine due to the use of grapes which were not harvested at the "optimal" maturity date. This optimal date is defined by enologists based on chemical analysis and their experience. The quality loss function therefore reflects enologists' perceptions of the effect of the deteriorated grapes on the quality of the wine. Quality factors have been considered in other agricultural applications (Yom Din and Zugman, 2003).

The model also considers another operational aspect: the routing of the harvesting operations, which is relevant in terms of the high costs or time induced by the need of moving the operations from one block to another.

The paper is structured as follows. In Section 2 we present a review of decision support tools in agriculture. In Section 3 we state the formulation of the model and discuss the use of a quality loss function. The detailed description of the model is presented in an Appendix. In Section 4 we present the solution procedure and discuss our first test example. In Section 5 we discuss and present results for a specific example corresponding to an actual vineyard. Finally, we state our conclusions in Section 6.

## 2. Decision support tools in agriculture

Since its origins, Operations Research has been an alternative to support decisions in the agricultural area, although traditionally judgment based on experience has been the basis for agricultural planning (France and Thornley, 1984). However, the increasing adoption of capital intensive technologies have stimulated the development of more formal planning tools, most of them based on Operation Research tools. In the agricultural sector several researchers have developed land management models where planning normally involves financial objectives, such as the maximization of the benefits, and factors, like a relatively stable level of income, or the fulfillment of certain goals (Glen, 1987). Several applications have been described in the literature, such as a mixed-integer programming planning (MIP) model for the fruit industry (Masini, 2003), a complex system integrating several optimization models to help plan operations and deliveries for a large company in the meat industry (Bixby et al., 2006), a MIP model used to determine the optimal postharvest handling of fresh vegetable crops (Aleotti et al., 1997), an improved harvesting and transportation planning approach using a

modeling framework composed of submodels of parts of the system (Higgins and Laredo, 2006), an LP model for planning the production of flowers (Caixeta-Filho et al., 2002), and an LP model that determines how to harvest the oranges in order to maximize the revenue (Caixeta-Filho, 2006). Furthermore, Lowe and Preckel (2004) present a brief review and call for future research in decision technologies for agribusiness problems.

The forest sector has been an intensive user of Operations Research tools, particularly in recent years in Chile, where production planning models and vehicle routing and dispatching models have been developed (Epstein et al., 1999). These have been implemented into software using clever heuristic procedures. The success of these applications has made it easier to apply the same techniques in other agricultural sectors, such as winemaking. Routing is also a relevant topic in agricultural operations and related areas, given the cost incurred in moving operations between different areas. Classical vehicles routing problem can be found for the particular case of the milk industry (Basnet et al., 1993).

Some specific applications have been developed for the grape harvesting problem. The risk factors associated with grape harvesting for juice production has been studied (Allen and Schuster, 2004). This is complemented with a study that shows that nonlinear inventory models are a good approach for perishable products, as they modify their quality with time (Chaudhuri and Giri, 1997).

The supply chain management concept is also relevant to help plan agricultural operations, e.g., the uncertainties of the wine supply chain in Australia (Islam and Quaddus, 1992). The complexities on defining adequate schedules for wine grapes harvesting has been considered, with a collaborative approach between different actors (Horn and Dunstall, 2004). The development we present in this paper complements these collaborative approaches as it provides the means to evaluate the costs of specific harvesting decisions.

## 3. Harvest planning

This section presents the development of the mixed integer linear programming model which takes into account various specific requirements which are relevant for the wine industry. The model considers an objective of cost minimization together with an objective of quality maximization of the harvested grapes. Both objectives might be considered separately in a real multiobjective framework, but we decided to combine them in a single objective function, which can be solved using standard optimization software and still allows the decision maker to visualize the trade-offs between both objectives.

### 3.1. Representing quality loss

The reduction in quality due to harvesting before or after the optimal date can be estimated in different ways, although it is a controversial issue among enologists. However, there is a clear agreement that some deterioration is produced if we harvest ahead of time. Delaying harvesting seems to be less dangerous, but it exposes the crop to an increasing danger of rain (Bordeu et al., 2002). One way of incorporating the fact that we are not indifferent regarding the harvesting date within the feasible window is through a quality loss function. This concept was originally developed in the manufacturing area and has had a significant impact in the so called robust quality approach (Taguchi and Clausing, 1990).

We incorporated this notion of quality in the model by including a cost associated to a specific harvesting decision. To harvest in the optimal date has no quality penalty; to harvest before or after generates a cost associated to the potential deterioration of the grapes and subsequent effect on the quality of the wine.

In order to understand the loss of quality, it is necessary to address that wines are categorized into quality groups starting at the premium level and going down to the reserve, the varietals, and finally the bulk wines. As the harvest decision deviates from the optimal date, the quality of the grapes is affected, so a premium wine quality grape could be *degraded* to a reserve wine quality grape, and if no action is taken it could be finally degraded into a bulk wine quality grape (MacCawley, 2002). This sequential degradation process of the grapes results in loss of revenue for the business, since the profit of a premium wine is much higher than one obtained by the bulk wine.

In order to quantify the degradation effect, some Chilean enologists were surveyed during 2003. They were asked at what deviation level from the optimal harvesting date they would degrade a premium quality grape to the other classes (Reserve, Varietal and Bulk). Table 1 shows the relative value assigned by enologists to the different classes of wines.

Table 1
Relative profit of wines

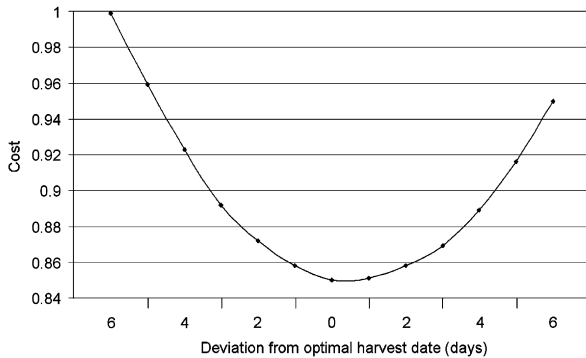| Wine/grape quality | Profit (100 = Premium) |
| --- | --- |
| Premium | 100 |
| Reserve | 62.6 |
| Varietal | 36.5 |
| Bulk | 8.1 |



Fig. 1. Quality loss function.

Enologists were also asked in the survey to evaluate the possible degradation of grapes harvested before or later than the optimal harvesting date. This gave us relative perceptions which, together with the relative value of wines, allowed us to define a parameter that can be incorporated as an extra cost associated to the decision variables which determine the amount harvested in a given day and block (Toloza, 2004). These cost figures correspond to a relative scale depending on the deviation with respect to the optimal day. Fig. 1 shows an example of the quality loss curve based on the survey taken to enologist in Chile during 2003. The cost indicated in the graph is a relative measure whose absolute value can be increased or decreased with respect to the other costs in the model (labor, transportation, etc.). This allows the decision maker to deal with the trade-off between operational cost minimization and quality maximization. We have used these specific figures in the data for the examples we develop in the following sections.

### 3.2. Mathematical formulation

This section describes the decision variables and the main constraints of the model. The detailed formulation is given in the appendix.

The aim of the model is to decide which blocks to harvest and when to do it. This translates into a decision variable indicating the volume of grapes (in kg) harvested from a given block in a given day, with the additional qualification of the destination winery and harvesting method (by hand or using machinery). This decision is affected by the estimated optimal harvest day and constrained by a feasibility window. These pieces of information are external to the model and provided by the decision maker. The quality loss function, as explained earlier, is translated into a specific cost in the objective function associated to this variable.

The formulation considers that the blocks can be harvested either by machine or by hand and the model has to compute how many hours of labor are needed in each case. It is assumed that a block can be assigned to a single winery only. Also, a minimum harvest activity in a given block is required if we decide to intervene the block. This requires introducing the following variables into the model:

$x_{jtkb}$: is the amount of grapes (in kg) harvested from block $j$ in day $t$, in harvest mode $k$, with destination $b$. Here, $k = 1$ corresponds to mechanical harvesting, $k = 2$ is manual harvesting.

$y_{jtkb}$: is a binary variable equal to 1 if harvesting of block $j$ is initiated in day $t$, in mode $k$, with destination $b$, and 0 otherwise.

$v_{jtk}$: is a binary variable equal to 1 if harvesting is taking place in block $j$ in day $t$, in mode $k$.

