Optimization of Energy Use in Pinto Bean Planting Systems: A Multi-Objective Genetic Algorithm Approach

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Abstract

Bean planting systems are essential to global agriculture, serving as a vital food source for many populations. Optimizing these planting methods is crucial for enhancing efficiency and reducing environmental impacts. This study evaluates the energy inputs and outputs associated with two pinto bean cultivation techniques: flat and strip systems. Conducted in Fars province, southern Iran, the research involved 90 farms, 60 employing flat systems and 30 utilizing strip systems. Energy consumption was assessed in MJ ha^{-1} for various inputs, including labor, machinery, diesel, chemical fertilizers, biocides, electricity, and seeds. The flat system exhibited energy consumption of 20,067.12 MJ ha^{-1}, while the strip system utilized 18,171.76 MJ ha^{-1}. In terms of yield, the flat system produced 3000 kg ha^{-1}, in comparison to 3500 kg ha^{-1} from the strip system. Energy efficiency metrics indicated that the strip system outperformed the flat system with a higher energy use efficiency ratio (3.85 against 2.99) and better energy productivity (0.19 kg MJ^{-1} vs. 0.15 kg MJ^{-1}). Additionally, the strip system demonstrated lower specific energy consumption at 5.19 MJ kg^{-1}, compared to 6.69 MJ kg^{-1} for the flat system. The net energy gain was also greater for the strip system, recording 51,828.24 MJ ha^{-1} versus 39,932.88 MJ ha^{-1} for the flat system. Overall, the results highlight the favorable energy requirements and efficiency of the strip planting method over the traditional flat system, underscoring its potential for optimized resource allocation in pinto bean cultivation. The MOGA results indicated that strip systems achieve substantial energy savings of 3749.11 MJ ha^{-1} (25.99%), compared to flat systems, which save 3707.62 MJ ha^{-1} (22.66%). This further highlights the efficiency benefits of strip planting.

Keywords: Bean planting systems, Energy consumption, Energy use efficiency, Multi-objective genetic algorithm

Introduction

Energy efficiency is increasingly acknowledged as a vital element of sustainable agricultural practices, particularly within crop production systems (Noorani *et al.,* 2023). This concept focuses on reducing energy consumption while either maintaining or enhancing productivity (Jamali *et al.,* 2021). Strategies to achieve this include the adoption of energy-efficient technologies, optimization of resource utilization, and improvement of operational methods (Amoozad-Khalili *et al.,* 2021). Energy efficiency's importance transcends mere cost savings; it is essential in mitigating greenhouse gas emissions and tackling challenges posed by climate change in agriculture. Given that agriculture significantly contributes to energy consumption and environmental degradation, optimizing energy use within these systems is crucial for promoting sustainability and minimizing the ecological footprint of the sector (Kaab *et al.,* 2023).

Pinto beans, scientifically known as *Phaseolus vulgaris*, are a widely cultivated variety of bean found in many regions around the globe (Fonseca Hernández *et al.,* 2023). Cultivating pinto beans involves several essential steps. First, soil preparation is critical, as these beans flourish in well-drained soil with a pH level ranging from 6.0 to 7.0. The soil should be rich in organic matter and nutrients, so it is important to till the soil and remove any weeds or debris prior to planting (Abad-González *et al.*, 2024). Next, planting typically occurs in the spring, following the last frost. Seeds can either be sown directly into the soil or started indoors and transplanted later. When planting, the seeds should be placed about 1-2 inches deep and spaced 2-4 inches apart in rows that are 18-24 inches apart (Bordonal *et al.*, 2018). Watering is another crucial aspect, as pinto beans require consistent moisture, particularly during dry spells. Care must be taken to avoid overwatering, which can cause root rot. It is best to water at the base of the plants to keep the foliage dry, as wet leaves can encourage disease. Fertilizing also plays a role in the successful growth of pinto beans. These plants are nitrogen-fixing, meaning they can utilize nitrogen from the air, but they may still benefit from an application of balanced fertilizer during the growing season (Heusala *et al.*, 2020). Weeding the area around pinto bean plants is important to prevent competition for nutrients and water. Regularly removing weeds by hand or using a hoe can help maintain a healthy growing environment without harming the plants. Harvesting usually occurs 90-120 days after planting, depending on the specific variety and environmental conditions (Mawof *et al.*, 2022). The beans are ready for harvest when the pods are plump and filled out, though not yet dried. To harvest, pull up the entire plant and remove the pods. Finally, once harvested, pinto beans must be dried thoroughly before storage. It's recommended to spread the beans in a single layer in a warm, dry area for 1-2 weeks until they are completely dry. For optimal preservation, store the dried beans in a cool, dark place in airtight containers (Altieri *et al.*, 2012).

