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Research Article

Stochastic Optimization for Job Generation in Angola's Crustacean Industry to 2050

Alcides Romualdo Neto Simbo*

Department of Mathematic, University November 11th, Cabinda, Angola

Abstract

Unemployment still affecting families of a country with potential resources and the implementation of government policies have been facing uncertainties, constraints and difficulties for providing jobs. This paper deals on generating new jobs in Angolan's Crustacean industry business through 2050. How stochastic optimization can be applied to create more jobs? Simulation method of forecasting, tree-stage stochastic optimization model considering 10 notable scenarios and belief modeling strategy for managing risks were applied involving two fishery cooperatives representatives in the probabilities assignment to each demand and availability scenarios in stage 2 and stage 3, resulting in expected revenues around 6,248,283,563.47 Kz and 259 new jobs annually in fishing. These results provides 9% more than the business's earnings, expecting to achieve 3,367 new jobs by 2037 and 6,734 new jobs to 2050. This could lead to the sale of 2,158.8 to 4,035.9 tons of crustaceans (striped grant, shrimp, crab, prawn, and lobster) abundant on the coasts of the provinces of Bengo, Benguela, Cabinda, Cuanza Sul, Icólio Bengo, Luanda, Namibe, and Zaire. To this end, mathematical algorithm were also developed for showing the precise, sequential and logical instructions to follow for helping government and decision-makers to achieve the objectives of unemployment rates reduction in Angola.

Keywords

Stochastic Optimization, Job Generation, Angola's Crustacean Industry

1. Introduction

Rising unemployment is an undeniable reality in contemporary societies, and self-employment appears to be a key solution to this problem as stated [1, 2]. A country's raw materials must be utilized effectively to serve as a basis for job creation and new employment opportunities.

Algorithms help define a set of precise, sequential and logical instructions for executing a task or solving a problem, as can be seen in [3, 4]. When programming a long-term phenomenon, the algorithm must integrate multi-stage stochastic programming and prediction models to account for uncertainties and constraints.

In a stochastic program modeled in T stages, the first stage typically represents the beginning of time (the present)—the moment at which decisions must be made. It is also considered deterministic because all parameters corresponding to the first-stage problem are observable and can be determined with good precision. Data related to subsequent stages are known only in a probabilistic sense, revealed at the beginning of each stage. To this end, a random variable with a known probability distribution is used to represent them. A stochastic optimiza-

*Corresponding author: simboal@yahoo.com.br (Alcides Romualdo Neto Simbo)

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tion model is any optimization model in which its parameters are uncertain and are represented as predictive models [5].

As shown in studies [6-18] and [3, 4] forecasting models, deterministic, stochastic optimization models and algorithms are widely used and allows for the estimation of ideal direct revenues from the sale of certain quantities of identified resources in a given sector, such as crustaceans in the fishing sector. These tools also aid in long-term planning despite future uncertainties in fishing [19]. They can be effective in strategic decision-making, generating additional funds that allow for increased employment. Algorithms are also widely applied in the decision-making process to provide rigor in the execution of processes and allow for error correction when certain results are not achieved. In countries like Angola, where most decisions follow administrative or political models, gaps in the drafting of laws and a lack of rigor in the implementation of policies are common due to interpretation problems or interference from influential groups.

According to studies [20-26], the main sources of uncertainty in availability and demand are related to fish mortality due to marine water pollution, variations in annual rainfall, and the forced migration of fish to the seas of neighboring countries, such as the Republic of the Congo, the Democratic Republic of the Congo, and Namibia, which impact the reduction or increase in catches and revenues. In the maritime and river areas of Angola, which encompass the coasts of the provinces of Bengo, Benguela, Cabinda, Cuanza Sul, Icólio Bengo, Luanda, Namibe, and Zaire, immense quantities and varieties of fish abound, such as crustaceans, mollusks, demersal fish, pelagic fish, and riverine fish. Currently, the sector employs approximately 113,368 people, generates around 246,617,594,646.47 Kz per year, and sells between 2,126.2 and 3,620.5 tons of various fish annually, although availability can reach up to 4,163.6 tons per year. In industrial fishing, there are 3,651 fishermen and 2,057 women fish processors, while in semi-industrial fishing, there are 1,174 fishermen and 4,379 women fish processors. In artisanal maritime fishing, 47,926 are fishermen and 10,460 are fish processors. In artisanal river fishing, 35,502 are fishermen and 8,219 are fish processors [19].

According to [19], these sources of uncertainty lead to the following scenarios for catches and demand:

1) *Pessimistic (Bad):* Characterized by a significant reduction in catches due to fish mortality from visible marine pollution (mainly caused by oil exploration), low rainfall, low reproduction rates, food shortages in seas and rivers, and fish migration to the seas of neighboring countries.

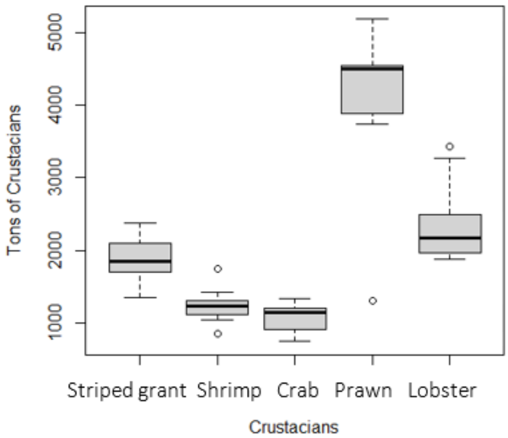
2) *Current (Baseline):* Characterized by a relative abundance in catches due to reduced fish mortality and lower marine pollution (mainly from oil exploration), moderate rainfall, average reproduction rates, adequate food availability in seas and rivers, and reduced fish migration to neighboring countries.

3) *Optimistic (Good):* Characterized by abundant catches due to a considerable reduction in fish mortality from minimized water pollution, high rainfall, high fish reproduction rates, the presence of abundant food in seas and rivers, and a significant reduction in fish migration to neighboring countries.

Values for numerous scenarios can be generated using various techniques, such as percentiles [9], simulation of random distributions (e.g., those that best fit the uniform, normal, exponential, and Gamma probability distributions), the centroid method, Benders decomposition, and resampling [11, 20] and among other techniques.

Source: Adapted by the author from Google

Figure 1. *Crustaceans sold in Angola.*



Source: Processed by the author using software R

Figure 2. *Variability of Crustaceans sold in Angola.*

A considerable number of mid-range and high-end establishments—including hotels, restaurants, and supermarkets in Luanda such as Terraza Talatona, Café del Mar, K Sushi, Nayaki, Vitruvio (Hotel Epic Sana), Lookal Mar, La Vigia, Peixe do Cabo, Bar Ssulo, Cervejaria Finiho, Mercado do

Peixe, Restaurante Marisqueira Forte Velho, Restaurant Bar Conves, Miami Beach, Pátio Luanda, Mupas Beach Resort, Jango Veleiro, Tamariz, Ipanema Mar, Maris Grill, Restaurante Brick, Restaurante Fundo do Mar, Finus Bar, Billionaire Luxury Lounge, Kitchen Restaurant, and Debonairs Palanca—as well as buyers from the middle, upper-middle, and upper classes, have shown significant interest in purchasing and consuming specific types of crustaceans (1 = Striped grunt, 2 = Shrimp, 3 = Crab, 4 = Prawn, and 5 = Lobster) according to studies [22-24], [26-28] and web site of marine fruit seller restaurants, as shown in Figure 1. Although studies indicate that the North and Central Coast of Angola host a total of 23 crustacean families, with a diversity of approximately 50 species as referred in [27], these crustaceans could have an optimal annual impact of 3% on global fish sales revenues by the year 2050 under the current scenario [19].

In this line of thought, *how stochastic optimization can be applied to create more jobs in Angola's Crustacean Industry through 2050*?

This research aimed to apply stochastic optimization for jobs generation in Angola's Crustacean Industry through 2050.

The paper presents the results of its application in the Angolan fishing sector based on optimal revenues from crustacean sales for the period 2016 –2050. It also presents the following topics: 1. Introduction, 2. Theoretical framework and design of stochastic models, 3. Methodology, 4. Algorithm definition, 5. Results and discussion, 6. Generation of new jobs in the crustacean business, and 7. Conclusion.

2. Theoretical Framework and Design of Stochastic Models

Algorithms (defined as sequences of precise instructions for executing tasks), prediction models, and stochastic optimization models are effective tools for solving complex problems, especially when considerable uncertainty and resource limitations impede solutions to issues such as unemployment. These tools indicate an optimal path to a solution. Decision-makers must adopt sensitive perspectives, and their actions must be coherent and directed toward achieving expected results. The parameters to be considered when modeling the optimization problem underlying the algorithm are dynamic and must be indicated a priori as illustrated in [5, 15]. Due to the uncertainties inherent in long-term decisions and the risks associated with undesirable scenarios, the quality of the solution that forms the basis for decision-making can be affected by the type of decision tree representing possible scenarios, the probabilities assigned to them based on expert beliefs, the accuracy of parameter prediction, and procedural errors [16].