These variables are connected by the following constraints:

$$x_{jtkb} \leqslant G_{jkb} v_{jtk}, \quad \forall j, t, k, b, \tag{1}$$

$$x_{jtkb} \geqslant V_k v_{jtk}, \quad \forall j, t, k, b, \tag{2}$$

$$y_{jtkb} \leqslant \sum_{s \leqslant t: W_{js}=1} v_{jsk}, \quad \forall j, t: W_{jt} = 1, \forall k, b, \tag{3}$$

$$v_{jtk} \leqslant \sum_b \sum_{s \leqslant t: W_{js}=1} y_{jskb}, \quad \forall j, t, k, \tag{4}$$

$$\sum_b \sum_{t: W_{jt}=1} y_{jtkb} \leqslant 1, \quad \forall j, k, \tag{5}$$

where $G_{jkb}$ is the total grape availability in block $j$, which has to be harvested by mode $k$ and sent to winery $b$. $V_k$ is the minimum volume that is profitable to handle using harvesting mode $k$ (below this number it makes no sense to harvest). The parameter $W_{jt}$ indicates whether block $j$ can be harvested at time $t$, that is, it specifies the maximum time window to harvest. These constraints insure

that, if a block is harvested, the volume harvested will be at least equal to a certain minimum.

The model also takes into account the short term routing of harvesting operations. This is relevant since transportation costs can be significant when moving equipment and labor teams from one area of the field to another. It can be reasonable to harvest some blocks earlier, if they are nearby and the quality effect is not significant. We therefore need decision variables to specify the sequence in which harvest operations are performed, in order to minimize transportation costs. This part of the model is, essentially, a traveling salesman problem (TSP) that can be represented either by the MTZ formulation (Miller et al., 1960) or by the subtour elimination formulation. A comparison between the MTZ formulation and the classic formulation of this hard combinatorial problem, emphasizes that in the first case (MTZ) only a polynomial number of variables and constraints need to be added (Pataki, 2003). In contrast, the classical formulation has an exponential number of constraints but is stronger in terms of the optimal value of the linear relaxation. The formulation works in a graph $G = (N, A)$ with $n$ nodes. We use a binary variable $u_{ij}$ equals to 1 if we go from node $i$ to node $j$ in the circuit, and a variable $\gamma_i$ which will correspond to the order in the sequence, and we assume that we start at node 1. The constraints of the MTZ formulation are as follows:

$$\sum_{j \neq i} u_{ij} = 1, \quad \forall i = 1, ..., n, \tag{6}$$

$$\sum_{i \neq j} u_{ij} = 1, \quad \forall j = 1, ..., n, \tag{7}$$

$$\gamma_i - \gamma_j + 1 \leqslant (n-1)(1 - u_{ij}), \quad \forall i, j, i \neq 1, \ j \neq 1, \tag{8}$$

$$\gamma_1 = 1; 2 \leqslant \gamma_i \leqslant n. \tag{9}$$

It can be easily proved that these constraints in fact eliminate the possibility of subtours in the solution. We have then introduced this formulation into our model. For this purpose, we assume that the operations start at an arbitrary block (say, the one with index 1), follow a circuit between the harvested blocks, and return to the original in the last period. This last movement incurs no relocation cost (actually a small cost was added to make the model work). Specifically, let $z_{ijtb}$ be equal to 1 if block $j$ is harvested after block $i$, beginning in day $t$, with destination $b$, and $\tau_{itb}$ be the order in the sequence of block $i$.

The basic TSP constraints using the MTZ formulation are:

$$\sum_{j \neq i} z_{ijtb} = y_{it2b}, \quad \forall i, t, b, \tag{10}$$

$$\sum_{i \neq j} z_{ijtb} = y_{jt2b}, \quad \forall j, t, b, \tag{11}$$

$$\tau_{itb} - \tau_{jtb} + 1 \leqslant (N-1)(1 - z_{ijtb}),$$
$$\forall i, j; \ i \neq 1, j \neq 1, \ \forall t, \tag{12}$$
$$2y_{it2b} \leqslant \tau_{itb} \leqslant N, \quad \forall i \geqslant 2, \ \forall t, b, \tag{13}$$
$$\tau_{1tb} = y_{it2b}; \quad z_{ijtb} \in \{0, 1\},$$
$$\tau_{itb} \geqslant 0, \ \forall i, t, b. \tag{14}$$

where $N$ is the total number of blocks. Note that variables $y_{itkb}$ will be equal to 1 only for the blocks in which harvesting is to begin on day $t$. We can think of the problem defined in an extended graph in which each node is of the form $(i, t)$, for a given block $i$ to be harvested starting in day $t$. Hence, the variable $y_{it2b}$ will only be equal to 1 for block $i$, for the period $t$ in which harvesting starts. Hence, we are actually defining a TSP only for the subgraph defined by those blocks and those specific time periods.

The other constraints of the model are basically those associated to the availability of labor and machinery, and the capacity constraints of the wineries. This last point is important since, as opposed to traditional production planning models, no inventory of harvested grapes is possible. Everything that is harvested has to be directed to a production plant within the day. Otherwise, grapes deteriorate and become unusable.

The resulting model is a mixed integer linear programming problem, which includes a TSP formulation.

An important aspect of the model is that the effect of weather can be represented through the quality loss function: if rain is expected in a forthcoming day, the corresponding quality cost coefficients are increased.

The model, which is described in detail in the appendix, covers a fixed planning horizon, although this is actually adaptable to the specific use of the model. At a tactical level, the model could be used to plan activities and manpower allocation for the whole harvesting season. In this case, the time interval could be a week and the main data will be the estimation of grapes availability. In a model like this, the consideration of the quality function is not as relevant as in the short term, so it can be

disregarded. The same happens with the operation routing part. However, in an operational planning environment, the whole model, as stated here, should be used. The time interval, in this case, will be days, with a planning horizon of a few weeks, and the quality parameters can be used to discriminate between different blocks. Under normal conditions the model will be used daily with a rolling horizon. This way, the actual harvest performed in different blocks can be used as a border condition for the next day. Also, any new information (like the weather report) can be used to update some of the parameters, like quality costs or estimated maturity date for grapes. Thus, the model will provide useful information to the vineyard administrator as well as to the enologist, for making decisions on the harvest schedule that consider the trade-off between operational costs and grape quality.

## 4. Solution procedure

The model was coded using AMPL and solved with Cplex 7.1 on a DEC Alpha machine. We also used the freely distributed GLPK solver in a Pentium machine. First, we performed a test on a base case to validate the model and then we executed some instances corresponding to a real harvesting situation of a vineyard in central Chile, owned by one of the largest wine producers in the country.

The base case contains fictitious data, although the order of magnitude of the cost, productivity, and capacity information is correct. This case is used to test normal or bad weather scenarios, as well as to study the influence of different approaches to the quality loss function. We also study the impact of the harvesting routing in the model. This base case consists of a planning horizon of 13 days, 20 blocks, 2 wineries, and a quality loss function that penalizes more an anticipation of harvest than the delay. The real case, which will be discussed later, corresponds to a planning horizon of 17 days, 40 blocks, 2 wineries (see Fig. 2). Note that AG corresponds to the central office, which is where the harvesting equipment is stored.

### 4.1. Base case

For the base case, the corresponding model has 6163 constraints and 2452 variables, 1415 of which are binary.

