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Genetic Mutation of Cowpea as a Constrained Stochastic Optimization Problem in Sustainability

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Abstract

The search for desirable qualities in crop using non-natural breeding techniques like genetic mutation has to ensure a balance between the pillars of sustainability (human, social, economic and environmental)- Candidate optimization crop breeds target food security and sufficiency for humans, improved income-earning capacity of farmers, better social (societal) interactions, and environmental protection. This is to ensure we meet the needs of the present generation while not compromising on the needs of future generations. However, uncertainties surround the genetic engineering process, potentially making genetic mutation for sustainability a constrained stochastic optimization (CSO) problem. Using series of experiments in Python programming, we applied genetic algorithm to the genetic mutation of cowpea, a tropical leguminous plant and protein-rich crop. Our experiments with genetic algorithm as a stochastic optimizer, confirmed that the evolution from the initial random string (initial cowpea species) to the target string (optimal cowpea solution) was smeared by uncertainties in the optimization-for-sustainability effort. In any case, cowpeas with the desired qualities of drought tolerance and high yield gradually emerged as we progressed from the first generation (M1) to subsequent generations with the aim of meeting the sustainability targets.

Keywords

Constrained stochastic optimization, Cowpea, Genetic mutation, Stochastic optimizer, Sustainability

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Introduction

Crop improvement programs are typically aimed at infusing certain traits in crops for purposes of food security and food sufficiency. Since natural plant breeding techniques takes time to inject desired traits in crops, attention is shifting to the use of genetic engineering (GE) techniques that deliberately mutate the genes of plants to obtain the desired outcomes (Firdous et al., 2019).

Genetic mutation may involve the use of chemical, physical or biological treatments of plants (Udhaya et al., 2019; Ugur et al., 2016; Rahnama & Sheykhhasan, 2016). In the context of sustainability which emphasizes meeting the needs of the present generation while protecting the needs of the future generation, plant breeding genetic engineering systems must take into cognizance the four pillars of sustainability (human, social, economic and environment) (Ben-Eli, 2015). This implies that deliberate crop improvement initiatives using agricultural biotechnology techniques like GE should ensure that the genetic mutation of crops strikes a balance between human capital, social capital, economic capital and environmental capital. Any desired traits induced in crops should protect human, societal, economic and environmental interests as part of conscious and concerted efforts to protect the needs of the present generation while not compromising the needs of the future generation.

Genetic mutation, by its nature, is a heuristic search for an optimal candidate crop solution with desirable traits, cutting across generations of offspring and using a search algorithm like genetic algorithm (GA) (Hassanat et al., 2019; Katoch et al., 2021). In view of the fact that the problem cannot be solved using deterministic method or formula, search and optimization techniques are used to guide the process from the initial crop genotype to the final crop genotype considered to the optimal solution. Like many search and optimization problems, genetic mutation is surrounded by many uncertainties and constraints. And the genetic mutation of cowpea for sustainability, as done in this study, is not an exception. Hence, we classify our problem as a constrained stochastic optimization (CSO) problem (Kossivi, 2019).

We subjected three genotypes of cowpeas (*dan muzakkari, gidigiwa,* and *dan mesera*) obtained from Kontagora in Niger State, Nigeria to chemical treatment (ethyl methyl sulphonate or EMS) and physical treatment (gamma irradiations or GI) (Mohamed et al., 2020; Roy et al., 2019) [9,10]. The treated seeds were planted and the first generation (M1) offspring observed in terms of phenotypic and genotypic traits. The study design is to cover three generations of the cowpea.

To guide our crop improvement program with reliable bioinformatic information, we model the genetic mutation of cowpea using GA, a stochastic optimizer (Liu, 2016). We also implemented GA using Python programming for series of experiments with a view to ascertaining if the genetic mutation of cowpea for sustainability is a constrained stochastic optimization problem.

Our motivation for the work is that genetic mutation of cowpea for sustainability should ensure a balance between the four pillars of sustainability (human sustainability, social sustainability, economic sustainability and environmental sustainability). This will in turn encourage both private and institutional investors in the agricultural biotechnology sector to willingly invest, given the assurance of policy commitment to balancing people, society, planet and profit.

The study aims at showing that the genetic mutation of cowpea for sustainability is a constrained stochastic optimization problem. The specific objectives are:

i. Demonstrate the genetic mutation of cowpea for drought-tolerance and high yield capability using physical and chemical mutagens.

ii. Show that plant breeding using genetic mutation takes into cognizance the pillars of sustainability.

iii. Model the genetic mutation of cowpea using genetic algorithm.

iv. Experiment with the genetic algorithm using Python programming.

v. Use the experimental outcomes to show that genetic mutation of cowpea is a constrained stochastic optimization problem.

