A BI-OBJECTIVE OPTIMISATION HARVEST AND PACK PLANNING DECISION-SUPPORT SYSTEM FOR TABLE GRAPE PRODUCER-EXPORTERS

J. Wium[1], J. Bekker[1*] & J. van Eeden[1]

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Contact details
* Corresponding author
jb2@sun.ac.za

Author affiliations
1 Department of Industrial Engineering, Stellenbosch University, Stellenbosch, South Africa

ORCID® identifiers
J. Wium
https://orcid.org/0000-0002-3317-2242

J. Bekker
http://orcid.org/0000-0001-6802-0129

J. van Eeden
http://orcid.org/0000-0001-9684-2357

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ABSTRACT

This paper presents a decision-support system developed to plan the harvest and packing of table grapes. Variability in harvest readiness and volume can significantly impact producer-exporters’ ability to meet market demands. The decision-support system incorporates planning aspects specific to table grape production, such as limiting transportation of unpacked stock, pack-to-order, and distinguishing between specific product requirements (i.e., packaging type and cultivar). This decision-support system uses several operational data sources. It assists decision-makers in minimising deviation from the demand plan and the distances harvest is transported between the orchards and processing sites. The conceptual architecture and software implementation tools to realise the decision-support system and a real-world case study are presented. The decision-support system accounts for multiple dynamic supply and processing network restrictions.

OPSOMMING

Hierdie artikel stel 'n besluitsteunstelsel voor wat ontwikkel is om die oes en verpakking van tafeldruiwe te beplan. Veranderlikheid in oesgereedheid en volume kan produsent-uitvoerders se vermoë om aan markvereistes te voldoen, aansienlik beïnvloed. Die besluitsteunstelsel inkorporeer beplanningsaspekte spesifiek vir tafeldruifproduksie, soos die beperking van vervoer van onverpakte voorraad, pak-vir-bestelling, en onderskeid tussen spesifieke produkvereistes (d.w.s. verpakkingstipe en kultivar). Hierdie besluitondersteuningstelsel gebruik verskeie operasionele databronne. Dit help besluitnemers om afwyking van die aanvraagplan en die afstande wat oes-opbrengs tussen die boorde en verwerkingaanlegte vervoer word, te minimeer. Die konsep-argitektuur en sagteware-implementeringsinstrumente om die besluitsteunstelsel te realiseer asook 'n werklike gevallestudie word aangebied. Die besluitsteunstelsel is verantwoordelik vir veelvuldige dinamiese aanbod- en verwerkingsnetwerkbeperkings.

1. INTRODUCTION

Decision-making in producing, processing, and distributing fresh fruit is complex. Products ripen at various times throughout a season, depending on the cultivar and weather, and can result in harvest and processing peaks. Planning processing and distribution activities can be problematic and have the qualities of a ‘push supply chain’ [1]. Fresh fruit is perishable, and maintaining post-harvest quality depends on handling techniques and sustaining the cold chain [2]. This study focuses on table grapes as a product.

The problem we focused on can be described as follows: A mega-producer of 28 table grape cultivars has 391 orchards distributed over a large geographical area spanning three provinces in South Africa. The table grapes ripen during specific time slots of the year, which dictate the harvest and packing time windows. Local and international customers order specific volumes of particular cultivars, while many require unique packing material. The mega-producer has 13 packing sites at different positions from the orchards. The packing sites have fixed capacities and various constraints; for example, the packing type (loose bunches or punnets). The produce is delivered to 53 target markets in 28 countries.

Planning the harvesting and packing of the product involves uncertainty and complex decision-making because materials, resources, and many role-players are involved. Owing to unforeseen changes that occur during the harvest period, it is often necessary to revise the harvest and pack plans, which may take hours or even days because of the manual process that is followed. A digital decision-support system (DSS) that sources data from existing and evolving data stores to create timely, quality decision suggestions could be of value to the mega-producer and key decision-makers. This paper presents the research done on the development of such a DSS.

Research on fresh produce production and processing decisions has a diverse commodity base, including citrus, pome fruit, vegetables, and wine grapes. Although this provides a strong reference for planning table grape production, it does not account for the specific problems faced by table grape producers:

- Table grapes are highly perishable, and harvesting at the right time is crucial for a quality end product. This requirement differentiates table grapes from longer-lasting commodities such as citrus or pome fruit, which can have a longer shelf life.
- Table grapes must enter the cold chain as soon as possible after harvesting. Post-harvest quality depends on maintaining the cold chain, careful handling, and packaging stock before transportation. Bruising table grapes during post-harvest activities can result in sub-prime marketability, whereas bruising of wine grapes has little impact on the end product.
- Sorting and classing grapes differs from pome and citrus owing to the manual processing that is required. Fruit with simplistic dimensions, such as apples and oranges, can be graded through automated machines. Class A fruit is separated from substandard fruit (classes B and C, which are sold at the local market or used for juice) as well as waste products on entering a pack site and further sorted by mechanical means according to market specifications. In contrast, table grapes are classed and graded in the vineyard before harvesting. The waste product is manually separated from the end product by cutting out individual rotten berries during the packing phase to limit double handling.