The full model was solved in a total of 15 min of CPU time, including the routing decisions. The schedule generated by the model can be seen in Figs. 3 and 4, which show a Gantt Chart indicating, for each day and for each block (also called quarter or sector), the total planned volume to be harvested, by hand and by machine, respectively. Note that the gray area indicates when harvesting is considered feasible, and a darker line indicates the estimated optimal harvest date.
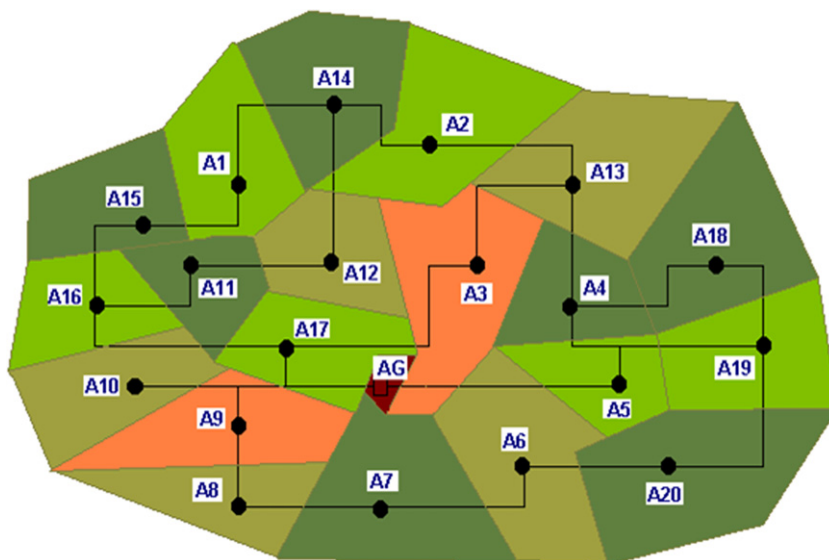


Fig. 2. Area of the base case problem.

**Planning Horizon**

| Block | Kgs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|-------|------|---|---|---|---|---|---|---|---|---|----|----|----|----|
| a1 | 40,000 | | | | 40,000 | | | | | | | | | |
| a2 | 84,860 | | 84,860 | | | | | | | | | | | |
| a3 | 84,550 | | 46,538 | | | 38,012 | | | | | | | | |
| a4 | 40,000 | | | | 40,000 | | | | | | | | | |
| a5 | 40,000 | | | 20,000 | 20,000 | | | | | | | | | |
| a6 | 82,280 | | | | | 56,037 | | 26,243 | | | | | | |
| a7 | 60,050 | | | | | 28,425 | 28,425 | 3,200 | | | | | | |
| a8 | 74,240 | | | | | | 68,063 | 6,177 | | | | | | |
| a9 | 43,000 | | | | | | | | | | 43,000 | | | |
| a10 | 43,000 | | | | | | | | | | 43,000 | | | |
| a11 | 68,632 | | | | | | | 52,350 | 16,282 | | | | | |
| a12 | 63,942 | | | | | | | | 63,942 | | | | | |
| a13 | 99,920 | | | | | | | | | 99,920 | | | | |
| a14 | 43,000 | | | | | | | | | | 43,000 | | | |
| a15 | 81,770 | | | | | | | | | | 38,389 | 7,970 | 35,411 | |
| a16 | 57,390 | | | | | | | | | | | 28,425 | 28,965 | |
| a17 | 43,000 | | | | | | | | | 35,338 | | 7,662 | | |
| a18 | 40,000 | | | 40,000 | | | | | | | | | | |
| a19 | 40,000 | | | 40,000 | | | | | | | | | | |
| a20 | 73,470 | | | | | | | | | | | | | 73,470 |

**Daily Evolution of Grapes (kgs.) Received in each Warehouse**

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|----|----|----|----|
| Warehouse 1 | | 0 | 84,860 | 100,000 | 100,000 | | 68,063 | 6,177 | 63,942 | 0 | 38,389 | 7,970 | 35,411 | 73,470 |
| Warehouse 2 | | 0 | 46,538 | 0 | 0 | 122,474 | 28,425 | 81,793 | 16,282 | 135,258 | 86,000 | 79,087 | 28,965 | 0 |

Optimal Harvest Date
Feasible Window

Fig. 3. Volume harvested in manual mode.

**Planning Horizon**

| Block | Kgs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|-------|------|---|---|---|---|---|---|---|---|---|----|----|----|----|
| a9 | 48,790 | | | | | | | | | 48,790 | | | | |
| a12 | 62,345 | | | | | | | | 62,345 | | | | | |
| a15 | 75,750 | | | | | | | | | | 75,750 | | | |
| a17 | 82,610 | | | | | | | | | 82,610 | | | | |
| a20 | 64,910 | | | | | | | | | | | | | 64,910 |

**Daily Evolution of Grapes (kgs.) Received in each Warehouse**

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|----|----|----|----|
| Warehouse 1 | | 0 | 0 | 0 | 0 | | 0 | 0 | 62,345 | 0 | 75,750 | 0 | 0 | 64,910 |
| Warehouse 2 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 131,400 | 0 | 0 | 0 | 0 |
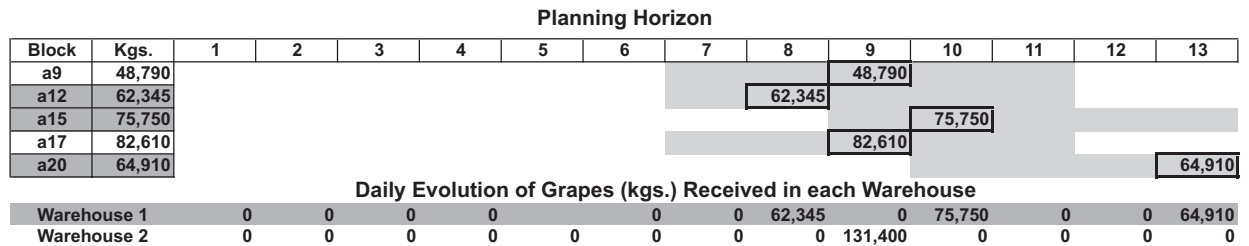
Fig. 4. Volume harvested in mechanical mode.

As expected, the volumes harvested in manual mode, shown in Fig. 3, concentrate around the optimal dates, whenever possible, given the effect of the quality loss function. However, due to the processing capacity of the winery, and constraints on the daily harvest amount, this can not be achieved in a 100%. The model will delay or anticipate harvest in some blocks when it is convenient from the point of view of quality and cost.

The volumes harvested in mechanical mode, shown in Fig. 4, are entirely harvested on the optimal day, thanks to the large productivity of harvesting machinery. Labor use, which is the required number of persons, either hired contractors or seasonal workers, is shown in Fig. 5.

This plan should be very helpful to vineyard managers, especially for the estimates they can get on labor usage, which allows them to plan in advance the requirements for the contractors and also to allow anticipating situations in which more personnel might be needed. The requirements per block also allow to structure the work teams that will be needed. The plan also provides a way of incorporating the enologist's requirements and perceptions through the quality loss function.

The planning model also generates the optimal sequence for the harvesting operations on a given day, so that the cost of relocating harvesting operations from one block to another is balanced with the operational cost and the quality penalty. In our example, the optimal routes are shown in

**Planning Horizon**

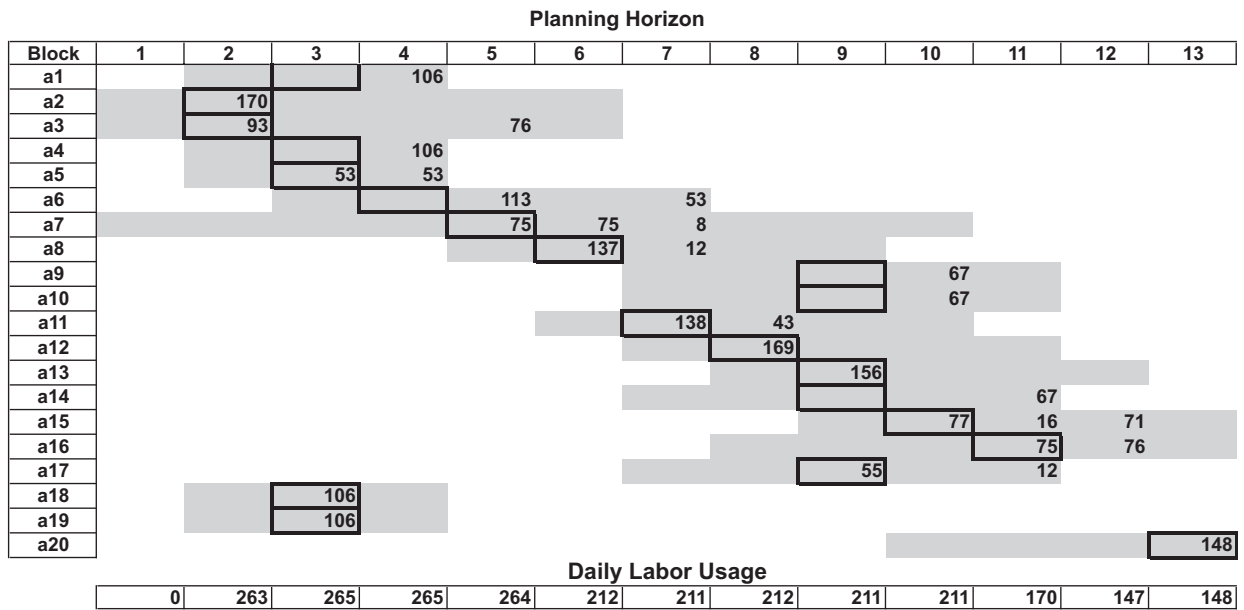| Block | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|-------|---|---|---|---|---|---|---|---|---|----|----|----|----|
| a1 | | | | 106 | | | | | | | | | |
| a2 | | 170 | | | | | | | | | | | |
| a3 | | 93 | | | 76 | | | | | | | | |
| a4 | | | | 106 | | | | | | | | | |
| a5 | | | 53 | 53 | | | | | | | | | |
| a6 | | | | | 113 | | 53 | | | | | | |
| a7 | | | | | 75 | 75 | 8 | | | | | | |
| a8 | | | | | | 137 | 12 | | | | | | |
| a9 | | | | | | | | | | 67 | | | |
| a10 | | | | | | | | | | 67 | | | |
| a11 | | | | | | | 138 | 43 | | | | | |
| a12 | | | | | | | | 169 | | | | | |
| a13 | | | | | | | | | 156 | | | | |
| a14 | | | | | | | | | | | 67 | | |
| a15 | | | | | | | | | | 77 | 16 | 71 | |
| a16 | | | | | | | | | | | 75 | 76 | |
| a17 | | | | | | | | | 55 | | 12 | | |
| a18 | | | 106 | | | | | | | | | | |
| a19 | | | 106 | | | | | | | | | | |
| a20 | | | | | | | | | | | | | 148 |

