UNIVERSIDADE DE SÃO PAULO

Escola de Engenharia de São Carlos

Multi-objective models for optimizing olive crop management for olive oil production

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EESC • USP

SERVIÇO DE PÓS-GRADUAÇÃO DA EESC-USP

Data de Depósito: 22/09/2023

Assinatura: ____________________

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Multi-objective models for optimizing olive crop management for olive oil production

Corrected Version

Master dissertation submitted to the São Carlos School of Engineering, to obtain the degree of of the Master in Science .

Concentration Area: Process and Operations Management

Advisor: Prof. Dr. Marcelo Seido Nagano

USP – São Carlos
September 2023

Fernando Alberto Montenegro dos Santos

Modelos multiobjetivos para otimização do gerenciamento da cultura de azeitona visando a produção de azeite de oliva

Versão Corrigida

Dissertação apresentada ao Escola de Engenharia de São Carlos, para obtenção do grau de Mestre em Ciencias .

Área de Concentração: Processos e Gestão de operações

Orientador: Prof. Dr. Marcelo Seido Nagano

USP – São Carlos
Setembro de 2023

Ficha catalográfica elaborada pela Biblioteca Prof. Dr. Sérgio Rodrigues Fontes da EESC/USP com os dados inseridos pelo(a) autor(a).

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363m

Montenegro dos Santos, Fernando Alberto
Multi-objective models for optimizing olive crop management for olive oil production / Fernando Alberto Montenegro dos Santos; orientador Marcelo Seido Nagano. São Carlos, 2023.

Dissertação (Mestrado) - Programa de Pós-Graduação em Engenharia de Produção e Área de Concentração em Processos e Gestão de Operações -- Escola de Engenharia de São Carlos da Universidade de São Paulo, 2023.

1. Agro-industry. 2. Olive oil. 3. Irrigation. 4. Mathematical model. 5. Multi-objective Programming. I. Título.

Eduardo Graziosi Silva - CRB - 8/8907

FOLHA DE JULGAMENTO

Candidato: Licenciado **FERNANDO ALBERTO MONTENEGRO DOS SANTOS.**

Título da dissertação: "Modelos multiobjetivos para otimização do gerenciamento da cultura de azeitona visando a produção de azeite de oliva".

Data da defesa: 21/08/2023

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ACKNOWLEDGEMENTS

Em primeiro lugar, quero agradecer a Deus por me dar força e sabedoria para realizar este projeto de pesquisa. Sem sua orientação e amor, nada disso teria sido possível.

Sou profundamente grato ao meu orientador de tese, Dr. Marcelo Seido Nagano, por sua valiosa orientação, conselhos e correções durante todo o processo. Sua experiência e rigor científico foram fundamentais para o desenvolvimento desta tese. Também gostaria de agradecer ao Professor Dr. Carlos Monardes Concha, que desde o início de meus estudos superiores vem me acompanhando e orientando meus conhecimentos. A Francisco Pérez Galarce, por seu apoio durante toda a pesquisa, suas sugestões e o tempo dedicado ao desenvolvimento deste trabalho. Ao Dr. Alfredo Candía Vejar, que me mostrou que, com paciência e dedicação, as metas são alcançáveis. À professora María Alejandra Peralta Müller, sem ela esta história não teria começado. Também gostaria de agradecer a Jorge Astudillo Gálvez, que me deu a oportunidade de obter os dados necessários para esta pesquisa e contribuiu com sua longa experiência no cultivo de oliva. A Luis Gallardo, que orientou os aspectos mais essenciais de minha vida com base na visão em Deus.

À minha família por seu amor incondicional, paciência e compreensão. Aos meus queridos pais, que sempre me incentivaram a seguir meus sonhos e me deram tudo o que eu precisava para minha educação. À minha avó, que sempre confiou em mim.

Por fim, quero agradecer à Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES - 001).

RESUMO

MONTENEGRO DOS SANTOS, F. A. **Modelos multiobjetivos para otimização do gerenciamento da cultura de azeitona visando a produção de azeite de oliva**. 2023. 70 p. Dissertação (Mestrado Processos e Gestão de Operações) – Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos – SP, 2023.

Este trabalho tem como objetivo desenvolver e aplicar dois modelos matemáticos para o gerenciamento otimo da colheita e da irrigação na cultura de azeitona no Chile, considerando diferentes objetivos e cenários. Os modelos são baseados em técnicas de programação matemática multiobjetivo, que permitem representar a complexidade e a incerteza do problema agrícola. Os resultados obtidos mostram que os modelos são capazes de gerar soluções eficientes e flexíveis que satisfazem os requisitos de produção, qualidade e contrato das culturas, bem como os critérios econômicos. Os modelos também permitem que o tomador de decisão escolha a melhor alternativa de acordo com suas preferências e restrições, bem como se adapte a mudanças e eventos indesejados que possam ocorrer durante o processo. Os modelos propostos são ferramentas úteis para a tomada de decisões em nível operacional no campo agrícola, pois facilitam a otimização e o controle das atividades de colheita e irrigação. Além disso, os modelos são flexíveis e adaptáveis a diferentes contextos e culturas, o que os torna aplicáveis a outras regiões ou problemas

Palavras-chave: Agro-indústria, Azeite de oliva, Modelo matemático, Irrigação, Programação Multiobjetivo.

ABSTRACT

MONTENEGRO DOS SANTOS, F. A. **Multi-objective models for optimizing olive crop management for olive oil production**. 2023. 70 p. Dissertação (Mestrado Processos e Gestão de Operações) – Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos – SP, 2023.

The objective of this work is to develop and apply two mathematical models for the optimal management of crop harvesting and irrigation in Chile, considering different objectives and scenarios. The models are based on multi-objective mathematical programming techniques, which allow representing the complexity and uncertainty of the agricultural problem. The results obtained show that the models are capable of generating efficient and flexible solutions that satisfy the production, quality and contract requirements of the crops, as well as economic criteria. The models also allow the decision maker to choose the best alternative according to his preferences and constraints, as well as to adapt to changes and undesired events that may occur during the process. The proposed models are useful tools for decision making at the operational level in the agricultural field, as they facilitate the optimization and control of harvesting and irrigation activities. In addition, the models are flexible and adaptable to different contexts and crops, which makes them applicable to other regions or problems.

Keywords: Agro-industry, Olive oil, Irrigation, Mathematical model, Multi-objective Programming.

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INTRODUCTION

By 2050, FAO forecasts that the world population will reach almost 9.7 billion people (FAO, 2017). Based on this, important decisions must be considered to ensure global food security. These decisions significantly affect the management of the agribusiness sector and its logistics, where accurate coordination between the different stages of the supply chain must be ensured. Two of the most important stages of the supply chain are cultivation and harvesting, which determine the quality and quantity of food.

Crop management and subsequent fruit harvesting is severely affected by variations in temperatures and adverse weather events, production problems such as productivity losses due to frost or strong winds; soil damage caused by rainfall, causing harvesting equipment to be unable to access flooded areas; significant variations in the availability of water resources, which may compromise crop irrigation. Under these conditions of uncertainty, innovative tools must be used to help decision making and establish efficient action plans.

In this sense, optimization tools are very useful to face these challenges, and mathematical programming has been used for a long time in agricultural logistics problems. The first level of planning is the strategic level, where different works have been developed. Considering the problem of crop land planning, (SARKER; QUADDUS, 2002) developed a tool based on multiple criteria decision-making (MCDM) in conjunction with a mathematical model to maximize benefits. To manage the problems associated with indiscriminate use of water resources in a semi-arid region in China, they developed a strategic dynamic adaptation tool. In view of the problems associated with pollution through the intensive supply of carbon to the atmosphere, they developed a linear programming model that optimizes infrastructure, agriculture, and logistics costs and also balances carbon emissions within the agri-food ecosystem.

Combining the strategic-tactical levels for a wheat supply chain for biofuel production, (ZHANG; HU, 2013) they developed a mixed integer linear programming (MILP) methodology to investigate the location of biofuel supply chain facilities, facility capacity at the strategic level, and biofuel production decisions at the operational level. On the other hand, (LI *et al.*, 2020) they studied the allocation of water resources and agricultural land under uncertainty. To achieve this, they used a model that combines fuzzy programming techniques with credibility constraints, mixed-integer nonlinear programming and Multi-objective programming. In view of the changes in agricultural markets and their distribution and logistics channels,(FLORES *et al.*, 2019) proposed an integrated supply chain planning tool for fresh vegetables that takes into consideration the characteristics and resources of three specific states in Mexico. Similarly, considering market changes and food demand,(HAJIMIRZAJAN *et al.*, 2021) presented a strategic planning framework from a large-scale crop supply chain perspective for National Growers Associations (NCAs). The framework helps to manage actions that help to coordinate the different activities between agricultural producers and the market, taking advantage of complementary climate and market opportunities to plan.

At a particularly tactical level, different authors have addressed the challenges of an agricultural supply chain. For the cultivation of tomatoes and peppers, (AHUMADA; VILLALOBOS, 2011) and (AHUMADA; Rene Villalobos; Nicholas Mason, 2012) developed mathematical programming models to address the challenges associated with field management. (AHUMADA; VILLALOBOS, 2011) proposed a MILP that in addition to taking care of aspects such as price estimation and resource availability, addresses more dynamic aspects such as product deterioration and inventory costs. Incorporating uncertainty into their study, they developed a model that seeks to generate crop and distribution plans in response to climate and demand variability. (ATALLAH; GÓMEZ; BJÖRKMAN, 2014) focused on the study of an expansion of a broccoli logistics network for the United States, using a production-transportation model. In view of the challenges posed by new regulations related to sustainability, (GALÁN-MARTÍN *et al.*, 2015) they developed one tool based on a multistage linear programming model that identifies optimal decisions on cropping plans. In relation to sustainable systems under water aspects, (DAS *et al.*, 2015) proposed a linear programming (LP) model for optimal allocation of land and water resources in eastern India. Through the formulation of a MILP, they sought to design a network by locating wholesale (hub) facilities to facilitate the efficient movement of food from production regions to places of consumption.

At a tactical-operational level we have the work of (JENA; POGGI, 2013), which through the implementation of a MILP addresses harvest planning problems arising in sugar and alcohol production from sugarcane in Brazil. Focusing on the harvesting and cultivation stage, they proposed a stochastic optimization framework to be developed for a set of identified regions with complementary climatic characteristics. (Mardani Najafabadi *et al.*, 2019) developed a structural multi-objective planning approach (PEMO), for different objectives, such as economic, social and environmental, separately and jointly, with the aim of providing agricultural solutions in a sector of Iran exposed to intense drought. Aspects related to quality-related losses at harvest and post-harvest are addressed by Blackburn, using melons and sweet corn as examples. Focusing on the harvest stage,(AHUMADA; VILLALOBOS, 2011) they developed an operational model that generates short-term planning decisions for the fresh produce industry.

Thus, as can be seen, mathematical models are used to address different challenges in agriculture at different stages of the production process and with various optimization objectives. In view of the presence of more than one objective, the multi-objective modeling approach is very useful. It is important to recognize that crop yields depend on factors such as climate, irrigation, soil and fertilizers. The right varieties should be chosen and the optimum amount of fertilizer should be applied to improve growth. Excessive use of fertilizers can damage the soil and the environment. In this sense, in the work of (JAIN; RAMESH; BHATTACHARYA, 2021), by means of multi-objective modeling they sought to maximize crop profit and minimize fertilizer use. For the solution of the problem they propose a hybrid algorithm that combines crow search (CSA) and particle swarming (PSO).

The importance of irrigation to crops is related to the fact that it allows them to obtain the water they need to develop optimally. Without adequate irrigation, crops can suffer from water stress, which affects their yield and quality. Water availability generates great uncertainty to plan crop irrigation and ensure optimality. In (ZHANG *et al.*, 2020) a new mathematical programming method named multi-objective chance-constrained programming approach for planning problems with uncertainweights (MCUW) is proposed, using this method to manage water resources in northern China. In a scenario where not only water resources are scarce, but also land availability limits field planning. To achieve this, they develop a multi-objective model to maximize net yield and arable area. In the work of (BOINDALA; OSTFELD, 2022) they propose a methodology for designing a water distribution system that takes into account multiple objectives and uncertainties, especially those related to demand. The methodology uses robust optimization and multi-objective optimization to achieve a design that is cost efficient and resilient.