Genetic Mutation and Genetic Algorithm

The key idea of genetic mutation is insertion of random genes in offspring in a bid to sustain the diversity in a given population as part of efforts to avoid premature convergence. The mutation operator is one of the three operators of genetic algorithm (GA) (Lim et al., 2017). Others are the selection operator and crossover operator. The selector operator is used to prioritize individuals with better fitness scores and give them the leverage to transfer their genes to subsequent generations. The crossover operator is used to represent mating between individuals that are selected using selection operator. Choosing the crossover sites is done randomly just as the genes in these crossover sites are exchanged to create a totally new individual or offspring. GA evolves a generation using any (or combination) of these operators upon creating it as an initial generation. Once a target string is given, GA produces the target string using a random string with the same length. The string is normally generated using characters like A-Z, a-z, 0-9, and special symbols which regarded as genes. Such string is called a chromosome or solution or individual. The number of characters in the random string which are different from characters in the target string at a particular index is referred to as the fitness score. Hence, any individual with lower fitness value is prioritized. The fitness score given to each individual shows the ability of the individual to be competitive. Stochastic search algorithms like GA seek for individual with optimal fitness value or near optimal score as criterion for convergence. GA keeps record of the population of individuals (chromosome/solutions) alongside their fitness scores such that individuals with better fitness scores are given more opportunity to reproduce compared to others. Also, individuals having better fitness scores are chosen to mate in a bid to produce improved offspring by the combination of chromosomes of parents. Since the population size is static, space for new arrivals has to be created. Consequently, some individuals die in the process which are replaced by new arrivals, resulting in the creation of new generation at the exhaustion of the mating opportunity of the old population. Over successive generations, better solutions are obtained just as the least solutions (least fit) die. Research has shown that, on average, every new generation has better genes than the individual (solution) of past generations which implies that new generations have superior “partial solutions” compared to those of previous generations. At the point where the offspring produced is not significantly different from the offspring produced by past populations, convergence of the population occurs. At this point, the algorithm in the context of the problem being solved, has converted to a set of solutions. Studies have shown that for every implementation, GA starts with a different random string, hence output differ for different implementation and this is the reason it is called a stochastic optimizer (Liu, 2016). Also, the algorithm sometimes gets stuck at a local optimum solution which can be improved upon by any of these methods: tweak mutation and crossover operators or update the fitness score calculation algorithm.

Constrained Stochastic Optimization Problem

Constrained stochastic optimization (CSO) problem is a problem that is hard to solve or cannot be solved using typical nonlinear or linear optimization (Mohamed & Huyen, 2001). These types of problems are characterized by the fact that all the variables or some are random variables. Random variables are used to represent uncertainties in a given system. These variables are used when there is fluctuation in problem parameters within significant range of values or when it is difficult to evaluate their expected values. Such problems exist in various domains such as genetic engineering, transport engineering, communication networks, etc. In these environments, the designer has to use CSO models since the systems have to be designed on a mid to long-term basis. Since solving a CSO problem with conventional methods is complicated, GA provides a simple but accurate solution using efficient computational techniques (Sanabria and Soh, 2004). Genetic mutation as a string manipulation using GA involves progressing from random string (initial solution) to target string (optimal solution) using the selection and mutation operators. The random string represents the uncertainties and constraints in the plant breeding and crop improvement initiative. Hence genetic mutation is an example of constrained stochastic optimization problem. In, the authors posited that GA is used in various optimization problems and are particularly useful in solving CSO problems. Reasons for using GA include robustness, it offers optimization over huge space state, and unlike traditional AI, it does not break when there is slight change in input or presence of noise. GA is applicable in CSO problems such as recurrent neural network, mutation testing, code breaking, learning fuzzy rule base, filtering and signal processing. To illustrate the use of GA, the authors used the method to find the optimum design of an Intranet server. Our present study aligns with this work by formulating the genetic mutation of selected cowpea as a string manipulation and implemented genetic algorithm using Python programming to find an optimal cowpea solution with drought tolerance and high yield traits

Plant Breeding and Sustainability

Plant breeding through genetic mutation can meet the sustainability requirements if it balances people, society, planet and profit (Joern et al., 2012). This implies that plant breeding has to be guided by a comprehensive plant genetic engineering system whose functional requirements and quality (non-functional requirements) we have specified respectively in Figure 1 (using the Use Case diagram) and in Table 1 below.