**Daily Labor Usage**

| 0 | 263 | 265 | 265 | 264 | 212 | 211 | 212 | 211 | 211 | 170 | 147 | 148 |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|

Fig. 5. Labor assignment in the planning horizon.

Table 2
Optimal harvesting tour for each facility

| Day | Warehouse 1 (B1) | Warehouse 2 (B2) |
|-----|------------------|------------------|
| 1 | | |
| 2 | ag → a3 → ag | ag → a2 → ag |
| 3 | | ag → a19 → a18 → a5 → ag |
| 4 | | ag → a1 → a4 → a5 → ag |
| 5 | ag → a3 → a7 → a6 → ag | |
| 6 | ag → a7 → ag | ag → a8 → ag |
| 7 | ag → a11 → a7 → a6 → ag | ag → a8 → ag |
| 8 | ag → a11 → ag | ag → a12 → ag |
| 9 | ag → a13 → a17 → ag | |
| 10 | ag → a9 → a10 → ag | ag → a15 → ag |
| 11 | ag → a16 → a14 → a17 → ag | ag → a15 → ag |
| 12 | ag → a16 → ag | ag → a15 → ag |
| 13 | | ag → a20 → ag |

Table 2, where the notation refers to the block codes indicated in Fig. 2.

### 4.2. Dealing with the weather

Probably the worst scenario during harvest season is rain, especially when it happens just a short time after the beginning of the harvesting period. To analyze the response of the model to this effect, we assume that rain has been forecasted for day three. To represent this situation, the quality loss function can be modified so that the penalty is increased in all those blocks that are planned for

harvesting at the forecasted day of rain and later (now the penalty is smaller for earlier dates and greater for the delay).

The harvest schedule for the base case, assuming rain is expected on the third day, is shown in Fig. 6. It can be clearly seen that in this situation the operations are scheduled much earlier than before, with 104% more activity in the first three days than in the previous schedule. As a result of the high concentration of the harvest during the first days, more labor is demanded, increasing the corresponding cost by 76%.

This illustrates the importance of introducing the weather factor in harvest planning since it can totally change the normal structure of the schedule.

### 4.3. Impact of the quality loss function

The effect of the quality loss function is very important in this harvesting planning model, since it influences the selection of the blocks to be harvested. Two extreme cases of the effect of this function on the schedule are analyzed in Figs. 7 and 8. The first shows the case in which the function strongly penalizes the deviations in relation to the optimal date, generating greater concentration of harvesting activity around this optimal date. Most detrimental in this situation is the strong demand for labor with respect to the base case, with an increase of 40.3%.
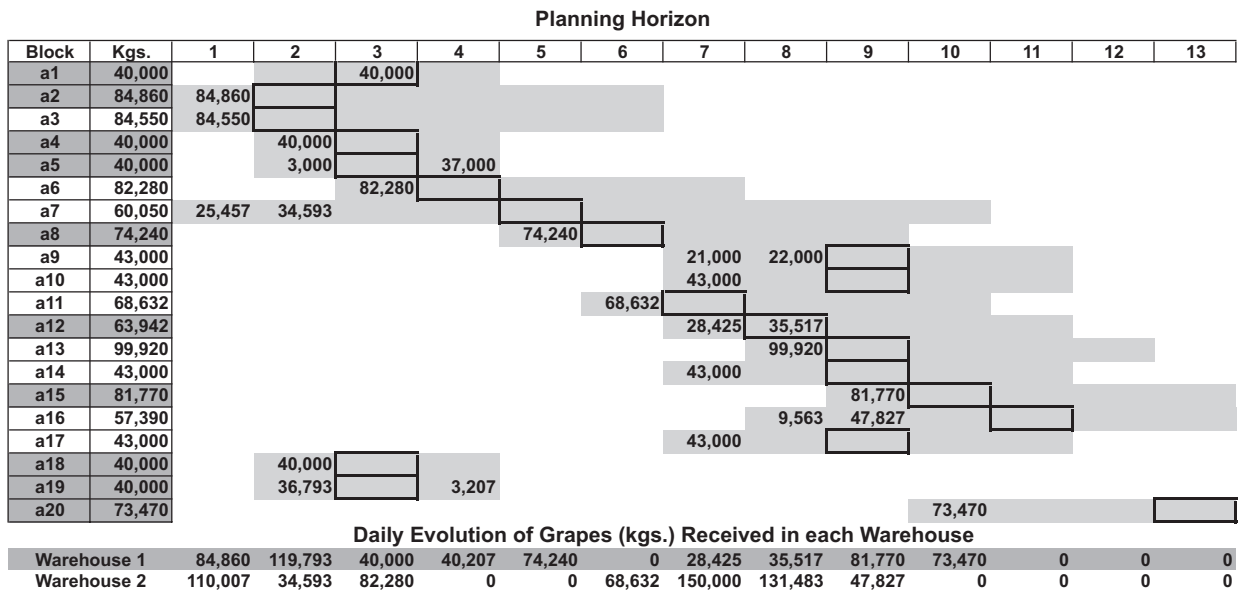
**Planning Horizon**

| Block | Kgs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a1 | 40,000 | | | 40,000 | | | | | | | | | | |
| a2 | 84,860 | 84,860 | | | | | | | | | | | | |
| a3 | 84,550 | 84,550 | | | | | | | | | | | | |
| a4 | 40,000 | | 40,000 | | | | | | | | | | | |
| a5 | 40,000 | | 3,000 | | 37,000 | | | | | | | | | |
| a6 | 82,280 | | | 82,280 | | | | | | | | | | |
| a7 | 60,050 | 25,457 | 34,593 | | | | | | | | | | | |
| a8 | 74,240 | | | | | 74,240 | | | | | | | | |
| a9 | 43,000 | | | | | | | 21,000 | 22,000 | | | | | |
| a10 | 43,000 | | | | | | | 43,000 | | | | | | |
| a11 | 68,632 | | | | | | 68,632 | | | | | | | |
| a12 | 63,942 | | | | | | | 28,425 | 35,517 | | | | | |
| a13 | 99,920 | | | | | | | | | 99,920 | | | | |
| a14 | 43,000 | | | | | | | 43,000 | | | | | | |
| a15 | 81,770 | | | | | | | | | | 81,770 | | | |
| a16 | 57,390 | | | | | | | | | 9,563 | 47,827 | | | |
| a17 | 43,000 | | | | | | | 43,000 | | | | | | |
| a18 | 40,000 | | 40,000 | | | | | | | | | | | |
| a19 | 40,000 | | 36,793 | | 3,207 | | | | | | | | | |
| a20 | 73,470 | | | | | | | | | | 73,470 | | | |

**Daily Evolution of Grapes (kgs.) Received in each Warehouse**

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Warehouse 1 | | 84,860 | 119,793 | 40,000 | 40,207 | 74,240 | 0 | 28,425 | 35,517 | 81,770 | 73,470 | 0 | 0 | 0 |
| Warehouse 2 | | 110,007 | 34,593 | 82,280 | 0 | 0 | 68,632 | 150,000 | 131,483 | 47,827 | 0 | 0 | 0 | 0 |

Fig. 6. Harvest schedule assuming it will rain on day 3.