In agriculture, harvesting is very important because it is when producers receive the benefits of their efforts and can provide food for people. However, harvesting also brings with it several challenges and hazards, such as weather, insects, diseases, post-harvest treatment, transportation and sale. With the aim of realizing sustainable selective logging management, they propose a mathematical model that seeks to maximize the diversity of remaining stands, marketable logs and the inverse of the distance between trees for logging points and log debarking. To demonstrate its application, they use data from the Brazilian rainforest with 566 trees and an area of 216 ha. Focusing on sugarcane harvest optimization, (SETHANAN; NEUNGMATCHA, 2016) proposed a multi-objective model that sought to minimize the harvested distance and maximize sugarcane yield. Focusing on the same crop, (Aliano Filho; A OLIVEIRA; MELO, 2023) sought maximization of total sucrose and fiber yield, minimization of total time spent harvesting and minimization of total transportation cost of harvesting equipment. Focusing on wine grape harvesting, (VARAS *et al.*, 2020) proposed a multi-objective mixed-integer model with focus on minimizing operating costs and maximizing grape quality. In order to satisfy the different points of view of the winemaker and the field manager, they are based on the actual operations of one of the three largest wineries in Chile.

As can be seen, different types of mathematical models are presented to face challenges in agro-industrial systems at different planning levels and different crops. Specifically, this paper focuses particularly on the olive oil production industry.

1.1 Objetives

The objective of this research is to study the use of multi-objective mathematical programming models applied in the olive oil industry.

To achieve this, the following specific objectives are defined:

- Review the scientific literature on multi-objective mathematical programming models and their application in the olive oil industry.
- Develop the most appropriate multi-objective mathematical programming models to address the harvesting and irrigation optimization problems encountered in the olive oil industry.
- Implement the selected multi-objective mathematical programming models in specialized software.
- Analyze the results obtained with the multi-objective mathematical programming models and propose recommendations to improve the yield, quality and sustainability of the olive oil industry based on the results of the multi-objective mathematical programming models.

1.2 Research project organization

This research project is structured in fouth chapters. Chapter 2 presents the study of olive crop replanning for olive oil production.

In chapter 2 the challenge of harvesting olives for oil production is addressed. A model is proposed with which to replan and coordinate the activities of different olive harvesting teams, in consideration with the processing capacity of the mill. The model is bi-objective, the first one seeks to maximize the olive oil production and the second one controls the deviations of the harvesting plans with respect to an initial plan, fixed at the beginning of the planning horizon ($t = 0$), all this under a novel methodology denominated as Non-Myopic Rolling Horizon. In chapter 3 the challenge of the adequate allocation of water to different sectors of an olive crop is addressed. The model is bi-objective wich seeks to prioritize allocation to more productive sectors, considering the driving costs of water. Lastly, the chapter 4 establishes the conclusions of the work carried out. Chapter 3 presents the work carried out for irrigation planning in an olive crop.

CHAPTER

2

A ROLLING HORIZON SCHEME FOR RESCHEDULING IN AGRICULTURAL HARVEST

2.1 Introduction

Agricultural supply chain planning models have been developed in different areas. Several papers have surveyed different models, like (GLEN, 1987) in farm planning, (WEINTRAUB; ROMERO, 2006) in agriculture and forestry, (AHUMADA; VILLALOBOS, 2009) in the agri-food supply chain, (SOTO-SILVA *et al.*, 2016) in the fresh fruit supply chain, (FUCHIGAMI *et al.*, 2018) in the fresh agri-food supply chain, and (TAŞKINER; BILGEN, 2021) in harvest and production planning. In the last decades, due to the complexity of the multi-echelon agriculture supply chains (BARBOSA, 2021; LEZOCHE *et al.*, 2020), various papers include components of risk and uncertainty existing in their typical stages: primary production (of raw products by farmers), production of semi-product by plants, and finished products and distribution (FUCHIGAMI *et al.*, 2018; ZHAO *et al.*, 2020). Uncertainty management in agriculture has been highlighted intensively in the last decade, (BORODIN *et al.*, 2016) and (BEHZADI *et al.*, 2018) provide excellent reviews, including most of the papers which handle the components of risk and uncertainty.

Harvest scheduling is a key activity in the agriculture supply chain's first stage of primary production. It is complex due to some characteristics shared by-products, like wine and olive oil. Harvesting is constrained to strict time windows where weather conditions, like rain and frost, can affect the ripening process of the crops and the ability to perform harvesting operations, like machine operations and manual labor (FERRER *et al.*, 2008; KUSUMASTUTI; DONK; TEUNTER, 2016; PINO *et al.*, 2022). Therefore, in this context, it is important to consider uncertainty a critical factor in operative plans. Thus, decision-makers must consider this component in the planning either within optimization models or in high-level policies.

Two approaches can be applied to deal with this underlying uncertainty; we can use proactive or reactive approaches. A proactive approach is considered a mitigation strategy and focuses on identifying and minimizing the impacts of the expected risks. Therefore, it requires predictive tools to identify risks, calculate their probabilities, and implement mitigation mechanisms. According to (BEHZADI *et al.*, 2018), such predictions could be difficult to achieve due to their nature-based uncertainty. Two of the most used proactive methods in agriculture supply chains are Stochastic Programming, in which probability distributions are assigned to uncertain parameters, and Robust Optimization, where uncertain parameters are modeled by interval or ellipsoidal uncertainty sets (BORODIN *et al.*, 2016; BEHZADI *et al.*, 2018).

Reactive approaches do not waste time simulating or modeling possible scenarios; they are focused on providing efficient solutions once the planning environment is modified. Rolling Horizon is a classic strategy to manage uncertainty reactively. Despite its intensive use in several industries, this approach has some problems when other decision-makers are involved, and the reactive plan changes previous commitments (SAHIN; NARAYANAN; ROBINSON, 2013).

Rescheduling in agricultural harvest is crucial because a baseline plan is usually challenging to maintain in actual operations. Several factors, like, for example, climatic events or disagreements in contracts with service providers or external suppliers, could create complicated scenarios in the context of harvesting operations. However, most proposed optimization models focus on generating an initial tactical plan. Reactive responses have some advantages since they can avoid assumptions about parameters, and the optimization model does not need to be converted into a more sophisticated and complex variant. Moreover, new technologies can be used efficiently to collect and update data during the harvest (JAYARAMAN *et al.*, 2016; KULBACKI *et al.*, 2018; EITZINGER *et al.*, 2019; DAUM *et al.*, 2018; PEREIRA *et al.*, 2018a).

In the context of harvest rescheduling, when a new harvest plan is generated, decision-makers must coordinate with several actors, such as service providers, which include both humans and machines. As a result, there are various reasons for avoiding high variability in the harvest plan and maintaining a stable schedule. First, since mills are often shared with a set of farmers when the initial harvest plan is generated, or a modification is made, other farms are also affected. Second, because automatic machines and human teams often come from outsourced suppliers, they define their commitments through contracts embodied in the baseline operative plan. Considering this, changes in the schedule require interfacing with the people responsible for these outsourced services, which can result in a complex negotiation process.

In this context, we focus on developing a procedure for reducing variability in the rescheduling process to avoid significant changes in the baseline plan and to minimize the *nervousness* consequently. *Nervousness* is a traditional concept in production planning under uncertainty defined as “the difficulty encountered in shifting of previously scheduled production setups because of new information obtained in a rolling horizon" according to (CARLSON;

JUCKER; KROPP, 1979) and (KAZAN; NAGI; RUMP, 2000).

Our main contributions can be summarized as follows.

(i) A non-myopic rolling horizon scheme is developed to reduce the variability in agriculture harvest plans. The method considers certain conditions of harvesting operations, e.g., commitments with suppliers and a mid-term planning horizon.

(ii) To reschedule within the rolling horizon scheme, a harvest replanning optimization model is formulated. The model is bi-objective. On the one hand, it is concerned with managing contracts and their fulfillment, while on the other hand, it seeks to maximize the amount of olive oil to be produced.

(iii) Two common sources of uncertainty in agricultural harvesting are analyzed, to which the proposed non-myopic rolling horizon scheme is applied. These scenarios are an extreme weather event and an underestimated yield.

This section is organized as follows. Section 2.2 presents related work of RH methods, highlighting papers that allow the management of contracts with suppliers and use variants of Rolling Horizon (RH) strategies. An optimization model for managing the variability in agricultural harvest plans within a non-myopic RH scheme is developed in Section 2.3. Section 2.4 provides a high-level methodology for running the non-myopic RH algorithm in smart farm environments. Experiments and an in-depth analysis of results are presented in Section 2.5. Lastly, conclusions and future work are discussed in Section 2.6.

2.2 Background

Over the last decades, RH schemes have been applied in several industrial contexts to solve optimization models which involve uncertainty. Some good examples of these applications are the distribution of cut flowers (NGUYEN; DESSOUKY; TORIELLO, 2014), container planning in harbors (ZHANG *et al.*, 2003; YANG *et al.*, 2018), wildland fire planning (CHOW; REGAN, 2011), health systems (ADDIS *et al.*, 2014), warehouse management (REVILLOT-NARVÁEZ; PÉREZ-GALARCE; ÁLVAREZ-MIRANDA, 2019), sawmill (HUKA; GRONALT, 2017), emissions trading (QUEMIN; TROTIGNON, 2021), and facility location (MARUFUZ-ZAMAN; GEDIK; RONI, 2016). From an algorithmic perspective, RH can be understood as a time-based decomposition (BASSETT; PEKNY; REKLAITIS, 1996). Given this, we can use this methodology to solve intractable models, dividing a long-term (e.g., a year) planning problem into a sequence of short-term (e.g., a week) decision problems with smaller temporal windows.

Even though the RH strategy has been applied in several contexts, its application in harvesting has been limited (RACHMAWATI *et al.*, 2014; KOSTIN *et al.*, 2011), and crucial characteristics of modern harvesting operations have not been considered. (RACHMAWATI *et al.*, 2014) applied a linear programming model for optimizing crop planning. This model used agronomic characteristics of the crops (e.g., accumulated heat) and temperature forecasts to update them. At the beginning of each period, a standard RH was applied. In (KOSTIN *et al.*, 2011), a customized RH algorithm was designed to optimize an integrated sugar/ethanol supply chain. The algorithm considers long-term and three-echelon decisions; a relaxed model is solved due to the high computational complexity in each RH iteration. The relaxed optimization model contains a set of integer decision variables associated with the control horizon, and the relaxed variables represent decisions after the control horizon. A significant reduction in running times of computational experiments was presented. Although several articles have recommended applying harvest scheduling models by using standard RH schemes (KARLSSON; RÖNNQVIST; BERGSTRÖM, 2003; FERRER *et al.*, 2008; RISYAHADI, 2015; LAMSAL; JONES; THOMAS, 2017), they did not propose ad-hoc implementation to agriculture (e.g., seasonal production and multiple decision-makers), nor they have modeled contracts with service providers.

Given the scarce literature on ad-hoc RH frames in agriculture, we divide our literature review into two parts. Firstly, in section 2.2.1, we present an overview of traditional strategies to define contracts along a supply chain; this section gives a conceptual frame to constrain the variability in reactive rescheduling. Next, in section 2.2.2, we select relevant boosted applications of RH, focusing on methodological aspects and managerial insights. These improved approaches influenced the design of our non-myopic and ad-hoc scheme of RH harvest scheduling.

2.2.1 Supply chain contracts

The harvest process in agriculture represents the first stage in the supply chain (SC). This stage involves several factors: external producers, external work teams, harvest machine suppliers, decision-makers in the field, and decision-makers in the mill. Agricultural planners typically mitigate these uncertain environments by signing contracts. Agricultural contracts have many different applications, from a way to protect from market price fluctuations (HONG *et al.*, 2023) to a way to protect from weather conditions variability impacting harvest yield through forward contracts (CHEN; RYAN, 2023).

(TSAY; NAHMIAS; AGRAWAL, 1999) provides a valuable review of contracts in the SC; for example, to incorporate previous contracts in updated schedules, a significant effort has been made to adapt RH strategies. In (TSAY; LOVEJOY, 1999), an RH framework for studying Quantity Flexibility (QF) in supply chain contracts was presented, assessing scenarios of non-stationarity demand. They concluded that flexibility is considered an added value in volatile contexts, but it follows a principle of diminishing returns. Moreover, they proposed managing the variability by utilizing the inventory. Obviously, this insight is not valid for service providers, so in highly service-based SC (e.g., processing foods or fresh fruit), more accurate decisions should be made to increase efficiency in volatile contexts. Similarly, in (BASSOK;

ANUPINDI, 2008), a Rolling Horizon Flexibility (RHF) approach is addressed, where the buyer must commit the goods or services for each period; this commitment is agreed upon when the planning horizon is started. They gave valuable managerial insights to planners; for example, (a) it is unnecessary to provide unlimited flexibility, and (b) the flexibility in responsive plans follows a diminishing returns law. These insights encourage us to develop a non-myopic rolling horizon since the traditional rolling horizon is completely flexible in its response; this flexibility harms the system (wasting time in negotiations) and service providers (*nervousness*).

