**OPTIMIZATION MODEL USING NONLINEAR PROGRAMMING AND ARTIFICIAL INTELLIGENCE TECHNIQUES FOR QUINOA PRODUCTION IN THE PUNO REGION**

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***Abstract*−− The present study presents the formulation of a new optimization model for quinoa production in the Puno region, one of the poorest areas of Peru, where climatic conditions characterized by extreme cold make it difficult to harvest many crops. Quinoa requires little water and has high nutritional value, making it a highly valued product in local and foreign markets and a valuable source of wealth generation for the inhabitants of the Altiplano. For the development of this model, nonlinear programming has been chosen due to its characteristics, such as constraints. The most relevant constraint is the interaction with the market to determine the selling price, which allows for a sensitivity analysis that considers both supply and demand. The contribution of the new optimization model lies in its ability to establish optimal conditions that maximize utility and minimize production costs and to determine the break-even point, which allows the producer to foresee situations in which losses are not incurred. The results obtained from the optimization model are consistent with historical values of quinoa commercialization. The most widely used artificial intelligence technique for optimization, genetic algorithms, has been applied in the present study, concluding that the sexual selection operator shows better results for nonlinear problems with constraints.**

***Keywords−−* Quinoa production, optimization, production systems, non-linear programming, genetic algorithms**

##### I. INTRODUCTION

Quinoa, considered a superfood due to its exceptional nutritional profile, has gained worldwide recognition for its health benefits and culinary versatility [1]. Puno, located in the Peruvian highlands, is one of the poorest regions of the country. Poverty in this area is influenced by its mountainous geography and extreme climate, which limit agricultural and economic opportunities. In addition, poor infrastructure and limited access to basic public services have perpetuated conditions of vulnerability. Puno's economy relies mainly on subsistence agriculture and livestock, activities that are regularly affected by frosts and droughts. Migration to other regions in search of better opportunities is common, affecting social cohesion and local development [2]. Quinoa is a remarkably resilient crop to adverse weather conditions, including extreme cold and limited water availability. Native to the Andean region, the plant has developed adaptations that allow it to thrive at high altitudes where other species cannot survive. Its ability to require little water makes quinoa a viable option for arid and semi-arid areas. Additionally, its resistance to cold allows it to withstand frosts, ensuring harvests even in severe climates [3]. Due to its high nutritional value and resilience to adverse weather conditions in the Puno region, quinoa is an invaluable source of wealth and food security for local communities. However, the efficient production and commercialization of this crop face challenges stemming from the complexity inherent in distribution systems and demand variability [4].

Therefore, the Peruvian government, through the National Institute of Agricultural Innovation (INIA) based in Puno, has allocated resources for the genetic improvement of quinoa, with the most notable result being the creation of a new quinoa variety known as INIA 446-ATIPAQ. This variety stands out for its high yield capacity and is expected to increase the economic profitability of small and medium producers by more than 60%. This new variety offers a yield of 3 to 4 tons per hectare. Additionally, it has tolerance to common pests and diseases, such as downy mildew, which will benefit the farmers' economy.



Figure 1. Quinoa INIA 446-ATIPAQ. Courtesy of INIA Puno headquarters

##### II. METHODS

### Location of the study

The study was conducted in the Puno region, known for its altitude and adverse climate, which presents significant challenges for agriculture. The operational center was established at the National University of Altiplano Puno, with approximate geographic coordinates of 15.8402° S latitude and 70.0219° W longitude. This strategic location allowed for direct access to academic resources and local expertise in agricultural production, particularly in research and development of quinoa, a crop of great economic and cultural relevance in the region. Additionally, the proximity to the farmland of the National Institute of Agricultural Innovation (INIA) located in the Salcedo district and to local farmers facilitated the collection of onsite data and the practical implementation of the proposed strategies, thereby enriching the findings of the study and ensuring that the developed solutions were consistent with the real production conditions in Puno.