Pinto beans, a staple food source for numerous communities globally, exemplify the challenges associated with conventional agricultural practices (Fonseca Hernández *et al.*, 2023). Traditional planting and harvesting methods for pinto beans typically incur high energy consumption and considerable environmental consequences. To combat these issues, researchers are increasingly employing advanced optimization techniques, such as multi-objective genetic algorithms (MOGA), to enhance the efficiency and sustainability of pinto bean production systems (Aghili Nategh *et al.*, 2021; Kaab *et al.*, 2019; Pourreza Movahed *et al.*, 2020). MOGA facilitates the simultaneous assessment of multiple objectives, including maximizing energy efficiency, minimizing greenhouse gas emissions, and optimizing economic returns, ultimately guiding the discovery of the most effective agricultural practices (Fathollahi-Fard *et al.*, 2023). In recent years, multi-objective optimization techniques have emerged as valuable tools for navigating the complex trade-offs inherent in agricultural systems. Genetic algorithms (GAs), modeled on the principles of natural selection, have proven effective for addressing optimization problems by exploring multiple solutions concurrently (Rahman & Szabó, 2021). By utilizing a MOGA framework to assess energy use in pinto bean planting systems, researchers can evaluate various factors, including yield enhancement, cost-effectiveness, and environmental impact reduction. This study delves into the use of MOGA in optimizing pinto bean planting systems, emphasizing the delicate balance between competing objectives intrinsic to agricultural production (Nategh *et al.*, 2021). By generating and iteratively refining a diverse array of potential solutions inspired by natural selection, MOGA aims to pinpoint optimal strategies that enhance energy use while diminishing environmental impact. This methodology not only underscores the trade-offs among various objectives but also provides a framework for developing sustainable farming practices that can adapt to the evolving challenges of climate change and resource scarcity (Pourreza Movahed *et al.*, 2020). One paper addresses low agricultural production efficiency by studying multi-objective optimization of sustainable agricultural structures using genetic algorithms. It reviews agricultural development, the status of optimization algorithms, and establishes a model for optimal industrial allocation. The improved genetic algorithm enhances both the economic value and sustainability of the agricultural structure (Zhou & Fan, 2018). The quest for energy optimization in pinto bean planting systems through a multi-objective genetic algorithm presents a promising pathway toward bolstering agricultural sustainability. By integrating advanced optimization techniques into farming practices, this research aspires to offer insightful contributions to sustainable agriculture and practical recommendations for improving energy efficiency in bean production systems. Growing concerns regarding sustainable agricultural practices have underscored the need to optimize energy use across various cropping systems (Rahman & Szabó, 2021). As a vital legume in numerous diets and a key crop in diverse agricultural settings, pinto beans serve as a crucial case study for investigating energy efficiency in planting systems. Traditional farming practices often result in significant energy consumption, driven by machinery usage, fertilizer applications, and irrigation techniques, which can exacerbate environmental challenges and diminish overall sustainability (Boix-Cots *et al.*, 2022). Energy consumption and its environmental impacts have become significant concerns in recent centuries. Agriculture, as both an energy user and bioenergy supplier, is crucial for global economics and food security. Research in developing countries shows inefficiencies in energy flow in crop production. To address this, MOGAs were used to optimize agricultural inputs, minimizing greenhouse gas (GHG) emissions while maximizing energy output and benefit-cost ratios. Results indicated a potential 28% reduction in energy use and a 33% decrease in GHG emissions in watermelon production, with a significant increase in the benefit-cost ratio (Shamshirband *et al.*, 2015).

Optimizing energy use in pinto bean planting systems is a key advancement in sustainable agriculture, balancing productivity and environmental impact. A MOGA addresses trade-offs between yield, energy consumption, and costs by simulating natural selection. Solutions are refined through selection, crossover, and mutation, identifying strategies that harmonize energy efficiency with economic viability. This adaptable approach integrates with precision farming and eco-friendly practices, enhancing sustainability and resource management. Ultimately, applying this algorithm can transform farming, promoting economic and environmental sustainability, contributing to food security, and addressing challenges like climate change.

This study seeks to harness MOGA to develop optimized planting strategies that lower energy consumption while maximizing agricultural outputs. By pinpointing best practices customized for the specific conditions of pinto bean cultivation, this research not only aims to enhance productivity but also supports the broader movement toward sustainable agriculture. The findings from this work are expected to extend beyond pinto beans, offering valuable insights applicable to other crops and farming systems facing similar sustainability challenges.

Materials and Methods

Background information about the studied region

The research was conducted in Fars province, located in southern Iran, spanning latitudes from $27^\circ\ 2'$ to $31^\circ\ 42'$ and longitudes from $50^\circ\ 42'$ to $55^\circ\ 36'$, with an area of 133,299 km^2 characterized by an arid and semi-arid climate (Ministry of Jihad-e-Agriculture of Iran, 2024). The location of the case study is illustrated in Figure 1.