(AMRANI-ZOUGGAR; DESCHAMPS; BOURRIÈRES, 2009) studied a Frozen Horizon & Flexibility Rate (FH & FLH) contract; it considered an initial rigid period (FH) followed by a flexible horizon which allowed modification of the commitments. The authors solved a linear programming model within an RH scheme to analyze its performance. The results presented an interesting trade-off between the lengths of FH & FLH, showing that longer FLH generates less inventory, and longer FH is associated with less impact due to variations. Recently, to mitigate the *nervousness* in the planning process, (DEMIREL; ÖZELKAN; LIM, 2018) presented a Flexibility Requirements Profile (FRP) strategy to update aggregate production plans and generate the production plans by solving a mixed-integer linear programming model. FRP allows changing plans within lower and upper bounds, which are modeled as constraints (lower and upper limits for production-decision variables) in an RH approach. (DEMIREL; ÖZELKAN; LIM, 2018) proposed two measures to evaluate the model performance, a metric based on the cost over the planning horizon and a metric to assess the plan variability. Experiments on two industries were conducted (textile and automotive); some advantages of FRP were shown since it reduces variability and sacrifices smaller costs than the standard aggregate production model. We propose exploiting these properties in harvest planning by incorporating enriched objective functions (or constraints) to mitigate the high variability when a rescheduling optimization model is solved.

2.2.2 Advanced rolling horizon approaches

Some literature reviews about RH have been published (CHAND; HSU; SETHI, 2002; SAHIN; NARAYANAN; ROBINSON, 2013). In (CHAND; HSU; SETHI, 2002), 200 papers were summarized; the studied papers were classified into the following five categories: horizon, model, sources of the horizon, method, and subject. Several managerial insights were provided concerning the horizon length and forecast horizon. The types of problems were: inventory management, production planning, scheduling/sequencing, plant location, machine replacement, cash management, capacity expansion, and warehousing. After that, a new review was provided in (SAHIN; NARAYANAN; ROBINSON, 2013), in which the globalization and outsourcing strategy were considered crucial. They established a taxonomy wherein the number of actors in the supply chain is highlighted, coming from the new environment that forces the reduction of the variability in the schedules and, consequently, the *nervousness* of decision-makers. Moreover, they proposed some research directions, like considering extensions of RH with multiple actors, multi-layer supply chains, and coordination among actors. We highlight that studies about agriculture were not mentioned in those reviews. Below we present some highlighted applications which designed adaptations to reduce the variability in rescheduling.

An RH method was presented in (PEREA-LOPEZ; YDSTIE; GROSSMANN, 2003) to update decisions and deal with uncertainty within an SC. The uncertainty is related to the demand, which can be well-estimated within the prediction horizon. The underline model is a multiperiod mixed-integer linear programming (multiperiod MILP) that includes different actors such as suppliers, manufacturing, distribution, and clients. Moreover, a model predictive control (MPC) was proposed to update decisions. The MPC algorithm is composed of two elements. The first solves a control problem (multiperiod MILP) to get optimal policies, whereas the second evaluates future system responses to previously found optimal policies. In (GLOMB; LIERS; RÖSEL, 2022) developed a new RH algorithm that incorporates constraints that seek to manage the quality of the solutions to be obtained. First, they test the applicability of the algorithm to batch-sizing problems. Then, they analyze the application of their RH approach with real-world tail-assignment problem instances in aircraft management, highlighting the efficiency of the algorithm in finding solutions very close to the optimum. The authors conclude that it is interesting to investigate how the RH approach can be extended to be able to guard against uncertainties.

In (ADDIS *et al.*, 2014), an advanced scheduling problem (ASP) was addressed. The practical problem consisted of matching patients from a waiting list with the available operating room blocks. The process involved uncertainty from two sources: surgery times and changes in the waiting list, which gave rise to applying an RH scheme. Note that a weekly update was considered; however, a more extended horizon was used in each rescheduling process, and a baseline plan was generated. After that, a new solution is found that does not differ too much from the baseline plan. They commented that it is a good idea in complex (time-consuming) models to start from a previous plan, but it can be hard to find a solution when the parameters change significantly. In the same context, (KAMRAN *et al.*, 2019) proposed an adaptive operating room planning and scheduling by means of an RH strategy. To face the chaos and conversions during the planning, they used a reserved slack policy, which considered assigning some rooms like slack capacity in a stochastic MILP. Some advantages of the reserved slack policy were increased flexibility and more efficient use of resources.

In (BISCHI *et al.*, 2017), a co-generation energy system was optimized by applying a MILP within an RH frame weekly. The model includes some uncertain parameters, such as ambient temperature, electric demand, heat demand, and fuel prices, which are updated in each RH iteration. The time window between updates is one week; upon making this decision, market characteristics of prices and model complexity are considered. The proposed iterative algorithm is composed of two sequential RH loops. In the first one, a typical week's energy consumption is assumed, and according to the previous week, this information is updated in the second loop.

The feasibility (constraints on incentives) is also forced in the second loop; hence, this loop is a method for repairing solutions.

(LIN; UZSOY, 2016) proposed a set of chance-constrained formulations for production planning within an RH scheme. They tried to tackle two drawbacks of RH strategies: first, the well-documented "end of horizon effect", which generates zero inventory in the last periods of planning, and second, like this work, the nervousness among supply chain actors due to changes in schedules. To manage these effects, they focused on improving the service level (employing a safety stock level), incorporating an uncertain demand into five optimization models with chance constraints. Experiments were conducted in a single-product and single-stage production planning system over four scenarios, showing a significant reduction in variability and maintaining the service level even considering highly uncertain demand. Recently, (TAVAGHOF-GIGLOO; MINNER, 2020) also used a chance-constrained model for ensuring the service level in stochastic lot-sizing models (uncertain demand). They compare the performance of two approaches, a stochastic dynamic program under RH planning and an integrated model. The integrated model endogenously sets dynamic safety stocks. They concluded that the RH approach is a better option only if we have great flexibility (capacity). Still, in the case of limited capacity (lower inventory and same-level service), integrated models outperform the dynamic alternative.

(HUKA; GRONALT, 2017) studied sawmill production planning under the co-production of several products. They created a MIP to model the real sawmill production planning problem. To solve this model, they mainly focus on heuristics to measure how much loss occurs in the sawmills because the heuristics known in the literature are easy to implement instead of exact algorithms. Also, they proposed some new variants of the heuristics. A sensitivity analysis in some parameters was carried out to measure the solutions' robustness. These parameters were mainly the storage of raw materials and products and whether there is a minimum demand percentage for them. They use RH to compare the heuristic behavior in different periods, and a multi-period approach is compared with a single-period one. Of the five heuristics studied, the best one, the heuristic E, outperformed the RH method. Also, the proposed MIP multi-period planning overcame the RH method. They conclude there is a conflict between RH planning and one-period planning. The decision-makers need to know the planning frequency precisely to maximize the benefit and profit through the tool. Commitments with third parties were not considered when replanning.

(ELKAMEL; MOHINDRA, 1999) developed a reactive scheduling model through a Mixed Integer Non-Linear Programming (MINLP) based heuristic, which uses an RH planning strategy and penalizes the deviations from the original scheduling. It penalizes the lot length as the squared difference between the old and new length. They seek to minimize the deviation due to its adverse effects on the plant, i.e., being disruptive, costly, and highly inefficient in preserving a smooth operation. The problem is linearized due to the difficulty of solving a nonlinear problem. The authors give importance to how disturbances are applied to the model. In particular, they divided the scheduling horizon into different sub-horizons. They view the reactive scheduling problem as having two stages: pre-processing and maintenance. They concluded that the longer the sub-horizon is, the improved quality of reactive modifications could be made, making sense considering more time to react to changes.

(TARHAN *et al.*, 2023) develop a multi-objective model for planning and routing of disaster response personnel with efficiency, equity, and risk objectives, subject to restrictions related to work and rest. This model seeks to respond to emergencies based on the needs of the users, relating the organization to the order of requirements. The resolution of the proposed model is made lexicographically on an RH sequentially and on a daily basis until the demand for all services is satisfied.

To sum up, in some contexts, advanced RH methods have been applied to deal with the variability (and nervousness) in re-planning. However, we did not find methodological adaptations or applications in harvest operations that considered it. To face this drawback, those approaches have incorporated longer planning horizons and have limited quality indexes (e.g., service level or plan variability) utilizing additional constraints. Considering these ideas, we propose an ad-hoc RH frame for planners in agriculture, meaning a scheme able to manage contracts, uncertain parameters, and additional operative constraints. This can be used as a quantitative tool to negotiate with service suppliers during complex harvest re-scheduling.

2.3 Notation and Problem Definition

This section presents an optimization model in the non-myopic RH context for the rescheduling problem. In particular, as previously noted, service suppliers play an essential role in modern monoculture farming. This relationship is typically managed by contracts, which ideally should be fixed, but sometimes the uncertain conditions force a renegotiation. The optimization model presented below considers a strategy to manage this situation.

Our rescheduling problem is modeled as a bi-objective model. Let RP be a mathematical programming model in which f is a vector of objective functions, $\mathscr{X}$ is the set of feasible harvest plans and t is a time-dependent parameter denoting periods from the time horizon discretization τ, where rescheduling is necessary. When solving this model in the period t, an optimal solution $\mathbf{x_t^*}$ is obtained. Each optimal solution $\mathbf{x_t^*}$ contains a set of decision variables x_{jtk}, representing the quantity of fruit (in tons) to be harvested in the lot $j \in J$ during the period $t \in \tau$, with the work team $k \in K$. Moreover, let r_{jtk} be a parameter that indicates the olives' quantity (in tons) harvested according to the baseline plan (and its commitments) in lot $j \in J$ during the day $t \in T$ with the work team $k \in K$.

$$f(\mathbf{x_t}^*) = \min\{f(\mathbf{x_t}) : \mathbf{x_t} \in \mathscr{X}\}. \tag{RP}$$

The bi-objective model RP considers two objective functions, $f(\mathbf{x_t}) = (f_1(\mathbf{x_t}), f_2(\mathbf{x_t}))$. The function f_1 involves a goal relevant to the particular context (e.g., the amount of olive oil produced or the cost of harvesting). OC_{jt} is the oil concentration in the olives in lot $j \in J$ during day $t \in T$, as a percentage. Then, f_1 is defined as follows:

$$f_1 = \sum_{j \in J} \sum_{t \in T} \sum_{k \in K} x_{jtk} OC_{jt} \tag{2.1}$$

The function f_2 is used for modeling contracts with the aim of controlling the discrepancy concerning the tactical plan. Since we seek to assess the trade-off between maintaining a stable plan and increasing olive oil production, f_2, named Punctual Contract, is defined as follows.

$$f_2 = \sum_{\langle j,t,k \rangle \in c} |x_{jtk} - r_{jtk}| \tag{2.2}$$

In this agricultural context, the definition of f_2 is appropriate because it measures the difference between the number of olives harvested in the initial plan and the replanning. An alternative function representing aggregated contracts allows significant differences in the utilization of resources like machines, generating inefficiencies in harvesting. Note also that, in the next bi-objective model RP proposed, f_1 is maximized, and f_2 is minimized.

2.3.1 Mathematical formulation (RP)

Despite agricultural harvest planning has been widely studied, rescheduling, which is essential in agriculture, has been less studied. In this section, we define an ad-hoc model for replanning. It is an adaptation of the proposed tactical model for harvesting olives (HERRERA-CÁCERES *et al.*, 2017). Below we present sets, variables, and parameters.

Sets

T	Set of days in the replanning horizon. $T = \{0, 1, 2, .., \lvert T \rvert\}$. $T' = T \setminus \{0\}$ where $t = 1$ is the first day of replanning and $t = 0$ is the day immediately prior to replanning and is used for harvest continuity.
M	Set of harvesting modes. M has a value of 1 for the harvesting machine mode, 2 for the mode of shaker A, 3 for the mode of shaker B, and 4 for the manual harvesting mode.
K	Set of work teams.

$K_m \subseteq K$ Subset of work teams that belong to the same harvesting model $m \in M$.

J Set of lots of olives.

C Set of signed contracts. Each contract $c \in C$ is defined by sets of triplets $\langle j,t,k \rangle$.

Variables

x_{jtk} Quantity of olives (in tons) harvested in lot $j \in J$ during day $t \in T'$ with work team $k \in K$.

f_c Measures the discrepancy as a linear function in the quantity of olives harvested for the established contracts $c \in C$.

o_{jt} Quantity of olives (in tons) in lot $j \in J$ not harvested yet at the end of day $t \in T$.

y_{jtk} Binary variable with a value of 1 if the harvesting in lot $j \in J$ is started on day $t \in T'$ with work team $k \in K$, and 0 otherwise.

h_{jtk} Binary variable with a value of 1 if lot $j \in J$ is harvested during day $t \in T$ with work team $k \in K$, and 0 otherwise.

Parameters

OC_{jt} Oil concentration in the olives in lot $j \in J$ during day $t \in T'$, as a percentage.

OL_{jt} Olives lost (in percentage) in lot $j \in J$ in day $t \in T'$ because of climatic phenomenon.

PD_{jk} Maximum harvesting productivity for the period (day) of work team $k \in K$, in the lot $j \in J$.