**Formulation of the optimization model**

The first step in formulating a nonlinear optimization model is to clearly define the objective of the problem and the context in which it applies. Nonlinear optimization is generally applicable to complex problems where the relationship between variables is not linear, distinguishing it from traditional linear methods [22]. In this case, we need to maximize profits, minimize costs, and

find the breakeven point that indicates when we have neither losses nor profits.

Decision variables are those elements that are controlled to achieve an optimal objective. In a nonlinear optimization model, these may include quantities of resources, levels of production, and prices, where changes in these variables nonlinearly influence the objective function and constraints [23].

The objective function is the mathematical expression that must be maximized or minimized. In many industrial and economic cases, the function is nonlinear due to cost or revenue characteristics that do not increase consistently. Common forms include quadratic or exponential functions that represent returns or costs of scale [24]. The constraints define the limits within which the optimal solution must be found. In nonlinear programming, constraints can also be nonlinear and are linked to resource capacities, technological limitations, or market conditions [22].

Once the model is solved based on a system of equations, the variables and constants must satisfy the Kuhn-Tucker conditions, meaning they must be greater than or equal to zero. After obtaining a numerical solution, the model must be validated using real data to assess its effectiveness. This process ensures that the model is not only mathematically correct but also useful and applicable in real contexts, which is essential for practical decision-making [22].

##### III. RESULTS

According to information from INIA, we have:

**Maximization of utility**

By integrating these elements into the optimization model, we seek not only to maximize profitability but also to promote responsible agricultural practices and contribute to the well-being of local farmers. In this way, the research aligns with sustainable development goals, promoting a holistic approach to quinoa marketing in the Puno Region [25].

This model is defined as the difference between the sales made and production costs. To simplify, numerical values have been scaled down by dividing them by one thousand. The goal is to find the global maximum in a formal nonlinear programming model so that the producer can make more informed decisions to maximize profits and minimize losses [26].

Utility = Sales – Production Costs …(1)

The production costs of quinoa mainly consist of labor and inputs. According to the information provided by the INIA Puno branch, the production costs amount to S/. 13,242.29.

Costs = 13242.00 \* Hectares …(2)

Sales are represented by production per hectare. According to the information from the INIA Puno branch, it is 1,200.00 kg per hectare multiplied by the number of hectares produced and the market selling price. The goal of this innovative model is to determine at what selling price maximum utility is achieved.

Sales = 1200 \* Hectares \* Selling Price (3)

Therefore:

*:* cultivated land in hectares

*:* selling price

*:* demand (current market)

*:* competition production

Then, the utility maximization function is:

(4)

Subject to the constraints:

; demand

Let PP be the selling price = S/. 17.00 (provided by INIA Puno branch). Solving, we have:

; selling price

; land in hectares

; Relationship of the competition's production with total demand.

With this, we propose the Lagrangian, which must satisfy the Kuhn-Tucker conditions:

(4.1)

(4.2)

(4.3)

(4.4)

(4.5)

(4.6)

(4.7)

(4.8)

Replacing (4.7) en (4.2)

In the ecuation (4.5)

Replacing (4.3)

Replacing (4.4)

Replacing (4.6)

Replacing (4.1)

Replacing

The maximum utility of S/. 1,638,000.00 occurs when the selling price is S/. 22.10 (Soles).

**Breakevent point**

In simple terms, it is the point where total revenues equal total costs, with neither losses nor profits. This concept is especially useful for businesses when evaluating the impact of changes in costs and selling prices on the units required to achieve profitability. Knowing this point allows managers to determine how many units must be sold to cover costs and provides a basis for making strategic decisions about pricing, costs, and market expansion, thus contributing to the long-term sustainability and profitability of the company [27].