2.1. Scenario Tree, Forecast of Availability, Demand, Prices and Probabilities for Each Scenario

The scenario tree of the stochastic optimization model underlying the presented algorithm, which comprises three stages, is illustrated in Figure 3.

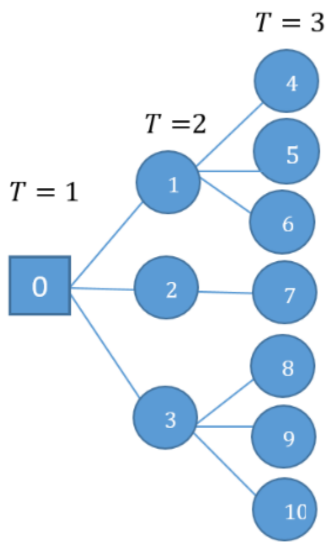
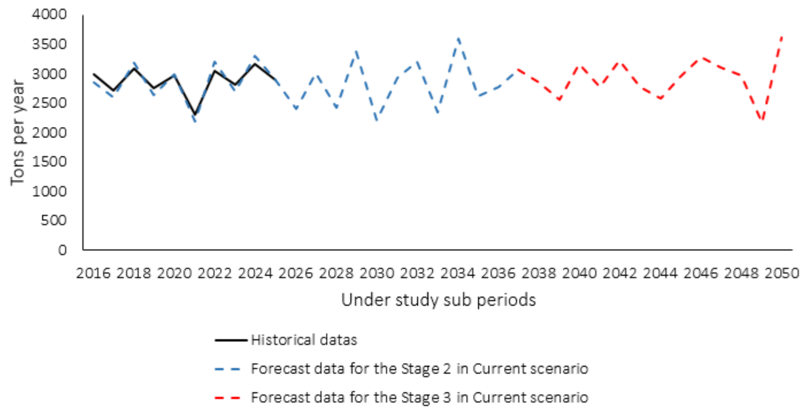


Figure 3. *Tree of notable three-stage and multi-expansionary scenarios.*

Source: Drafted by the author according to Angolan's notable scenarios

The parameters for each notable scenario of the stochastic optimization model are defined based on the means $mean(Y_t) = \mu_Y$, $mean(y_t) = \mu_y$ and standard deviations $sd(Y_t) = \sigma_Y$, $sd(y_t) = \sigma_y$ of the historical data, as well as on forecasts of the availability Y_t and total annual demand y_t for the M resources (crustaceans) identified in the first stage. After testing a distribution associated to the historical data, forecast can be done using R software and applying simulation method and among others. In this study, for Angola, normal distribution for the ρ historical data applying the Shapiro-Wilk test, $n = 3\rho$ terms of the time series that fit the data distribution were generated, where 3ρ is the total number of forecast values for the current (fundamental) scenario. Using the command $y_t \leftarrow rmorm(n = 3\rho, mean = \mu_y, sd = \sigma_y)$ for demand and a similar command for availability, we obtained the values illustrated in Figure 4 and Figure 5.

The forecast values for the current scenario were obtained by simulating random variables using the known mean and standard deviation, following the method applied in [11].



Source: Plotted by the author using data from the references [22-24], [26-28] and it's forecast applying Software R and MS-Excel

Figure 4. *Demand forecasts.*

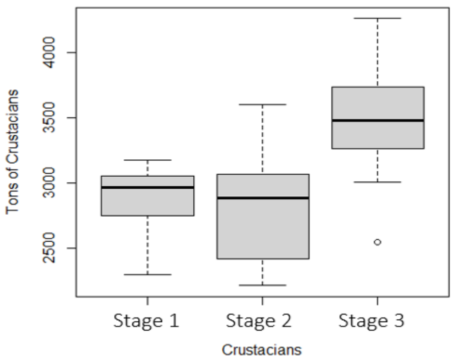
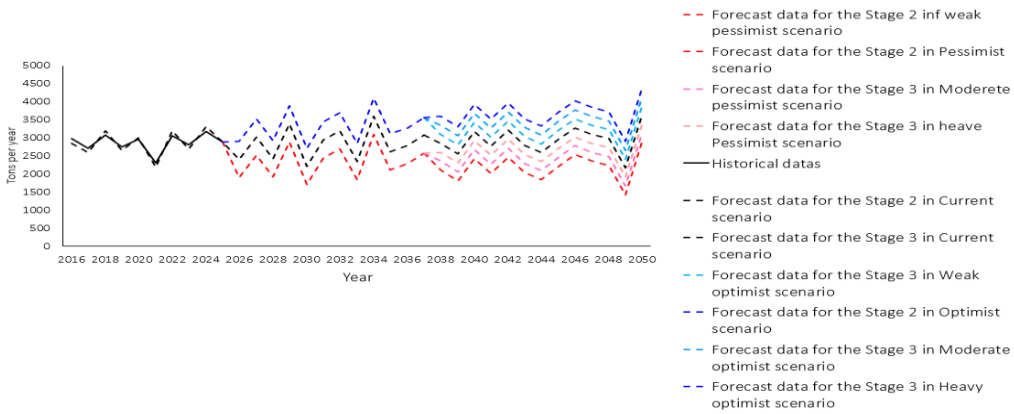


Figure 5. *Demand's variability for the stages under study in the current scenario.*

Source: Plotted by the author using data from the references [22-24], [26-28] and it's forecast applying Software R

According to Figure 4 and Figure 5, the forecasts show a reduction in demand during the second stage, followed by an increase in the third stage. These values served as the basis for generating data for the other notable scenarios. The parameters for the subsequent stages and notable scenarios were generated by taking the means of the forecasts for the current scenario and amplifying the standard deviations σ_y and σ_Y by an integer multiplier k within the interval $[-3; 3]$, resulting in the sets $\{Y_t + k\sigma_Y\}$ and $\{y_t + k\sigma_y\}$. This approach provides maximum variation amplitudes of 4σ for the second stage and 6σ for the third stage. Each integer value of k generates what we call a notable scenario. However, k can also take continuous values within the same interval $[-3; 3]$, potentially generating millions of non-notable scenarios. For the second stage, $k\epsilon\{-2, 0, 2\}$, and for the third stage, $k\epsilon\{-3, -2, -1, 0, 1, 2, 3\}$. According to Chebyshev's Theorem, at least $100(1 - 1/\mathrm{k}^2)\%$ of the forecast data values will fall within these ranges, accounting for more than 75% of data in the second stage and more than 89% in the third stage [29].

For example, Figure 6 illustrates the forecasts of total crustacean demand in Angola from 2016 to 2050, categorized by scenario.



Source: Plotted by the author using software R and MS-Excel

Figure 6. *Forecasts of crustaceans demand in Angola from 2016 to 2050 in tons.*

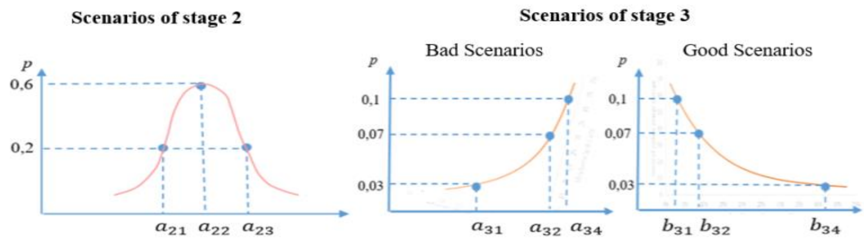


Figure 7. *Risk management strategies for assigning demand probabilities to scenarios.*

Source: constructed by author applying the belief modeling method of risk management

$$a_{21} = mean(y^2 - 2\sigma_y),\ a_{22} = mean(y^2),\ a_{23} = mean(y^2 + 2\sigma_y);\ a_{31} = mean(y^3 - 3\sigma_y),\ a_{32} = mean(y^3 - 2\sigma_y),\ a_{33} = mean(y^3),\ a_{34} = mean(y^3 - \sigma_y);\ b_{31} = mean(y^3 + \sigma_y),\ b_{32} = mean(y^3 + 2\sigma_y),\ b_{33} = mean(y^3),\ b_{34} = mean(y^3 + 3\sigma_y)$$