Fig. 1. The area of study in Fars province, Iran

The study involved 90 farms, comprising 60 that utilized flat cultivating systems and 30 that employed strip cultivating systems. A random survey was conducted with pinto bean producers to collect data on various agricultural input parameters, including seed quantities, fertilizer use, biocide application, energy sources, equipment and machinery, cultivated land areas, and Pinto bean yields. The sample size was determined using the method outlined in Eq. (1) (Cochran, 1977), and data collection was performed through in-person interviews.

$$\boldsymbol{n} = \frac{\frac{z^2pq}{d^2}}{1 + \frac{1}{N}(\frac{z^2pq}{d^2} - 1)} \quad (1)$$

The sample size (n) needed is calculated using the number of farms in the target population (N), a reliability coefficient (z) of 1.96 for a 95% confidence level, an estimated population attribute proportion (p) of 0.5, the complement of the estimated proportion (q) also at 0.5, and an allowable error deviation from the average population (d) of 0.05.

Energy use analysis

Energy analysis involves evaluating and assessing the energy consumption and efficiency of systems, buildings, or processes (Ghasemi-Mobtaker, Kaab, & Rafiee, 2020). This process includes gathering data on energy usage, pinpointing areas of waste, and formulating strategies to reduce consumption and enhance efficiency. Energy analysis can be applied across various sectors, such as residential, commercial, industrial, and transportation (Kaab *et al.*, 2019). It enables organizations and individuals to comprehend their energy usage patterns, identify potential savings, and make informed choices regarding energy conservation. Common methodologies in energy analysis include energy audits and energy modeling (Ghasemi-Mobtaker, Kaab, Rafiee, & Nabavi-Pelesaraei, 2022). These tools facilitate the quantification of energy consumption and identification of energy-saving opportunities. Ultimately, energy analysis is vital for promoting energy efficiency, decreasing greenhouse gas emissions, and meeting sustainability targets. It supports informed decision-making, propels energy conservation initiatives, and contributes to a more sustainable and resilient energy future. The energy equivalent of each input is outlined in Table 1.

Table 1- Conversion factors of energy inputs and outputs in the production of pinto bean

Item	Unit	Energy equivalent (MJ unit^{-1})	Reference
A. Input			
1. Human labor	h	1.96	(Mohammadi & Omid, 2010)
2. Machinery	kg yr^{-1a}	62.70	(Kaab, Khanali, Shadamanfar, & Jalalvand, 2024)
3. Diesel fuel	L	56.31	(Ghasemi-Mobtaker, Akram, & Keyhani, 2012)
4. Chemical fertilizers	kg		
(a) Nitrogen		78.10	(Hosseinzadeh-Bandbafha, Safarzadeh, Ahmadi, Nabavi-Pelesaraei, & Hosseinzadeh-Bandbafha, 2017)
(b) Phosphate		17.40	(Zangina, Suleiman, & Ahmed, 2023)
(c) Potassium		13.70	(Ramedani *et al.*, 2019)
5. Biocides	kg	250.00	(Khosruzzaman, Asgar, Karim, & Akbar, 2010)
7. Electricity	kWh	12.00	(Mandal *et al.*, 2015)
8. Seed	kg	20.00	(Boydston *et al.*, 2018)
B. Output			
1. Pinto bean	kg	20.00	(Boydston *et al.*, 2018)

[a] the economic life of machine (year)

Energy indicators refer to the metrics used to evaluate and monitor energy consumption, efficiency, and performance. These indicators offer meaningful insights into energy usage trends, highlight opportunities for improvement, and guide decisions aimed at optimizing energy use and minimizing costs (Hassan Ghasemi-Mobtaker *et al.*, 2024). Common energy indicators encompass energy intensity, energy efficiency ratios, energy consumption per production unit, and energy cost per output unit. Some of these indicators are outlined in equations (2) to (5). Businesses, industries, and governments can leverage these indicators to oversee and enhance their energy usage and sustainability initiatives.

$$\text{Energy use efficiency} = \frac{\text{Output energy (MJ)}}{\text{Input energy (MJ)}} \tag{2}$$

$$\text{Energy productivity} = \frac{\text{Production (kg)}}{\text{Input energy (MJ)}} \tag{3}$$

$$\text{Specific energy} = \frac{\text{Input energy (MJ)}}{\text{Production (kg)}} \tag{4}$$

$$\text{Net energy} = \text{Output energy (MJ)} - \text{Input energy (MJ)} \tag{5}$$

MOGA analysis

MOGA comprises multi criteria decision-making units (DMUs) that are associated with mathematical optimization problems when more than one objective function is to be quickly optimized. Multi-objective optimization (MOO) has been used in many fields, including preparation, economics, and engineering, where optimal decisions are entailed to be derived in the presence of compensation among multiple inconsistent objectives. Typical examples of MOO problems include maximizing tranquility while minimizing costs in purchasing a car, and minimizing emission of pollutants and fuel use while simultaneously maximizing vehicle performance, etc. There can be three or even more objectives in actual problems (Abidi *et al.*, 2018).