For the breakeven point, we consider the following equation:

(5)

; demand

; agricultural land

(5.1)

(5.2)

(5.3)

(5.4)

(5.5)

(5.6)

Replacing (5.4)

Replacing (2.1)

Replacing (2)

Replacing in Z

This indicates that the breakeven point occurs when the minimum selling price is S/. 11.00 (Soles). That is to say, we must sell at least at S/. 11.00 to avoid losses.

**Cost minimization**

Cost minimization is a key objective for any organization seeking to improve its operational efficiency and maximize profitability. This process involves identifying and reducing unnecessary expenses while optimizing the use of resources without compromising the quality of the product or service. Tools such as cost analysis, linear programming, and the implementation of digital technologies provide effective approaches to achieve these objectives [28]. Many authors mention that the focus of optimization should be on cost minimization, as the market is tyrannical and it is difficult to influence the selling price. To formulate the minimization model, it is necessary to analyze the cost structure provided by INIA in Table 1, which also shows the variable assigned for the cost minimization model.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **COST DESCRIPTION** | **Variable** | **Unit of measure** | **Quantity** | **Unit cost (S/.)** | **Total Cost** |
| A. Direct Costs |  |  |  |  | 11,968.41 |
| 1. Production costs |  |  |  |  | 11,398.49 |
| 1.1 Activities with direct labor |  |  |  |  | 6,522.50 |
| Soil analysis | X1 |  |  |  | 22.50 |
| Soil sample collection |  | workday | 0.50 | 45.00 | 22.50 |
| LAND PREPARATION | X1 |  |  |  |  |
| Extraction and collection of stones |  | workday | 2.00 | 45.00 | 90.00 |
| Distribution of manure in the soil |  | workday | 4.00 | 45.00 | 160.00 |
| Tractor operator assistant |  | workday | 2.50 | 45.00 | 112.50 |
| **PLANTING, FERTILIZATION, AND FERTILIZATION** | X1 |  |  |  |  |
| Herbicide application |  | workday | 2.00 | 45.00 | 90.00 |
| Mixing of fertilizers |  | workday | 0.50 | 45.00 | 22.50 |
| Seed disinfection |  | workday | 0.50 | 45.00 | 22.50 |
| Bed preparation of furrows |  | workday | 1.00 | 45.00 | 45.00 |
| Manual planting |  | workday | 3.00 | 45.00 | 135.00 |
| Application of fertilizers |  | workday | 1.50 | 45.00 | 67.50 |
| Manual covering |  | workday | 1.00 | 45.00 | 45.00 |
| **CULTURAL WORK** | X1 |  |  |  |  |
| Ornithological control (emergence) |  | workday | 4.00 | 45.00 | 180.00 |
| 1st Weeding |  | workday | 12.00 | 45.00 | 540.00 |
| 1st Rouging and thinning |  | workday | 2.00 | 45.00 | 90.00 |
| Opening of drains |  | workday | 1.00 | 45.00 | 45.00 |
| Complementary fertilization |  | workday | 1.00 | 45.00 | 45.00 |