The work in this paper contributes to the body of knowledge by providing a unique real-world case for harvest and processing decisions for table grapes. Second, the DSS presented here allows for coordination between harvest fields and production facilities. It incorporates planning specific market demands in a 'push supply chain' environment in which the product is produced long before demand realises, and the adjustments required in a real-world setting. Last, the DSS presented in this study incorporates a geographically diverse setting with multiple farms and processing sites. The DSS allows for the bi-objective optimisation of two selected key performance indicators.

The paper is organised as follows. Section 2 provides a brief review of the literature on the fresh produce decision-making domain for harvest and production decisions. Section 3 presents a model-based bi-objective optimisation DSS for the tactical planning of harvest and processing table grapes. Section 4 reports findings from a real case comparing human decision-making with the DSS model. The final section (Section 5) provides recommendations for future work.

2. HARVEST AND PROCESSING MODELS IN THE FRESH PRODUCE DECISION-SUPPORT DOMAIN

An analysis of five systematic literature reviews ([3], [4], [5]; [6]; [7]) on harvest and processing decision support identified the following research key opportunities:

1. A need exists for more integrated harvest and processing planning models, especially in the coordination between harvest fields and production facilities ([3], [4]). Kusumastuti *et al.* [5] established that, where harvest and production decisions are modelled together, a central processing unit is considered as opposed to geographically diverse farms and processing facilities. Taskiner and Bilgen [7] observed research opportunities to explore the complexities emanating from multi-farm and processing facility cases.
2. Product diversity varied with specific handling techniques, leading to a need for commodity-specific models, as opposed to generic fresh produce models [7].
3. An often-neglected aspect of research models is the heterogeneity in products (such as variety and packaging types). This includes complexity in real-world authentic scenarios in case studies or hypothetical cases. Soto-Silva *et al.* [6] noted that only five of the 28 articles they reviewed were based on existing databases; the rest all used hypothetical data or described the application to real cases.
4. Research in the field navigates towards hypothetical cases, with a limited number of authors using real data sets to validate their research. This raises the question of the applicability of those models that are based on hypothetical data. Taskiner and Bilgen [7] established a need for models that could assume the complexities of large real data sets, such as metaheuristics, mat heuristics, and hybrid

solutions. Soto-Silva *et al.* [6] reviewed models applied (real or case study models) to the fresh fruit industry only. They included 28 articles published between 1976 and 2015, studying all supply chain aspects. Of these 28 articles, only three focused on both harvest and production decisions.

5. Most studies reviewed focused on economic aspects, such as maximising profit or minimising costs. They note that there might be a benefit in exploring more specific objectives relevant to a specific problem [7].

These reviews focused on the modelling approaches, decision types, and main themes of past papers. From the opportunities listed above and the desire to develop a DSS that would be useful in a real-world case, we identified related work to modelling approaches.

Table 1 summarises the harvest and processing decisions support models researched by others in the field. A combination of hypothetical cases (HC), case studies (CS), and real cases (RC) was studied. The table indicates that 16 of the 27 articles used mixed integer linear programming (MILP) and mixed integer programming (MIP). Stochastic programming (SP) was used where uncertainty had to be modelled, such as Munhoz and Morabito [25] using robust optimisation (RO). In one case, fuzzy logic was used to model production uncertainties [23].

Table 1: Previous modelling approaches

Reference	Type	Model	Method	Objective
Miller *et al.* [8]	RC	LP	Fuzzy logic	Min. cost
Munhoz and Morabito [9]	CS	LP	Goal prog.	Min. costs, min. deviation from mean product ratio
Kazaz [10]	RC	SP	Exact	Max. profit
Caixeta-Filho [11]	RC	LP	Exact	Max. production, max. total revenue
Ferrer *et al.* [12]	RC	MILP	Heuristics	Min. operational cost, penalise quality loss
Arnaout and Maatouk [13]	HC	MILP	Heuristics	Min. costs (with quality penalty)
Vlah Jeric and Soric [14]	HC	MIP	Heuristics	Max. producer profit
Bohle *et al.* [15]	HC	SP	RO	Min. operational cost, min. quality loss
Rong *et al.* [16]	CS	MILP	Exact	Min. costs
Ahumada and Villalobos [17]	CS	MIP	Exact	Max. revenue
Ahumada and Villalobos [18]	CS	MIP	Exact	Max. income
Ahumada *et al.* [19]	HC	SP	Exact	Max. revenue
Munhoz and Morabito [20]	CS	SP	RO	Min. total cost
Rocco and Morabito [21]	RC	LP	Exact	Min. costs
Catalá *et al.* [1]	CS	MILP	Lexicographic	Min. total negative deviations of sales, max. total profit
Basso and Varas [22]	CS	MIP	MH	Min. order delay, final completion, and processing time
Ghezavati *et al.* [23]	CS	MIP	Exact	Max. profit
Herrera-Cáceres *et al.* [24]	RC	MILP	Exact	Max. production
Grillo *et al.* [25]	RC	MILP	AW	Max. total profit, max. mean product freshness
Cheraghalipour *et al.* [26]	CS	MILP	MH	Min. cost, max. responsiveness to customers
Cano Marchal *et al.* [27]	HC	SP	Exact	Max. profit
Jeric and Soric [28]	HC	MIP	MH	Max. profit, min. delivery cost
Roghanian and Cheraghalipour [29]	CS	MIP	MH	Min. costs, CO2 emissions, max. customer responsiveness
Varas *et al.* [30]	RC	MILP	MH	Min. costs, max. quality
Tan and Cömden [31]	HC	SP	Exact	Max. total profit
Gómez-Lagos *et al.* [32]	CS	MIP	MH	Min. cost of harvesting, fruit lost, harvest days
Trivedi *et al.* [33]	CS	ILP	Exact	Min. cost