**Planning Horizon**

| Block | Kgs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a1 | 40,000 | | | | 40,000 | | | | | | | | | |
| a2 | 84,860 | | 84,860 | | | | | | | | | | | |
| a3 | 84,550 | | 84,550 | | | | | | | | | | | |
| a4 | 40,000 | | | 40,000 | | | | | | | | | | |
| a5 | 40,000 | | | 40,000 | | | | | | | | | | |
| a6 | 82,280 | | | | 82,280 | | | | | | | | | |
| a7 | 60,050 | | | | | 60,050 | | | | | | | | |
| a8 | 74,240 | | | | | | 74,240 | | | | | | | |
| a9 | 43,000 | | | | | | | | | | 43,000 | | | |
| a10 | 43,000 | | | | | | | | | 7,080 | 35,920 | | | |
| a11 | 68,632 | | | | | | | 68,632 | | | | | | |
| a12 | 63,942 | | | | | | | | 63,942 | | | | | |
| a13 | 99,920 | | | | | | | | | 99,920 | | | | |
| a14 | 43,000 | | | | | | | | | | 43,000 | | | |
| a15 | 81,770 | | | | | | | | | | 29,110 | 52,660 | | |
| a16 | 57,390 | | | | | | | | | | | 54,390 | 3,000 | |
| a17 | 43,000 | | | | | | | | | 43,000 | | | | |
| a18 | 40,000 | | | 11,309 | 28,691 | | | | | | | | | |
| a19 | 40,000 | | | 40,000 | | | | | | | | | | |
| a20 | 73,470 | | | | | | | | | | | | | 73,470 |

**Daily Evolution of Grapes (kgs.) Received in each Warehouse**

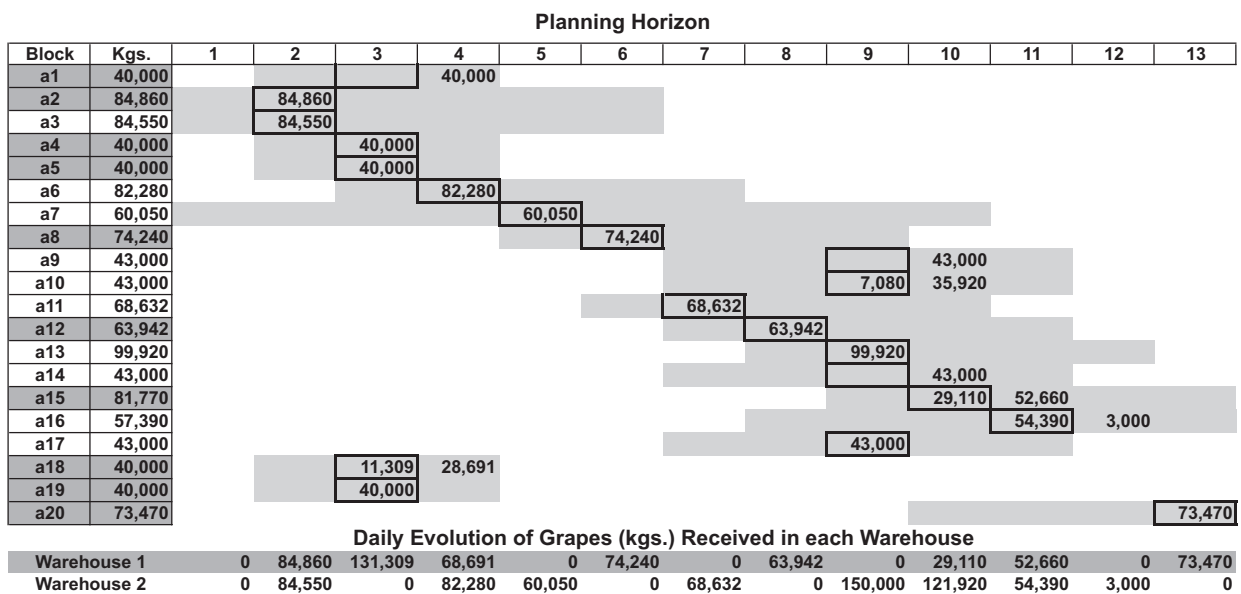| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Warehouse 1 | | 0 | 84,860 | 131,309 | 68,691 | 0 | 74,240 | 0 | 63,942 | 0 | 29,110 | 52,660 | 0 | 73,470 |
| Warehouse 2 | | 0 | 84,550 | 0 | 82,280 | 60,050 | 0 | 68,632 | 0 | 150,000 | 121,920 | 54,390 | 3,000 | 0 |

Fig. 7. Harvest schedule with a strong penalty quality loss function.

However, if the quality loss function were indifferent to the deviations from the optimal date (a flat penalty pattern), the schedule changes significantly, giving the best possible allocation of labor, due to the possibility of extending harvesting operations through time. With respect to the base case, labor requirements are reduced by 35%. On the other hand, the elimination of the quality effect in the objective function produces a significant increase in processing time for the solver. This is due to the fact that the presence of quality factors implicitly introduces a relative importance or priority to the decision variables. As it is well known, this can favor a Branch and Bound search significantly.
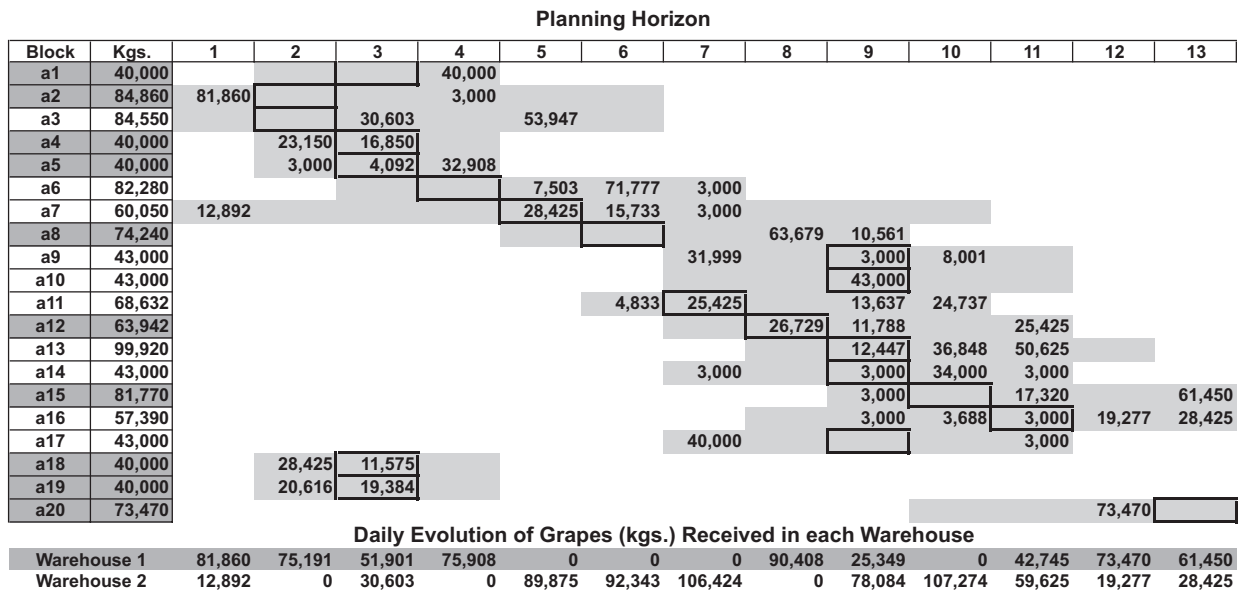
**Planning Horizon**