| Hilling |  | workday | 10.00 | 45.00 | 450.00 |
| Machinery operator |  | workday | 1.00 | 45.00 | 45.00 |
| 1st phytosanitary treatment |  | workday | 2.00 | 45.00 | 90.00 |
| Ornithological control |  | workday | 20.00 | 45.00 | 900.00 |
| 2nd weeding |  | workday | 6.00 | 45.00 | 270.00 |
| Frost control |  | workday | 1.00 | 45.00 | 45.00 |
| 2nd phytosanitary treatment |  | workday | 2.00 | 45.00 | 90.00 |
| Hail control |  | workday | 1.00 | 45.00 | 45.00 |
| Selection of kernels |  | workday | 2.00 | 45.00 | 90.00 |
| **HARVEST** | X1 |  |  |  |  |
| Collection of selected panicles |  | workday | 2.00 | 45.00 | 90.00 |
| 2nd sorting |  | workday | 3.00 | 45.00 | 135.00 |
| Installation of drying racks |  | workday | 1.00 | 45.00 | 45.00 |
| Threshing assistants |  | workday | 2.00 | 45.00 | 90.00 |
| Transport of grain to storage |  | workday | 1.00 | 45.00 | 45.00 |
| Secado de grano y desbrozado |  | workday | 2.00 | 45.00 | 90.00 |
| **Bagging and sewing** |  | workday | 2.00 | 45.00 | 90.00 |
| **Stacking of bags** |  | workday | 0.50 | 45.00 | 22.50 |
| **Loading and unloading in Tahuaco and Salcedo** |  | workday | 2.00 | 45.00 | 90.00 |
| **POST-HARVEST** | X1 |  |  |  |  |
| **Selection operator** |  | workday | 2.00 | 45.00 | 90.00 |
| **Bagging and weighing at the processing facility** |  | workday | 1.00 | 45.00 | 45.00 |
| **Loading and unloading in storage** |  | workday | 1.00 | 45.00 | 45.00 |
| **Bagging and weighing in storage** |  | workday | 1.00 | 45.00 | 45.00 |
| **Labeling and sewing** |  | workday | 1.00 | 45.00 | 45.00 |
| **Storage** |  | workday | 1.00 | 45.00 | 45.00 |
| **Weighing and loading** |  | workday | 1.50 | 45.00 | 67.50 |
| **Weighing, labeling, sewing, and stacking** |  | workday | 1.00 | 45.00 | 45.00 |
| **TECHNICAL ASSISTANCE** | X3 |  |  |  |  |
| **RESIDENT Technical Assistance** |  | time/  person | 0.10 | 2,100.00 | 210.00 |
| **AGRICULTURAL TECHNICIAN Assistance** |  | time/  person | 0.225 | 1,800.00 | 405.00 |
| **FIELD ASSISTANT (Participation)** |  | time/  person | 1.00 | 1,025.00 | 1,025.00 |
| **1.2 MACHINERY AND EQUIPMENT LAND PREPARATION** | X4 |  |  |  |  |
| **Plowing (Agricultural tractor with plow)** |  |  |  |  |  |
| **Harrowing (Agricultural tractor with harrow)** |  | Hrs/maq | 4.00 | 70.00 | 280.00 |
| **Leveling (Agricultural tractor with grader)** |  | Hrs/maq | 2.50 | 70.00 | 175.00 |
| **Cross harrow (Agricultural tractor with cross harrow)** |  | Hrs/maq | 1.50 | 70.00 | 105.00 |
| **Ridging (Agricultural tractor with ridger)** |  | Hrs/maq | 2.50 | 70.00 | 175.00 |
| **CULTURAL WORK** |  | Hrs/maq | 2.00 | 70.00 | 140.00 |