RC: Real case; CS: Case study; HC: Hypothetical case; LP: Linear programming; SP: Stochastic programming; MILP: Mixed integer linear programming; MIP: Mixed integer programming; RO: Robust optimisation; MH: Metaheuristics; AW: Additive weighting; Min.: Minimise; Max.: Maximise.

Multi-objective optimisation was used in 12 of the studies, with only seven of these using metaheuristics as a solution approach. The metaheuristic (MH) methods used included those requiring the decision-maker to have a preference before running the model (a priori), such as the lexicographic method [1], weighted Tchebycheff [30], and additive weighting (AW) [25]. A posteriori methods exploring the Pareto set included the non-dominated sorting algorithm II (NSGA-II) ([26], [28], [29]) and the greedy randomised adaptive search procedure (GRASP) [32]. Jeric and Soric [28] concluded that they were the first to use multi-objective methods in the integrated planning of supply and production of perishable goods.

Most authors focused their models on the economic impact of the decision, with models favouring either cost savings or increasing revenue. Both Ferrer et al. [12] and Varas *et al.* [30] considered cost and quality as individual objectives, whereas Grillo *et al.* [25] included mean product freshness with total profit in a bi-objective model. Besides maximising total profit, Catalá *et al.* [1] aimed to minimise the total deviation from the customer demand, thus parallelling this study. Cheraghalipour *et al.* [26] also attempted to meet customer demands; however, they focused on the reverse logistics of the citrus supply chain. Gómez-Lagos *et al.* [32] presented a three-objective model, attempting to minimise the harvest days, fruit lost owing to failed maturity, and the harvesting cost.

Several studies used a penalty function, omitting quality as an objective. These studies penalised the main objective with a quality loss function in a single-objective optimisation model ([12], [22]).

None of the studies identified and evaluated focused on table grapes, with a limited number focusing on customers' specific market needs. The studies did not consider the geographical spread of farms and processing sites as was done in this study. Recommendations from these studies allude to the need for multi-objective techniques to approach the complexity often established in real-world cases.

Next, the design of the decision-support system is described.

3. DESIGN OF THE DECISION-SUPPORT SYSTEM

The design of the DSS is based on user and stakeholder requirements. Interviews were conducted with diverse groups to do a user requirement elicitation. The selected stakeholders are all part of the decision-making, and all are affected by the outcomes of decisions made. The interviews were transcribed, and the system requirements were analysed using the six-step process of thematic analysis by Braun and Clarke [34] and Maguire and Delahunt [35]. The following roles were interviewed, with an indication of their level of decision-making:

1. Strategic: strategic financial manager (SFM) and chief marketing manager (CMM)
2. Tactical: logistics manager (LM) and production manager of managers (PUMoM)
3. Operational: data analyst (DA), production unit managers (PUMs) and pack site managers (PSMs)

The thematic analysis yielded design drivers for the DSS. Apart from that the available data sources that affect harvest and pack plan decisions were identified and analysed. The data sources are presented next.

3.1. Data sources

These data sets required by the DSS are as follows; the relationships are shown in Figure 1. The arrows indicate flow of data.

1. Market plan: the plan is dictated by customers and changes throughout the year. The LM and CMM maintain it.
2. Harvest estimate: this estimate is a guide for decision-makers to plan. It is based on historical data and is inaccurate since environmental factors such as rain or extreme temperatures can affect the yield.
3. Packaging material: if the harvest and pack plan changes, it may affect the packing materials needed. Materials often depend on the customer and require unique printing.
4. Pack capacity: this was a major topic during the interviews. The pack sites have many factors to consider during planning, including constraints like the number of staff, range (loose fruit or punnets), and the number of changeovers required.
5. Budget: the seasonal income and expenses are estimated and monitored to dictate what must be produced and when it should be sold.

6. Pack actual: this is a record of the actual product packed and shipped to date during the season and is used to adjust real execution to achieve planned delivery.
7. Pack and harvest plan: the harvest and pack plan are pivotal as it represents the union of two evolving plans, such as the market plan and the harvest estimate. It also represents the link between tactical planning and operational realities. The harvest and pack plan guides the production managers on which customer orders to serve weekly. The plan may be disturbed by realities like downtime at a pack site.

With the stakeholder requirements defined and the data sources known, the architecture of the DSS could be developed and is subsequently presented.