| Block | Kgs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|-------|------|---|---|---|---|---|---|---|---|---|----|----|----|----|
| a1 | 40,000 | | | | 40,000 | | | | | | | | | |
| a2 | 84,860 | 81,860 | | | 3,000 | | | | | | | | | |
| a3 | 84,550 | | | 30,603 | | 53,947 | | | | | | | | |
| a4 | 40,000 | | 23,150 | 16,850 | | | | | | | | | | |
| a5 | 40,000 | | 3,000 | 4,092 | 32,908 | | | | | | | | | |
| a6 | 82,280 | | | | | 7,503 | 71,777 | 3,000 | | | | | | |
| a7 | 60,050 | 12,892 | | | | 28,425 | 15,733 | 3,000 | | | | | | |
| a8 | 74,240 | | | | | | | | 63,679 | 10,561 | | | | |
| a9 | 43,000 | | | | | | | 31,999 | | 3,000 | 8,001 | | | |
| a10 | 43,000 | | | | | | | | | 43,000 | | | | |
| a11 | 68,632 | | | | | | 4,833 | 25,425 | | 13,637 | 24,737 | | | |
| a12 | 63,942 | | | | | | | | 26,729 | 11,788 | | 25,425 | | |
| a13 | 99,920 | | | | | | | | | 12,447 | 36,848 | 50,625 | | |
| a14 | 43,000 | | | | | | | 3,000 | | 3,000 | 34,000 | 3,000 | | |
| a15 | 81,770 | | | | | | | | | 3,000 | | 17,320 | | 61,450 |
| a16 | 57,390 | | | | | | | | | 3,000 | 3,688 | 3,000 | 19,277 | 28,425 |
| a17 | 43,000 | | | | | | | 40,000 | | | | 3,000 | | |
| a18 | 40,000 | | 28,425 | 11,575 | | | | | | | | | | |
| a19 | 40,000 | | 20,616 | 19,384 | | | | | | | | | | |
| a20 | 73,470 | | | | | | | | | | | | 73,470 | |

**Daily Evolution of Grapes (kgs.) Received in each Warehouse**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|----|----|----|----|
| Warehouse 1 | 81,860 | 75,191 | 51,901 | 75,908 | 0 | 0 | 0 | 90,408 | 25,349 | 0 | 42,745 | 73,470 | 61,450 |
| Warehouse 2 | 12,892 | 0 | 30,603 | 0 | 89,875 | 92,343 | 106,424 | 0 | 78,084 | 107,274 | 59,625 | 19,277 | 28,425 |

Fig. 8. Schedule with a "flat" quality loss function.

### 4.4. Routing of harvesting operations

Incorporating harvesting routes in the model is important, since it allows the representation of set-up costs associated to harvesting a block. When route optimization is not considered in the objective function, the total cost (including operations relocation cost) increases by 20%. This is a significant increase, given the large size of some Chilean vineyards (741 acres or more). If routing is not incorporated, the schedule might be affected by severe inefficiencies, implying delays in harvesting and the corresponding impacts on the quality of the grapes.

On the other hand, considering harvest routing increases the complexity of the problem. This is due to the fact that the routing problem is essentially a TSP, which is a well known hard combinatorial problem. The proposed model represents the TSP using the already mentioned MTZ formulation, which has the advantage of eliminating cycles with only a polynomial number of additional constraints instead of the exponential number required by the standard subtour elimination constraints. However, it is a weaker formulation. In spite of this, for problems with at most 40 blocks and a planning horizon of 15 days, we have been able to obtain the optimal solution using Branch and Bound in less than 10 min of CPU time, although 15 min is more typical.

### 4.5. A proposed heuristic approach

Although 10 min would still be acceptable in most situations, larger problems could require solution times that would make this approach impractical for many industrial applications. To make things worse, solution times for this kind of problems are hard to predict. In order to be able to use the proposed model in a commercial software it has to be able to find solutions for very large problems in a reasonable time. This requires using a heuristic to solve the routing part of the problem. We propose a simple heuristic approach which subordinates the routing decisions to the harvesting scheduling. This is based on the fact that routing does not affect the production outcome. The real effects are the ones considered in the harvest schedule. We implemented the following approach:

1. Solve the scheduling problem together with the routing part, but considering the linear relaxation of the problem (we restrict the variables $z$ in the model to be continuous and $0 \leqslant z \leqslant 1$). We solve this problem and obtain a harvest schedule.
2. Then, given the schedule of blocks from the previous step, we apply a TSP heuristic (specifically the 2-opt procedure) to the routing part of the problem (Lawler et al., 1985).

This relaxed approach is, of course, inferior to the optimal solution, but can be solved much faster. We
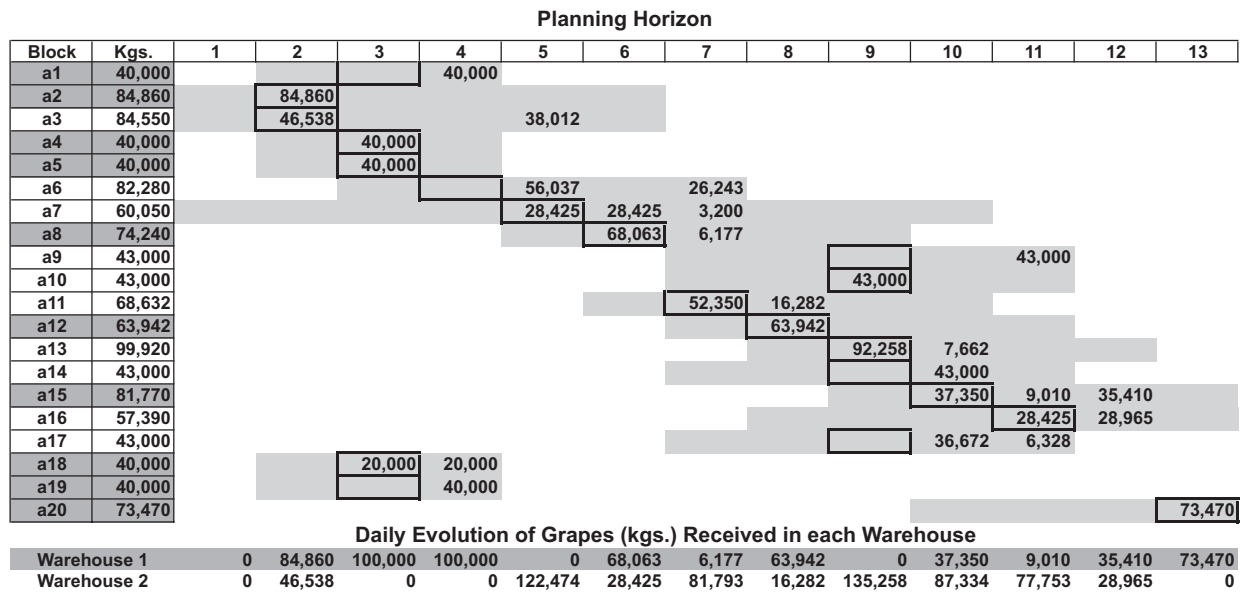
**Planning Horizon**

| Block | Kgs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a1 | 40,000 | | | | 40,000 | | | | | | | | | |
| a2 | 84,860 | | 84,860 | | | | | | | | | | | |
| a3 | 84,550 | | 46,538 | | | 38,012 | | | | | | | | |
| a4 | 40,000 | | | 40,000 | | | | | | | | | | |
| a5 | 40,000 | | | 40,000 | | | | | | | | | | |
| a6 | 82,280 | | | | | 56,037 | | 26,243 | | | | | | |
| a7 | 60,050 | | | | | 28,425 | 28,425 | 3,200 | | | | | | |
| a8 | 74,240 | | | | | | 68,063 | 6,177 | | | | | | |
| a9 | 43,000 | | | | | | | | | | | 43,000 | | |
| a10 | 43,000 | | | | | | | | | 43,000 | | | | |
| a11 | 68,632 | | | | | | | 52,350 | 16,282 | | | | | |
| a12 | 63,942 | | | | | | | | 63,942 | | | | | |
| a13 | 99,920 | | | | | | | | | 92,258 | 7,662 | | | |
| a14 | 43,000 | | | | | | | | | 43,000 | | | | |
| a15 | 81,770 | | | | | | | | | | 37,350 | 9,010 | 35,410 | |
| a16 | 57,390 | | | | | | | | | | | 28,425 | 28,965 | |
| a17 | 43,000 | | | | | | | | | | 36,672 | 6,328 | | |
| a18 | 40,000 | | | 20,000 | 20,000 | | | | | | | | | |
| a19 | 40,000 | | | | 40,000 | | | | | | | | | |
| a20 | 73,470 | | | | | | | | | | | | | 73,470 |

**Daily Evolution of Grapes (kgs.) Received in each Warehouse**

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Warehouse 1 | | 0 | 84,860 | 100,000 | 100,000 | 0 | 68,063 | 6,177 | 63,942 | 0 | 37,350 | 9,010 | 35,410 | 73,470 |
| Warehouse 2 | | 0 | 46,538 | 0 | 0 | 122,474 | 28,425 | 81,793 | 16,282 | 135,258 | 87,334 | 77,753 | 28,965 | 0 |

Fig. 9. Schedule with relaxed routing.

did not attempt to elaborate on this heuristic, since our objective in this part was to provide a fast approach to find a good feasible solution.