For a typical MOO problem, there cannot exist a solitary resolution that is able to optimize every objective. Instead, there exist unlimited numbers of Pareto optimal solutions, which are all considered good solutions. As such, the objectives are to determine a set of Pareto optimal solutions, or quantify trade-offs in fulfilling various aims, or assign a solitary resolution that can fulfil largely intrinsic priorities of a decision maker (DM) (Hu *et al.*, 2017).

An MOO problem is an optimization problem involving multi-objective functions. A typical MOO problem is expressed mathematically as Eq. (6):

$$\min(f_1(x), f_2(x), \ldots, f_k(x)) \quad s.t. x \in X \tag{6}$$

where the set X signifies the possible set of determination directions and the integer $k \geq 2$ denotes the number of aims. The possible set usually comprises some constraint functions. Furthermore, the objective function vector is expressed as Eq. (7):

$$f : X \to \Re^k,\ f(x) = (f_1(x),..., f_k(x))^T \quad (7)$$

where x signifies a possible solution and $f(x) \in \Re$ denotes the compatibility of the possible solution. Pareto optimal solutions provide a way to solve this limitation. In real-world cases, the dissolutions that are not overmatched by other dissolutions across the entire search area constitute the collection of Pareto optimal solutions. The underlying significance is that these dissolutions cannot be altered for each purpose without inevitably compromising at least one of the other objectives (Konak *et al.*, 2006).

This study presents a technique used in MOGA to address these contradictory objectives simultaneously when solving MOO problems. GA usually functions by a set of chromosomes, which is named the population. The population is usually initialized randomly. As the calculation progresses, the population includes fitter and fitter solutions, and eventually it converges towards a solitary dissolution. GA employs two factors to produce new dissolutions from existing ones, crossover and mutation. During crossover operation, the chromosomes are re-composed to generate new chromosomes, resulting in viable offspring. In selecting chromosomes from the population, parents prioritize those that exhibit a higher compatibility function. Using a repetitious crossover operator, a good chromosome gene is expected to be more visible in the population and eventually converge to a single solution. The mutation operator furnishes a random transformation to the characteristics of the chromosome. In a generic GA, the mutation ratio is usually low. Whilst the crossover operation attempts to guide towards a convergent population with similar chromosomes in the population, the mutation operation again enters the genetic diversity of the population and helps to escape from local optimum. The proliferation comprises selection of chromosomes for the subsequent generation. Different fitness functions in GA include proportionate choices, grading, and competition, etc. (Deb *et al.*, 2003). GA is considered one of the best customary artificial intelligence (AI) methods owing to its robustness (Taghdisian *et al.*, 2015). Older systems of AI usually reverse, even if the outputs are only altered to a slight extent (Habibi-Yangjeh *et al.*, 2009). Moreover, when it comes to operating an exceptional conditional space, multimodal conditional space GA offers considerable advantages compared to other popular optimization techniques (Arthur *et al.*, 2016).

Given its population-based methodology, GA is well suited to solve MOO problems. A single-objective GA can be configured to deliver a set of multiple solutions in a single step. The capability of GA to probe different regions of a dissolution space presents it feasible to determine various sets of dissolutions for hard difficulties by multimodal, interchangeable, and non-convex dissolutions spaces. The crossover manager of GA is able to extract accurate solutions to various objectives, identifying new solutions in unexplored sectors of the Pareto front. As such, GA has been one of the most popular heuristic method to solve MOO problems (Mousavi-Avval *et al.*, 2017).

In this study, MOGA is employed for MOO in pinto bean production with two objectives comprising: (1) Minimizing energy consumption, (2) Maximizing the performance of pinto bean farms. The aim function is demonstrated as follows:

$$F_{\max/\min} = \sum_{i=1}^{j} C_i X_i + e_i \quad (8)$$

where C_i denotes model coefficient, X_i denotes variable inputs, and $F_{max/min}$ signifies the objective function to be minimized or maximized. When tackling an optimization problem, the MATLAB workbox solely permits the minimization of the target goal function. Therefore, for a maximized objective function, it must be multiplied by (-1).