Figure 1. Use Case diagram showing functional requirements of a plant genetic engineering system

The diagram shows that the typical genetic traits stakeholders in agriculture (such as farmers, agricultural biotechnologist, regulatory agencies, etc.) seek in crops include insect pest resistance, disease resistance, drought resistance, longer shelf-life, higher yield, faster growth, herbicides tolerance and increased nutritional value. However, in inducing these traits into the plant, there has to a balance between human requirements, societal requirements, economic requirements, and environmental requirements for sustainability. This is the reason why genetically modified organisms (GMOs) or genetically modified crops are rejected in some climes for the fear that though such crops ensure food sufficiency and security (human needs), they constitute environmental hazards (Muzhinji & Ntuli, 2021; Akinbo et al., 2021). Therefore, the antagonist of GMOs say they don't comply with sustainability standards. For plant breeding through genetic mutation to be sustainable, the crop improvement program and plant breeding genetic engineering system has to take into cognizance the quality (non-functional) requirements we outlined in Table 1 below.

Table 1. Non-functional (quality) requirements of the plant genetic engineering system

SN	Quality (non-functional) requirements	Explanation
1.	Human health safety	The GM breed should be safe for human consumption.

2.	Environmental protection	The new breed should not be harmful to the environment.
3.	Moderate use of pesticide	Growing the GM species should be with moderate use of pesticide.
4.	Moderate use of herbicide	Application of herbicide should be modest.
5.	Ensure farmers' health	Growing the GM crop should not be detrimental to the health of producers (farmers).
6.	Seed and pollen drift (invasive species vs native species)	Growing the new (invasive) crop should not mean extinction of native species.
7.	Herbicide-resistant super weeds	Breeding of the GM crop should not encourage emergence of herbicide-resistant weeds.

The consideration of both the functional and non-functional (quality) requirement in the genetic mutation exercise, for example, will ensure high income for farmers (economic or profit pillar), provide food in terms of quality and quantity (human pillar), offer safety as well as protect native species of crops (societal or social pillar), and protect the environment (planet or environmental pillar). This is a practical demonstration of how the balance between the pillars of sustainability could be struck such that we meet the needs of the present generation as well as meet the needs of future generation.

Related Work

In (Mohamed et al., 2020), mutation breeding was used as a tool for crop improvement with a view to improving yield and general polygenic traits. Because the male sterile system used for hybridization is lacking in cowpea, the study focused on creating variation using chemical mutagens with a view to inducing genetic variability, analyzing how sensitive different morphological traits are to chemical mutagens, fixing LD 50 value for Ethyl Methane Sulphonate (EMS) and study M1 generation genetic variability. The induction of genetic variability in the Vamban 2 cowpea variety was achieved using eight treatments (10, 20, 30, 40, 50, 60, 70 and 80 mM) of chemical mutagen EMS after which the LD50 values obtained based on observations on root length, seed germination, and shoot length under laboratory conditions. Raising the M1 generation was done under field conditions to evaluate parameters like single plant yield, 100 seed weight, number of seeds per pod, number of pods per plant, number of branches per plant, pollen fertility, germination of seeds, plant height at maturity. The study outcomes indicated that increased concentration of EMS had negatively correlation with yield characters and phenotypic expression. The researchers observed that in marginal lands, cowpea is essential component of sustainable agriculture just as it is a good source of protein with amino acids such as tryptophan and lysine. The paper added that it is a nutritious grain legume cultivated extensively in semiarid and arid tropics and has free metabolites or other toxins. However, the study only considered chemical mutagen of cowpea unlike our present study that uses both chemical mutagen EMS and physical mutagen gamma irradiation. Also, while this study targeted the induction of the male sterile system used for hybridization in cowpea, our genetic variability effort in this current study targets drought tolerance in cowpea

In (Udhaya et al., 2019), the researchers found out that gamma rays and EMS effectively created mutations in moringa plant with lower biological damage. The study therefore recommended that both mutagens can be used to induce moringa with desirable mutations. To arrive at this conclusion, the study used gamma rays and EMS to induce mutation in a moringa variety (PKM-1). Observations made on seed germination and survivability revealed that increased dose of the mutagens reduced chances of germination and survival when compared with the untreated control. The study was carried out against the backdrop that the main aim of plant breeding is to modify and improve on the genetic structure of crops to meet specific demands of farmers. However, to tackle the challenge of low genetic variation using natural means, breeders now patronize mutation breeding. Gamma irradiation (application of gamma rays) and EMS are now widely used to induce mutation in several plant species. While the study dwelt on the combined use of both physical and chemical mutagens for mutations in plants (particularly moringa) to achieve farmers demands, our present study specifically focused on using both physical and chemical mutagens for achieving drought tolerance in cowpea. Also, the current study formulated genetic mutation as a constrained stochastic optimization problem that requires a non-exhaustive method like GA for solving the problem. .