OS_j Quantity of olives in tons at the start of the replanning horizon in lot $j \in J$.

CP_t Capacity of the oil mill in tons to process olives on day $t \in T'$.

Q_{jk} 1, if the last lot $j \in J$ is being harvested during day $t = 0$ with work team $k \in K$, and 0 otherwise.

r_{jtk} Quantity of olives (in tons) to be harvested according to the baseline plan in lot $j \in J$ during the day $t \in T'$, with the work team $k \in K$.

Considering that, the rescheduling model (RP) can be formulated as follows:

$$\max \quad \sum_{j\in J}\sum_{t\in T}\sum_{k\in K} x_{jtk} OC_{jt} \tag{f_1}$$

$$\min \quad \sum_{c\in C} f_c \tag{f_2}$$

In this operative rescheduling model, the objective function (f_1) considers a maximization of the olive oil production. The objective function (f_2) is related to the distance (discrepancy) between the original contracts (r_{jtk}) and the new ones (x_{jtk}) with $\langle j,t,k\rangle \in c$ and $c \in C$.

subject to:

$$f_c \geq x_{jtk} - r_{jtk} \qquad \forall \langle j,t,k\rangle \in c \tag{2.3}$$

$$f_c \geq r_{jtk} - x_{jtk} \qquad \forall \langle j,t,k\rangle \in c \tag{2.4}$$

$$h_{j0k} = Q_{jk} \qquad \forall j \in J, \forall k \in K \tag{2.5}$$

$$y_{jtk} + h_{j(t-1)k} \geq h_{jtk} \qquad \forall j \in J, \forall t \in T', \forall k \in K \tag{2.6}$$

$$\sum_{t\in T}\sum_{k\in K} y_{jtk} \leq 1 \qquad \forall j \in J \tag{2.7}$$

$$\sum_{j\in J} h_{jtk} \leq 1 \qquad \forall t \in T, \forall k \in K \tag{2.8}$$

$$o_{j0} = OS_j \qquad \forall j \in J \tag{2.9}$$

$$o_{j(t-1)}(1 - OL_{jt}) - \sum_{k\in K} x_{jtk} = o_{jt} \qquad \forall j \in J, \forall t \in T' \tag{2.10}$$

$$PD_{jk}h_{jtk} \geq x_{jtk} \qquad \forall j \in J, \forall t \in T', \forall k \in K \tag{2.11}$$

$$\sum_{j\in J}\sum_{k\in K} x_{jtk} \leq CP_t \qquad \forall t \in T' \tag{2.12}$$

$$y_{jtk} \in \{0,1\} \qquad \forall j \in J, \forall t \in T', \ \forall k \in K \tag{2.13}$$

$$h_{jtk} \in \{0,1\} \qquad \forall j \in J, \forall t \in T, \ \forall k \in K \tag{2.14}$$

$$x_{jtk} \geq 0 \qquad \forall j \in J, \forall t \in T', \forall k \in K \tag{2.15}$$

$$o_{jt} \geq 0 \qquad \forall j \in J, \forall t \in T \tag{2.16}$$

In (2.3) and (2.4), relationships are established to handle the discrepancy as a linear function.In (2.5), the operational continuity for those lots being harvested the day before the rescheduling is stated. Also, those lots are forced to continue their harvest. In (2.6), it is defined that the harvest must be carried out continuously without interruptions. In (2.7), it is allowed to start harvesting once per lot within the feasible window. The resources related to capacity for one lot per day are restricted by (2.8). The remaining olives to be harvested are defined in (2.9). In contrast, in (2.10), an equation is generated to balance the available olives in each day, thereafter previous harvest, and losses due to weather events. Reviewing whether this minimum has been reached since contracts were established is important as the harvest season progresses. In (2.11), the productive capacity of the resources is respected. In (2.12), it is established that the quantities harvested must respect the mill's processing capacity. Finally, in (2.13)-(2.16), the nature of the variables is defined. The presented model will be used in the following section as a crop plan generator.

2.4 Non-myopic Rolling Horizon methodology for harvest rescheduling

To mitigate the impact of uncertainty during harvest, we illustrate our RH approach in Figure 1. This considers a parameter update step, limiting the discrepancy between harvest contracts and service suppliers. Two highlighted differences concerning the classic RH methods are proposed:

- Firstly, at the beginning of the harvest, unlike traditional RH, in our non-myopic strategy, the harvest horizon (HH) has the same length as the planning horizon (PH). PH represents the time window optimized by each rescheduling mathematical programming model, reduced in each replanning. The Control Horizon (CH) length defines the rescheduling frequency, which is constant (a week). This length is conditioned by the information certainty related to the model's key parameters, the values of which are usually updated weekly.
- Secondly, an ad-hoc optimization model (RP) is solved in each CH; this model limits the discrepancy from the baseline plan. In the first iteration, incorporating information about the whole harvest window, the baseline plan is generated, and the contracts are signed. Therefore, despite updating those parameters weekly and rescheduling, our strategy is non-myopic since medium-term information is considered during the baseline plan generation.

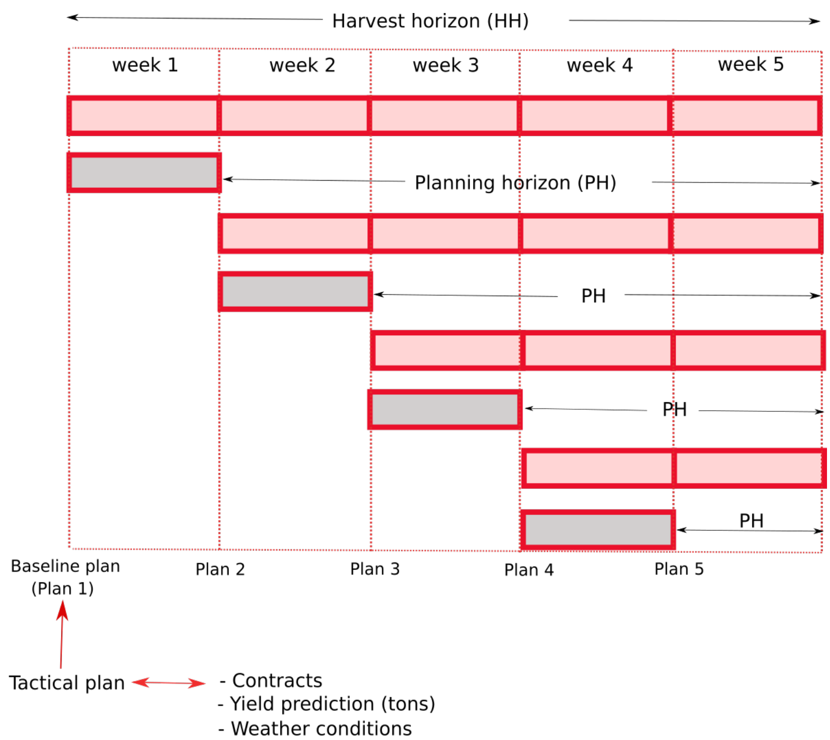

Figure 1 – Non-myopic Rolling Horizon Strategy. The pink blocks represent the planning horizon, and the grey blocks the control horizon.

A description of each step of the methodology is presented below.

step 0 **Initialization:** A standard harvest planning model (SP) is executed, generating the baseline plan (BP) and signing the contracts with service suppliers. Once the optimal solution $\mathbf{x_t^*}$ is obtained, the optimal variables values x_{jtk}^* define the parameters r_{jtk} as the BP. In this step, the HH and CH windows are defined. Due to unexpected events (e.g., frost and rain) in the agricultural harvest, it is suitable to define a CH of seven days (rescheduling weekly). Lastly, the number of iterations (It) is calculated, where It is estimated by $\frac{\mathrm{HH}}{\mathrm{CH}}$. A counter of iterations is initialized $i = 0$.

step 1 **Update parameters:** The uncertain parameters can be updated by using modern devices in smart farming environments. For example, some essential and uncertain parameters in harvest are related to the amount of fruit in lots, the processing capacity of the olive mill, weather conditions, and the productive capacity of the harvesting equipment. Couple of examples for updating some of these parameters are presented.

Let o_{ji} be a parameter that represents the amount of fruit not harvested yet (available) in lot j on day i. OS_j is a parameter that models the available fruit at the beginning of the season in lot j, which is updated in each iteration. Lastly, x_{jtk} is the decision variable that represents the fruit harvested in lot j on day t by the work team k. Let's suppose that PH begins on day $i = t'$; hence, the amount of fruit available must be updated as follows:

$$o_{jt'} = OS_j - \sum_{t \leq t'-1} \sum_{k \in K} x_{jtk}, \forall j \in J. \tag{2.17}$$

Let $Q_{jtk} \in \{0,1\}$ be a parameter that takes the value 1 if lot j was harvested on day t by the work team k, 0 otherwise, in the original plan. Let $h_{jtk} \in \{0,1\}$ be a binary decision variable that takes the value 1 if lot j is harvested on day t with the work team k, and 0 otherwise. Furthermore, $y_{jtk} \in \{0,1\}$ is a binary decision variable that takes the value 1 if the harvesting in lot j, on day t, is started by work team k, and 0 otherwise.

Constraints (2.18) and (2.19) model the harvest continuity. Specifically, constraint (2.18) fixes the initial status (i.e., each lot j) for rescheduling of each resource at day $t-1$ (1 day prior to rescheduling). Then, through inequation (2.19), the harvest proceeds with the information obtained from the executed plan. Note that τ represents the set of days within the PH window to reschedule.

$$h_{j(t-1)k} = Q_{j(t-1)k} \qquad \forall j \in J, \forall k \in K \tag{2.18}$$

$$y_{jtk} + h_{j(t-1)k} \geq h_{jtk} \qquad \forall j \in J, \forall t \in \tau, \forall k \in K \tag{2.19}$$

In the case of a resource failure (e.g., $k = 1$), we can set a downtime window ($dt \subseteq \tau$) by adding the set of constraints (2.20), limiting the activity of this resource, as follows:

$$y_{jt1} = 0 \qquad \forall j \in J, \forall t \in dt. \tag{2.20}$$

step 2 **Solve RP:** To face the rescheduling problem, an RP model is applied. Once the parameters and some variables are updated, this model is solved.

step 3 **Stopping condition:** Update the iteration counter: $i = i + 1$. If $i \geq It$, the iterative process has ended. Otherwise, go back to step 1.

We adapt the optimization model presented in (HERRERA-CÁCERES *et al.*, 2017) to apply and compare the proposed methodology. Since it is also used to define the baseline plan when replanning, this model is named SP. We aim for this procedure to reduce variability in the rescheduling process in order to avoid significant changes in the base plan that may result in greater nervousness for decision-makers.

2.5 Results analysis

In this section, we study the Non-myopic Rolling Horizon performance from different perspectives. First, in Section 2.5.1, the case study and the implementation environment are presented. After that, in Section 2.5.2, the variability of harvest plans and olive oil production are analyzed by using two unfavorable and critical scenarios in olive harvesting operations: climatic events and error estimation about the amount (tons) of fruit in lots.

2.5.1 Case study and implementation

Case study: The instance considers a planning horizon of 45 days and 63 lots of trees. The lots belong to seven olive varieties, each with its own oil accumulation curve. Several working methods are required for carrying out the harvesting operations due to the field's diversity. In this sense, some work teams are more suitable for places with difficult access, such as slopes or hillsides. A summary of relevant parameters in our experiments is presented in Table 1.

Harvest mode	Quantity available	Harvesting capacity per lot (tons)
Machine	1	180
Shaker A	1	26
Shaker B.1	1	12
Shaker B.2	1	6
Manual	7	10.7

Table 1 – Equipment used in harvesting and its capabilities

Implementation:

The mathematical model was solved by Gurobi 10 solver, coded in Python 3.6. The computer used to run the models has a processor AMD Rayzer 5 3450U with Radeon Vega Mobile Gfx 2.10 GHz and 8 GB of RAM. Optimum values were reached within 7,200 seconds.

2.5.2 Non-myopic Rolling Horizon applied to critical harvesting scenarios

We present two experiments based on undesired scenarios that may occur during harvesting to evaluate the impact of the RP approach. The scenarios are related to fruit estimation and weather conditions. In each scenario, we apply our methodology and compare it to the traditional SP, evaluating a punctual contract. To solve the RP model, we apply a traditional weighted sum (blended) approach. Then, the weighted sum objective is:

$$\min Z = \alpha f_1^* + (1-\alpha) f_2^*,$$

$0 \leq \alpha \leq 1$, and f_1^*, f_2^* are normalized objective functions. Since f_1^* is maximizing, it is defined that $f_1^* = -f_1^*$. To normalize the objectives, we use the standard 0-1 min-max scaling that is defined as follows:

$$f^* = \frac{f - f_{\text{min}}}{f_{\text{max}} - f_{\text{min}}},$$

where f_{min} and f_{max} are obtained from single-objective optimization models[1].