When testing this approach on our base case, relaxing the routing variables produced very little change in the scheduling pattern (compare Figs. 9 and 3), using the same relative quality penalties of the original model. After applying 2-opt, we obtain a feasible solution which is 8.1% more expensive than the optimal route from the integrated model. These operations requires 12 s of CPU time for Branch and Bound plus an additional marginal time for the heuristic, which compares very favorably with respect to the 10–15 min solution time of the mixed integer model. This heuristic could probably be improved by increasing the solution time, which is something we will work on in the future. However, as we will later see, even the solution obtained by the heuristic should be a significant improvement over their current judgement-based scheduling.

## 5. A real application

This problem corresponds to a vineyard in the central zone of Chile with 40 blocks, 17 days, and 2 wineries. This generates a model with 7834 rows and 19,691 variables, of which 4520 are binary. The whole model was solved in approximately 30 s using the decomposition heuristic approach compared to 15 min for obtaining an optimal solution using the exact Branch and Bound procedure. For the sake of space, we do not exhibit the full solution of the model, but we discuss some of the results regarding labor usage and costs incurred by the model. When comparing the optimal plan generated by the model using the exact Branch and Bound with the actual plan of the previous season, we observed that the model scheduled harvesting so that labor variability is reduced by 18.5%. This allows the vineyard to offer its contractors a more stable schedule of labor usage. Recent legal restrictions in Chile are stimulating a more stable pattern of hiring in agriculture and other industries, and so this result might become an important policy issue. Table 3 compares the labor usage results generated by the model with the actual ones.

The planning model tends to favor the best allocation of manpower, compared to what was actually planned. The number of hired workers is reduced by 60% (contractors) and the maximum number is reduced by 30%. Both factors, added to the decrease in 27% of the daily standard deviation of the use of workers, allowing substantial reduction in the vulnerability of manual harvest, reducing also the potential need of machinery, which is expensive and potentially harmful to high quality grapes.

Looking at the cost figures is even more interesting. Table 4 shows the comparison between the operational costs and quality penalties in the actual plan

Table 3
Comparison between optimal solution manpower usage and actual usage

| Number of workers | Assigned in the model | Actual use | % variation |
|---|---|---|---|
| Minimum | 103 | 0 | – |
| Maximum | 201 | 286 | −29.7 |
| Deviation | 41 | 57 | −27.4 |
| Workers hired | 109 | 272 | −59.8 |

Table 4
Comparison between optimal and actual costs

| | Actual costs | Optimal costs |
|---|---|---|
| Operational cost | 22,155 | 18,666 |
| Quality penalty | 4,254 | 561 |
| Total costs | 26,409 | 19,227 |

with those of the optimal plan. Operational cost includes labor and machinery costs, together with operation routing. In this case, the labor cost is by far the most important, making 98% of total costs.

Overall, the optimal plan generated by the model is much better than the actual plan that was applied in that season. There is an 86.7% of decrease in *quality penalty*, together with a 16% reduction in labor costs. This is very good considering the short horizon (17 days) and also shows that the actual solution implemented (probably based on "good judgment") was far from efficient.

## 6. Conclusions

We have presented a model to help schedule the harvesting operations in the wine industry. In addition to the different cost factors associated to manpower and machinery, and the corresponding resources constraints, our model incorporates two issues that are very relevant for the wine industry: grape quality and routing of harvesting operations. The quality of the grapes is incorporated into the model through the concept of a quality loss function. The routing of the harvesting operations is also important due to the costs incurred and the impact on the time and movement of harvested grapes, a factor which also affects quality. The model balances the operation costs together with the quality aspects so that a "compromise" schedule is generally obtained. This proposed schedule should be a solid basis of discussion between the enologist and the field managers to obtain a final harvest scheduling.

The model is solved using standard mathematical programming software in a reasonable time. The decomposition approach proposed provides also a way of simplifying the solution of the problem without incurring in excessive deterioration of the solution.

These benefits of the model are more evident in the real industrial case presented, where there is a decrease in operational costs of 27% with respect to the actual figures obtained using planner's judgement. Furthermore, a 16% decrease in labor costs with a more stable labor usage were also obtained.

The model we have presented can be used in different settings depending on the characteristics of a particular winery. For small wineries that have their own vineyard, which is usually small and close to the main facilities, the routing specific parts of the model might not be very relevant and can easily be deactivated. The rest of the model features, on the other hand, are still very relevant as many of these small *boutique* wineries have a strong commitment to quality. On the other hand, for a large winery, the model might provide a useful tool for large scale resource allocation, including the consideration of operation routing, as distances might be more significant in this case.

The main contribution of this research is the solution of a relevant practical problem in an industrial sector of increasing importance. However, this model can also be extended to handle other problems of agricultural industries, and is a contribution to the use of operations research techniques in agriculture. This model is currently being developed as a commercial software in the context of the research project that funded this research. We expect that this development will have an important impact on improving operations management in the wine industry.

## Appendix A. Detailed model description

This appendix contains the detailed description of the model. First, the index sets are defined, followed by all parameters. Then we present the variables, objective function and constraints.

### A.1. Sets of indexes

$J_1$: Set of blocks suitable for mechanical harvest.
$J_2$: Set of blocks suitable for manual harvest.
$J := J_1 \cup J_2$.
$K$: Set of harvesting modes, $k \in K = \{1, 2\}$, $k = 1$ is mechanical harvest and $k = 2$ is manual harvest.

### A.2. Model parameters

$D_{ij}$: Distance between blocks $i$ and $j$, $i, j \in J$.
$Q_{jt}$: Quality factor (cost) for block $j \in J$ in period $t$.
$H$: Hiring cost for adding one unit of labor.
$F$: Cost of firing or reducing one unit of labor.
$C_k$: Unit cost of productive resource $k$. For $k = 1$ it is cost per hour of machine and for $k = 2$ it is cost per worker.
$P_{kj}$: Productivity of a unit of productive resource $k$ in kg/day, when used in block $j$, $j \in J$.
$G_{jkb}$: Estimated kg of grapes in block $j \in J$ harvested in mode $k \in K$, with destination to winery $b$.
$W_{jt}$: Harvesting window parameter indicating whether block $j$ can be harvested at period $t$. It is 1 if possible, 0 if not.
$L_{kbt}$: Processing capacity of winery $b$ for grapes harvested in mode $k$ at period $t$.
$B_{jtk}$: Maximum volume that can be harvested in block $j$ at time $t$ using harvesting mode $k$.
$A_t$: Machine availability, in hours, in period $t$.
$M$: a "big M" value.
$R$: Operations relocation cost in \$ per kilometer.
$V_k$: Minimum volume to be harvested from a block using $k$ harvesting mode.
$\lambda$: Penalty parameter used for the relative balance between operational and quality costs.
$N$: Minimum number of contractors needed.
card($J$): number of elements in the set $J$, number of blocks.