Results and Discussion

Energy use analysis

Table 2 illustrates the energy inputs and outputs associated with two different planting systems used in pinto bean production: Flat and Strip. It outlines various energy inputs for each system, including human labor, machinery, diesel fuel, chemical fertilizers (nitrogen, phosphate, and potassium), biocides, electricity, and seeds. The energy consumption for these inputs is expressed in MJ ha^{-1} for both systems. For the flat planting system, the total energy usage amounts to 20,067.12 MJ ha^{-1}, whereas the strip system records a total of 18,171.76 MJ ha^{-1}. Additionally, the table presents the production yields in kilograms for each system: the Flat system yields 3000 kg (equivalent to 60,000 kg ha^{-1}), while the strip system yields 3500 kg (or 70,000 kg ha^{-1}). This information sheds light on the energy efficiency and productivity of the two planting approaches, enabling stakeholders to make informed decisions regarding resource allocation and productivity in pinto bean farming. Figure 2 illustrates the distribution of energy sources used in different planting systems for pinto bean production. This depiction likely highlights the various energy inputs involved in cultivating pinto beans across multiple agricultural methods. These inputs may encompass human labor, machinery, fertilizers, pesticides, water, electricity, and other necessary resources for bean cultivation. By examining this distribution, researchers and farmers can evaluate the energy efficiency and sustainability of the various planting systems employed in pinto bean production. Efficient energy use in crop production can reduce greenhouse gas emissions (GHG) and promote sustainable agriculture. The study utilizes a MOGA to optimize energy inputs and reduce GHG emissions in wetland rice production in Malaysia. The findings indicated that farmers are using 37.8% more energy than needed for transplanting and 40% more for broadcast seeding. By implementing MOGA, GHG emissions could be decreased by 95.89 kg CO_2eq ha^{-1} for transplanting and by 236.13 kg CO_2eq ha^{-1} for broadcast seeding. Notably, even with reduced energy inputs, crop yields remained robust at 9.4 tonnes ha^{-1} and 9.2 tonnes ha^{-1}, respectively (Elsoragaby *et al.*, 2020).

Table 2- Energy inputs and outputs of different planting systems production of pinto bean

Item	Planting system			
	Flat land		Strip	
	Unit per ha	Energy use (MJ ha^{-1})	Unit per ha	Energy use (MJ ha^{-1})
1. Human labor (h)	350.00	686.00	300.00	588.00
2. Machinery (kg)	26.00	1630.20	35.00	2194.50
3. Diesel fuel (L)	32.00	1801.92	46.00	2590.26
4. Chemical fertilizers (kg)				
(a) Nitrogen	150.00	11715.00	150.00	9372.00
(b) Phosphate (P_2O_5)	50.00	870.00	40.00	696.00
(c) Potassium	20.00	274.00	20.00	274.00
5. Biocides (kg)	3.00	750.00	2.50	625.00
6. Electricity (kwh)	45.00	540.00	36.00	432.00
8. Seed (kg)	90.00	1800.00	70.00	1400.00
Total energy use (MJ)	**-**	**20067.12**		**18171.76**
B. Output (kg)				
1. Flat	3000.00	60000.00	-	-
1. Strip	-	-	3500.00	70000.00