In (Sanabria & Soh, 2004), the authors focused on constrained stochastic optimization (CSO) problem. They defined CSO problems as problems that are hard to solve or cannot be solved using typical nonlinear or linear optimization. These types of problems are characterized by the fact that all the variables or some are random variables. Random variables are used to represent uncertainties in a given system. These variables are used when there is fluctuation in problem parameters within significant range of values or when it is difficult to evaluate their expected values. Such problems exist in various domains such as genetic engineering, transport engineering, communication networks, etc. In these environments, the designer has to use CSO models since the systems have to be designed on a mid to long-term basis. Since solving a CSO problem with conventional methods is complicated, the study recommended GA since it provides a simple but accurate solution using efficient computational techniques. To illustrate the use of GA, the authors used the method to find the optimum design of an Intranet server. The article advocated the use of GA for solving various optimization problems, CSO problems inclusive. Our present study aligns with this work by emphasizing that the genetic mutation of cowpea for sustainability is a CSO problem. We also formulated the genetic mutation of cowpea as a string manipulation using GA and implemented the algorithm using Python programming.

In (Liu, 2016), the researchers emphasized that GAs are well used in many fields like bioinformatics, engineering, economics, manufacturing, etc. They stressed that stochastic optimization problems are useful in control systems and power electronics where there is need to choose optimum parameters that guarantee least noise impact and peak control effect for vast majority of designs. Solving this problem is difficult using the exhaustive search method particularly when the search domain is large or infinite. Rather, a heuristic search algorithm like GA can be used to solve such problems. Since real-life problems with noise are hard to assess and they need huge computation effort, the study proposed a single objective GA which integrates computing budget allocation into the selection operator instead of being used during evaluation of fitness. The researchers also carried out studies on a multi-objective GA. This GA performs comparison of the integration of diverse methods of computing budget allocation into any of the evaluation or the environmental selection steps. These comparisons which take into cognizance different levels of noise are performed on stochastic problems which are derived from standard multi-objective optimization problems. Despite classifying GA as a stochastic optimizer, the work did not mention how GA could be used for optimization in cowpea improvement program as done in this current study.

In (Cui & Xiong, 2020)), the authors studied and evaluated the drought-tolerant ability in Arkansas cowpea genotypes. The research used the drought tolerant lines as parents for breeding.

The study emphasized that aside the fact that Cowpea [Vigna unguiculate (L.) Walp.] is a healthy, nourishing and multipurpose leguminous crop, it is highly drought-resistant. In the literature, reports have it that cowpea lines are highly tolerant to drought, thus many can survive under hot and dry conditions for more than 40 days. For this study, the researcher used a total of 36 University of Akansa breeding lines to screen drought tolerance at the seedling stage. Using randomized complete block design (RCBD), the experiment was carried out in a greenhouse with two replicates which were arranged in a split-plot manner. Having subjected the cowpea to drought stress for four weeks, three drought-tolerant related characters were obtained and analyzed. Though we agree with the author that cowpea can survive in environments with scanty rainfall and thus considered to be naturally drought-tolerant, there is need to expand the genetic variability of cowpea to withstand the unfolding hash climate-induced conditions like extreme drought. Hence, the present study is inducing drought-tolerant trait in cowpea using genetic breeding as a crop improvement program.

The work in (Mukhtar, 2021) focused on the biological mutation of cowpea and the sustainability requirements. For genetic variability of the crop so as to resist the insect-pest pod borer, maruca vitrata, cowpea was treated with the cry1Ab gene of a bacteria, Bacillus thuringiensis (Bt). This mutation resulted in a variant of cowpea called Sampea 20-T, the first genetically modified (GM) food in West Africa and the first genetically modified organism (GMO) cowpea variety in the world. It was developed through multiple partnerships with a private sector partner donating the Bt genes while the technology for transforming the cowpea was provided by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) of Australia. The article explained further that CSIRO collaborated with the Institute for Agricultural Research (IAR) of Nigeria and other African countries' agencies for product development. Another partner, African Agricultural Technology Foundation (AATF), coordinated the partnership as well as negotiated the transfer of intellectual property rights. To meet the sustainability requirements of balancing human sustainability, social sustainability, economic sustainability and environmental sustainability, the commercial release of Sampea 20-T in Nigeria in 2019 followed the approval by the National Varietal Committee. So far, the seeds have been made available to farmers. Before now, Nigeria had enacted a biosafety law which empowered the National Biosafety Management Agency (NBMA) to offer comprehensive services for the regulation of GMOs in a bid to balance people, society, planet and profit as pillars of sustainability. The two agencies mandated by law to regulate GMOs in Nigeria are NBMA and National Biotechnology Development Agency (NABDA). While NABDA formulates biotechnology policy, NBMA focuses on the biosafety regulations of biotechnology- derived products. This study focused on the biological mutation of cowpea for insect-pest resistance while our current study uses chemical and physical mutation of cowpea for drought-tolerant resistance.