| **Raised furrow or hilling (Agricultural tractor with plow)** |  |  |  |  |  |
| **HARVEST AND POST-HARVEST** |  | Hrs/maq | 3.00 | 70.00 | 210.00 |
| **Mowing and Threshing (Selector)** |  |  |  |  | 350.00 |
| **1.3 INPUTS FEED** |  | Hrs/maq | 5.00 | 70.00 | 350.00 |
| **CERTIFIED Seed** |  |  |  |  |  |
| **FERTILIZERS** | X5 |  |  |  |  |
| **Diammonium Phosphate** |  | Kg | 10.00 | 20.00 | 200.00 |
| **Potassium Chloride** | X5 |  |  |  |  |
| **Urea** |  | Kg | 115.00 | 5.53 | 635.95 |
| **1.2 MACHINERY AND EQUIPMENT LAND PREPARATION** |  | Kg | 96.00 | 5.49 | 527.04 |
| **Plowing (Agricultural tractor with plow)** |  | Kg | 90.00 | 4.80 | 432.00 |
| AGROCHEMICALS |  |  |  |  |  |
| Metalaxyl + Mancozeb+C7  Fungicide (Hieloxil, Hieloxil Mix 72, RIDOMIL GOLD 68 WP) | X6 | Kg | 1.50 | 45.00 | 67.50 |
| Lambda cyhalothrin  Insecticide (Aikido, Lamdex, Karate Zeon, Real) | X7 | Liter | 1.00 | 150.00 | 150.00 |
| Mancozeb 100%  Fungicide (Manzate, Mancozeb, Aikido, Lamdex) | X7 | Liter | 2.00 | 45.00 | 90.00 |
| Alcohol Polivinílico  Agricultural adhesive (Adherente, Hampifol, Taxi Wett, Asperwet) | X7 | Liter | 0.25 | 20.00 | 5.00 |
| **1.4 OTHERS FUEL** |  |  |  |  |  |
| **Gasoline** | X8 |  |  |  |  |
| **Diesel** |  | gallon | 10.00 | 23.00 | 230.00 |
| **PROCESSING AND CERTIFICATION** |  | gallon | 20.00 | 21.00 | 420.00 |
| **Certification service** | X9 |  |  |  |  |
| **Materials for certification cards** |  | Service | 1.00 | 470.00 | 470.00 |
| **OTHERS** |  | Service | 1.00 | 180.00 | 180.00 |
| **Starter rockets** (Technology adopted by INIA for hail prevention) | X10 |  |  |  |  |
| **Phosphorus** |  | Dozen | 1.00 | 45.00 | 45.00 |
| **Sulfur** |  | Unit | 1.00 | 1.00 | 1.00 |
| **Plastic for covering** |  | Kilo | 0.50 | 20.00 | 10.00 |
| **Drying racks** |  | meters | 50.00 | 4.00 | 200.00 |
| **Covers for manure distribution** |  | Unit | 5.00 | 10.00 | 50.00 |
| **Sticks** |  | Unit | 4.00 | 5.00 | 20.00 |
| **Raffia** |  | Unit | 3.00 | 15.00 | 45.00 |
| **Bags** |  | Unit | 2.00 | 2.00 | 4.00 |
| **Needles** |  | Unit | 50.00 | 2.00 | 100.00 |
| **Bags with logo** |  | Unit | 1.00 | 1.00 | 1.00 |
| **2. GENERAL EXPENSES** |  | Unit | 40.00 | 2.50 | 100.00 |
| **Contingencies (5% of production costs)** | X11 |  |  |  |  |
| **B. INDIRECT COSTS** |  | Other | 0.05 | 11,940 | 597.05 |
| **Administrative expenses (5% of direct costs)** | X12 |  |  |  |  |
| **Technical assistance service from the specialist (3% of monthly salary)** |  | Other | 0.05 | 12,538 | 626.90 |
| **Depreciation (1% of machinery and equipment)** |  | Other | 0.03 | 2,100.00 | 63.00 |
| **1.4 OTHERS FUEL** |  | Other | 0.01 | 1,435.00 | 14.35 |
| TOTAL COSTS | | | | S/. 13,242.29 | |