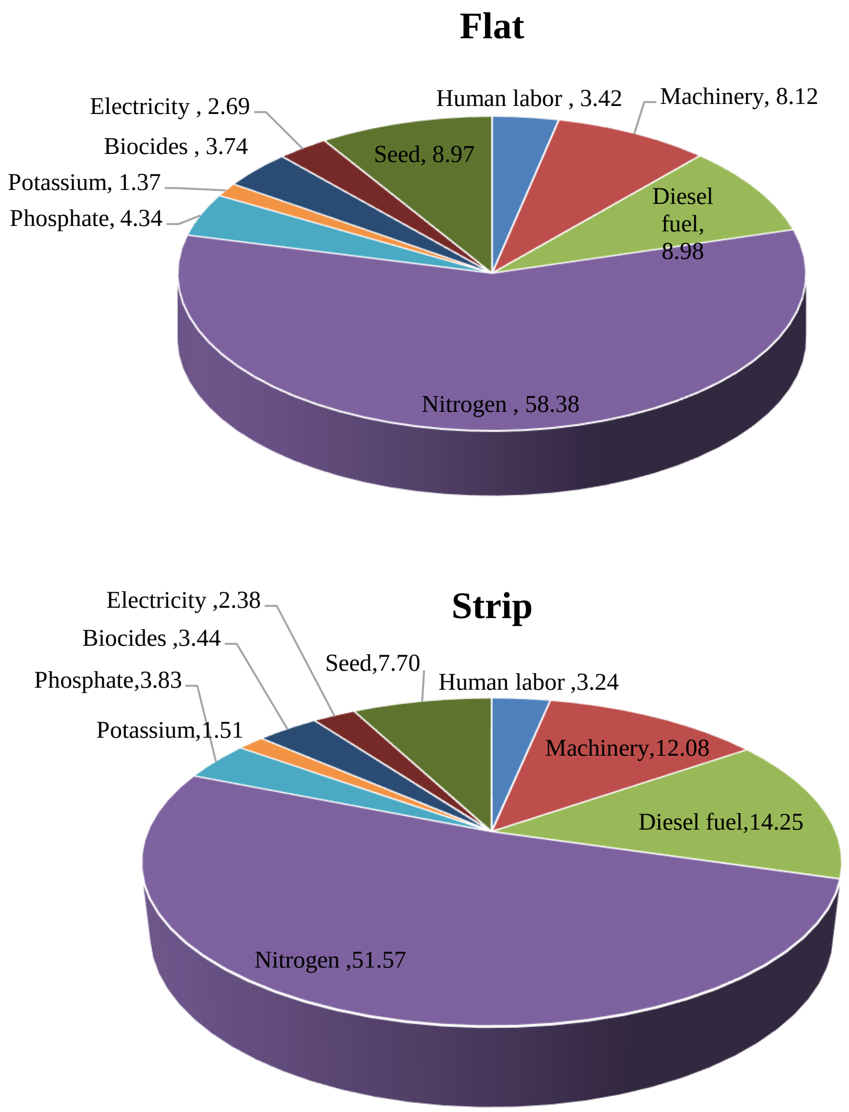

Fig. 2. Distribution of energy sources for the production of pinto beans in flat and strip planting systems

The information presented in Table 3 offers a comparative analysis of energy-related metrics for pinto bean production under two different planting systems: flat and strip. Firstly, the strip system exhibits a significantly higher energy use efficiency of 3.85, in contrast to the flat system's 2.99. This ratio reflects how effectively energy inputs are utilized during production. Secondly, when examining energy productivity, the strip system again outperforms the flat system with values of 0.19 kg MJ^{-1} versus 0.15 kg MJ^{-1}. This indicates greater output relative to energy consumption in the strip system. In terms of specific energy, the strip system shows an advantage with a lower value of 5.19 MJ kg^{-1} compared to 6.69 MJ kg^{-1} for the flat system, revealing that it requires less energy for production. Furthermore, the net energy gain is significantly higher in the strip system, reaching 51,828.24 MJ ha^{-1}, compared to 39,932.88 MJ ha^{-1} in the flat system. This metric illustrates the overall energy balance and productivity per unit area. In summary, the data indicates that the strip planting system demonstrates superior performance regarding energy efficiency, productivity, and net energy gain when compared to the flat planting system for pinto bean production. One study compared energy consumption in sugarcane production at Salman Farsi Sugarcane Agro-Industrial Company, Iran, highlighting that plant cane requires more energy than ratoon cycles but is less efficient. Recommendations included optimizing machinery use and irrigation. The research also assessed health impacts, species loss, and cost differences, advocating for improved sustainability practices (Behnia *et al.*, 2025).

Table 3- Different energy indices for the different planting systems of pinto bean production

Energy indices (unit)	Planting system	
	Flat	**Strip**
Energy use efficiency (ratio)	2.99	3.85
Energy productivity (kg MJ^{-1})	0.15	0.19
Specific energy (MJ kg^{-1})	6.69	5.19
Net energy gain (MJ ha^{-1})	39932.88	51828.24

Optimization results

MOGA is a sophisticated method for addressing multi-criteria decision-making units (DMUs) within mathematical optimization frameworks, particularly when involving the simultaneous optimization of multiple objective functions. In many real-world scenarios, such as in engineering and economics, MOO is crucial for making optimal decisions when faced with conflicting objectives. For instance, in purchasing a vehicle, one may aim to maximize comfort while minimizing costs. Typical MOO problems often yield a multitude of Pareto optimal solutions, which represent trade-offs between the different objectives, rather than a sole optimal solution. A fundamental characteristic of MOO problems is that no single solution can achieve perfection for every objective. Instead, one seeks to identify a set of Pareto optimal solutions or to quantify trade-offs that fulfill various objectives. Mathematically, an MOO problem is represented as an optimization problem involving multiple objective functions, typically expressed through specific equations where the solution set is subject to various constraints.

In this context, MOGA is employed to handle conflicting objectives effectively. The algorithm operates on a population of potential solutions, represented as chromosomes. This population is initially generated randomly, and through successive iterations, the algorithm refines the solutions, guiding them towards more optimal states. Essential to this process are two genetic operators: crossover and mutation. Crossover allows for the recombination of existing chromosomes to produce offspring solutions, while mutation introduces random alterations, promoting diversity and assisting in escaping local optima. GA's selection mechanisms, including proportionate selection and tournament selection, drive the reproductive process, allowing fitter chromosomes to propagate through generations. This adaptability makes GA a robust method for solving complex optimization problems, especially in multi-modal landscapes typical of MOO. This study utilizes MOGA to optimize pinto bean production with the dual objectives of minimizing energy input and maximizing farm performance. The objective functions incorporated in the analysis consider various inputs and their associated energy requirements. The results in Table 4 indicate that the strip planting method outperforms the flat planting method in terms of energy efficiency across several input categories. For instance, in human labor energy requirements, strip systems require 470.23 MJ ha^{-1}, leading to a 25.05% energy saving compared to 547.15 MJ ha^{-1} for flat systems. Similarly, for machinery, strip systems demand more overall energy but achieve significant savings in other input categories, such as nitrogen and phosphate, where they show lower energy requirements and higher percentage savings. The total energy inputs and savings reinforce the finding that strip planting consistently offers lower energy demands and better energy-saving benefits than flat systems, highlighting its efficacy in pinto bean production.