Probabilities assigned to each scenario:

$$p^{w^{\Omega^-}} = 0{,}1;\ p^{w^{\delta^3}} = 0{,}07;\ p^{w^{\Omega^+}} = 0{,}03$$

$$p^{\Omega^-} = 0{,}2;\ \ p^{\delta^2} = 0{,}6;\ p^{\Omega^+} = 0{,}2;\ p^{w^{-\Omega^-}} = 0{,}03;\ p^{w^{-\delta^3}} = 0{,}07;\ p^{w^{-\Omega^+}} = 0{,}1;\ p^{,\delta^3} = 0{,}6$$

The uncertainty associated with scenario occurrence increases with a longer time horizon, which necessitates risk management when modeling or assigning probabilities to each scenario. Thus, depending on the beliefs and experiences of decision-makers (cooperatives and fishing companies), the application of risk-neutrality, risk- affection, and risk-aversion strategies may be observed. According to the tree in Figure 3 and the distributions in Figure 6, probabilities were assigned to each scenario using the probability distributions shown in Figure 7, as illustrated in studies [30-32]. Stage 1 represents the already-observed historical dataset, while Stages 2 and 3 represent uncertainties; the more distant the time horizon, the greater perceived uncertainties. Stage 2 presents three notable scenarios $\{\Omega^+, \delta^2, \Omega^-\}$, corresponding to the optimistic, current, and pessimistic scenarios, respectively. Stage 3 presents seven notable scenarios: three good scenarios $\{w^{-\Omega^+}, w^{-\delta^3}, w^{-\Omega^-}\}$, the current scenario δ^3, and three bad scenarios$\{w^{\Omega^+}, w^{\delta^3}, w^{\Omega^-}\}$. The assignment of probabilities to each demand or availability scenario depends on the specific context of each location where the stochastic model is applied, provided the scenario configuration is similar to that in Figure 3. In the case of Angola, the probability models are similar to those in Figure 7. For Stage 2, according to representatives from fishing cooperatives such as AVOPESCAS and COOPERATIVA DE APOIO À PESCA ARTESANAL NKUSSA, SCRL, it is more likely that demand values will cluster around the current scenario, leading to the use of probability distribution (1). For Stage 3, these stakeholders had no specific expectations due to the more distant time frame. As researchers, we helped them to be more cautious with good-case scenarios by adopting a risk-averse strategy with probability distribution (2). The probability of the current scenario remains the same for all stages, and its distribution is modeled by expression (3). We went more ambitious with bad scenarios by adopting a risk-affection strategy with probability distribution (4) as referenced in [32].

$$p^{\Omega_j}\left(y_{\{t_2\}}\right) = a_l e^{b_l\left(\frac{y_{\{t_2\}} - \mu_y}{\sigma_y\sqrt{2\pi}}\right)^2};\ \ a_l, b_l > 0 \tag{1}$$

$$p^{\omega_\theta}\left(y_{\{3\}}\right) = a_l e^{b_l(y_{\{3\}} + k\sigma_y) + c_l}\ ;\ a_l > 0, b_l, c_l < 0 \tag{2}$$

$$p^{\delta^2}\left(y_{\{t_2\}}\right) = \ p^{\delta^3}\left(y_{\{t_3\}}\right) = a_l e^{b_l\left(\frac{y_{\{t_2\}} - \mu_y}{\sigma_y\sqrt{2\pi}}\right)^2} = a_l e^{-b_l\left(\frac{y_{\{t_3\}} - \mu_y}{\sigma_y\sqrt{2\pi}}\right)^2};\ \ a_l, b_l > 0 \tag{3}$$

$$p^{\omega_\theta}\left(y_{\{3\}}\right) = a_l e^{b_l(y_{\{3\}} + k\sigma_y) + c_l};\ \ a_l, b_l, c_l > 0 \tag{4}$$

Probabilities for bad scenario at Stage 3.

Over time, the price series C_{mt} generally varies around its mean μ_{c_m} with a standard deviation σ_{c_m}, but not to the extent that it generates distinct scenarios like those for resource availability and demand. In Angola's case, price forecasts are made using a normal distribution $N(\mu_{c_m}, \sigma_{c_m})$ over defined future periods.

2.2. Problems Formulation

We consider a given fisheries sector, represented by A, with specific employability areas $A_1, A_2, \dots, A_\beta$. The current total number of jobs, N, is divided into $N_1, N_2, \dots, N_\beta$ across the areas of A, stratified by categories $XY_1, XY_2, \dots, XY_\beta$ and $XX_1, XX_2, \dots, XX_\beta$. These jobs are supported by the sales revenue Rv generated from M identified types of crustaceans, which have an availability Y_t and demand y_t over the initial time periods $\{t_1\} = 1,2, \dots, \rho$.

Problem MV a: For a selected subset of resources available for commercialization, with annual sales quantities $x_1, x_2, x_3, \dots, x_\mathrm{M}$ (in tons) of the M crustaceans, total demand y_t, and total annual availability Y_t, determine the optimal sales revenue rv^* and the optimal quantities x_m^* to be sold for each time period in stage $\{t_1\} = 1,2, \dots, \rho$. Specifically, determine $rv^*, x_1^*,\ x_2^*, x_3^*, \dots, x_M^*$.

Problem MV b: Determine the optimal expected revenue $E(rv^*)$ and expected quantities $E(x_1^*), E(x_2^*), \dots, E(x_M^*)$ from the sale of M crustaceans, along with the optimal expected number of new jobs $E(n^*)$ to be generated over the future periods $\{t_2\} = \rho + 1, \dots, 2\rho$ and $\{t_3\} = 2\rho + 1, \dots, 3\rho$. These new jobs are distributed as $E(n_1^*), E(n_2^*), \dots, E(n_\beta^*)$ across the employability areas of A.

Problem MV c: What are the precise, sequential and logical instructions for solving problems MVa and MVb?

2.3. Design of Deterministic and Stochastic Optimization Models

For stage 1, $\{t_1\} = 1,2, \dots, \rho$, the following situations are observed:

The sales revenues for each time period in step $\{t_1\} = 1,2, \dots, \rho$ are determined by

$$rv = \sum_{m=1}^{M} c_m x_m \tag{5}$$

Where c_{mt} are the unit costs and x_m the decision variables representing the quantities in tons to be sold of each resource;

To satisfy demand and respect availability, the following constraints must be observed: $mean(y_t) \le \sum_{m=1}^{M} x_m \le mean\ (Y_t)$ (6);

The percentage of each resource and its relation to total demand obeys the constraints $x_m \le \left(mean(y_{mt})/(\sum_{t=1}^{\rho} y_t)\right) \sum_{m=1}^{M} x_m$ (7);

The non-negativity constraint are given by $x_m \ge 0, m = 1, 2, \dots, M$ (8);

Thus, Problem MVa is represented by the model presented in the expression (MVa) below.

$$Max\ rv = \sum_{m=1}^{M} c_m x_m$$

$$s.t:$$

$$mean\ (y_t) \le \sum_{m=1}^{M} x_m \le mean\ (Y_t) \tag{6}$$

$$x_m \le \left(mean(y_{mt})/(\textstyle\sum_{t=1}^{\rho} y_t)\right) \sum_{m=1}^{M} x_m \tag{7}$$

$$x_m \ge 0, m = 1, 2, \dots, M \tag{8}$$

For the stages 2 and 3, $\{t_2\} = \rho + 1, \dots, 2\rho$ and $\{t_3\} = 2\rho + 1, \dots, 3\rho$ the following situations are observed:

Expected sales revenues are given by the expression below:

$$rv = 10^3 \times \left[\sum_{m=1}^{M} c_m x_m + \sum_{j=1}^{3} \sum_{\Omega_j \in \Omega} p^{\Omega_j} \left(\sum_{m=1}^{M} c_m^{\Omega_j}\ x_m^{\Omega_j}\right) + \sum_{\theta=1}^{7} \sum_{\omega_\theta \in \mathrm{W}} p^{\omega_\theta} \left(\sum_{m=1}^{M} c_m^{\omega_\theta}\ x_m^{\omega_\theta}\right)\right] \tag{9}$$

Where:

1) $j = 1,2,3;\ \Omega_j \in \Omega = \{\Omega^+, \delta^2, \Omega^-\}$ are notable scenarios observed in Stage 2, the optimistic, current and pessimistic with respective probabilities $p^{\Omega_j} \in \{p^{\Omega^+}, p^{\delta^2}, p^{\Omega^-}\}$;
2) $\theta = 1,2, \dots, 7$; $\omega_\theta \in \mathrm{W} = \{\mathrm{w}^{\Omega^+}, \mathrm{w}^{\delta^3}, \mathrm{w}^{\Omega^-}, \delta^3, \mathrm{w}^{-\Omega^+}, \mathrm{w}^{-\delta^3}, \mathrm{w}^{-\Omega^-}\}$ are notable scenarios observed in Stage 3, the strong optimistic, moderate optimistic and weak optimistic, current, strong pessimistic, moderate pessimistic and weak pessimistic, with respective probabilities $p^{\omega_\theta} \in \{p^{\mathrm{w}^{\Omega^+}}, p^{\mathrm{w}^{\delta^3}}, p^{\mathrm{w}^{\Omega^-}}, p^{\delta^2}, p^{\mathrm{w}^{-\Omega^+}}, p^{\mathrm{w}^{-\delta^3}}, p^{\mathrm{w}^{-\Omega^-}}\}$;
3) $c_m^{\Omega_j}$ and $c_m^{\omega_\theta}$ are the incremental values of the unit costs of the resources quantities to be sell in Stage 2 and Stage 3;

The decision variables also obey the following constraints:

$$mean\ (y_{\{t_2\}} + k\sigma_y) \le \sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} \le mean\ (Y_{\{t_2\}} + k\sigma_Y) \tag{10}$$

Demands satisfaction and respect for the limits available in stage 2, where $k\epsilon\{-2., 0, 2\}; \Omega_j \in \Omega = \{\Omega^+, \delta^2, \Omega^-\}$;

$x_m + x_m^{\Omega} \le \left(mean(y_{mt)})/\ (\sum_{t=1}^{\rho} y_t)\right)(\sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega})$ (11)

Percentages of each resources in stage 2, where $k\epsilon\{-2, 0, 2\}; \Omega_j \in \Omega = \{\Omega^+, \delta^2, \Omega^-\}$;

$$mean\ (y_{\{t_3\}} + k\sigma_y) \le \sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} + \sum_{i=1}^{n} x_m^{\mathrm{W}} \le mean\ \left(Y_{\{t_3\}} + k\sigma_Y\right) \tag{12}$$

Demand satisfaction and respect for available limits, related to resources in stage 3, $k\epsilon\{-3,-2,-1,0,1,2,3\}$; $\Omega_j \in \Omega = \{\Omega^+, \delta^2, \Omega^-\}$; $\omega_\theta \in \mathrm{W} = \{\mathrm{w}^{\Omega^+}, \mathrm{w}^{\delta^3}, \mathrm{w}^{\Omega^-}, \delta^3, \mathrm{w}^{-\Omega^+}, \mathrm{w}^{-\delta^3}, \mathrm{w}^{-\Omega^-}\}$;

$$x_m + x_m^{\Omega} + x_m^{\mathrm{W}} \le \left(mean(y_{mt})/(\textstyle\sum_{t=1}^{\rho} y_t)\right)(\textstyle\sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} + \sum_{m=1}^{M} x_m^{\mathrm{W}}) \quad (13)$$

Percentages of each resources in stage 3 where $\omega_\theta \in \mathrm{W} = \{\mathrm{w}^{\Omega^+}, \mathrm{w}^{\delta^3}, \mathrm{w}^{\Omega^-}, \delta^3, \mathrm{w}^{-\Omega^+}, \mathrm{w}^{-\delta^3}, \mathrm{w}^{-\Omega^-}\}$;

$$x_m^{\Omega^+} \ge 0, x_m^{\delta^2} \le 0, x_m^{\Omega^-} \le 0, x_m^{\mathrm{w}^{\Omega^+}} \ge 0,\ x_m^{\mathrm{w}^{\delta^3}} \ge 0,\ x_m^{\mathrm{w}^{\Omega^-}} \ge 0,\ x_m^{\delta^3} \ge 0, x_m^{\mathrm{w}^{-\Omega^+}} \le 0,\ x_m^{\mathrm{w}^{-\delta^3}} \le 0,\ x_m^{\mathrm{w}^{-\Omega^-}} \le 0, \text{ where } m = 1,2,\dots,M \quad (14)$$

Non-negativity and negativity constraints on the decision variables of Stage 1, Stage 2 and Stage 3, related to the variation in demand.

Problem MVb in tons is represented by the model shown in the expression below.

$$Max\ rv = 10^3 \times \left[\textstyle\sum_{m=1}^{M} c_m x_m + \sum_{j=1}^{3}\sum_{\Omega_j \in \Omega} p^{\Omega_j}\left(\sum_{m=1}^{M} c_m^{\Omega_j} x_m^{\Omega_j}\right) + \sum_{\theta=1}^{7}\sum_{\omega_\theta \in \mathrm{W}} p^{\omega_\theta}\left(\sum_{m=1}^{M} c_m^{\omega_\theta} x_m^{\omega_\theta}\right)\right]$$

$$s.t:$$

$$mean\ (y_t) \le \textstyle\sum_{m=1}^{M} x_m \le mean\ (Y_t)$$

$$x_m \le \left[mean(y_{mt})/(\textstyle\sum_{t=1}^{\rho} y_t)\right]\sum_{m=1}^{M} x_m$$

$$x_m \ge 0$$

$$mean\ (y_{\{t_2\}} + k\sigma_y) \le \textstyle\sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} \le mean\ (Y_{\{t_2\}} + k\sigma_Y)$$

$$x_m + x_m^{\Omega} \le \left(mean(y_{mt})/\ (\textstyle\sum_{t=1}^{\rho} y_t)\right)(\sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega})$$

$$mean\ (y_{\{t_3\}} + k\sigma_y) \le \textstyle\sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} + \sum_{i=1}^{n} x_m^{\mathrm{W}} \le mean\ (Y_{\{t_3\}} + k\sigma_Y)$$

$$x_m + x_m^{\Omega} + x_m^{\mathrm{W}} \le \left(mean(y_{mt})/(\textstyle\sum_{t=1}^{\rho} y_t)\right)(\sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} + \sum_{m=1}^{M} x_m^{\mathrm{W}})$$

$$x_m^{\Omega^+} \ge 0, x_m^{\delta^2} \le 0, x_m^{\Omega^-} \le 0, x_m^{\mathrm{w}^{\Omega^+}} \ge 0,\ x_m^{\mathrm{w}^{\delta^3}} \ge 0,\ x_m^{\mathrm{w}^{\Omega^-}} \ge 0,\ x_m^{\delta^3} \ge 0, x_m^{\mathrm{w}^{-\Omega^+}} \le 0,\ x_m^{\mathrm{w}^{-\delta^3}} \le 0,\ x_m^{\mathrm{w}^{-\Omega^-}} \le 0$$

where $m = 1,2,\dots,M$; $k\epsilon\{-3,-2,-1,0,1,2,3\}$; $\Omega_j \in \Omega = \{\Omega^+, \delta^2, \Omega^-\}$,, $\omega_\theta \in \mathrm{W} = \{\mathrm{w}^{\Omega^+}, \mathrm{w}^{\delta^3}, \mathrm{w}^{\Omega^-}, \delta^3, \mathrm{w}^{-\Omega^+}, \mathrm{w}^{-\delta^3}, \mathrm{w}^{-\Omega^-}\}$

3. Methodology

A wide range of references was used, with emphasis on scientific articles concerning algorithms, machine learning, time series, and stochastic optimization, along with reports from the Ministry of Fisheries and the Sea and the National Institute of Statistics of the Republic of Angola for the period 2016-2024 as shown in [3-20] and [21-28]. These reports provided insights into the annual historical reality, particularly regarding employment data in the fisheries sector, catches, demand, prices, sector structure, involved agents, revenues, scenarios, and all other information necessary for the research from studies [21-28]. The collected data and information were used to generate time series, forecast data via simulations, develop scenarios for the sub-periods 2025-2037 and 2038-2050, and create a long-term, three-stage advanced stochastic optimization model. The presented algorithm consists of parameter forecasting, modeling, stochastic optimization of sales revenue, and finally, the generation of new job numbers in the fishing sector. Machine learning tools were employed, primarily R version 4.1.2 for parameter forecasting, graphics plotting and CPLEX version 2.0 for solving the stochastic optimization model. Python was used to test the algorithm by integrating R version 4.1.2 and CPLEX version 2.0 environments to determine its properties: 1) Input, 2) Output, 3) Definition, 4) Correctness, 5) Finite duration, 6) Pre-effectiveness, and 7) Generality as recommended in [4], using structure of the Extended Syracuse Algorithm. The investigation of these properties will be the focus of future research. Microsoft Excel were also used for construction of elementary graphics.

Two staff members of fishing cooperatives AVOPESCAS and COOPERATIVA DE APOIO À PESCA ARTESANAL NKUSSA, SCRL answered a question for determining the probability assigned to each scenario of the stage 2 and stage 3, procedure usually followed for belief modeling when the probabilities are not clear, involving experts in a certain phenomenon in observation.