None of the above-mentioned research work formulated the genetic mutation of cowpea for sustainability as a constrained stochastic optimization problem as done in this current research. Neither did any attempt to implement GA in Python programming and execute the program for experimental proof that GA is a stochastic optimizer as carried out in our present study.

Methodology

The study obtained cowpeas and treated them for drought-tolerance trait. The cowpeas were selected from Kontagora in Niger State, Nigeria because the area produces the largest quantity of cowpeas in Niger State and known in Nigeria as one of the cowpea hot-beds. The three selected cowpeas (dan muzakkari, gidigiwa, and dan mesera) were chosen based on high yield capacity. The three genotypes of cowpeas were treated chemically using ethyl methyl sulphonate (EMS) and physically using gamma irradiations (GI). For the chemical mutagen, four EMS doses were administered (200G+0.372mol, 400G+0.372mol, 600G+0.372mol, 800G+0.372mol) per variety of cowpea. For the physical mutagen, four GI doses were administered (200G, 400G, 600G, 800G) were administered per variety. Three replicates of each treated seed were produced. The untreated seed had neither EMS or GI and served as the control for assessing the drought-tolerance mutagenic effect of EMS and GI on the cowpeas.

Both treated and untreated cowpeas were planted in the botanical garden of the Plant Science Department of Federal University of Technology, Minna, Nigeria in the first generation (M1) and their offspring observed for both phenotypic and genotypic traits induced by the chemical and physical treatments. The study will span three generations: first generation (M1), second generation (M2) and third generation (M3). The offspring of one generation will serve as input for the next generation. However, this report covers experiments performed in M1.

Since our primary target is to examine mutation-induced drought tolerance in the cowpeas and conduct heuristic search for optimal cowpea trait, we used GA to model the genetic mutation as a string manipulation, with the target string `mutation-induced drought tolerant cowpea` as follows:

```
Target_Cowpea_String = “mutation-induced drought tolerant cowpea”

Length(Target_Cowpea_String) = 40

Random_Cowpea_String = “tttaaa!!!!&&&&&7777%%%%%5555ffff999$$$rr”

Number_of_Generations = N

For I= 1 to N

  Length(Random_Cowpea_String) = 40

    Fitness_Score_or_Genetic_Distance = 0

    For K = 1 to 40

         If Target_Cowpea_String(K) != Random_Cowpea_String(K)

            Fitness_Score_or_Genetic_Distance                                 =
Fitness_Score_or_Genetic_Distance + 1

    If Fitness_Score_or_Genetic_Distance > 0

        For I = 1 to 40

            New_Cowpea_String(I) = Random_Cowpea_String(I)+GI+EMS

    Random_Cowpea_String = New_Cowpea_String
```

In Figure 2 below, the flowchart shows the process for the mutation-induced drought-tolerance trait in the cowpea.