2.5.2.1 Extreme weather event (Scenario 1)

Scenario 1 is related to a weather risk during the olive harvesting activities. It means that the initial assumptions for generating the baseline plan (BP) have changed, forcing adaptation to the new weather conditions (for example, imminent risk of rain). Our approach tries to maintain the commitments with the suppliers. To represent this scenario, we bring one that was presented by (HERRERA-CÁCERES *et al.*, 2017), where it was considered a penalization (reduction) in the quantity of fruit to be harvested. The model then tries to maximize the olive oil production, harvesting at the optimal point, comparing the trade-off between loss due to weather risk and loss for harvesting before the period of the maximum output. The olives losses are manifested between days 19 and 22 of the planning horizon, losing 70% of those available each day. This loss only affects some lots with special conditions, i.e., those that are exposed to fruit loss due to their location.

[1] **Case** $\min f$**:** Let f_{min} be the optimal solution in the single-objective problem. Let f_{max} be the unbounded constraint value from an optimization model considering the other objective. **Case** $\max f$. Let f_{max} be the optimal solution in the single-objective problem. Let f_{min} be the unbounded constraint value from an optimization model considering the other objective.

This experiment assumes that the new weather conditions are gathered just before the harvest rescheduling. Under these circumstances, it is necessary to have a method to assist in the negotiation, especially in a scenario in which available fruit is lost in the field. Scenarios in which olives are lost for different reasons than climatic conditions, e.g., insect effects, poor crop management, etc., are analogous to the ones studied in this section. The decision-maker can reduce the *nervousness* of collaborators by maintaining the commitments close to the baseline plan.

Different replannings have been generated with the RP model, considering three days of analysis; days 7, 14, and 21 for the generation of harvesting plans. Each replanning obtains a Pareto Frontier with different points of interest for the decision-makers.

For this scenario, the results are presented in Figure 3. It can be seen that as we replan, looking at the horizontal axis of Figure 3, the value of the objective function f_1 is decreasing when a greater day of replanning is considered. This is due to the fact that as the harvest horizon advances, more fruit has been harvested, and less is left to be harvested. On the other hand, it can be seen that the maximum values of f_2, in the vertical axis, are decreasing in value. This is due to the fact that in the first days, there is more flexibility to generate plans that are very similar to the baseline plan (BP).

To verify the deployment of the harvest plans, as they change as the prioritization of one of the two objective functions changes, Table 2 is presented. It shows the aggregate harvest quantities over the entire planning horizon for each work team. Looking at Table 2, we can identify that both plans, a and b, harvest lower quantities compared to the BP. This is due to the fact that there was an adverse effect that meant fruit was lost from the field; with this, the initial conditions have changed. The differences between plans a and b are explained by the fact that plan a, in the punctual manner, seeks to be more similar to the baseline plan (prioritizing f_2), while plan b seeks to maximize the amount of oil to be obtained.

	Day 7			Day 14			Day 21		
Harvest Mode	BP	*a*	*b*	BP	*a*	*b*	BP	*a*	*b*
Machine	3,124.4	2,906.4	3,084.6	2,595.9	2,686.4	2,732.5	1,500.0	1,627.9	1,719.1
Shaker A	462.3	476.1	452.4	462.3	428.9	438.0	304.4	286.8	308.5
Shaker B.1	289.6	256.5	256.5	232.6	207.9	207.9	148.6	124.3	149.6
Shaker B.2	69.0	120.8	120.8	69.0	94.6	94.5	41.8	52.6	55.0
Manual 1	171.8	174.2	174.2	171.8	168.4	168.3	103.9	93.6	93.6
Manual 2	247.4	233.6	180.7	202.7	219.2	174.2	134.3	146.4	137.4
Manual 3	162.8	216.2	216.2	162.8	196.5	196.5	110.2	122.0	122.6
Manual 4	190.6	173.9	207.3	190.6	169.9	179.0	126.4	95.7	105.5
Manual 5	163.3	200.2	227.1	163.3	190.8	190.8	92.9	123.6	124.2
Manual 6	167.7	186.9	186.9	167.7	172.6	182.4	97.7	97.7	97.7
Manual 7	202.8	185.4	185.4	175.9	169.5	169.3	101.0	94.6	101.2
Total	5,251.6	5,130.2	5,292.1	4,594.5	4,704.7	4,733.4	2,761.2	2,865.2	3,014.4

Table 2 – Scenario 1. Harvest quantities for each resource for the different replanning days. BP is the baseline plan, a and b are the lower and upper endpoints of the Pareto Frontier presented in Figure 3.

Lots	WT	Day_21	Day_22	Day_23	Day_24	Day_25	Day_26	Day_27	Day_28	Day_29	Day_30	Day_31	Day_32	Day_33	Day_34	Day_35	Day_36	Day_37
1	1														166.16			
3	7	10.70	10.70	10.70	10.70	4.78	10.70	10.70										
4	2											26.00	26.00	7.18				
5	1											71.31						
6	1										133.70							
7	1						180.00	136.79										
8	5						10.70	6.04										
10	1				158.04													
11	3								12.00	12.00	12.00	12.00	12.00	6.43				
12	8								10.70	10.70	10.70	9.68						
13	2														26.00	26.00	8.50	
14	6													10.70	10.70	10.70	10.70	10.12
15	2	26.00	26.00	26.00														
18	8	10.70	10.70	10.70	10.70		10.70	10.70										
19	10											10.70	4.15					
20	11											2.43						
21	4											3.64						
23	10						10.70	5.64										
26	6											9.00						
28	4						6.00	4.46										
29	1												73.45					
30	7								10.70	10.70	10.70	10.70	10.70	9.82				
33	5	10.70	10.70	10.70	10.70	10.70												
35	2						26.00	10.12										
37	9	10.70	10.70	10.70	10.70	0.63	10.70	10.70										
38	4	6.00	6.00	6.00	6.00	6.00												
39	1					140.63												
42	2				26.00	9.83												
43	4								6.00	6.00	2.35							
44	1								91.75									
45	6								10.70	10.70	0.57							
47	11						10.70	6.69										
48	1									145.24								
49	1			173.82														
50	6	10.70	10.70	10.70	10.70	8.58	10.70	10.70										
53	11	10.70	10.70	10.70	10.70	10.70												
54	10	10.70	10.70	10.70	10.70	10.70												
55	1															82.62		
56	5								10.70	10.70	10.70	1.78						
57	9								10.70	10.70	10.70	10.70	10.70	10.70	4.81			
58	10								10.70	10.70	2.07							
59	11								10.70	10.70	10.40							
60	2								26.00	26.00	22.86							
61	1	76.05	180.00															
63	3	12.00	12.00	12.00	12.00		12.00	9.42										

Figure 2 – Harvest planning obtained from day 21 to the end of the horizon (BP). The WT column indicates the working team with which the olive harvest is to be carried out. Each work team is assigned a color. The cells indicate the quantity harvested in each lot daily and with the corresponding work team.

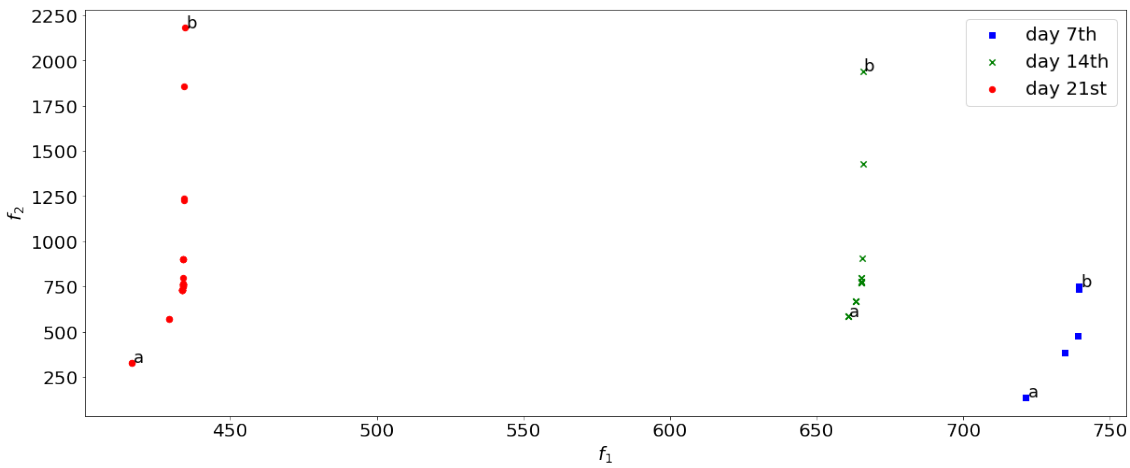

Figure 3 – Pareto Frontier, Scenario 1 with punctual type contract.

A more detailed look at what the harvest plans look like is shown in Figure 2. The WT column indicates the working team with which the olive harvest is to be carried out. Each work team is assigned a color. The cells indicate the quantity harvested in each lot daily and with the corresponding work team. It shows a part of the baseline plan from day 21 to the end of the harvest season. We can verify that the harvest is carried out continuously in a lot as long as there is availability in the mill. This plan can be compared with the plans shown in Figure 4 and 5. Regarding the plan shown in Figure 4, we can understand that it is a plan that seeks to be as similar as possible to the baseline plan; therefore, it can be seen that the allocation of lots and work teams is the same between the new plan Figure 4 and the baseline plan Figure 2. However, a rigid allocation in view of an adverse scenario can lead to inefficiency in the use of resources since the harvesting quantities are no longer the same as in the baseline plan. For this, the plan presented in Figure 5 presents a different allocation of lots, with seven changes of resources and lots with respect to the baseline plan, but with higher amounts of olive harvesting.

2.5.2.2 *Underestimated harvest yield (Scenario 2)*

Since fruit estimation is a well-known challenge in agriculture (GÓMEZ-LAGOS *et al.*, 2023), Scenario 2 is presented as an underestimated fruit forecast scenario. The experiment considers a higher amount (20%) of olives in lots when rescheduling is generated. This scenario has the opposite effect to the one presented in the previous section. In this case, there is a greater amount of fruit available in the field. While it may be a beneficial scenario in terms of higher productivity, resources committed under the baseline plan may already be committed to delivering services in other fields in parallel.

An expected effect of this event is related to the fact that if we try to be as close as possible to the baseline plan, that is, to look for small discrepancy values (low values for f_2), we will be losing olive oil production (low values of f_1). This is explained by the fact that the baseline plan is generated with less fruit.

Lots	WT	Day_21	Day_22	Day_23	Day_24	Day_25	Day_26	Day_27	Day_28	Day_29	Day_30	Day_31	Day_32	Day_33	Day_34	Day_35	Day_36	Day_37
1	1														60.54			
3	7	10.70	10.70	10.70	10.70	4.78	10.70	0.42										
4	2											26.00	1.49					
5	1											71.31						
6	1										133.70							
7	1						180.00	136.79										
8	5						10.70	6.04										
10	1				158.04													
11	3								12.00	12.00	12.00	12.00	12.00	6.43				
12	8								10.70	10.70	10.70	9.68						
13	2														26.00	26.00	8.50	
14	6													10.70	10.70	10.70	10.70	10.12
15	2	26.00		26.00														
18	8	10.70	10.70	10.70	10.70		10.70	0.42										
19	10											10.70	4.15					
20	11											2.43						
21	4											3.64						
23	10						10.70	5.64										
26	6											9.00						
28	4						6.00	4.46										
29	1												73.45					
30	7								10.70	10.70	10.70	10.70	10.70	9.82				
33	5	10.70	10.70	10.70	10.70	0.21												
35	2						26.00	10.12										
37	9	10.70	10.70	10.70	10.70	0.63	10.70	0.42										
38	4	6.00	6.00	6.00	6.00	0.12												
39	1					140.63												
42	2				26.00	9.83												
43	4								6.00	6.00	2.35							
44	1								91.75									
45	6								10.70	10.70	0.57							
47	11						10.70	6.69										
48	1									145.24								
49	1			173.82														
50	6	10.70	10.70	10.70	10.70	8.58	10.70	0.42										
53	11	10.70	10.70	10.70	10.70	0.21												
54	10	10.70	10.70	10.70	10.70	0.21												
55	1															82.62		
56	5								10.70	10.70	10.70	1.78						
57	9								10.70	10.70	10.70	10.70	10.70	10.70	4.81			
58	10								10.70	10.70	2.07							
59	11								10.70	10.70	10.40							
60	2								26.00	26.00	22.86							
61	1		180.00															
63	3	12.00	12.00	12.00	12.00		9.87											

Figure 4 – Scenario 1. Harvesting plan for point *a* in Figure. 3

Lots	WT	Day_21	Day_22	Day_23	Day_24	Day_25	Day_26	Day_27	Day_28	Day_29	Day_30	Day_31	Day_32	Day_33	Day_34	Day_35	Day_36
1	1	5.38	180.00														
3	7	10.70	10.70	10.70	10.70	5.20	10.70										
4	2					10.47	26.00	26.00									
5	1											71.31					
6	1										133.70						
7	1						180.00	136.79									
8	5						10.70	6.04									
10	1				158.04												
11	3								12.00	12.00	12.00	12.00	12.00	6.43			
12	8								10.70	10.70	10.70	9.68					
13	2														26.00	26.00	8.50
14	1															52.91	
15	2	26.00	26.00														
18	8	10.70	10.70	10.70		0.10	10.70	10.70									
19	10											10.70	4.15				
20	4												2.40				
21	4											3.64					
23	10						10.70	5.64									
26	11											9.00					
28	4						6.00	4.46									
29	6							10.70	10.70	10.70	10.70	10.70	10.70	10.70	0.02		
30	7							10.42	10.70	10.70	10.70	10.70	10.70				
33	5	10.70	10.70	10.70	10.70	0.21											
35	2			26.00	11.20												
37	9	10.70	10.70	10.70	10.70	1.06	10.70										
38	4	6.00	6.00	6.00	6.00	0.12											
39	1					140.63											
42	3					11.21	12.00	12.00									
43	4								6.00	6.00	2.35						
44	1									90.84							
45	2											21.44					
47	11						10.70	6.69									
48	1												140.96				
49	1			173.82													
50	6	10.70	10.70	10.70	10.70	9.01	10.70										
53	11	10.70	10.70	10.70	10.70	0.21											
54	10	10.70	10.70	10.70	10.70	0.21											
55	1														83.45		
56	5								10.70	10.70	10.70	1.78					
57	9							10.70	10.70	10.70	10.70	10.70	10.70	5.48			
58	10								10.70	10.70	2.07						
59	11								10.70	10.70	10.40						
60	2								26.00	26.00	22.86						
61	1								171.26								
63	8	12.00	12.00	12.00	10.07												

Figure 5 – Scenario 1. Harvesting plan for point *b* in Figure 3.