Therefore, the proposed cost minimization model is the following:

(6)

Subject to the constraints:

;;;;;;;;;;.

According to interviews with experts, it is very difficult to do without each of the factors for quinoa production, so we have opted to reduce the cost of daily wages, which is also consistent with the customs of Ayni. Therefore, upon solving, we find that the minimum cost of the daily wage could be reduced to S/. 41.2

**Genetic algorithms**

Genetic algorithms are search techniques that have their origin in biology through the process of natural selection [29]. These algorithms initially consist of a population of solutions, also known as individuals or chromosomes, that evolve over time. They select fit individuals for reproduction according to a fitness function that evaluates their performance. Subsequently, the individuals are combined to produce new

offspring, usually through a process called crossover, in which parents exchange their genetic material. Some small random mutations are also introduced in some offspring to maintain genetic diversity. The new individuals may replace the entire previous population or only a part of it. The specific way in which individuals are replaced is described by strategies contained within the algorithm [30].

Table 1. Recommended parameters for genetic algorithms

|  |  |
| --- | --- |
| Parameter | Value |
| Population size | 20,100,200,400 |
| Crossover probability | 0.65 |
| Mutation probability | 0.08 |

The fitness function for maximizing production is shown in the following pseudocode:

*Function fitness(X1, X2)*

*return 1200\*X1\*X2 -13200.00\*X1*

Since this is a nonlinear programming problem with constraints, it is necessary to make comparisons to verify if the fitness value meets certain conditions, according to the following function:

*Function condition(X, Y, Z)*

*X≤100*

*X4=0.25*

*if (x<=100 && Z>=0 && Y<=34-(20.4x)/Z +17X4 && Z≤150) return true; return false;*

To determine the performance of the selection operators: Sexual Selection (SS) or Tournament Selection (ST), we implemented a program in C++. In which we executed 1000 generations. As a result, it was found that the SS operator achieves the global maximum on average in generation 45.6; and the ST operator achieves the global maximum on average in generation 91. In other parameters, such as the number of generations that achieve the global maximum, the SS operator performs better. In conclusion, the SS operator has better performance, confirming the reviewed literature.

**Neural networks**

Based on the objective function and the constraints, it has been possible to formulate a neural network model [32]. In Python, the libraries TensorFlow, NumPy, and Scikit-learn have been used. First, 1000 random samples were generated using a normal distribution function to train the machine learning model.

The structure of the defined neural network is:

model = Sequential([

Dense(64, input\_dim=4, activation='tanh',

kernel\_regularizer=tf.keras.regularizers.l2(0.01)),

Dropout(0.1),

Dense(64, activation='tanh', kernel\_regularizer= tf.keras.regularizers.l2(0.01)),

Dense(1)])

Being

Dense(64, …): It indicates that a dense layer, also known as a fully connected layer, is being created with 64 units or neurons. Each neuron in a dense layer is connected to all the neurons in the previous layer.

input\_dim=4: This sets the input with 4 distinct features. It is defined in the first layer of a model to establish the input size that the network expects.

Activation='tanh': Defines the activation function that the neurons in this layer will use. 'tanh' is the hyperbolic tangent function, which maps the input value to the range [-1, 1].

kernel\_regularizer=tf.keras.regularizers.l2(0.01) : L2 regularization adds a penalty on the loss value based on the magnitude of the weights, controlled by the constant 0.01. This prevents the weights of the network from becoming too large and reduces overfitting.

Dropout(0.1): This is a regularization technique used in neural networks to prevent overfitting during training. 0.1 means that 10% of the neurons in the previous layer will be randomly deactivated during each training step.

Dense(1): Defines a dense layer in the neural network with a single output neuron.

The following optimizer has been used:

optimizer =

tf.keras.optimizers.Adam(learning\_rate=0.0001)

tf.keras.optimizers.Adam: Adam is one of the most commonly used neural network optimizers. It combines the best of two distinct optimizers: AdaGrad, which is popular with sparse data problems, and RMSProp, a tunable approach with a learning rate.

learning\_rate=0.0001: This is an important hyperparameter for the learning rate value. This number defines how large a step your system takes in the unknown direction of the loss function. Therefore, a low value, such as 0.0001, means that your systems will take tiny steps. It is advisable to give it an increasingly smaller value than this for fine-tuning when you want to improve convergence. However, you will need to run for a long time [33].

For training, 200 epochs were used with 10 samples before the batch update.