One study utilized a MOGA to optimize mixing energy, economic, and environmental indices in canola production. Data were gathered from oilseed farms in Mazandaran, Iran. A life cycle assessment evaluated environmental emissions, while econometric modeling identified relationships among energy inputs and three outputs: emissions, energy output, and productivity. The MOGA model aimed to maximize output energy and benefit-cost ratio, while minimizing emissions. Results showed a 32.1% reduction in emissions, with increases of 24.1% in output energy and 14.2% in benefit-cost ratio. Reductions in chemical use further benefited environmental, energy, and economic aspects (Mousavi-Avval *et al.*, 2017). Energy consumption and environmental damage from agriculture have increased in recent centuries. A study used life cycle assessment to evaluate the impacts of chickpea production, employing data envelopment analysis and MOGA techniques. Data from 110 enterprises during the 2014-2015 season revealed that MOGA significantly reduced energy requirements to 27,570.61 MJ ha^{-1}, a 17% decrease compared to DEA's 31,511.72 MJ ha^{-1}. MOGA also lowered environmental impacts, reducing acidification potential by 29% and global warming potential by 10%. Overall, MOGA outperformed DEA in optimizing energy use and minimizing environmental impacts (Elhami *et al.*, 2016).

Another study investigated biodiesel production from waste cooking palm oil containing 6% free fatty acids. The process involves both esterification and trans-esterification, which were simulated and optimized using Aspen Plus and Excel-based multi-objective optimization techniques. The findings indicate that this method is more efficient, reducing organic waste by 32% and decreasing heat duty requirements by 39%. Additionally, it is 1.6% more profitable (Patle *et al.*, 2014).

Table 4- Optimum energy requirement and saving energy of different planting systems of pinto bean production

Input	Optimum energy requirement (MJ ha^{-1})		Saving energy (MJ ha^{-1})		Saving energy (%)	
	Flat	Strip	Flat	Strip	Flat	Strip
1. Human labor	547.15	470.23	138.85	117.77	25.38	25.05
2. Machinery	1356.14	1872.65	274.06	321.85	20.21	17.19
3. Diesel fuel	1426.42	2145.35	375.5	444.91	26.32	20.74
4.Nitrogen	9546.23	7125.49	2168.77	2246.51	22.72	31.53
5.Phosphate	640.00	487.00	230.00	209.00	35.94	42.92
6.Potassium	210.56	210.56	63.44	63.44	30.13	30.13
7. Biocides	650.00	510.25	100.00	114.75	15.38	22.49
8. Electricity	410.00	326.54	130.00	105.46	31.71	32.30
9. Seed	1546.00	1274.58	254.00	125.42	16.43	9.84
Total energy input	**16359.50**	**14422.65**	**3707.62**	**3749.11**	**22.66**	**25.99**

Conclusion

The evaluation of pinto bean cultivation methods in Fars province, southern Iran, underscores the significant advantages of adopting the strip planting system over the traditional flat system. The comprehensive analysis of energy inputs and outputs demonstrates that the strip system not only consumes less energy—18,171.76 MJ ha^{-1} compared to the 20,067.12 MJ ha^{-1} required by the flat system—but also produces higher yields, with 3,500 kg ha^{-1} against the 3,000 kg ha^{-1} from the flat method. This translates into a more favorable energy efficiency ratio (3.85 versus 2.99) and enhanced energy productivity (0.19 kg MJ^{-1} compared to 0.15 kg MJ^{-1}), reflecting the efficacy of the strip system in optimizing resource allocation and reducing environmental impacts. Moreover, the net energy gain of the strip system, at 51,828.24 MJ ha^{-1}, surpasses that of the flat system, which records 39,932.88 MJ ha^{-1}. This substantial difference in energy performance illustrates the pressing need for transformation in agricultural practices, advocating for a shift that aligns with global sustainability goals in food production. The findings from this study not only highlight the economic viability of the strip planting method but also suggest profound implications for future agricultural practices as the sector faces mounting pressures to enhance efficiency and reduce carbon footprints. To realize the benefits of strip planting, it is essential to promote educational initiatives aimed at training farmers and agricultural workers in its principles. Enhanced understanding of the technique's advantages—including energy savings and improved yields—will empower farmers to adopt this innovative approach. Furthermore, supportive policy measures, such as grants and subsidies for sustainable agricultural practices, should be prioritized to encourage the transition towards more energy-efficient methodologies. Overall, the current research advocates for a critical reassessment of traditional farming techniques. By encouraging the adoption of modern, efficient alternatives like the strip planting system, stakeholders can pave the way for a more sustainable future in pinto bean cultivation—one that promotes both environmental stewardship and economic prosperity. The urgency of such a transformation is paramount as agriculture evolves to meet global challenges, ensuring food security while safeguarding our planet's resources.