Data simulation method were applied using the command

$y_t \leftarrow rmorm(n = 3\rho, mean = \mu_y, sd = \sigma_y)$ for forecasting demand and a similar command for availability, knowing the mean and standard deviation of the historical demand data to generate a time series of data that fit a normal distribution.

$$E(x^*) = N \times E(rv^*)/RV - E(n^*) \tag{15}$$

$$E(n_i^*) = n_i \times E(x^*)/N \tag{16}$$

The number of new jobs generated per year was calculated by applying the simple rule of three based on optimal sales revenues, using the formulas (15) and (16), where: N = Total annual jobs generated by the fishing sector in the current scenario; RV is the General revenues observed by the sector in the current scenario; $E(rv^*)$ is an Optimal revenues expected from shellfish sales; $E(n^*) + E(x^*)$ is the Current number of jobs generated with optimal shellfish sales revenue; $E(x^*)$ is the Incremental number of new jobs generated with optimal shellfish sales revenue; $E(n^*)$is an Optimal number of jobs that should be generated with optimal shellfish sales revenue; n_i is the Total number of existing employees in stratum i by type of activity; accounting for a 9% deduction. A proportional stratified distribution was applied across relevant employment sectors. Using the cumulative function, the total number of new jobs generated by the crustacean business was predicted for the periods 2025–2037 and 2038–2050, as shown in Figure 8.

Forecasted values of demand, availability and prices were validated applying statistical normality test of Shapiro-Wilk according to studies [7-12]. The normality condition was observed, as can be seen in the Table 1, leading the means to represent the parameters introduced in the stochastic optimization model. Optimization model were validated by making comparison between historical revenues and the optimal revenue of the same stage 1, resulting 9% more for optimal revenue, as shown in Table 5, that provided 259 new jobs per year, totalizing 6,734 through 2050, impacting positively for job growth in Angola’s Crustacean Industry.

Table 1. *Normality test of demand forecasts in the current scenario from 2016 to 2050.*

Sub period 2016-2024	Sub period 2025-2037	Sub period 2038-2050
> library (read.xls)	> library (read.xls)	> library (read.xls)
>y_t1<-read.xls ("demanda.xls")	>y_t2<-read.xls ("Predict1demanda.xls")	>y_t3<-read.xls ("Predict2demanda.xls")
> shapiro.test (y_t1)	> shapiro.test (y_t2)	> shapiro.test (y_t3)
Shapiro-Wilk normality test	Shapiro-Wilk normality test	Shapiro-Wilk normality test
data: y_t1	data: y_t2	data: x_t3
W = 0.89858, p-value = 0.24	W = 0.96686, p-value = 0.8541	W = 0.98575, p-value = 0.9966

Source: Tests done by the author with the use of software R

Table 2. *Annual demands and availability of Crustacean, in tons.*

	Scenarios	Demands		Availability	
		Mean	Standard deviation	Mean	Standard deviation
Stage 1 (2016-2024)	Current	2,873,4	249.04	3,304.4	286.4
	Optimistic	3,372.5		3,877.2	
Stage 2 (2025-2037)	Current	2,837.6		3,263.3	
	Pessimistic	2,375.3		2,731.6	
	Strong Optimistic	3,620.5		4,163.6	
Stage 3 (2038-2050)	Moderate Optimistic	3,371.5		3,877.2	
	Weak Optimistic	3,122.4		3,590.8	
	Current	2,927.8		3,367.0	

Scenarios	Demands		Availability	
	Mean	Standard deviation	Mean	Standard deviation
Strong Pessimistic	2,624.3		3,018.0	
Moderate Pessimistic	2,375.3		2,731.6	
Weak Pessimistic	2,126.2		2,445.2	

Source: Values obtained by author with the use of software R

Table 3. *Annual Prices of 1 kg each Type of crustacian.*

	Striped grant	Shrimp	Crab	Prawns	Lobster
Stage 1 (2016-2024)	1,893.5	1,244.7	1,076.3	4,073.9	2,384.4
Stage 2 (2025-2036)	1,743.5	1.237.5	1,126,9	3,525.3	2,576.9
Stage 3 (2037-2050)	1,801.4	1,239.0	1,031.1	3,737.2	2,399.1

Source: Values obtained by author with the use of software R

4. Algorithm Definition

This section presents an intelligent algorithm that interconnects parameter forecasting (demand and availability data) in annual tons of crustaceans sold in Angola. It uses data simulation, integrated autoregressive models with moving averages, a one-stage deterministic optimization model, a three-stage advanced stochastic optimization model with three notable scenarios in the second stage and seven notable scenarios in the third stage, and a calculation of the total number of new jobs and their stratified allocation by job type in fishing (fishermen and fish processors in industrial and semi-industrial fishing, artisanal fishing, and marine fishing). From the declaration of the input and output variables to their definition, there are 83 lines of code, including 59 lines of instructions for executing a finite number of precise algorithm instructions, as detailed below:

Algorithm Optimal number of new jobs generation for long horizon period ρ to $\rho 3$

1: *input:* Problems MV1 and MV2 instance data,

2: Number of identified M resources with ρ historical data, 2ρ number of values to forecast until stage 2, and 3ρ number of values to forecast until stage 3,

3: Total of historical income RV of al resources in business,

4: Total of historical N cumulative jobs with M resources in business,

5: Historical cumulative jobs with M resources in business by type of job n_i,

6: Integer variables $m \leftarrow 1$ to M, $p \leftarrow 0$ to 3, $d \leftarrow 0$ to 3, $p \leftarrow 0$ to 3, $P \leftarrow 0$ to 3, $D \leftarrow 0$ to 3, $Q \leftarrow 0$ to 3, k← -3 to 3, $i \leftarrow$ 1 to α,

7: Float variables a_l, b_l, c_l,

8: Period Steps $1{:}3\rho$,

9: Stage steps: Stage 1← $1{:}\rho$, Stage 2← $(\rho+1){:}2\rho$, Stage 3← $(2\rho+1){:}3\rho$,

10: Tuple $Y_{mt} \leftarrow \{Y_{m1}, Y_{m2}, \dots, Y_{m\rho}\}$ of historical ρ values of the availability with the *mean* (Y_t) at Stage 1,

11: Tuple $y_{mt} \leftarrow \{y_{m1}, y_{m2}, \dots, y_{m\rho}\}$ of historical ρ values of the demands with the *mean* (y_t) at Stage 1,

12: Tuples $C_{mt} \leftarrow \{c_{m1}, c_{m2}, \dots, c_{m\rho}\}$ of historical prices of each resource with the *means* (c_{mt}) at Stage 1,

13: Standard deviation of availability σ_Y and standard deviation of demand σ_y at Stage 1,

14: $\Omega_j \in \Omega = \{\Omega^+, \delta^2, \Omega^-\}$ notable scenarios observed in Stage 2, the optimistic, current and pessimistic with respective probabilities $p^{\Omega_j} \in \{p^{\Omega^+}, p^{\delta^2}, p^{\Omega^-}\}$, $j = 1,2,3$,

15: $\theta = 1,2,\dots,7$; $\omega_\theta \in \mathrm{W} = \{\mathrm{w}^{\Omega^+}, \mathrm{w}^{\delta^3}, \mathrm{w}^{\Omega^-}, \delta^3, \mathrm{w}^{-\Omega^+}, \mathrm{w}^{-\delta^3}, \mathrm{w}^{-\Omega^-}\}$ are notable scenarios observed in Stage 3, the strong optimistic, moderate optimistic and weak optimistic, current, strong pessimistic, moderate pessimistic and weak pessimistic, with respective probabilities $p^{\omega_\theta} \in \{p^{\mathrm{w}^{\Omega^+}}, p^{\mathrm{w}^{\delta^3}}, p^{\mathrm{w}^{\Omega^-}}, p^{\delta^2}, p^{\mathrm{w}^{-\Omega^+}}, p^{\mathrm{w}^{-\delta^3}}, p^{\mathrm{w}^{-\Omega^-}}\}$,

16: Decision parameters representing crustaceans' availability $mean(Y_{\{t_2\}} + k\sigma_Y), k\epsilon\{-2,\ 0,\ 2\}$ of the scenarios at Stage 2, 17: Decision parameters representing the demand of crustaceans $mean\left(y_{\{t_2\}}+k\sigma_y\right), k\epsilon\{-2,\ 0,\ 2\}$, of scenarios at Stage 2,

18: Decision parameters representing quantities of the crustacean's availability $mean(Y_{\{t_3\}}+k\sigma_Y), k\epsilon\{-3,-2,-1,0,1,2,3\}$ of scenarios at Stage 3,

19: Decision parameters representing quantities of the crustacean's demand $mean\left(y_{\{t_3\}}+k\sigma_y\right),\ k\epsilon\{-3,-2,-1,0,1,2,3\}$ of scenarios at Stage 3,