	Day 7			Day 14			Day 21		
Harvest Mode	BP	*a*	*b*	BP	*a*	*b*	BP	*a*	*b*
Machine	3,124.4	3,012.0	3,530.8	2,595.9	2,672.6	3,303.6	1,500.0	1,769.5	1,972.5
Shaker A	462.3	507.8	610.4	462.3	460.6	498.8	304.4	328.9	372.3
Shaker B.1	289.6	256.5	307.3	232.6	215.1	241.7	148.6	135.5	153.2
Shaker B.2	69.0	120.8	134.8	69.0	100.5	106.9	41.8	57.3	62.0
Manual 1	171.8	174.2	233.2	171.8	174.2	224.5	103.9	102.1	129.6
Manual 2	247.4	233.6	252.0	202.7	219.2	241.0	134.3	156.7	175.0
Manual 3	162.8	216.2	259.2	162.8	202.9	218.4	110.2	132.3	145.6
Manual 4	190.6	173.9	236.5	190.6	169.9	140.2	126.4	106.0	124.5
Manual 5	163.3	200.2	274.5	163.3	190.8	228.5	92.9	133.8	147.3
Manual 6	167.7	186.9	266.9	167.7	183.1	193.9	97.7	106.1	156.2
Manual 7	202.8	185.4	219.5	175.9	180.0	204.5	101.0	103.1	137.4
Total	5251.6	5,267.5	6,325.1	4,594.5	4,768.9	5,602.0	2,761.2	3,131.3	3,575.6

Table 3 – Scenario 2. Harvest quantities for each resource for the different replanning days. BP is the baseline plan, *a* and *b* are the lower and upper endpoints of the Pareto Frontier presented in 6. .

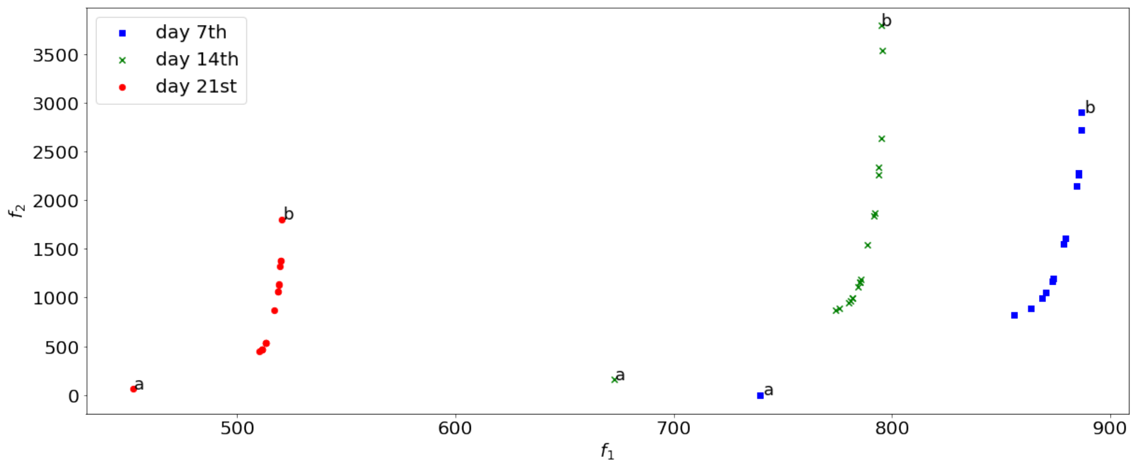

Figure 6 – Pareto Frontier, Scenario 2 with punctual type contract.

Indeed, the effect mentioned above can be seen in Figure 6. In it, we can see that for each of the replanning days (7, 14, and 21), there is an extremely lower point on the Pareto Frontier. This point represents a plan very similar to the baseline plan; however, we can observe that if we move away from resembling this baseline plan, i.e., we allow f_2 to get worse, we can understand that we gain higher olive oil production, higher values of f_1.

Lots	WT	Day_21	Day_22	Day_23	Day_24	Day_25	Day_26	Day_27	Day_28	Day_29	Day_30	Day_31	Day_32	Day_33	Day_34	Day_35	Day_36	Day_37
1	1														166.16			
3	7	10.70	10.70	10.70	10.70	4.78	10.70	10.70										
4	2											26.00	26.00	7.18				
5	1											71.31						
6	1										133.70							
7	1						180.00	136.79										
8	5						10.70	6.04										
10	1				158.04													
11	3								12.00	12.00	12.00	12.00	12.00	6.43				
12	8								10.70	10.70	10.70	9.68						
13	2														26.00	26.00	8.50	
14	6													10.70	10.70	10.70	10.70	10.12
15	2	26.00	10.40	26.00														
18	8	10.70	10.70	10.70	10.70		10.70	10.70										
19	10											10.70	4.15					
20	11											2.43						
21	4											3.64						
23	10						10.70	5.64										
26	6											9.00						
28	4						6.00	4.46										
29	1												73.45					
30	7								10.70	10.70	10.70	10.70	10.70	9.82				
33	5	10.70	10.70	10.70	10.70	8.67												
35	2						26.00	10.12										
37	9	10.70	10.70	10.70	10.70	0.63	10.70	10.70										
38	4	6.00	6.00	6.00	6.00	4.86												
39	1					140.63												
42	2				26.00	9.83												
43	4								6.00	6.00	2.35							
44	1								91.75									
45	6								10.70	10.70	0.57							
47	11						10.70	6.69										
48	1									145.24								
49	1			173.82														
50	6	10.70	10.70	10.70	10.70	8.58	10.70	10.70										
53	11	10.70	10.70	10.70	10.70	8.67												
54	10	10.70	10.70	10.70	10.70	8.67												
55	1															82.62		
56	5								10.70	10.70	10.70	1.78						
57	9								10.70	10.70	10.70	10.70	10.70	10.70	4.81			
58	10								10.70	10.70	2.07							
59	11								10.70	10.70	10.40							
60	2								26.00	26.00	22.86							
61	1	36.00	180.00															
63	3	12.00	12.00	12.00	12.00		12.00	9.10										

Figure 7 – Scenario 2. Harvesting plan for point *a* in Figure 6.

Lots	WT	Day_21	Day_22	Day_23	Day_24	Day_25	Day_26	Day_27	Day_28	Day_29	Day_30	Day_31	Day_32	Day_33	Day_34	Day_35	Day_36	Day_37	Day_38
1	1														180.00	19.20			
3	7	10.70	10.70	10.70	10.70	5.90	10.70	10.70											
4	2											26.00	26.00	18.86					
5	10								10.70	10.70	10.70	10.70	10.70	10.70	10.70	10.24			
6	1										160.44								
7	1						180.00	136.79	62.38										
8	5						10.70	9.37											
10	1									180.00									
11	3								12.00	12.00	12.00	12.00	12.00	12.00	7.29				
12	8								10.70	10.70	10.70	10.70	7.14						
13	2														26.00	26.00	20.44		
14	6													10.70	10.70	10.70	10.70	10.70	9.70
15	2	10.40	26.00																
18	8		10.70	10.70	10.70	10.66	10.70	10.70											
19	5												10.70		6.85				
20	4														2.83				
21	4											4.37							
23	10						10.70	8.88											
26	6											10.70	0.10						
28	4					0.55	6.00	6.00											
29	1												88.15						
30	7								10.70	10.70	10.70	10.70	10.70	10.70	10.70	0.65			
33	5	10.70	10.70	10.70	10.70	8.67													
35	2					17.64	26.00												
37	4	10.70	10.70	10.70	10.70	10.70	10.70						1.07						
38	3	6.00	6.00	6.00	6.00	4.86													
39	1					168.76													
42	2			17.29	26.00														
43	4								6.00	6.00	5.19								
44	1											106.86							
45	6								10.70	10.70	4.91								
47	11						10.70	10.14											
48	1													167.48					
49	1			180.00	28.30														
50	6	10.70	10.70	10.70	10.70	10.47	10.70	10.70											
53	11	10.70	10.70	10.70	10.70	8.67													
54	10	10.70	10.70	10.70	10.70	8.67													
55	1																98.16		
56	5								10.70	10.70	10.70	8.43							
57	9							10.70	10.70	10.70	10.70	10.70	10.70	10.70	8.20				
58	11												10.70	10.70	5.62				
59	11								10.70	10.70	10.70	5.93							
60	2							12.04	26.00	26.00	26.00								
61	1	36.00	180.00																
63	3	12.00	12.00	12.00	12.00		12.00	9.10											

Figure 8 – Scenario 2. Harvesting plan for point *b* in Figure 6.

To see how plans can change in terms of quantities harvested, Table 3 is presented. It shows the harvested quantities by the different work teams for BP and both points *a* and *b*. Firstly, what can be seen is that both plans *a* and *b* harvest more fruit than the BP. This is explained by the effect of the error in the estimation of fruit in the field and the subsequent generation of the baseline plan under these conditions. Analyzing the new plans, it can be seen that if we prioritize to resemble the BP (point *a*), we sacrifice fruit available in the field since we could place ourselves at point *b* with higher production. This should be left to the decision makers and analyze if the cost of respecting labor contracts is higher than the opportunity cost of taking advantage of a larger harvest. An important comparison is to see how the lots are better harvested in the plan presented in Figure 8 (point *b*) compared to the plan presented in Figure 7 (point *a*). It can be seen that one extra day is dedicated to some lots (for example, 1, 4, and 30). On the other hand, if we seek to resemble the baseline plan, Figure 2, we would be interested in taking the plan presented in Figure 7. In it, we can see that there are no changes in the allocation between lots and work teams, and the harvest lots are similar.

2.6 Conclusions

In agricultural harvesting, a Non-myopic Rolling Horizon methodology for rescheduling was presented. The approach allows coping with the dynamic agricultural environment and its undesired events by managing the variability between updated and baseline plans. Through this approach, we incorporate underlying factors of harvest operations, such as contracts with service providers and adverse scenarios.

BP can find solutions for rescheduling after critical scenarios involving uncertain parameters. Moreover, using our methodology, it was possible to empirically verify a decrease in variability. Different Pareto frontiers were generated in the different scenarios studied, and it was possible to observe the flexibility needed to cope with different field conditions. In summary, this approach can be useful for agricultural decision-makers at the operational level, allocating resources following critical harvest scenarios.

Future works could focus on the application of rescheduling to other harvesting models. Also, different contract-related functions could be studied to identify their impact on variability plans. Finally, this methodology could be improved with a scenario-based baseline plan that considers a robust approach to uncertainty and minimizes variability.

CHAPTER 3

MULTI-OBJECTIVE MODEL FOR IRRIGATION.

3.1 Introduction

The agricultural sector has suffered a significant increase in its functions and despite this, it is contrasted with a decrease in the availability of water, which is necessary for crops to be productive. The trend is that there is less and less availability of water resources and together with global warming, generate a complex scenario for food security (PEREIRA *et al.*, 2018b). Due to this, it can be understood that irrigation management is not only important for the productive factor associated with field performance, but also has a social and environmental role, recognizing that agriculture is the sector that requires more water to carry out its activities, consuming about 70% of all water used worldwide. That is why in recent times the influence of irrigation and the use of fertilizers on fruits, has taken an important relevance by researchers (ZHOU *et al.*, 2020a).