Authors Contribution

R. Raisi: Data acquisition, Text mining, technical advice, Methodology

M. Gholami Parashkoohi: Supervision, Validation, Software cervices

H. Afshari: Technical advice, Visualization, Review and editing services

A. Mohammadi: Numerical/computer simulation, Validation

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بهینه‌سازی مصرف انرژی در سامانه‌های کاشت لوبیا چیتی: با رویکرد الگوریتم ژنتیک چندهدفه

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چکیده

سامانه‌های کاشت لوبیا برای کشاورزی جهانی ضروری است و به‌عنوان یک منبع غذایی حیاتی برای بسیاری از جمعیت‌ها عمل می‌کند. بهینه‌سازی این روش‌های کاشت برای افزایش کارایی و کاهش اثرات زیست‌محیطی بسیار مهم است. این مطالعه ورودی‌ها و خروجی‌های انرژی مرتبط با دو تکنیک کشت لوبیا چیتی را ارزیابی می‌کند: سیستم‌های تخت و نواری. این تحقیق که در استان فارس، جنوب ایران انجام شد، شامل ۹۰ مزرعه، ۶۰ مزرعه با استفاده از سیستم‌های تخت و ۳۰ با استفاده از سیستم نواری بود. این ارزیابی مصرف انرژی بر حسب مگاژول در هکتار برای نهاده‌های مختلف از جمله نیروی کار، ماشین‌ها، گازوئیل، کودهای شیمیایی، سموم شیمیایی، برق و بذر را پوشش می‌دهد. سامانه تخت مصرف ۲۰۰۶۷/۱۲ مگاژول در هکتار را نشان می‌دهد، در حالی‌که سیستم نواری از ۱۸۱۷۱/۷۶ مگاژول در هکتار استفاده می‌کند. از نظر عملکرد، سامانه تخت ۳۰۰۰ کیلوگرم در هکتار در مقایسه با ۳۵۰۰ کیلوگرم در هکتار برای سامانه نواری تولید می‌کند. این مطالعه بیشتر معیارهای بهره‌وری انرژی را بررسی می‌کند و عملکرد برتر سامانه نوار را با نسبت کارایی مصرف انرژی بالاتر (۳/۸۵ در مقابل ۲/۹۹) و بهره‌وری انرژی بیشتر ۰/۱۹ کیلوگرم بر مگاژول در مقایسه با ۰/۱۵کیلوگرم بر مگاژول برجسته می‌کند. معیارهای انرژی خاص نشان می‌دهد که سامانه نواری انرژی کمتری به‌ازای هر کیلوگرم لوبیا تولیدشده مصرف می‌کند ۵/۱۹ در مقابل ۶/۶۹ مگاژول بر کیلوگرم علاوه بر این، سود خالص انرژی برای سامانه نواری با ۵۱۸۲۸/۲۴ مگاژول در هکتار بالاتر است، در مقابل ۳۹۹۳۲/۸۸ مگاژول در هکتار برای سامانه تخت یافته‌ها بر نیازهای بهینه انرژی برای هر دو سامانه تأکید می‌کنند، به‌طور کلی، نتایج، نیازمندی‌های انرژی مطلوب و کارایی روش کاشت نواری را نسبت به سیستم مسطح سنتی نشان می‌دهد و بر پتانسیل آن برای تخصیص بهینه منابع در کشت لوبیا چیتی تاکید می‌کند. نتایج الگوریتم ژنتیک چندهدفه نشان داد که سامانه‌های نواری در مقایسه با سامانه‌های مسطح کـه ۳۷۰۷/۶۲ مگا ژول در هکتار (۲۲/۶۶ درصد) صرفه‌جویی می‌کنند، به میزان قابل‌توجهی ۳۷۴۹/۱۱ مگاژول در هکتار (۲۵/۹۹ درصد) صرفه‌جویی انرژی می‌کنند. این بیشتر مزایای کارایی کاشت نواری را برجسته می‌کند.

واژه‌های کلیدی: الگوریتم ژنتیک چندهدفه، سامانه‌های کاشت لوبیا، کارایی مصرف انرژی، مصرف انرژی

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