20: Float decision variables representing quantities of resources to sell x_m at Stage 1,

21: Float decision variables representing optimal incremental quantities of resources for sell by scenarios $x_m^{\Omega^+}, x_m^{\delta^2}, x_m^{\Omega^-}$ at Stage 2,

22: Float decision variables representing optimal incremental quantities of resources for sell by scenarios $x_m^{w^{\Omega^+}}, x_m^{w^{\delta^3}}, x_m^{w^{\Omega^-}}, x_m^{\delta^3}, x_m^{w^{-\Omega^+}}, x_m^{w^{-\delta^3}}, x_m^{w^{-\Omega^-}}$ at Stage 3,

23: *Output*: Historical revenue income, Optimal revenue income and quantity of optimal resource would be sell at Stage 1, rv, rv^*, x_m^*, expected revenue income, optimal solution of the problem MVb, optimal expected value of the decision variables solutions of the problem on Stage 2 and Stage 3 by scenarios, $E(rv^*)$, S_2^*, $\{x_m^*+x_m^{*\Omega_j}; x_m^*+x_m^{*\Omega_j}+x_m^{*\omega\theta}\}$, total of effective jobs with optimal income, total number of new generated jobs, and number of new jobs for each area of job A_i: $E(n^*)+E(x^*)$, $E(x^*), E(n_i^*)$;

24: *Begin*

25: *For* $t = 1$ to ρ, $m = 1$ *to* M *do*

26: $rv = 10^3 \times \sum_{m=1}^{M} c_m x_m$

27: c_m =*mean* (C_{mt})

28: σ_Y = sd (Y_t)

29: σ_y = sd (y_t)

30: σ_{C_m} = sd (C_{mt})

31: (MV a) = model (MV 1)

32: S_1^*= solve (MV a)

33: $(rv^*, x_1^*, x_2^*, \dots, x_M^*) = Solve\ (Max\{\ 10^3 \times \sum_{m=1}^{M} c_m x_m\ \ s.t{:}\ mean(y_t) \le \sum_{m=1}^{M} x_m \le, x_m \le$

$$mean(Y_t), \left(mean\left(y_{mt}\right)/\left(\sum_{t=1}^{\rho} y_t\right)\right) \sum_{m=1}^{M} x_m, x_1 \ge 0, x_2 \ge 0, \dots, x_M \ge 0\})$$

34: *End For*

35: *For* $t = \rho + 1$ *to* 3ρ, $m = 1$ *to* M, p = 0 to 3, d = 0 to 3, q = 0 to 3, $S = 0$, P = 0 to 3, D = 0 to 3, Q = 0 to 3, $i = 1$ *to* α *do*

36: Shapiro.test (Y_t)

37: Shapiro.test (y_t)

38: Shapiro.test (C_{mt})

39: *If* p-values > 0.05 *Then*

40: $Y_t \cup Y_{\{t_2\}} \cup Y_{\{t_3\}} \leftarrow rnorm(n = 3\rho,\ \ mean = mean(Y_t)$, sd $= \sigma_Y)$

41: $y_t \cup y_{\{t_2\}} \cup y_{\{t_3\}} \leftarrow nrnorm(n = 3\rho$, mean $= mean(y_t)$, sd$= \sigma_y)$

42: $C_{mt} \cup C_{mt}^2 \cup C_{mt}^2 \leftarrow rnorm(n = 3\rho,$ mean $= c_m$, sd$= \sigma_{C_m})$

43: c_m^2 = mean(C_{mt}^2)

44: *Else*

45: Generate models $Y_{t,\{t_2\},\{t_3\}} = ARIMA(p,d,q)$

46: Select model $Y_{t,\{t_2\},\{t_3\}} = ARIMA(p,d,q)$ with lowest AIC

47: Generate models $y_{t,\{t_2\},\{t_3\}} = arima(p,d,q)$

48: Select model $y_{t,\{t_2\},\{t_3\}} = arima(p,d,q)$ with lowest AIC

49: Generate models $C_{mt} = arima(p,d,q)$

50: Select model $C_{mt} = arima(p,d,q)$ with lowest AIC

51: $Y_{\{t_2\}} \cup Y_{\{t_3\}}$← predict ($ARIMA\ p\ d\ q$, n.ahead = 2ρ) for $Y_{\{t_2\},\{t_3\}}$

52: $y_{\{t_2\}} \cup y_{\{t_3\}}$← predict ($arima\ p\ d\ q$, n.ahead = 2ρ) for $y_{\{t_2\},\{t_3\}}$

53: $C_{mt}^2 \cup C_{mt}^3$← predict ($arima\ p\ d\ q$, n.ahead = 2ρ) for C_{mt}

54:

$mean(Y_{\{t_2\}}+k\sigma_Y) = mean(\text{predict } (ARIMA\ p\ d\ q, \text{n.ahead} = 2\rho\ ) + \text{k}\sigma_Y\ ), mean(y_{\{t_2\}}+k\sigma_y) =$

$mean\left(\text{predict } (ARIMA\ p\ d\ q, \text{n.ahead} = 2\rho\ )\right),$

55:

$mean(Y_{\{t_3\}}+k\sigma_Y) = mean(\text{predict } (ARIMA\ p\ d\ q, \text{n.ahead} = 3\rho\ ) + \text{k}\sigma_Y\ ), mean(y_{\{3\}}+k\sigma_y) =$

$mean\left(\text{predict } (ARIMA\ p\ d\ q, \text{n.ahead} = 3\rho\ )\right),$

56: c_{mt}^2 = mean(predict $(arima\ p\ d\ q, \text{n.ahead}\ = \rho)$) for C_{mt}^2

59: $c_{mt}^3 = mean(\text{predict } (C_{mt}^3 = arima\ p\ d\ q, \text{n.ahead}\ = \ \rho))$ of C_{mt}^3

60: *For al* $S > 0$

61: Generate models $SARIMA(p,d,q) \times (P,D,Q)$ for $Y_{\{t_2\}}\,or\ y_{\{t_2\}}$ or $Y_{\{t_3\}}or\ y_{\{t_3\}}$ or C_{mt}^2 or C_{mt}^3

62: Select models $SARIMA(p,d,q) \times (P,D,Q)$ with lowest AIC for $Y_{\{t_2\}}\,or\ y_{\{t_2\}}$ or $Y_{\{t_3\}}or\ y_{\{t_3\}}$ or C_{mt}^2 or C_{mt}^3

63: *Update* $Y_{\{t_2\}}\,or\ y_{\{t_2\}}$ or $Y_{\{t_3\}}or\ y_{\{t_3\}}$ or C_{mt}^2 or C_{mt}^3 replacing $arima\ p\ d\ q$ by $SARIMA\ p\ d\ q \times\ P\ D\ Q$

64: *End For al*

65: *End Else*

66: *End if*

67: *For* $p^{\Omega^-} = 0{,}2$; $p^{\delta^2} = 0{,}6$; $p^{\Omega^+} = 0{,}2$; $p^{w^{-\Omega^-}} = 0{,}03$; $p^{w^{-\delta^3}} = 0{,}07$; $p^{w^{-\Omega^+}} = 0{,}1$; $p^{,\delta^3} = 0{,}6$; $p^{w^{\Omega^-}} = 0{,}1$; $p^{w^{\delta^3}} = 0{,}07$; $p^{w^{\Omega^+}} = 0{,}03$ *do*

68: (MV b) = model (MV 2)

69: S_2^*= solve (MV b)