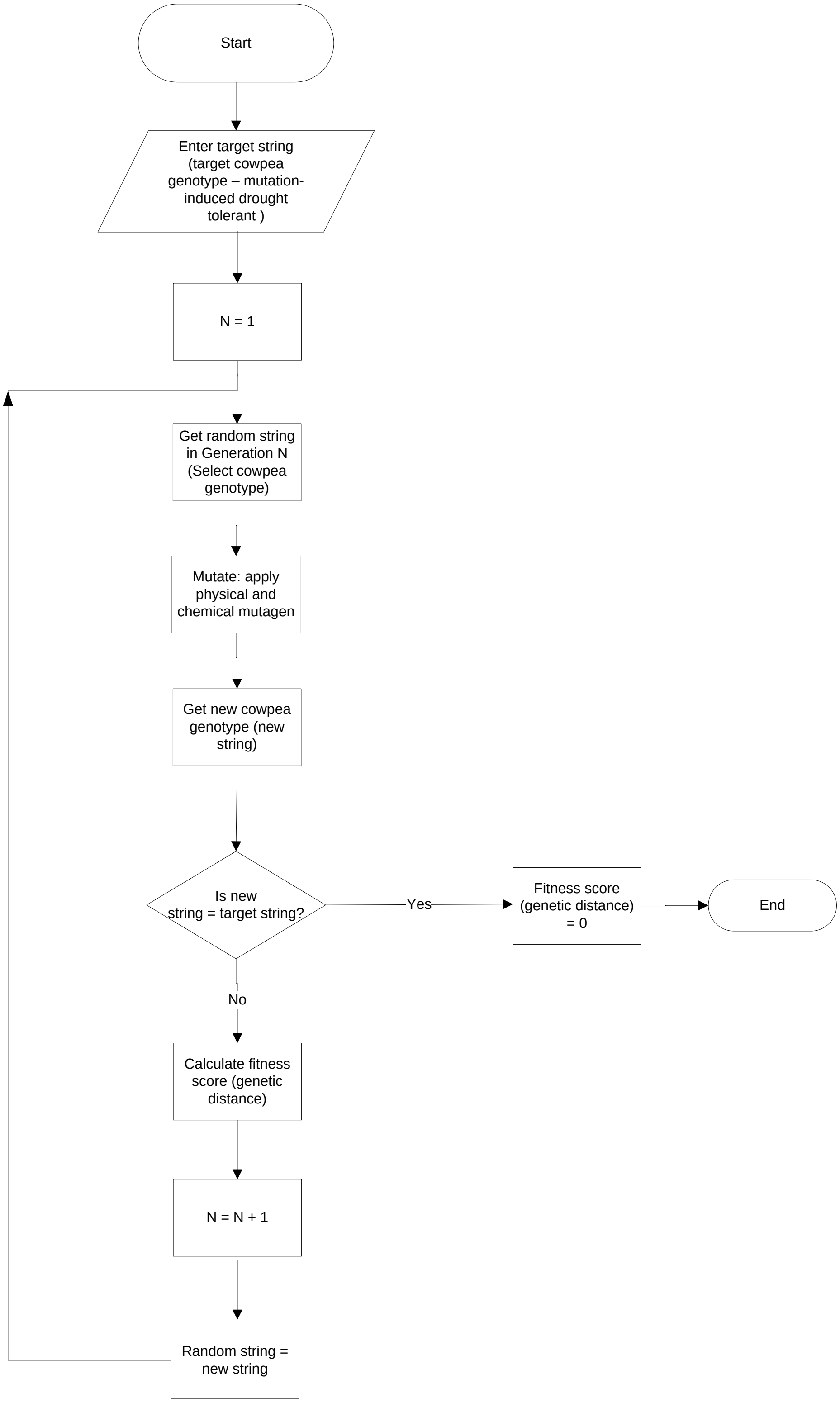

Figure 2. Process flow for the application of genetic algorithm in the genetic mutation of cowpea for drought tolerance.

We carefully studied the offspring of the M1 generation and those with better fitness score (genetic distance) were selected for the second (M2) generation. In Table 2, we show series of analyses that would be conducted on the offspring of M1, M2 and M3 to gain greater insights into the mutagenic effects of treating the cowpeas with EMS and gamma rays for drought tolerance across the cowpea improvement value chain.

Table 2. Analyses that would be carried out on candidate cowpea offspring across the three (3) generations of the study.

Generation	Analyses	Target	Remark
First (M1)	Physiological Analysis	Observe physical parameters of the cowpea plants	
	Statistical analysis using genetic distance	Verify the yield content to determine drought tolerance capability.	Yield content is measured by (1) number of leaves (2) number of pods per plant (3) Height of plant, etc.
Second (M2)	Phytochemical analysis	Ascertain both mineral content and ash content	Verify levels of phosphorus, calcium, potassium, zinc, iron and magnesium in M2 cowpea offspring. Mineral content analysis focuses on mineral content of fresh cowpea seeds while ash content analysis focuses on mineral content of dry cowpea offspring seeds.
Third (M3)	Sytogenetics	Study of chromosomes and their structures	
	Molecular genetics	Study of genes at the DNA level	

The algorithm we designed as diagrammatically illustrated in the flowchart in Figure 2 was implemented in Python programming and executed. The results obtained and discussion follow below.