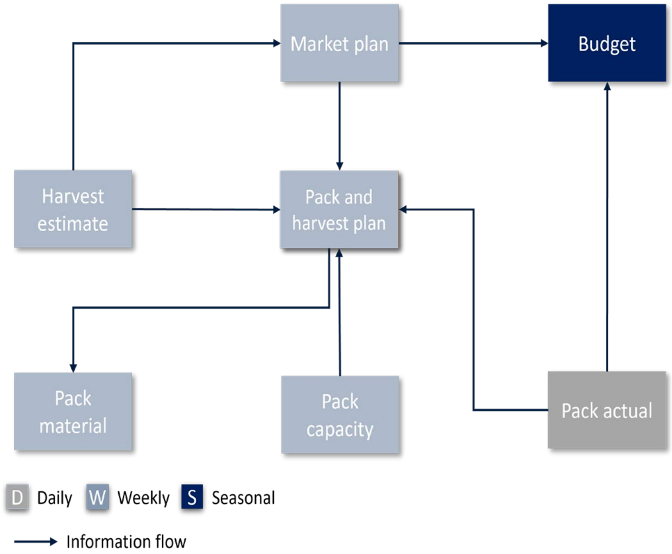


Figure 1: Data sets that affect harvest and pack decisions

3.2. Proposed architecture

The proposed architecture of the DSS is shown in Figure 2 and is briefly discussed next.

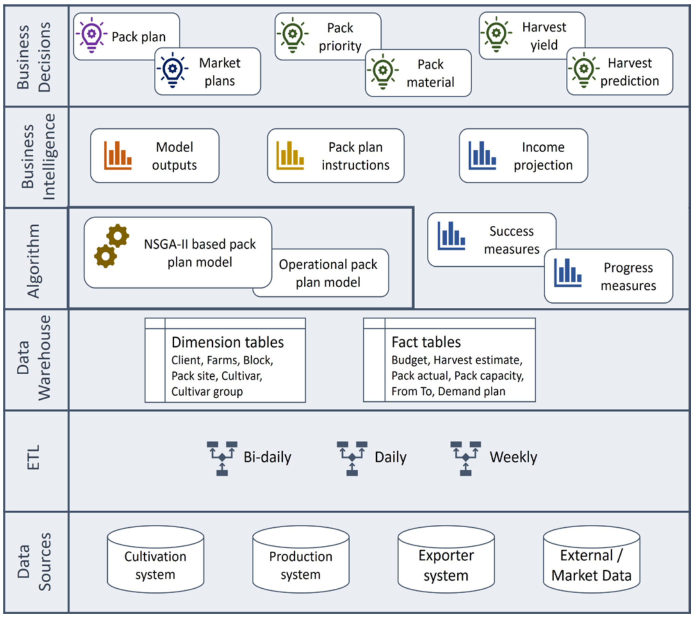


Figure 2: Proposed DSS architecture

Sprague [36] advised that a DSS includes a user interface, a database, and an analytical method. In this study, a MySQL database represents a warehouse. The extract transform and load (ETL) process, model, and email push notification application are written in Python 3.8, while Microsoft Power BI and Plotly (a Python graphing library) is used for data presentation. We used open-source technologies to make replication of the DSS possible without additional third-party licensing requirements. The technologies used for the DSS are shown in Table 2.

Table 2: Enabling technologies for the decision-support system

Operating system	Ubuntu 20.04.4 LTS: GNU/Linux 5.4.0-100-generic x86 64
Data pipeline (ETL)	Python 3.8, Crontab
Database	MySQL: 8.0.28-0ubuntu0.20.04.3 (Ubuntu)
Model and Bot	Python 3.8
Data visualisation systems	Plotly, Microsoft Power BI, Microsoft Excel

The data sources provide transactional data piped via the ETL process to a structured data warehouse. A good pack plan with two objectives is searched for by a multi-objective optimisation (MOO) algorithm called NSGA-II [37]. There is a plethora of MOO algorithms available, and we selected NSGA-II due to its popularity – it was outside the scope of this study to find the most suitable algorithm for the DSS. This is a study on its own and will be done in the future. The results of the MOO and other important user-specific insights are presented with business intelligence software Plotly, Microsoft Power BI and Microsoft Excel. These insights help formulate business decisions during the harvest and pack period.

The heart of the DSS is the bi-objective optimisation model used for the tactical planning of the harvest and processing of table grapes. Sharma [38] provides a review of multi-objective optimisation techniques. The model is presented next.

3.3. Bi-objective optimisation model

The following defines a tactical planning model for harvest and processing decisions in a producer-exporter environment with multiple table grape production and processing sites.

Indices

o Orchards, $o \in \{1, . . . , O\}$
v Varieties, $v \in \{1, . . . , V\}$
p Pack sites, $p \in \{1, . . . , P\}$
j Packaging type of the considered demand, $j \in \{1, . . . , J\}$
t Pack weeks in the planning horizon, $t \in \{1, . . . , T\}$
c Customers, $c \in \{1, . . . , C\}$
g Variety group of the considered demand, $g \in \{1, . . . , G\}$
f Farms to include in pack planning, $f \in \{1, . . . , F\}$
i Index for each demand combination of customer c, variety group g, pack type j, and pack week t, $i \in \{1, . . . , I\}$
b Index for each harvest estimate combination of orchard, variety, and pack week, $i \in \{1, . . . , B\}$