70: $(E(rv^*); x_m^* + x_m^{*\Omega_j};\ x_m^* + x_m^{*\Omega_j} + x_m^{*\omega\theta}) =$

$$Solve\{Max\ rv = 10^3 \times \left[\sum_{m=1}^{M} c_m x_m + \sum_{j=1}^{3} \sum_{\Omega_j \in \Omega} p^{\Omega_j} \left(\sum_{m=1}^{M} c_m^{\Omega_j} x_m^{\Omega_j}\right) + \sum_{\theta=1}^{7} \sum_{\omega_\theta \in W} p^{\omega_\theta} \left(\sum_{m=1}^{M} c_m^{\omega_\theta} x_m^{\omega_\theta}\right)\right]; s.to: mean(y_t) \leq \sum_{m=1}^{M} x_m \leq mean(Y_t),$$

$$x_m \leq \left(mean(y_{mt})/(\sum_{t=1}^{\rho} y_t)\right) \sum_{m=1}^{M} x_m, mean\left(y_{\{t_2\}} + k\sigma_y\right) \leq \sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} \leq mean\left(Y_{\{t_2\}} + k\sigma_Y\right),\ x_m + x_m^{\Omega} \leq \left(mean(y_{mt})/ (\sum_{t=1}^{\rho} y_t)\right)(\sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega}), mean\left(y_{\{t_3\}} + k\sigma_y\right) \leq \sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} + \sum_{i=1}^{n} x_m^{W} \leq mean\left(Y_{\{t_3\}} + k\sigma_Y\right),\ x_m + x_m^{\Omega} + x_m^{W} \leq \left(mean(y_{mt})/(\sum_{t=1}^{\rho} y_t)\right)(\sum_{m=1}^{M} x_m + \sum_{m=1}^{M} x_m^{\Omega} + \sum_{m=1}^{M} x_m^{W}), x_m \geq 0, x_m^{\Omega^+} \geq 0, x_m^{\delta^2} \leq 0, x_m^{\Omega^-} \leq 0, x_m^{W^{\Omega^+}} \geq 0,\ x_m^{W^{\delta 3}} \geq 0,\ x_m^{W^{\Omega^-}} \geq 0,\ x_m^{\delta 3} \geq 0, x_m^{W^{-\Omega^+}} \leq 0,\ x_m^{W^{-\delta 3}} \leq 0,\ x_m^{W^{-\Omega^-}} \leq 0\}$$

71: $S_2^* = \{E(rv^*); x_m^*, x_m^* + x_m^{*\Omega_j}; x_m^* + x_m^{*\Omega_j} + x_m^{*\omega_\theta}\}$
72: *If* $0 < [E(rv^*)/rv] \leq 1$ *Then*
73: No new job to generate
74: *Else*
75: $E(x^*) = N \times E(rv^*)/RV - E(n^*)$
76: *For* $i = 1$ *to* α *do*
77: $E(n_i^*) = n_i \times E(x^*)/N$
78: *End For*
79: *End Else*
80: *End If*
81: *End For*
82: *End For*
83: *End*

5. Results and Discussion

5.1. Algorithm Stochastic Model Results

For the period 2016 to 2050, the optimal sales revenues for Crustaceans would be and could be those presented in Table 4.

***Table 4**. Results of the stochastic optimization model.*

n	Cod	Expected annual optimum values in tons from 2025 to 2050										
		Stage 1	Stage 2			Stage 3						
		Value in Tons	Pessimistic scenario	Current scenario	Optimistic scenario	Weak pessimistic scenario	Moderate pessimistic scenario	Strong pessimistic scenario	Current scenario	Weak optimistic scenario	Moderate optimistic scenario	Strong optimistic scenario
Striped grant	$E(x_1^*)$	1,354.3	1,119.5	1,314.9	1.406,6	884.7	1.119,5	1,119.5	1,379.9	1,471.6	1,437.8	1,681
Shrimp	$E(x_2^*)$	363.1	300.2	352.6	363,1	237.3	300.2	300.2	369.9	394.6	683.4	457.5
Crab	$E(x_3^*)$	1,027.9	847.3	1,025	1.096,6	669.6	847.3	847.3	1,044.5	1,113.9	1,096.6	1,196
Prawns	$E(x_4^*)$	462.8	382.6	419.5	462,8	302.4	382.6	382.6	471.6	502.9	543	583.1
Lobster	$E(x_5^*)$	96.3	82	96.3	103.1	64.8	82	82	101.1	107.8	116.4	118.3
Total tons to be sold		3,304.4	2,731.6	3,208.3	3,432.1	2,158.8	2,731.6	2,731.6	3,367	3,590.8	3,877.2	4,035.9
Expected optimal revenues (in Kz)		6,241,47 5,435.81		6,241,167,980.26					6,248,591,019.02			
							6,248,283,563.47					

Source: Values obtained by author with the use of software CPLEX 2.0.

The three-stage, 10-scenario stochastic model, with three scenarios in the second stage and seven in the third, provides optimal global expected revenues of 6,248,283,563.47 kz, against 556,859,380,427.6 Kz of current situation. To achieve this important results, and reaching 259 jobs per year it shall be necessary to make the policies update end improve significant effort to correspond with the following annual results:

For the initial stage, the optimal annual sales results would be 1,354.3 tons of Striped grant, 363.1 tons of Shrimp, 1,027.9 tons of Crab, 462.8 tons of Prawns, and 96.3 tons of Lobster. At that stage, total sales would be 3,304.4 tons of crustaceans and would generate optimal revenues of 6,241,475,435.81 kz.

In the second stage, with three scenarios, the expected optimal revenues are 6,241,167,980.26 kz, with expected optimal annual sales for the pessimistic scenario of 1,119.5 tons of Striped grant, 300.2 tons of Shrimp, 847.3 tons of Crab, 382.6 tons of Prawns, and 82 tons of Lobster, totaling 2,731.6 tons of crustaceans. For the current scenario, sales are expected to be 1,119.5 tons of Striped grant, 352.6 tons of Shrimp, 1,025 tons of Crab, 419.5 tons of Prawns, and 82 tons of Lobster, totaling 2,731.6 tons of crustaceans. For the optimistic scenario, it is expected to sell 1,406.6 tons of Striped grant, 363.1 tons of Shrimp, 1,096.6 tons of Crab, 462.8 tons of Prawns, and 103.1 tons of Lobster, totaling 3,432.1 tons of crustaceans.

In the third stage, with seven scenarios, the expected optimal revenues are 6,248,591,019.02 kz, with expected optimal annual sales for the weak pessimistic scenario of 884.7 tons of Striped grant, 237.3 tons of Shrimp, 669.6 tons of Crab, 302.4 tons of Prawns, and 64.8 tons of Lobster, totaling 2,158.8 tons of crustaceans. For the moderate pessimistic scenario, sales are expected to be 1,119.5 tons of Striped grant, 300.2 tons of Shrimp, 847.3 tons of Crab, 382.6 tons of Prawns, and 82 tons of Lobster, totaling 2,731.6 tons of crustaceans. For the strong pessimistic scenario, the same, it is expected to sell 1,119.5 tons of Striped grant, 300.2 tons of Shrimp, 847.3 tons of Crab, 382.6 tons of Prawns, and 82 tons of Lobster, totaling 2,731.6 tons of crustaceans. For the current scenario, it is expected to sell 1,379.9 tons of Striped grant, 369.9 tons of Shrimp, 1,044.5 tons of crab, 471.6 tons of prawns, and 101.1 tons of lobster, totaling 3,367 tons of crustaceans. For the weak optimistic scenario, it is expected to sell 1,471.6 tons of Striped grant, 394.6 tons of shrimp, 1,113.9 tons of crab, 502.9 tons of prawns, and 107.8 tons of lobster, totaling 3,590.8 tons of crustaceans. For the moderate optimistic scenario, it is expected to sell 1,437.8 tons of Striped grant, 683.4 tons of shrimp, 1,096.6 tons of crab, 543 tons of prawns, and 116.4 tons of lobster, totaling 3,877.2 tons of crustaceans. For the strong optimistic scenario, it is expected to sell 1,681 tons of Striped grant, 457.5 tons of Shrimp, 1,196 tons of Crab, 583.1 tons of Prawns, and 118.3 tons of Lobster, totaling 4,035.9 tons of crustaceans.

5.2. Model Validation Comparing with 2016 Data

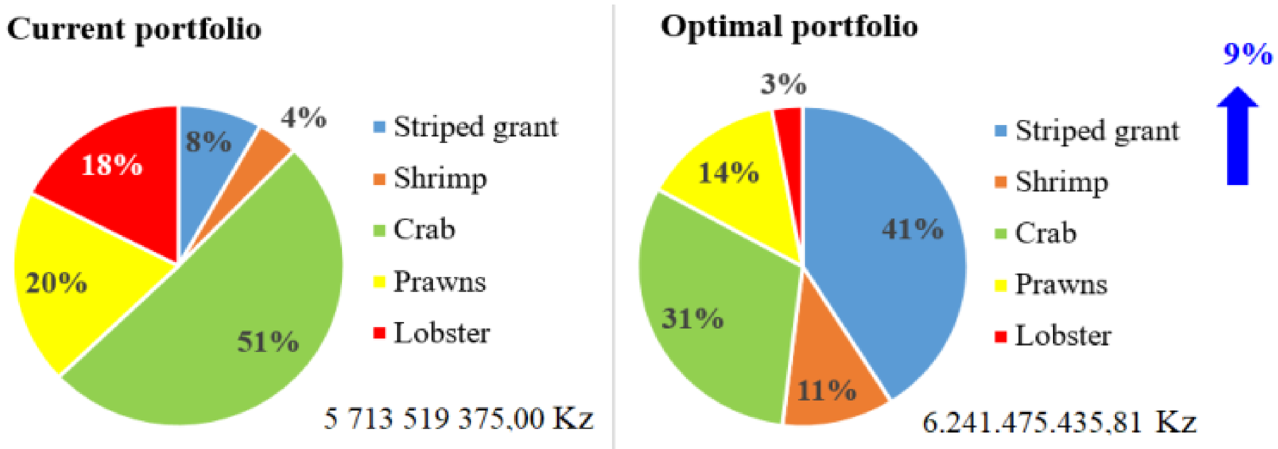
In 2016-2024, availability totaled 3,304.4 tons of crustaceans yearly, leaving demand at 2,982.7. Therefore, substituting data into the optimization model yields the comparative results as can be observed in the Table 5:

Table 5. *Comparison between current and optimal results.*

Cod		Optimal	Observed	Increment
Striped grant	x_{12}	1,354.3	244.8	
Shrimp	x_{12}	363.12	121.55	
Crab	x_{12}	1,025	1,508.75	
Prawn	x_{12}	462.8	584.8	
Lobster	x_{12}	99.2	522.75	
TOTAL TONES		3,304.4	2,982.65	
TOTAL SELS INCOME		6.241.475.435,81 Kz	5 713 519 375,00 Kz	9%

Source: Values obtained by author with the use of Ms-Excel and software CPLEX 2.0

The sales portfolio should undergo transformations from the current state to the optimal state, as shown in the graphs in Figure 8:



Source: Values obtained by author with the use of Ms-Excel

Figure 8. *Sales portfolio with and without the model 2016-2024.*

6. Generation of New Jobs in the Crustacean Business

With RV = 246,617,594,646.47 Kz the fishing sector employs N = 113,368 workers and by the simple rule of three $E(rv^*)$ = 6,248,283,563.47 Kz with crustaceans, generating $E(n^*) + E(x^*)$ = 2,873 workers, from which the increase $E(x^*)$ = 259 new jobs per year is deduced, corresponding to 9% of the valid increase. Considering the observed employability data and using the formulas (15) and (16), $E(x^*) = N \times E(rv^*)/RV - E(n^*)$ and $E(n_i^*) = n_i \times E(x^*)/N$, where:

N = Total annual jobs generated by the fishing sector in the current scenario;

RV = General revenues observed by the sector in the current scenario;

$E(rv^*)$ = Optimal revenues expected from shellfish sales;

$E(n^*) + E(x^*)$ = Current number of jobs generated with optimal shellfish sales revenue;

$E(x^*)$ = Incremental number of new jobs generated with optimal shellfish sales revenue;

$E(n^*)$ = Optimal number of jobs that should be generated with optimal shellfish sales revenue;

n_i= Total number of existing employees in stratum i by type of activity;

The results in Table 6 are obtained bellow:

Table 6. *Stratification of new jobs by year in the crustacean business until 2050.*

	Industrial fishing	Semi-industrial fishing	Artisanal fishing		SUBTOTAL
			Maritime	River	
Fishermen	8	3	109	81	202
Processors	5	10	24	19	57
TOTAL	13	13	133	100	259

Source: Values obtained by author with the three simple rule based in current values of jobs in fishery sector

Table 7. *Annual expected optimal increment in tons from 2025 to 2050.*

		Stage 1	**Annual expected optimal increment in tons from 2025 to 2050**									
			Stage 2			**Stage 3**						
	Cod	**Value in Tons** x_m^*	**Pessimistic scenario** $x_m^{*\Omega^-}$	**Current scenario** $x_m^{*\delta^2}$	**Optimistic scenario** $x_m^{*\Omega^+}$	**Weak pessimistic scenario** $x_m^{\omega^{-*\Omega^-}}$	**Moderate pessimistic scenario** $x_{j+2\ i}^{\omega^{-*\delta^3}}$	**Strong pessimistic scenario** $x_m^{\omega^{-*\Omega^+}}$	**Current scenario** $x_m^{*\delta^3}$	**Weak optimistic scenario** $x_m^{\omega^{*\Omega^-}}$	**Moderate optimistic scenario** $x_m^{\omega^{*\delta^3}}$	**Strong optimistic scenario** $x_m^{\omega^{*\Omega^+}}$
Striped grant	x_1^*	1,354.3	-234.8	-39.4	52.3	-234.8	0	0	65	65	31.2	326.7
Shrimp	x_2^*	363.1	-62.9	-10.6	0	-62.9	0	0	17.4	31.5	320.3	94.4
Crab	x_3^*	1,027.9	-180.6	-2.8	68.7	-177.7	0	0	19.4	17.3	0	168.1
Prawns	x_4^*	462.8	-80.2	-43.3	0	-80.2	0	0	52.1	40.1	80.2	120.3
Lobster	x_5^*	96.3	-14.3	0	6.7	-17.2	0	0	4.8	4.8	13.4	22
INCRE-MEN-TOS TOTAIS		0	-572.8	-96.1	127.7	-572.8	0	0	158.7	158.7	445.1	731,5
RECEITAS ÓPTIMAS ANUAIS (Kz)		6,241,475,435.81		-307,455.55					7,115,583.21			
							6,248,283,563.47					

Source: Results of stochastic optimization model

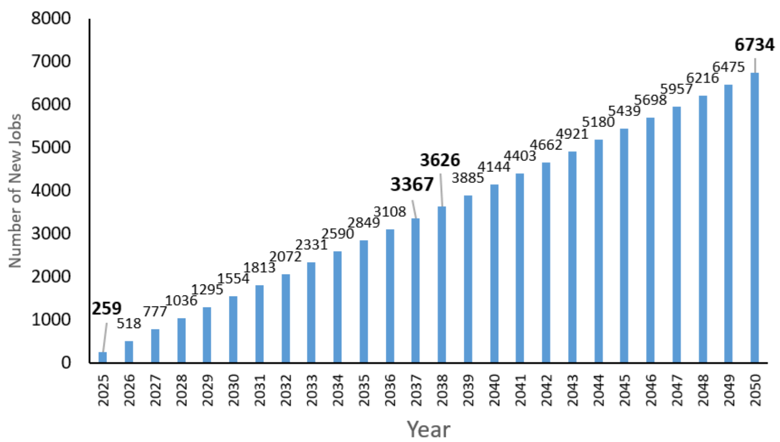
$RP = 6{,}241{,}475{,}435.81$ Kz; Recourse Problem solution

$WS_{j+1} = -307{,}455.55$ Kz; Wait and See for first and second stage

$WS_{j+2} = 7{,}115{,}583.21$ Kz; Wait and See for first and third stage

$EV = 6{,}248{,}283{,}563.47$ Kz; Expected Income

Artisanal fishing, especially offshore fishing, will continue to provide more jobs, particularly for fishermen. This reality should encourage the development of this group of workers and support from the government and banks to enable them to develop their activities.



Source: Plotted by the author using the cumulative function $f(x_{t+1}) = f(x_t) + 259$, where $t = 1, \ldots, 24$ and $f(x_1) = 259$.

Figure 9. *Cumulative function of the number of jobs until 2050 in the crustacean business.*

259 new jobs will be created in fishing each year. By the end of the second stage, in 2037 around 3,367 new jobs will have been created, and by the end of the third Stage, around 6,734 new jobs will have been created. These results are encouraging for employment policy and for shellfish traders in Angola.

7. Conclusion

The algorithm presented is a good tool for directing efforts in stages, which must be adhered to to achieve optimal results in terms of revenue and employment in the fishing sector. Despite the uncertainties and according to forecasts of current and future catch levels and demand, it is possible to affirm that the shellfish business is promising and can be part of the solution to the unemployment problem in Angola if algorithms with precise instructions are adopted that include stochastic forecasting and optimization models to generate optimal sales revenue and simultaneously create new jobs. The involvement of the population, business owners, the government, restaurants, and other customers in the shellfish business allows us to affirm that the fishing sector in Angola has and will have a significant impact on the national economy and employment. The presented algorithm can generate annual sales of 6.25 billion kwanzas and 259 new jobs in the crustacean business, accumulating 3,367 new jobs by 2037 and 6,734 new jobs by 2050. These results are encouraging for employment policy and for crustacean traders in Angola. Artisanal maritime fishing will continue to generate more jobs, particularly for fishermen. This reality should motivate the training of this group of workers and support from the government and banks to enable them to develop their activities. The presented algorithm consists of parameter forecasting, modeling, and stochastic optimization of sales revenue, and finally, the generation of new job numbers in the fishing sector.

Abbreviations

AVOPESCAS	Associação de Venda Organizada e Pescas
SCRL	Soiedade Comercial Retalista de Luanda

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Author Contributions

Alcides Romualdo Neto Simbo is the sole author. The author read and approved the final manuscript.

Conflicts of Interest

The author declare that no conflicts of interest related to this research.

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