Results and Discussion

The outcomes of the three experiments are shown in Tables 3, 4 and 5. In all the three experiments, the target string (optimal solution) is “mutation-induced drought-tolerant cowpea” obtained at a fitness score of 0. The initial random string generated in each experiment differs. The ability to generate random string as well as generate different random strings in different experiments for the same problem confirms that GA is a constrained stochastic optimizer (Kossivi, 2019; Liu, 2016).

Table 3. Experiment 1 results

Generation	Random String	Fitness Score
Generation 1	`Jdt?iiG&5"Bq=g0dD/B4P9evy[- 4gunLBkK&mw)`	36
Generation 2	`String: Jdt?iiG&5"Bq=g0dD/B4P9evy[- 4gunLBkK&mw)`	36
Generation 3	`Jdt?iiG&5"Bq=g0dD/B4P9evy[- 4gunLBkK&mw)`	36
Generation 4	`Jdt,iiG& "Bq,g0d;C{qPqevy[! 4gun2BKKw;w)`	35
Generation 5	`2B(PldT/WwnFjc dgMRn tyHYd)2e}2{j"TKwIea`	33
Generation 6	`2B(PldT/WwnFjc dgMRn tyHYd)2e}2{j"TKwIea`	33
Generation 7	`J3t8Mion3"n1,budp ZUPqTHXtL e&Z;2cX}2}e)`	31
Generation 8	`J3t8Mion3"n1,budp ZUPqTHXtL e&Z;2cX}2}e)`	31
Generation 9	`J3t8Mion3"n1,budp ZUPqTHXtL e&Z;2cX}2}e)`	31
Generation 10	`J3t8Mion3"n1,budp ZUPqTHXtL e&Z;2cX}2}e)`	31
….	….	…
Generation 9409	`mutation-induced dr}ught tolerant cowpea`	1
Generation 9410	`mutation-induced dr}ught tolerant cowpea`	1
Generation 9411	`mutation-induced dr}ught tolerant cowpea`	1
Generation 9412	`mutation-induced drought-tolerant cowpea`	0

We observed further that in experiment 1 in Table 3 above, convergence of the algorithm took place at the 9412th generation while the initial fitness score (generation 1) is 36. The initial random string is `Jdt?iiG&5"Bq=g0dD/B4P9evy[- 4gunLBkK&mw)`.

Table 4. Experiment 2 results

Generation	Random String	Fitness Score
Generation 1	`f%evEqv)-%s1;)J#&HrJ4UgwgKF& w?N/ jqjB#"`	38
Generation 2	`f%evEqv)-%s1;)J#&HrJ4UgwgKF& w?N/ jqjB#"`	38
Generation 3	`Bu;R]1ncWia8j2]V18XHZgET:]F?v:HdlW.t#Uqa`	36

Generation 4	`Bu;R]1ncWia8j2]V18XHZgET:]F?v:HdlW.t#Uqa`	36

Generation 5	`iVt!(6ULGyyK`
	`uidFh1o5]JtsQDqT09A7 kM/q`
	`T`
		35

Generation 6	`i1t` `u;onIZ}-foiR$YGx&gtDYsf 0H9MG Ho/Y[4`	34
Generation 7	`dus![on]-iqX6#]g KrYQgTtop4?]/K]z0jwcp6D`	32
Generation 8	`dus![on]-iqX6#]g KrYQgTtop4?]/K]z0jwcp6D`	32
Generation 9	`Cut(uto]!A&u%O_V QJl&ghR KfS=H:K5 HS!p` `{`	31
Generation 10	`Gut(u;opJZ-#{Oi71oJLZght ?f M2a$5 5oYp5z`	29
….	….	…
Generation 9714	`mutation-ind=ced drought tolerant cowpea`	1
Generation 9715	`mutation-ind=ced drought tolerant cowpea`	1
Generation 9716	`mutation-ind=ced drought tolerant cowpea`	1
Generation 9717	`mutation-induced drought tolerant cowpea`	0

In the second experiment as shown in Table 4 above, GA converged at the 9717th generation with fitness score of 0. The initial random string is `f%evEqv)-%s1;)J#&HrJ4UgwgKF& w?N/jqjB#"` with initial fitness score (generation 1) of 38.