Sets

d_i [c, g, j, t] List of combinations i, of customer c, of variety group g, with pack type j, with a demand to be packed in week t
h_b [o, v, t] List of combinations b of orchard o, with variety v, to be harvested in pack week t
V_g List of varieties part of variety group g O_f List of orchards part of farm f
E_{bi} List of harvest estimates b that meet the criteria for demand i
S_{pi} List of pack sites p with the capacity to meet the criteria for demand i
T_{ibp} List of all demands i that have harvest estimates (E_{bi}) and pack capacity options (S_{pi})
P_{vg} Customer preferences for variety v in variety group g

$$R_{cv} \begin{cases} 0 & \text{if the customer c may not receive variety v} \\ 1 & \text{allowed} \end{cases}$$

$$N_{op} \begin{cases} 0 & \text{if produce from orchard o may not pack at pack site p} \\ 1 & \text{allowed} \end{cases}$$

Parameters

K_{op} Distance between orchard o and pack site p
L_{pjt} Capacity (kg) of pack site p for pack type j in week t
H_{ovt} Harvest estimate (kg) of orchard o with variety v harvested in week t
D_{cgjt} Demand (kg) of customer c for variety group g in pack type j for week t
A_c Priority for customer c

Decision variables

Q_{ovpjtc} Quantity (kg) of product allocated to customer c from orchard o with a variety v packed in pack site p in pack type j in week t, towards meeting demand combination i.

Objective functions

The two objective functions are:

$$\min Z_1 = \sum_{c=1}^{C}\sum_{g=1}^{G}\sum_{j=1}^{J}\sum_{t=1}^{T} D_{cgjt} - \sum_{o=1}^{O}\sum_{v=1}^{V}\sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{c=1}^{C} R_{cv}Q_{ovpjtc} \text{ [kg], and} \quad (1)$$

$$\min Z_2 = \frac{\sum_{c=1}^{C}\sum_{o=1}^{O}\sum_{p=1}^{P}\left(\sum_{v=1}^{V}\sum_{j=1}^{J}\sum_{t=1}^{T} Q_{ovpjtc}\right)\times K_{op}}{\sum_{o=1}^{O}\sum_{v=1}^{V}\sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{c=1}^{C} Q_{ovpjtc}} \text{ [km].} \quad (2)$$

Equation(1) measures the deviation between the total demand and the total allocated stock in the pack plan. It is important for the producer to meet customer demand, so the ideal of zero deviation between delivered mass and demanded mass is pursued. Equation (2) measures the distance that one kilogram of stock has to travel to be packed. Both objectives are minimised.

Constraints

Allocation to pack site p for pack type j in week t should be less than the pack capacity Lpjt in pack site p for pack type j in week t:

$$\sum_{c=1}^{C}\sum_{o=1}^{O}\sum_{v=1}^{V} Q_{ovpjtc} \leq L_{pjt}, \forall p \in P, \forall j \in J, \forall t \in T. \quad (3)$$

Allocation of grapes from orchard o of variety v in week t should be less than the harvest estimate Hovt for that orchard o for variety v in week t:

$$\sum_{c=1}^{C}\sum_{p=1}^{P}\sum_{j=1}^{J} Q_{ovpjtc} \leq H_{ovt}, \forall o \in O, \forall v \in V, \forall t \in T. \quad (4)$$

Allow only feasible orchard o to pack site p combinations according to list Nop, where

$$\sum_{c=1}^{C}\sum_{v=1}^{V}\sum_{j=1}^{J} Q_{ovpjtc} \times N_{op} = 0, \forall o \in O_f, \forall p \in P. \quad (5)$$

The total allocation of variety group g to customer c in week t less than total demand Dcgjt:

$$\sum_{p=1}^{P}\sum_{o=1}^{O}\sum_{j=1}^{J} Q_{ovpjtc} \leq D_{cgjt}, \forall v \in V_g, \forall g \in G, \forall p \in P, \forall c \in C, \forall t \in T. \quad (6)$$

The above model was implemented in the DSS, and the outcomes of the DSS was evaluated via a case study and subsequent interviews with the originally interviewed end users. This qualitative validation process ensured end-user satisfaction regarding the DSS outputs, as explained during the requirement interviews. The case study is described next.

4. PERFORMANCE COMPARISON OF THE MODEL WITH THE HUMAN-DRIVEN SYSTEM

The solutions created by the DSS were compared to the results of the human-driven system currently used at a large South African producer-exporter. Data from the 2022 table grape harvesting season were used for the comparison. Currently, the logistics manager (LM) manually creates and adjusts the pack plan. Keeping the system up to date in a frequently changing environment becomes arduous and takes several hours to adjust. The data analyst (DA) for the group mentioned that it takes the LM nearly three weeks to develop an initial plan before the season starts.

Maintaining and adjusting the input data (pack capacities, harvest estimates, and demands) is a team effort, with little quality assurance performed on some of the input parameters. The following issues complicate a like-for-like comparison because the two systems work with various input parameters – one system works with known parameters in the dataset, the other does not (the human system uses input data provided via phone calls that is not recorded in the data):

1. The manual entry planning data and pack capacities are over-allocated during certain weeks or sites. Pack capacities need to be more adequately maintained and adjusted since adjusting pack capacities at a site often occurs through a phone call with the PSM.

2. Harvest estimates for grapes sourced from farms owned by the subject company (internal producers) are maintained and checked by the DA. Harvest estimates for externally sourced farms (external) do not update their harvest estimates as accurately as internal producers.