### A.3. Decision variables

$x_{jtkb}$: Kilograms harvested in block $j$, at period $t$, in mode $k$, routed to winery $b$.
$y_{jtkb}$: Binary variable with value 1 when block $j$ initiate harvesting at period $t$, in harvesting mode $k$, routed to winery $b$, and 0 otherwise.
$v_{jtk}$: Binary variable indicating if there is harvest or not in block $j$, during period $t$, and in harvesting mode $k$.
$z_{ijtb}$: Binary variable that is 1 when an operation moves from block $i$ to block $j$ in period $t$ and with destination winery $b$; 0 otherwise.
$\tau_{jtb}$: Variable used to eliminate subtours in the MTZ formulation. It represents the position inside the cycle of block $j$, at period $t$, routed to winery $b$.
$w_t^H$: Number of workers hired at period $t$.
$w_t^F$: Number of workers hired at period $t$.
$u_{jtk}$: Productive resources used in block $j$ at period $t$. It is a continuous variables such that for $k = 1$ it is machine hours and for $k = 2$ it is number of workers.

### A.4. Objective function

$$
\text{Min} \sum_{k,j,t} C_k u_{jtk} + H \sum_t w_t^H + F \sum_t w_t^F
$$
$$
+ R \sum_{i,j,t,b:i\neq j} D_{ij} z_{ijtb} + \lambda \sum_{j,t,k,b} Q_{jt} x_{jtkb}. \tag{15}
$$

### A.5. Constraints

#### A.5.1. Harvesting, capacity and minimum volume

$$
\begin{aligned}
&\sum_{j\in J} x_{jtkb} \leqslant L_{kbt}, && \forall k,b,t, \\
&\sum_t x_{jtkb} = G_{jkb}, && \forall k,b,j, \\
&x_{jtkb} \leqslant G_{jkb} v_{jtk}, && \forall t,b,k,j, \\
&x_{jtkb} \geqslant V_k v_{jtk}, && \forall t,b,k,j, \\
&\sum_b x_{jtkb} \leqslant B_{jtk}, && \forall j,t,k, \\
&\sum_b y_{jtkb} \leqslant M v_{jtk}, && \forall j,t,k, \\
&v_{jtk} \leqslant \sum_{b,s\leqslant t:W_{js}=1} y_{jskb}, && \forall t,k,j, \\
&y_{jtkb} \leqslant \sum_{s\leqslant t:W_{js}=1} v_{jsb}, && \forall j,t:\; W_{jt}=1,\; \forall k,b, \\
&\sum_b \sum_{t:W_{jt}=1} y_{jtkb} \leqslant 1, && \forall k,b,j, \\
&\sum_t \sum_k v_{jtk} \geqslant 1, && \forall j\in J:\; G_{jkb}\neq 0, \\
&y_{jtkb} \leqslant W_{jt}, && \forall t,k,b,j, \\
&\sum_b x_{jtkb} \leqslant P_{kj} u_{jtk}, && \forall j,t,k, \\
&\sum_{j\in J2} u_{jt2} = \sum_{j\in J2} u_{j(t-1)2} + w_t^H - w_t^F, && \forall t\geqslant 2, \\
&\sum_{j\in J1} u_{jt1} \leqslant A_t, && \forall t,j\in J2, \\
&u_{jt2} \geqslant N v_{jt2}, && \forall t,j\in J2.
\end{aligned} \tag{16}
$$

#### A.5.2. Harvesting routing (from the MTZ formulation)

$$
\begin{aligned}
&\tau_{jtb} \geqslant \tau_{itb} + 1 - (\text{card}(J)-1)(1-z_{ijtb}), && \forall t,b;\; i,j\in J2;\; i\neq j;\; W_{it}\neq 0;\; W_{jt}\neq 0, \\
&\sum_{j\neq i} z_{ijtb} = y_{it2b}, && \forall t,b,i\in J:\; W_{it}\neq 0, \\
&\sum_{i\neq j} z_{jitb} = y_{jt2b}, && \forall t,b,j\in J:\; W_{jt}\neq 0, \\
&\tau_{1tb} = y_{1t2b}, && \forall t:\; W_{1t}\neq 0,\; \forall b, \\
&\tau_{jtb} \geqslant 2 y_{jt2b}, && \forall j,t\in J:\; W_{jt}\neq 0,\; \forall b, \\
&\tau_{jtb} \leqslant \text{card}(J), && \forall j,t\in J:\; W_{jt}\neq 0,\; \forall b.
\end{aligned} \tag{17}
$$

## A.5.3. Other constraints

$$z_{ijtb}, v_{jtk}, y_{jtkb} \in \{0,1\}, \qquad \forall t, b, k, i, j,$$
$$w_{ti}^H, w_{ti}^F, u_{jtk}, x_{jtkb}, \tau_{jtb} \geqslant 0, \quad \forall t, b, k, i, j. \tag{18}$$

## References

Aleotti, L., Araujo, R., Yahya, R., 1997. Selection of postharvest technology routes by mixed-integer linear programming. International Journal of Production Economics 49 (2), 85–90.

Allen, F., Schuster, E., 2004. Controlling the risk for an agricultural harvest. Manufacturing & Service Operations Management 6 (3), 225–236.

Altieri, M., Faeth, P., 1994. Sustainable agriculture. Encyclopedia of Agricultural Science 4, 239–247.

Basnet, C.B., Clark, D.N., Foulds, L.R., 1993. A decision support system approach to milk tanker routing. Control and Cybernetics 22, 131–144.

Bixby, A., Downs, B., Self, M., 2006. A scheduling and capable-to-promise application for Swift & Company. Interfaces 36(January–February), 131–144.

Bordeu, E., Mira, P., Rivadeneira, R., 2002. Madurez Fenológica: Experiencia en Chile. Tópicos de Actualización en Viticultura y Enología 2002, 190–192.

Caixeta-Filho, J., 2006. Orange harvesting scheduling management: A case study. The Journal of the Operational Research Society 57 (6), 637.

Caixeta-Filho, J., van Swaay-Neto, J., Wagemaker, A., 2002. Optimization of the production planning and trade of lily flowers at Jan de Wit Company. Interfaces 13 (1), 13–46.

Chaudhuri, K., Giri, B., 1997. Deterministic models of perishable inventory with stock-dependent demand rate and nonlinear holding cost. European Journal of Operational Research 105, 467–474.

Epstein, R., Morales, R., Seron, J., Weintraub, A., 1999. Use of OR systems in the Forest Chilean Industry. Interfaces 29, 7–29.

France, J., Thornley, J., 1984. Mathematical Models in Agriculture. Butterworths, London.

Glen, J., 1987. Mathematical models in farm planning: A survey. Operations Research 35, 641–665.

Higgins, A., Laredo, L., 2006. Improving harvesting and transport planning within a sugar value chain. The Journal of the Operational Research Society 57 (4), 367.

Horn, M., Dunstall, S., 2004. Optimising operational logistics using negotiated scheduling. In: Proceedings of the Conference of Australian Institute of Transport Research. Melbourne, Australia.

Islam, N., Quaddus, M., 1992. An appraisal of uncertainties in the western australian wine industry supply chain. In: 49th Annual Conference of the Australian Agricultural and Resource Economics Society.

Lawler, E.L., Lenstra, J.K., Rinnooy Kan, A.H.G., Shmoys, D.B. (Eds.), 1985. The Traveling Salesman Problem. Wiley, Chichester.

Lowe, T., Preckel, P., 2004. Decision technologies for agribusiness problems: A brief review of selected literature and a call for research. Manufacturing & Service Operations Management 6 (3), 201–208.

Mac Cawley, A., 2002. Sistema de Apoyo a la Planificación de Cosecha en Vinos. Master's Thesis. Engineering School of Pontificia Universidad Católica de Chile.

Masini, G., 2003. Supply chain planning optimization in the fruit industry. CEPAC Working Paper. ⟨http://cepac.cheme.cmu.edu/pasilectures/bandoni/FOCAPO%202003m-4%20.pdf⟩.

Miller, C.E., Tucker, A.W., Zemlin, R.A., 1960. Integer programming formulation of traveling salesman problems. Journal of the ACM 7 (4), 326–329.

Pataki, G., 2003. Teaching Integer Programming formulations using the traveling salesman problem. SIAM Review 45 (1), 116–123.

Taguchi, G., Clausing, D., 1990. Robust quality. Harvard Business Review January/February, 65–75.

Toloza, S., 2004. Construcción de un Sistema de Apoyo a las Decisiones de Cosecha de Uva para Vinos basado en Herramientas de Optimización. M.Sc. Thesis, Engineering School, Pontificia Universidad Católica de Chile.

Yom Din, G., Zugman, Z., 2003. Incorporating changes in cherry quality into a model of storage and selling schedules. Acta Horticulturae 604, 677–682.