##### Running the program for 200 epochs shows that the loss consistently decreases from 1.1653 to 0.0028, which implies that the model is learning to finely tune the training data and provides better performance compared to other activation functions like ReLU. The predicted data has also turned out to be consistent

##### V. CONCLUSIONS

The new proposed model has optimized the quinoa production process, according to information provided by INIA Puno. This model focuses on profit maximization, the breakeven point, and cost minimization. Its main novelty lies in the ability to analyze scenarios in light of market fluctuations, which facilitates the determination of the selling price. Quinoa is a native species of great importance to the region, recognized for its high nutritional value and its ability to grow in the harsh climatic conditions of Puno. With the aim of improving the productivity of farmers, INIA has developed the INIA 446-ATIPAQ quinoa variety, which is expected to increase production for farmers in Puno by more than 60% and also be resistant to diseases. Therefore, it is essential to seek formal methods that allow for a more effective analysis of the production process of this highly valued species, even in the international market.

Various optimization methods have been studied, with nonlinear programming with constraints being the most suitable, given that the main constraint is the selling price. This price must be determined based on market analysis and its fluctuations between supply and demand. The model also considers competition production and evaluates the possibility of incorporating more production into the market. According to the simulated scenarios, this model allows for the prediction of recession phenomena, that is, if the market is saturated, which could lead to a drop in selling prices and potentially result in economic losses. Regarding cost minimization, this can be achieved through the optimization of factors such as labor and its associated costs. The proposed models have been validated considering the Kuhn-Tucker conditions.

Among the artificial intelligence techniques considered, we have chosen genetic algorithms for their ability to search for optima, primarily based on the selection of individuals with the best fitness to generate optimal populations. According to the reviewed literature, sexual selection and tournament selection operators have demonstrated the best results. The tests conducted indicate that the sexual selection operator has shown the best performance. Therefore, genetic algorithms present themselves as a viable technique for obtaining optima in nonlinear programming problems with constraints. Regarding neural networks, the tanh activation function has yielded better results. The optimizer used has been Adam with a learning rate of 0.0001, showing consistently lower losses during training and predicting data that is consistent with real data

##### REFERENCES

[1] J. Hernández Rodríguez, “La quinua, una opción para la nutrición del paciente con diabetes mellitus,” *Rev. Cuba. Endocrinol.*, vol. 26, no. 3, p. 0, 2015.

[2] INEI, “Encuesta Nacional de hogares sobre condiciones de vida y pobreza,” 2020.

[3] K. S. Murphy and J. Matanguihan, *Quinoa: Improvement and sustainable production*. New York: John Wiley & Sons, 2015.

[4] A. Carimentrand, A. Baudoin, P. Lacroix, D. Bazile, and E. Chia, “Las dinámicas de comercialización de la quinua en los países andinos:¿ qué oportunidades y retos para la agricultura familiar campesina?” Centre de coopération internationale en recherche agronomique pour le …, 2014.

[5] Ministerio de Desarrollo Agrario y Riego, *Reporte Estadístico - Quinua*. Ministerio de Desarrollo Agrario y Riego, 2021.

[6] Minagri, *Costos de producción papa*. Ministerio de Agricultura y Riego, 2020.

[7] R. A. R. Flores, “Production Model for Irrigation Improvement Projects Implemented in Cusco-Peru Using System Dynamics,” in *2019 IEEE World Conference on Engineering Education (EDUNINE)*, IEEE, 2019, pp. 1–6.

[8] M. J. Silva Salinas, “Implementación de un algoritmo de aprendizaje de máquina para la optimización del sistema hardware en una FPGA,” 2023.

[9] H. A. Taha, *Investigación de operaciones*. Pearson Educación, 2004.

[10] G. Alberti *et al.*, “Reciprocidad e intercambio en los Andes peruanos,” 1974.

[11] C. B. Hanampa Quispe and S. E. Huayta Bolivar, “La transformación del Ayni en la comunidad de Carmen Alto–Challhuahuacho,” 2022.

[12] J. Zhong, X. Hu, J. Zhang, and M. Gu, “Comparison of performance between different selection strategies on simple genetic algorithms,” in *International conference on computational intelligence for modelling, control and automation and international conference on intelligent agents, web technologies and internet commerce (CIMCA-IAWTIC’06)*, IEEE, 2005, pp. 1115–1121.