3. Internal harvest estimates are over-allocated week-by-week by the LM. A conversation between the LM and the PUM will cause a decision not documented or reflected in the harvest estimate data.

4. The manual pack plan does not allocate harvest estimates at an orchard level as this is at a too granular level for the LM to maintain. Pack plans are produced and managed by considering farms and cultivars, rather than individual orchards. This additional feature distinguishes the proposed tactical model from the current system but prohibits an exact 'like-for-like' comparison.

5. The assignments of orchards to pack sites are subjective and vary from week to week, i.e., assigning an orchard to a pack site may be allowed during the planning of the current week but may become infeasible the following week.

To compare the existing human system with the model, a realistic parameter set was selected to imitate internal company heuristics used by the LM. In this parameter set, sites, where farms can have produce packed are limited to a small sample based on proximity, organizational structure, and history. Only produce from internal farms (i.e., no in-sourcing of stock) was used because internal harvest estimates are well maintained by the operational teams and are checked by the DA.

Figure 3 displays the result of running the model for 15 November 2021 and comparing it to the actual plan created by the manual process on that date. The manual plan yields a deviation from demand of 6.54 million units for objective 1 and 18 km for objective 2 ("deviation" means the difference between what was ordered and what could be supplied). Since all solutions on the Pareto frontier are equally good, we arbitrarily selected the solution pointed out by the red arrow for discussion (Solution A in Figure 3). The solution is at coordinates (25.37 km, 5 729 973 units). The selected solution has an improved deviation from demand of 12% less than the manual solution, while the latter provides 18 km as opposed to the 25.37 km obtained via the optimisation model of the DSS. (The values of the total deviation to the right of Solution A differ, but the differences are not clear due the scale of the vertical axis.)

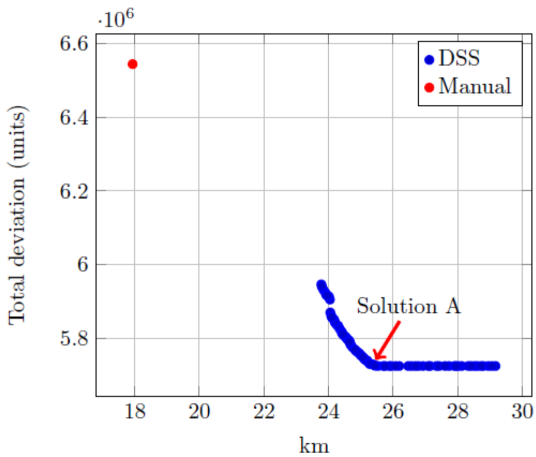


Figure 3: Comparison between the single solution of the manual plan and solutions of the DSS

The NSGA-II algorithm allocates more harvest to the demands, resulting in a lower value for objective 1, but higher objective 2 value (km). This can be ascribed to the NSGA-II algorithm allocating more harvest to allowable pack sites further away from the farm than the manual plan. Site 6 in Tables 3 and 4 is a good example. The DSS allocates 922 235 units, whereas the manual plan only allocates 721 750 units. All the farms feeding this site are shown in Table 4. The DSS allocates 29 598 units from Farm 15, whereas the manual process only allocates 5 982 units. The resulting distance for this combination is the same (as the pack site is located 160.17 km from the farm), but the total distance for the solution (all farms supplying site 6) results in 26.3 km compared to 8.58 km). Another example is 'Farm 10': it was allocated 73 235 units by the model vs. 35 292 units by the manual plan. The distance between 'Site6' and 'Farm10' is 128.25 km. This illustrates that, overall, the DSS solution allocates much more produce to be packed (which is desired), but the produce will be transported further on average than the distance of the manual plan.

Table 3: Assignment values comparison between solutions derived from the manual plan and Solution A of the DSS

Pack site	DSS (units)	Manual plan (units)	DSS (km)	Manual (km)
Site 3	575 523	403 395	3.0	2.53
Site 4	370 395	281 161	2.5	2.51
Site 5	402 585	288 779	1.9	1.79
Site 6	922 235	721 750	26.3	8.58
Site 9	139 847	105 129	5.2	4.09
Site 14	710 004	405 711	34.5	36.70
Site 22	163 714	167 567	1.0	1.00
Site 30	279 646	232 359	36.6	36.57
Site 35	197 514	239 781	32.1	24.40
Site 36	560 859	282 514	106.6	93.56
Site 41	266 937	456 740	2.7	0.75
Site 51	129 556	316 027	16.5	16.46