Table 5. Experiment 3 results

Generation	Random String	Fitness Score
Generation 1	`qSE==hT m/2K8c1d$J:8ANAJvs(p=%qw ;;yv/g`	37
Generation 2	`qSE==hT m/2K8c1d$J:8ANAJvs(p=%qw ;;yv/g`	37
Generation 3	`dS?m]I` `L/g//cwH$t:dBgpA?aXp4&G}X Vw/Y=@`	36

Generation 4	dS?m]I L/g//cwH$t:dBgpA?aXp4&G}X Vw/Y=@	36
Generation 5	$fEZVim6]iDK8A?d1JHTxNAL twp=Xqw) nn#v@H	35
Generation 6	Uf# ki36wioD],ed MyPh5$%JmmD_-C39 2[GY7?	34
Generation 7	Tne SiY.mID/GQed$dy9tg]LJq$-4vz9 2oC2=S	33
Generation 8	{{,Zvi.F&lGI4Q?dIdy-8gtwQtd-Q0G)9 c75p%m	32
Generation 9	qu?[=i nwiiLMc? Hd,8&NW1?1HueFq)t Yoy2z3	30
Generation 10	TuE[=i nwI4Lsc5 AI8&NoL?tHueFz)t coY2pO	29
….	….	…
Generation 14335	mutation-induced drought toEerant cowpea	1
Generation 14336	mutation-induced drought toEerant cowpea	1
Generation 14337	mutation-induced drought toEerant cowpea	1
Generation 14338	mutation-induced drought tolerant cowpea	0

In Table 5 above, the results of experiment 3 are displayed. The GA generated an initial random string qSE==hT m/2K8c1d$J:8ANAJvs(p=%qw ;;yv/g with a fitness score of 37. The algorithm converged at the 14338th.

Across the three experiments, the we can see from the outputs that sometimes the algorithm got stuck at a local optimum solution (plateau). For example, in the experiment 1, this happened in Generations 5 and 6 while in experiment 2, an instance of plateau could be seen in Generations 7 and 8. In experiment 3, the GA got stuck at a local optimum solution in Generations 14335, 14336, and 14338. Improving on plateau can be achieved by updating fitness score calculation algorithm or by tweaking the mutation operator.

The above experimental results and analyses have confirmed that GA, like deep neural network (DNN), exhibits stochastic optimization (Okewu et al., 2019). For the same problem of applying genetic mutation to cowpea for sustainability, GA did not only generate different random strings in the three experiments, it also converged at different generations. While DNN generates random variables, GA generates random string though both are heuristic search and optimization algorithms that work towards convergence to an expected value. The difference between the expected value and actual value in GA is called fitness score while in DNN it is referred to as error value. Once the fitness score/error is zero or within a limit of tolerance, the stochastic optimizer is said to have converged.

The search for an optimal cowpea solution that is drought-tolerant and balances the sustainability factors of human, social, economic and environmental factors has been the focus of this study. Outcomes of the field experiment and results of the computational experiments in the first (M1) generation point to the fact that the cowpea improvement program is leading to production of cowpeas that can resist drought imposed by climate change as well as strike a balance between the pillars of sustainability. Hence, the initiative will tackle hunger (human factor), improve farmers' income-earning capacity (economic factor), ensure that native species of cowpeas don't go into extinction (social factor), and protect the ecology (environmental factor).

So far, we have achieved the five (5) specific objectives outlined earlier in this article: we demonstrated mutation-induced drought tolerance in cowpeas using chemical and physical treatments. We also showed how sustainability can be achieved in plant breeding programs using genetic mutation. The study equally modelled the mutation of cowpea using GA and implemented the algorithm using Python programming. Finally, our experimental results confirmed that the genetic mutation of cowpea for sustainability is a constrained stochastic optimization problem.

Conclusion

Plant breeding using genetic mutation in this study targeted the injection of drought-tolerant trait and high-yield trait in cowpea. However, the search for an optimal candidate cowpea solution has to ensure sustainability in terms of the balance between human, social, economic and environmental factors. The genetic mutation of cowpea using chemical mutagen (EMS) and physical mutagen took into consideration the human pillar (tackling hunger and immune-deficiency), social pillar (food sufficiency and security), economic pillar (farmers' income-earning capacity) and environmental pillar (impact of chemical and physical treatments on environment). In view of the uncertainties surrounding the search for an optimal cowpea offspring with the desired traits (drought tolerance and high-yield), the search is considered to be a constrained stochastic optimization problem in sustainability. The outcomes of the computational experiments have confirmed this. This is evident in the fact that though all the different experiments used the same target string as input, the random strings produced during the iterations in each experiment were different. Besides addressing the sustainability requirements, this study presents an experimentally verified empirical case of optimization which is an addition to the body of knowledge of the constrained stochastic optimization community. In future research, the mutagenic effects of EMS and gamma irradiation on the cowpea offspring in the second and third generations would be closely studied towards further improvement of the cowpea for drought-tolerant traits.

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