[13] O. Al Jadaan, L. Rajamani, and C. R. Rao, “Improved Selection Operator for GA.,” *J. Theor. Appl. Inf. Technol.*, vol. 4, no. 4, 2008.

[14] F. Villada, N. Muñoz, and E. García, “Aplicación de las Redes Neuronales al Pronóstico de Precios en el Mercado de Valores,” *Inf. tecnológica*, vol. 23, no. 4, pp. 11–20, 2012.

[15] K. S. Goh, A. Lim, and B. Rodrigues, “Sexual selection for genetic algorithms,” *Artif. Intell. Rev.*, vol. 19, pp. 123–152, 2003.

[16] P. C. Jennings, S. Lysgaard, J. S. Hummelshøj, T. Vegge, and T. Bligaard, “Genetic algorithms for computational materials discovery accelerated by machine learning,” *NPJ Comput. Mater.*, vol. 5, no. 1, p. 46, 2019.

[17] J. H. Guzmán-Bautista, “Competitividad de la quinua perlada para exportación: el caso de Puno,” *Ing. Ind.*, no. 031, pp. 91–112, 2013.

[18] S. Romo, A. Rosero, C. Forero, and E. Céron, “Potencial nutricional de harinas de Quinua (Chenopodium Quinoa W) variedad piartal en los Andes colombianos primera parte,” *Biotecnol. en el Sect. Agropecu. y Agroindustrial*, vol. 4, no. 1, pp. 112–125, 2006.

[19] F. Condeña Almora and E. Chauca Retamozo, “Análisis económico de la cadena de valor de Quinua (chenopodium quinoa) en Ayacucho 2015,” 2016.

[20] M. A. Luque Araoz, “Políticas agroecológicas y exportación de quinua blanca de la zona sur de la región Puno al mercado de Canadá, 2017,” 2021.

[21] L. L. Soncco Mendoza, “Incidencia de los costos por procesos continuos en la producción y comercialización de quinoa y su rentabilidad económica en la Provincia de Melgar-Departamento Puno 2016 Caso: Asociación Tikary Pampa Jatun Sayna-Macari,” 2017.

[22] M. S. Bazaraa, H. D. Sherali, and C. M. Shetty, “Lagrangian duality and saddle point optimality conditions,” *Nonlinear Program. Theory Algorithms,* pp. 199–242, 2013.

[23] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2004.

[24] S. J. Wright, “Numerical optimization.” 2006.

[25] N. Y. Mannarino, “Agricultura responsable e impuestos provinciales,” 2020.

[26] D. Bertsimas, K. O. Allison, and W. R. Pulleyblank, *The analytics edge*. Dynamic Ideas LLC Belmont, MA, USA, 2016.

[27] J. J. Weygandt, P. D. Kimmel, and D. E. Kieso, *Financial accounting*. John Wiley & Sons, 2019.

[28] F. Hillier and G. Lieberman, “Introduction to Operations Research with Student Access Card.” McGraw-Hill Science/Engineering/Math, 2010.

[29] M. G. Pose, “Introducción a los algoritmos genéticos,” *Dep. Tecnol. la Inf. y las Comun. Univ. Coruña*, 2000.

[30] D. E. Golberg, “Genetic algorithms in search, optimization, and machine learning. Addion Wesley,” *Reading*, 1989.

[31] J. G. Digalakis and K. G. Margaritis, “An experimental study of benchmarking unctions for genetic algorithms,” *Int. J. Comput. Math.*, vol. 79, no. 4, 2002.

[32] I. Goodfellow, Y. Bengio, and A. Courville, \*Deep Learning\*. Cambridge, MA, USA: MIT Press, 2016.

[33] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," en \*International Conference on Learning Representations (ICLR)\*, San Diego, CA, USA, 2015.