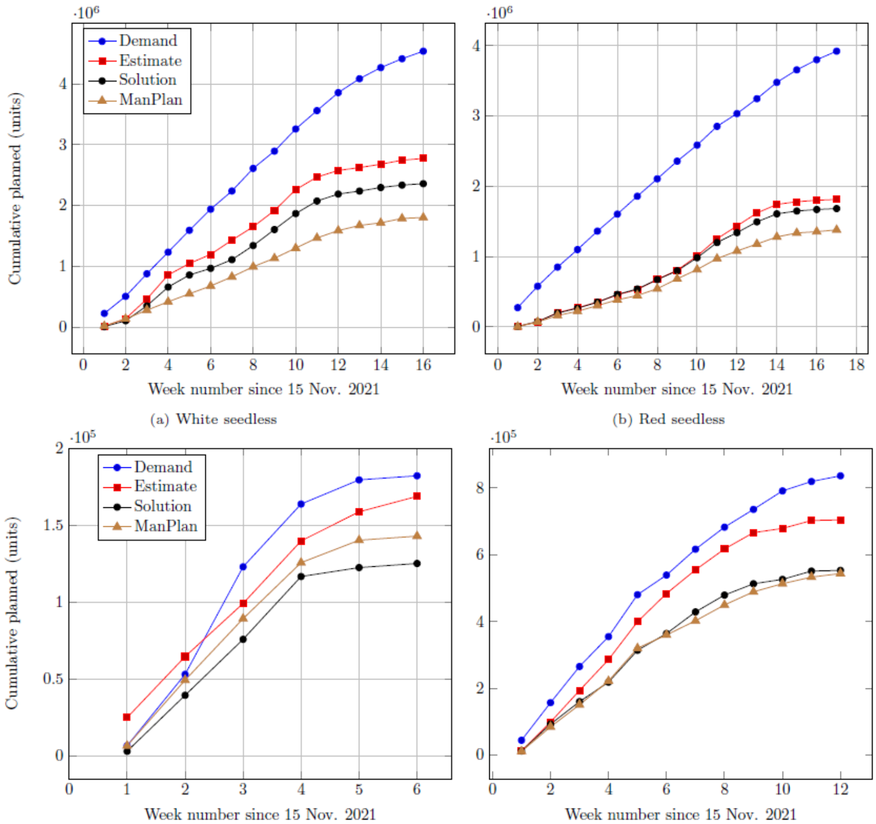
Table 4: Fitness of manual plan compared to one algorithm solution for Site 6

Farm	DSS (units)	Manual (units)	DSS (km)	Manual (km)
Farm15	29 598	5 982	160.17	160.17
Farm19	44 553	1 800	128.78	128.78
Farm10	73 235	3 529	128.25	128.25
Farm12	56 535	3 208	67.20	67.20
Farm8	21 233	2 778	15.17	15.17
Farm16	697 081	672 690	0.33	0.33

Note that the sites are the same number of kilometers from one another for both solutions. The difference comes in with the total km for the solutions (shown by Pack site 6 in Table 3 – 26.3 km vs 8.56 km). These values represent the distance one kilogram must travel to be packaged.

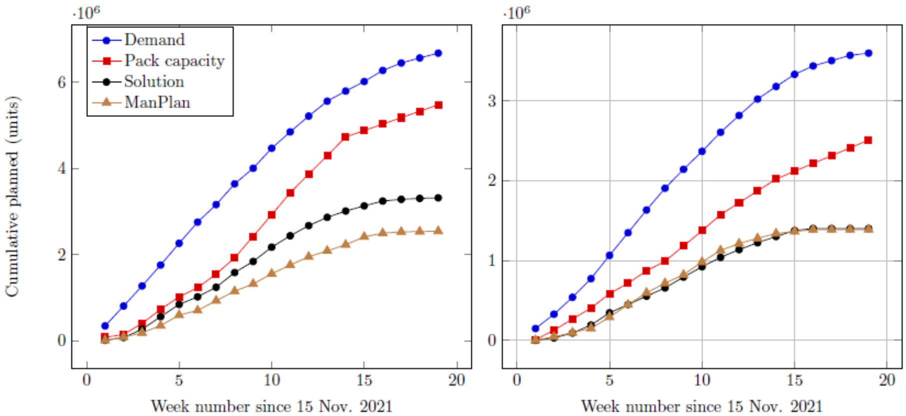
Invariably, allocating more stock to options further away results in a differently weighted answer. The user can limit allocation between farms and sites too far away but will then be restricted in the number of units that may be packed.

Figures 4 and 5 present comparisons of the cumulative harvest estimate and pack capacity allocations for different cultivars. The black line and circle markers, denoting the cumulative allocation by the DSS, consistently displays an allocation pattern similar to the harvest estimate in white seedless and red seedless grapes (the two largest cultivar groupings). Black seedless grapes indicate a similar allocation pattern between the manual and DSS plans.



(a) White seedless
(b) Red seedless
(c) Pink seedless
(d) Black seedless

Figure 4: Cumulative harvest estimate allocation as from dates indicated



(a) Loose
(b) Punnet

Figure 5: Cumulative pack capacity allocation (as on 15 November 2021)

An example of capacity allocation is shown in Table 5, which compares the results of the DSS with that of the manual plan over a given period for pink seedless grapes. The allocation percentage is calculated as the ratio of the units allocated by the DSS and the pack capacity. The DSS never exceeds available capacity, while the manual allocation either exceeds or under-allocates the capacities. Under-allocation is due to the human manager reacting to heuristic rules from experience and making short-term decisions on an ad hoc basis. The deviation values are calculated as the ratio of the DSS allocation to the pack capacity, and the ratio of the manual allocation to the pack capacity.

Table 5 further shows the restriction in packing capacity for the sites allocated to the farm producing pink seedless grapes in weeks 1–2 of 2022. Pink seedless grapes are allocated 100% of capacity in the first week of January when the manual system allocates more of the harvest estimate.