In view of the above challenges, the activity of irrigation scheduling takes on great relevance to keep crops productive while maintaining an adequate allocation of a scarce resource. With respect to the higher productivity required by the increase in the world population and climate variability, the adaptation of irrigated agriculture includes efforts such as changes in cropping patterns, design of reservoirs with greater catchment capacity and increased groundwater pumping.

In particular, the northern part of Chile is one of the most arid places in the world, recognizing that the central-northern part is being exposed to a mega-drought (MESEGUER-RUIZ *et al.*, 2020). Specifically, the region of Coquimbo (32S-29S), has important variations regarding annual rainfall and the increase or decrease of them, responds to the presence of the El Niño phenomenon, concentrating in the winter season (May to September) (MONTECINOS *et al.*, 2016). In addition to this risk of having rainfall in some years and not in others, the region is exposed to competition for water resources promoted by the demographic increase in the main cities of the region, increased mining and agricultural activity (ALIMENTACIóN, 2010). According to (AGRARIAS, 2018), there is a mismatch between water supply and demand, where surface water provides 430 million m^3 and demand is close to 530 million m^3, making it necessary to fill the shortfall with groundwater.

Due to this scenario of uncertainty, one of the main variables to be defined is the amount of water needed to carry out irrigation throughout the growing season, from fruit growth to harvest. Considering that, depending on the amount of water available in the region's reservoirs, they will influence the amount of water to be delivered through a fixed number of shares corresponding to the entities associated with the canal, which transports water from the reservoirs to the ponds arranged to store the water for the crops. The fact that the rainfall trend in the study region fluctuates and maintains a downward trend, causes part of the minimum water needed for the crops to be acquired through purchases from water supply companies. Once the minimum amount of water to irrigate the crops is established, the planning of the different irrigation sectors must be carried out, including the amount lost through evapotranspiration, seeking to meet the minimum required for the crops to be productive.

Regarding these challenges, the application of mathematical programming methods can make an important contribution. In response to this opportunity, this paper develops a multi-objective model for irrigation scheduling for a field in the Coquimbo region, Chile. Our model allows prioritizing certain sectors based on their historical productivity, in order to do the best possible in scenarios in which uncertainty exists and water availability is low. Our contribution can be summarized as follows.

(i) A bi-objective mathematical model to plan the irrigation season in an olive crop, seeking to maximize the productivity of the quarters and minimizing the costs of water extraction and expulsion.

(ii) The mathematical model is applied to an olive crop in the region of Coquimbo, Chile.

This article is organized as follows. In Section 3.2, work related to irrigation scheduling using mathematical models is presented. A multi-objective model for crop irrigation is presented in section 3.3. Section 3.4 provides information related to the study region. Experiments and in-depth analysis of the results are presented in Section 3.5. Lastly, the conclusions and future work are discussed in Section 3.6.

3.2 Background

Different authors have studied the challenge of irrigation scheduling in crops, which are exposed to water availability problems, where water is often insufficient to ensure that the plantations are irrigated with their minimum requirement. In view of this complex scenario, (KHAN; JAIN, 2015) developed a model that allows optimal irrigation scheduling, allocating water to various crops (wheat, barley, mustard and gram) seeking to reduce the water stress to which they are exposed, trying to maximize the net benefits. The solution to this problem is through the adaptation of the dynamic programming technique, the seasonal water allocation is done through combinations of canal and groundwater. In addition to the water difficulties presented by some areas of the planet, it must consider the increase in population and its relationship with food security. In the presence of these challenges, (WARD; CRAWFORD, 2016) develop an integrated empirical optimization model using positive mathematical programming (PMP), which helps to forecast cropping patterns and farm incomes under two scenarios; one maintaining the status quo without considering water storage capacity and another in which capacity is added.

For the optimal irrigation planning of a river basin in southern Iran, they generate a tool that considers water, technical, agronomic and economic aspects, where two mixed integer nonlinear programming models (MINLP) are used. The solution of these models is through a simulation-optimization approach, coupling a modular simulation model and an optimization model based on evolutionary algorithms. For optimal irrigation and fertilizer scheduling (NGUYEN *et al.*, 2017) propose simulation-optimization framework which is optimized using the ant colony algorithm (ACO). When water availability is very limited, farmers must select which crop from the available ones to irrigate, to help this decision (BOU-FAKHREDDINE *et al.*, 2016) develop a nonlinear optimization model for multiple crop planning (MCP) and water allocation, seeking to maximize the net benefit of crops. The solution of this model in a first instance is by linear relaxation to then use two metaheuristic algorithms, Simulated Annealing (SA) and Particle Swarm Optimization (PSO). Addressing the multi-crop problem, they develop two models for water and field management. The first model focuses on generating key parameters to help farmers' decision making along with an irrigation plan and the second one, allows adding rainwater to irrigation plans.

Often the water resources available in a given area are shared with the resident community and are not used exclusively for agricultural crops. In this sense, planning takes a role not only of production but also social. For this challenge (JIANG *et al.*, 2019) present regulatory model for optimal water management, seeking to maximize agricultural benefits while ensuring the fulfillment of rural demand. Coordinating resources for economy, society and ecology, (ZHAO *et al.*, 2017) establish a linear fractional programming model to maximize water productivity in the presence of water resources allocation for agriculture. A correct demand estimation allows minimizing water misuse and even, helps to maintain crop productivity (ZHOU *et al.*, 2020b). In view of this, (ZHOU *et al.*, 2020b) develops a channel scheduling model where the greatest amount of water is supplied to each channel, minimizing soil detour and salinity. Regarding the estimation of water demand (ELBAKIDZE; SCHILLER; TAYLOR, 2017) develop a function, which is generated through a mathematical model that considers the flexibility of farmers in the application of water on their crops. Water pricing policies along with the generation of efficient irrigation schemes is studied by (OHAB-YAZDI; AHMADI, 2016). For the generation of these policies with a fair price for the farmer, the authors perform a mathematical programming model with the objective of maximizing the net benefit of water allocation.

(CHEN *et al.*, 2016) address the optimal scheduling of multiple crop irrigation in coordination with the operation of reservoirs and ponds. They achieve this by using two models: one that is responsible for generating reservoir and pond operational plans and another, is responsible for optimizing the allocation of water to crops. The solution of these models is through an adaptation of the artificial bee colony algorithm. In the same sense, (RUBIO-CASTRO *et al.*, 2016) address the planning of a water management network defined as a multiperiod optimization problem and formulated as a MINLP, where the design of an irrigation network is studied considering water use, reuse and regeneration in a field constituted by several croplands. Both the coordination of plowing and irrigation tasks are addressed by (KHEYBARI; SALEHPOUR, 2015), for which two mathematical models are proposed, the first one focuses on minimizing the time required to perform the plowing tasks and the second one is in charge of defining the optimal instants of the opening of the irrigation valves.

When pursuing more than one objective related to crop production and its relationship to water use, multi-objective models are useful. (LALEHZARI *et al.*, 2016) uses this approach to maximize both (1) net benefit and (2) relative water use efficiency. A non-dominated sorting genetic algorithm (NSGAII) is employed to solve this problem. Bearing in mind the cost of water pumping, they develop a multi-objective model trying to minimize the pumping costs while maximizing the water pressure at critical moments, considering the minimum volumes requested by the crops. (GUO *et al.*, 2020) develop a framework based on the AquaCrop model to optimize the winter wheat irrigation schedule for different hydrological scenarios. The presented framework includes the use of a model that targets crop yield, water use efficiency (WUE) and economic benefit of irrigation. In the presence of the risk of water shortage (LI *et al.*, 2019), they develop a stochastic multi-objective nonlinear programming (SMONLP) model for the generation of irrigation water allocation plans, balancing the interactions between societal, economic and resource sectors. Mismanagement in water use have motivated (ZHANG *et al.*, 2019) to develop an entropy-based multi-objective interval stochastic interval programming (EMISP) approach. The benefits of this approach relate to balancing multiple production and ecological objectives while considering uncertainty conditions.

Aspects related to power supply flexibility are addressed by (GOLMOHAMADI; ASADI, 2020). In their work, they first propose a model that allows generating an irrigation plan, considering water supply and booster pumps. Along with this, a stochastic approach is generated in order to provide a response to the water demand to meet the requirements in long, medium and short term periods. In view of a water shortage scenario, they seek to maximize the benefits of irrigation schemes, where this is done by using a two-stage stochastic quadratic programming model with fuzzy intervals. Under the same water shortage scenario, under constraints such as agricultural land availability and crop water requirement, (ZHANG *et al.*, 2020) propose an entropy-based multi-objective interval stochastic programming model (EMISP). Studying the design of an irrigation system including a reservoir and the downstream irrigation network, they propose a stochastic mathematical programming model, which includes uncertain factors such as reservoir inflow, water demands, crop yields, product selling price, and production costs. (ZHANG; LI; GUO, 2017) seek to respond to the management uncertainties and complexities of irrigation systems through an interval-based fuzzy interval-based fuzzy credal constraint programming (IIFCCP) model. Seeking to keep crops in good condition, they develop a model that minimizes mismanaged water and due to changing climatic conditions, they propose a rescheduling strategy.

As a conclusion of this section, several works have been proposed to address the irrigation problem through the use of optimization models, together with the application of mathematical programming. From this, we seek to contribute to the problem of generating irrigation schedules, considering extraction costs and water supply to the olive crop, in addition to maximizing productivity.

3.3 A multi-objective model for irrigation planning

The model can be formulated as follows:

3.3.1 Sets, Variables and Parameters

Sets

T	Total period in days of the planning horizon.
J	Set of lots of olives.
K	Set of wells.
	Variables
x_{jt}	Quantity of water (in m^3) to be irrigated in the lot $j \in J$ during the period $t \in T$.
A_t	Quantity in m^3 of water stored in the dam in period $t \in T$.
w_{kt}	Water pumped from wells $k \in K$ during period $t \in T$, measured in m^3.
I_{jt}	Hours of irrigation of the $j \in J$ quarters for the day $t \in T$.
U_{jt}	Maximum water requirement in lot $j \in J$, during the period $t \in T$.
	Parameters
Q_j	Cost of water supply to lots $j \in J$.
C_k	Cost of drawing water from the well $k \in K$.
D_k	Water availability of well $k \in K$ in m^3.
P_j	Productivity of the lot $j \in J$, measured in $(\frac{Kg}{m^3})$.
R_j	Flow rate delivered by the drippers $(\frac{m^3}{hour})$ in lot $j \in J$.

ρ_j	Number of drippers per hectare of lot $j \in J$.
S_j	Area in hectare of lot $j \in J$.
$Tmax$	Maximum hours for an irrigation shift.
e_t	Percentage of water loss associated with transportation.
B_j	Hydric requirement for one season (m^3) for lot $j \in J$.

3.3.2 Mathematical modeling

$$\max \quad \sum_{j \in J} \sum_{t \in T} P_j \cdot x_{jt} \tag{f_1}$$

$$\min \quad \sum_{k \in K} \sum_{t \in T} C_k \cdot w_{kt} + \sum_{j \in J} \sum_{t \in T} Q_j \cdot x_{jt} \tag{f_2}$$

subject to:

$$U_{jt} \geq x_{jt} \qquad \forall j \in J, \forall t \in T \tag{3.1}$$

$$A_{t+1} = A_t \cdot (1 - e_t) + \sum_{k \in K} w_{kt} - \sum_{j \in J} x_{jt} \qquad \forall t \in T \tag{3.2}$$

$$\sum_{j \in J} \sum_{t \in T} x_{jt} \leq \sum_{t \in T} A_t \tag{3.3}$$

$$\sum_{t \in T} x_{jt} \geq B_j \qquad \forall j \in J \tag{3.4}$$

$$\sum_{t \in T} w_{kt} \leq D_k \qquad \forall k \in K \tag{3.5}$$

$$U_{jt} = I_{jt} \cdot R_j \cdot \rho_j \cdot S_j \qquad \forall j \in J, \forall t \in T \tag{3.6}$$

$$I_{jt} \leq Tmax \qquad \forall j \in J, \forall t \in T \tag{3.7}$$

$$A_t \geq 0 \ \forall t \in T \tag{3.8}$$

$$w_{kt} \geq 0 \ \forall k \in K, \forall t \in T \tag{3.9}$$

$$x_{jt}, U_{jt}, I_{jt} \geq 0 \ \forall j \in J, \forall t \in T \tag{3.10}$$

Regarding the objective functions, f_1 seeks to maximize crop productivity. Note that P_j represents the crop productivity associated with the amount of water added. f_2 seeks to minimize the electricity costs associated with extraction and subsequent boosting. Equation (3.1) defines that the amount of water to be irrigated must be between a minimum range required by the sector and an associated maximum. The water balance is given in equation (3.2), where the losses associated with transport and evapotranspiration are included. In (3.3) it is established that what can be irrigated can be at most what is available.For each lot, the minimum water requirement must be met (3.4). In (3.5) the amount of water that can be extracted is limited to the maximum available. Finally, in (3.6) the nature of the variables is established.