Table 5: Example of packing capacity allocation (percentage of pack capacity) for sites processing pink seedless grapes ('22-01' means week 1 of year 2022)

Type	Week	Site	Pack capacity (units)	DSS (units)	Manual (units)	DSS (%)	Manual (%)
Loose	22–01	Site 5	35 640	35 641	31 520	100	88%
		Site 41	15 681	15 681	23 183	100%	148%
	22–02	Site 5	35 640	35 639	40 772	100%	114%
		Site 41	15 681	15 146	17 335	97%	111%
Punnet	22–01	Site 3	74 497	7 497	34 487	100%	46%
		Site 4	56 925	56 926	55 067	100%	97%
		Site 5	24 502	24 502	26 208	100%	107%
		Site 41	10 454	10 454	19 464	100%	186%
	22–02	Site 3	74 497	74 496	28 000	100%	38%
		Site 4	56 925	56 368	10 139	99%	18%
		Site 5	24 502	24 502	14 903	100%	61%
		Site 41	10 454	10 455	22 000	100%	210%
Total			435 398	434 307	323 078		
	Total deviation from capacity for period over all sites:					99.74%	74.20%

The DSS spreads the load throughout the system equally and it can, therefore, be concluded that the DSS is better at allocating demands based on the input variables.

This study indicates that a DSS could help the LM plan further into the future and adapt to an ever-changing environment. Comparing a model-generated plan with an actual plan indicated an increasing divergence between the human and machine plans. The plan provided by the DSS can allocate demands to a specific orchard, whereas this level of granularity adds excessive complexity, which is problematic for a human decision-maker to maintain.

Since several farms can pack product at various sites, changes in one part of the plan merit updating the entire plan. The DSS finds sensible, feasible solutions amidst the changing environment. Human decision-makers often neglect the reallocation opportunities and rely on interpersonal relations to fix sudden changes to a node in the plan. As the business scales, or if the logistics team changes internally, this institutional knowledge must adapt or be transferred to another human. The risk remains that human decision-makers can leave their posts while the company loses the years of institutional knowledge and relationships built on the person.

Human decision-makers can change and restrict allocation informally. When using the DSS, emphasis must be adjusted to solidifying business rules prohibiting informal decision-making.

The DSS provided a better solution in a significantly shorter time compared to the system used by the company. It also allows for the refinement of options, as the DSS can be applied every time the business status changes.

To conclude, the DSS output provides pack plan instructions from which business decisions can be made (Figure 2). A three-week planning process can now be executed within four hours while using the mathematical model presented in (1) – (6). The manual method is cumbersome, reactive and does not guarantee good solutions. Note that the DSS is descriptive, not prescriptive – it shows what good scenarios are available but does not force the decision-maker to accept any solution.

5. CONCLUSIONS AND FUTURE WORK

A decision-support system (DSS) for harvest and processing planning for table grape producers was presented. The DSS uses a mathematical formulation of two conflicting objectives and several constraints. A metaheuristic, NSGA-II, was implemented to find feasible bi-objective solutions of harvest and processing plans in reasonable time. A case study with real-world data was used to evaluate the quality of the solutions. The case study comparison shows that a DSS can facilitate improved decisions and save time by producing a Pareto-optimal set of solutions in four hours or less, while the manual process took up to three weeks to develop an initial plan of which the quality was not known. With the developed DSS, the role of the human decision-maker shifts from detailed logistics to finding the trade-offs among the Pareto-optimal solutions. Adjustments to frequent changes can be incorporated considering the entire interconnected system and support the LM to focus on communication and coordination. More demand can be serviced when the model is granted more processing facilities. Internal company heuristics restrict this to simplify decision-making parameters. An algorithm can easily handle this added complexity, providing improved options and alleviating the human from details.

The DSS and its embedded mathematical model are unique and contribute to the following gaps identified in Section 2:

- The study focused on table grape producer-exporters' harvest and processing decisions. It considers the commodity-specific handling requirements not found in the existing literature. The two objectives of the model set it apart from past models. Many past models focussed only on the economic impact of models.
- This model focussed on meeting the specific demand requirements and ensuring that it can be packed as close to the source as possible to limit transportation quality degradation of highly perishable products.
- It incorporates planning of specific market requirements for customers with frequent changes to supply and processing abilities (order-to-promise).
- A geographical spread of farms and processing plants was used for the case study. The model is built to find the best possible solution for packing stock at the closest possible facility while meeting as much customer demand as needed.
- Instead of using traditional economic performance measures, two conflicting objectives were formulated: the mass of fruit deviating from the target (kilogram, minimised) and the distance each kilogram a product is transported (km).

Future work will include incorporating grape quality and sizing into the model. At the time of writing, this data was not available from source systems and had to be excluded. Including vessel schedules in the model can ensure that an order is completed before loading. A restriction on accreditation for a customer-pack-site combination can be beneficial to cater to instances with market restrictions on export fruit. Parts of the DSS have been implemented by the producer-exporter and full-scale implementation remains an ongoing process.

Only the NSGA-II was used to establish a bi-objective feature for the DSS, and other metaheuristics should be evaluated for suitability (efficacy, speed) in the DSS.

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