3.4 Case study: Cultivation of the Coquimbo region, Chile

The objective of this case study is to present the usefulness of the proposed model for decision makers, based on a crop located in the region of Coquimbo, Chile. The water availability of the area is given by the accumulated amount of water in the reservoirs and the extraction capacity of the respective wells. The northern zone of Chile is being affected by a prolonged drought, which has repercussions on the amount of water that can be maintained in the reservoirs. Therefore, at present, the water available comes from the wells located within the crop field. There are two wells with capacities of 1,146 and 103,437 m^3 per month. The farm has a total of 207.9 hectares of olive trees. Table 4 presents the data for the field under study for the 2022 season. The area of each quarter, the water irrigated for the growing season, the olive production obtained and the corresponding productivity are presented. The irrigation system used is drip irrigation, so it is estimated that around 10% is lost through water transport (e_t). The drippers have a capacity to irrigate 4 m^3 per hour.

Lot	Irrigation per month (m^3)	Olives (kg)	Surface (hectares)	Yield (kg/m^3)	$dippers/ha$
1	1,263.78	8,817.00	17.20	0.58	3,331
2	1,764.02	1,866.00	23.00	0.09	3,331
3	1,198.06	2,230.00	18.00	0.16	3,331
4	1,840.79	4,884.00	5.20	0.22	3,331
5	1,903.31	16,291.00	19.16	0.71	3,331
6	7,427.62	29,998.00	26.25	0.34	3,239
7	6,249.29	9,134.00	21.44	0.12	3,239
8	3,244.17	3,869.00	12.70	0.10	3,239
9	1,322.73	8,247.00	3.94	0.52	3,239
10	4,218.67	35,544.00	8.84	0.70	3,239
11	4,256.85	17,527.00	8.92	0.34	3,285
12	3,378.75	20,057.00	7.08	0.49	3,285
13	3,388.30	17,174.00	7.10	0.42	3,285
14	3,034.98	20,586.00	5.10	0.57	3,285
15	2,981.73	49,258.00	5.20	1.38	3,285
16	2,600.20	28,939.00	4.70	0.93	3,285
17	2,323.59	43,027.00	4.20	1.54	3,285
18	2,295.71	37,555.00	4.30	1.36	3,285
19	1,975.38	34,570.00	3.70	1.46	3,285
20	1,014.38	7,411.00	1.90	0.61	3,285

Table 4 – Olive field data for the season 2022.

3.5 Results

3.5.1 Implementation and code

The mathematical model was solved by Gurobi 10 solver, coded in Python 3.6. The computer used to run the models has a processor AMD Rayzer 5 3450U with Radeon Vega Mobile Gfx 2.10 GHz. and 8 GB of RAM. Optimum values were reached under 3,600 seconds.

3.5.2 Lexicographic approach

Due to the origin of the case study, an approach to reduce costs and maximize the productivity of the olive orchards, this approach has been chosen. A hierarchical or lexicographic approach assigns a priority to each objective, and optimizes for the objectives in decreasing priority order. At each step, it finds the best solution for the current objective, but only from among those that would not degrade the solution quality for higher-priority objectives.

3.5.3 Planning for one month of operation

In this section, the application of the mathematical model presented above to irrigation scheduling in an olive grove crop is studied together with the data of the case study. One month of work is considered, with daily scheduling. In accordance with the lexicographic solution approach of the model, two scenarios are presented. In the first one, the aim is to do the best possible with respect to the productivity of the field; on the other hand, the second scenario seeks to minimize extraction and irrigation costs. Table 5 shows the values of the objective functions. Note that in the case of scenario 1, higher crop productivity is obtained at a higher cost. For the case of scenario 2, costs are optimized but crop productivity is sacrificed. The details of the irrigation schedules for each scenario are presented in Table 6 and 7. The main considerations that can be drawn are that depending on the scenario in which the company finds itself, it can opt for one strategy or another with the objective of doing the best possible in view of scarce resources.

	f_1	f_2
Scenario 1	124,131	5,689,035
Scenario 2	13,566	1,310,371

Table 5 – Values of the objective functions obtained according to the scenario to be optimized.

3.6 Conclusions and Future Work

In this work, a multi-objective mathematical model has been developed to plan crop irrigation, considering two objectives: maximizing productivity and minimizing extraction and

	Lot j																			
Day t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	6	18	7	20	47	197	115	71	1	109	14	49	70	16	852	743	664	656	564	27
2	33	24	30	2	15	37	176	57	4	16	61	58	79	54	852	743	664	656	564	10
3	31	31	2	7	3	122	8	37	17	79	63	3	17	7	852	277	664	656	564	17
4	25	29	2	18	23	87	147	10	1	18	87	25	40	62	852	55	664	656	564	6
5	30	7	10	16	25	146	127	24	26	112	117	6	58	40	852	62	664	656	564	4
6	34	8	25	37	4	123	110	33	15	13	107	19	60	43	852	50	664	656	564	10
7	0	25	21	51	41	48	151	49	25	70	111	37	83	56	852	51	664	656	564	11
8	15	42	1	37	1	201	105	59	13	20	81	26	93	4	852	13	664	656	564	9
9	3	36	22	19	11	170	176	48	6	22	100	20	38	38	852	32	664	656	564	5
10	16	20	26	40	30	45	79	14	28	19	8	62	22	76	852	44	664	656	564	14
11	29	23	31	0	29	144	110	46	19	75	23	93	78	37	852	8	664	656	564	25
12	35	43	22	45	28	100	10	18	26	35	39	9	75	81	852	743	664	656	564	13
13	17	27	24	31	46	36	44	69	25	103	78	48	73	79	852	743	664	656	564	19
14	12	16	8	45	48	160	134	57	27	117	98	49	19	37	852	12	664	656	564	10
15	17	6	18	9	6	35	52	36	0	70	50	55	55	21	852	71	664	656	564	13
16	16	1	8	15	28	32	41	47	10	32	47	70	62	4	852	743	664	656	564	5
17	23	44	31	0	31	200	24	49	32	55	50	89	61	19	852	37	664	656	564	18
18	2	49	10	43	32	17	144	46	9	94	7	46	30	55	852	18	664	656	564	25
19	31	40	19	22	5	144	114	6	29	45	63	34	70	17	852	743	664	656	564	20
20	18	34	22	16	40	77	170	62	32	13	30	53	87	38	852	743	664	656	564	19
21	7	10	0	1	43	191	66	68	37	120	118	71	5	59	852	743	664	656	564	15
22	25	12	6	42	27	197	88	31	3	113	64	66	18	7	852	12	664	656	564	2
23	20	42	25	39	3	23	105	58	7	109	2	31	85	46	852	16	664	656	564	23
24	15	47	19	36	37	44	108	13	26	116	2	67	10	6	852	743	664	656	564	5
25	32	33	30	8	0	66	176	79	22	91	16	1	16	58	852	74	664	656	564	13
26	28	47	15	37	8	95	72	68	22	70	94	62	79	73	852	29	664	656	564	7
27	1	11	20	6	33	19	173	18	12	83	27	60	94	18	852	58	664	656	564	27
28	3	31	11	28	52	119	104	87	16	8	111	62	95	24	852	743	664	656	564	24

Table 6 – Irrigation plan in m^3 for the different lots of olives for 28 days. Scenario 1.

	Lot j																			
Day t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	28	19	21	1	26	81	11	80	7	99	26	9	62	40	33	45	35	22	27	28
2	25	39	5	36	11	143	30	2	24	7	58	71	45	44	31	31	54	41	26	15
3	15	25	17	27	13	31	114	9	26	55	55	72	25	24	33	59	29	51	43	6
4	31	19	21	15	5	202	127	75	3	39	14	80	85	56	16	72	41	52	24	10
5	20	3	28	41	43	46	16	24	21	55	2	51	45	74	27	58	18	25	26	17
6	1	26	7	45	20	97	114	60	22	59	51	44	71	68	50	31	6	43	19	25
7	4	25	7	31	18	117	122	67	29	95	67	27	65	58	28	14	66	35	18	19
8	17	35	17	52	44	193	109	36	30	3	80	56	62	67	21	21	64	56	51	27
9	18	23	22	50	37	127	132	56	20	116	85	12	12	42	10	10	34	14	47	2
10	25	24	17	35	2	101	58	68	28	89	110	3	86	82	3	25	24	14	25	27
11	15	13	10	22	12	195	99	44	31	21	17	95	44	21	68	48	7	12	22	19
12	7	41	1	23	44	165	104	26	26	73	66	94	20	4	79	65	33	48	9	7
13	11	29	30	3	25	128	130	17	32	106	42	32	60	48	30	32	21	58	48	10
14	32	13	3	2	26	134	142	31	10	78	77	17	45	40	11	19	8	32	48	6
15	35	44	32	3	37	70	68	7	13	97	10	86	83	44	74	15	17	51	49	5
16	31	2	11	41	53	111	156	16	16	39	76	85	63	36	14	20	46	8	38	2
17	3	1	19	39	17	82	171	91	22	90	118	44	44	31	36	69	9	21	45	29
18	21	35	30	28	3	185	17	79	17	44	77	7	69	53	31	74	59	43	21	26
19	19	38	19	10	48	100	58	36	3	3	40	92	71	16	6	22	41	33	30	2
20	23	40	23	12	35	128	176	17	9	118	96	92	96	69	64	71	53	59	20	5
21	25	37	31	46	53	175	43	15	31	92	76	68	76	43	51	20	4	51	30	2
22	27	29	8	45	8	130	53	82	31	118	48	7	65	77	56	5	40	62	43	26
23	36	3	18	28	33	174	167	83	4	60	17	74	35	58	3	1	10	45	24	19
24	8	39	18	14	49	36	4	39	16	25	81	78	16	83	6	43	55	53	19	8
25	22	14	4	42	6	60	109	67	16	111	11	6	67	39	47	73	26	15	2	2
26	25	33	22	45	52	37	108	4	25	86	121	4	72	12	27	16	17	61	10	25
27	19	23	1	15	16	95	147	13	15	103	7	11	9	4	59	54	24	12	26	11
28	12	2	13	6	32	112	38	83	23	49	44	93	86	21	73	38	65	61	16	5

Table 7 – Irrigation plan in m^3 for the different lots of olives for 28 days. Scenario 2.

irrigation costs. The model has been applied to a case study in the region of Coquimbo, Chile, where the behavior of the system has been analyzed under two scenarios: one with budget flexibility and the other with economic restrictions.

The results obtained show that the model is capable of generating two different irrigation schedules, depending on the scenario in which the decision-maker finds themselves. For the scenario with budget flexibility, an irrigation plan is proposed that seeks to optimize field productivity, using more water and energy to meet crop needs. For the scenario with economic constraints, an irrigation plan is proposed that minimizes costs but meets the minimum crop requirements, using less water and energy but sacrificing part of the production.

The proposed model is a useful tool for efficient water resource management in agriculture, as it allows evaluating the impact of different irrigation alternatives in terms of productivity and costs. In addition, the model is flexible and adaptable to different climatic, hydrological and agronomic conditions, which makes it applicable to other regions or crops. As future works, it is suggested to incorporate other environmental or social criteria in the multi-objective model, as well as to consider uncertainty in the input and output data.

CHAPTER 4

CONCLUTIONS

In this work, two mathematical models have been developed for crop harvesting and irrigation scheduling and rescheduling, considering different objectives and scenarios. The models have been applied to case studies in Chile, where the performance of the agricultural system under dynamic and uncertain conditions has been evaluated.

The results obtained show that the models are capable of generating efficient and flexible solutions for the management of resources and operations in the agricultural sector, taking into account economic, productive and contractual aspects. The models allow the decision-maker to choose the best alternative according to his preferences and constraints, as well as to adapt to changes and undesired events that may occur during the process.

The proposed models are useful tools for decision making at the operational level in the agricultural field, as they facilitate the optimization and control of harvesting and irrigation activities. In addition, the models are flexible and adaptable to different contexts and crops, which makes them applicable to other regions or problems.

The importance of mathematical models in agricultural management is understood and their usefulness lies in the fact that they provide basic criteria and tools to better manage and interpret agricultural activity, meet the demands of new technologies to produce in highly competitive global markets while safeguarding natural resources, and make medium- and long-term decisions under similar experimental conditions. Mathematical models also make it possible to represent each stage of the agricultural production process and seek to optimize both the maximization of production volumes and the minimization of costs associated with cultivation and harvesting. Mathematical models also help to evaluate the impact of different climatic, hydrological and agronomic variables on agricultural yields and to reduce the uncertainty and risk involved in agricultural production.

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