



OPTIMIZATION OF SOIL DATA USING GENETIC ALGORITHM APPROACHES

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Abstract: Crop yield in agriculture depends upon weather conditions, nature of soil, amount of fertilizer. Optimization of parameters can help reduce cost component. Two patterns of the soil data are under study. Each pattern comprises of first six parameters and all nine parameters respectively. Ph value, soil EC, Phosphorous, Potassium, urea, T.S.P, M.O.P, Moisture, Temperature. Range of data variables is considered as per magnitude of parameters in the pattern. Optimized values of the variables have been achieved using genetic algorithm and presented in Table 1 and Table 2. The value for one of the optimized values lie within the target limits whereas the other lies beyond range in study with six parameters. The values lie within set limits range when optimized with all nine parameters. The study can be extended to more patterns.

I. INTRODUCTION

Agriculture need water for irrigation purpose and has to compete with households and water utilized in industrial sector. Different consumptions and utilizations of water are there in different sectors. Demand of water is not price sensitive. Agriculture can utilize recycled water. Reliability of water is important in domestic and industrial usage. [1] The work is focused on agriculture routing planning for farmers field. Intra-field distance in machinery is proposed when traversing all tracks. Environment change influences the timeline to feed water and other fertilizers where cost and reduction in CO₂ need optimization of fleet size. [2] Innovation applies information received from multi objective optimization to discover management practices in agriculture, reducing the risk of variations in climate and its impact on crop yields. [3] The work explores path ways for optimizing sustainability in agriculture. Recommendation derived from exploration of sustainability at levels offer insight that are valuable for government authorities. [4] In this work applications of Artificial intelligences in agriculture are explored. Irrigation, weeding applications employ sensors and embedded systems in robots and drones saving access utilization of water, pesticides maintaining the fertility of soil. Manpower is utilized improving the productivity. [5] The work shows impact of environmental

constraints while studying farm activities in planning and crop rotation. Constraints come from life cycle assessment. The constraints studied in the work are green house gas emission and European Union common agriculture policy. [6] In this study agriculture policies are taken as constraints while studying and analyzing land resource and food demand. Two stage model find compromise optimization for feasibility and disaster impact. The two stage models optimize the staple crop spatial distribution in administrative districts in china. [7] Planting, harvesting, crop monitoring etc. are being influenced by machine learning approaches, AI. Vision system improve decision making in agriculture automation. Such technologies improve crop yield by 15 to 20%, reduce investment and enable efficient farming. [8] Training data is required for machine learning models. Data is collected in central database. As information is gathered at one location, it is susceptible to abuse. Federal learning (FL) is a promising direction in these models as these can resolve privacy and security issues as actual data set is not required for training. Multiple clients can train model in decentralized points and data resides with the owner. [9] Precision agriculture has been influenced by integration of Machine learning and agriculture intelligence. AI vision systems enhance prompt decision making in agriculture automation. crop health is influenced by AI, AI vision for pesticide applications. Challenges occur in data privacy and there are scalability constraints. [10] Farmers and people dealing in agriculture field utilize critical information and thereafter make informed decision. The information might include soil variability. Nutrient inputs, combination of various fertilizers. Optimal parameters are used to maximize crop yield with the help of data mining and machine learning technique. [11]

II. METHODOLOGY:

Genetic algorithm has been applied to soil data. Only two patterns comprising six parameters and nine parameters respectively from carrot data taken from soil data have been used in this work. Thus, number of variables is two. Population size has been ten. The fitness function helps to optimize the parameters. For recording different



observations, different population sizes can be used. The mean fitness value is -100.085 and best fit value is -186.138

has been recorded as presented in Figure1.

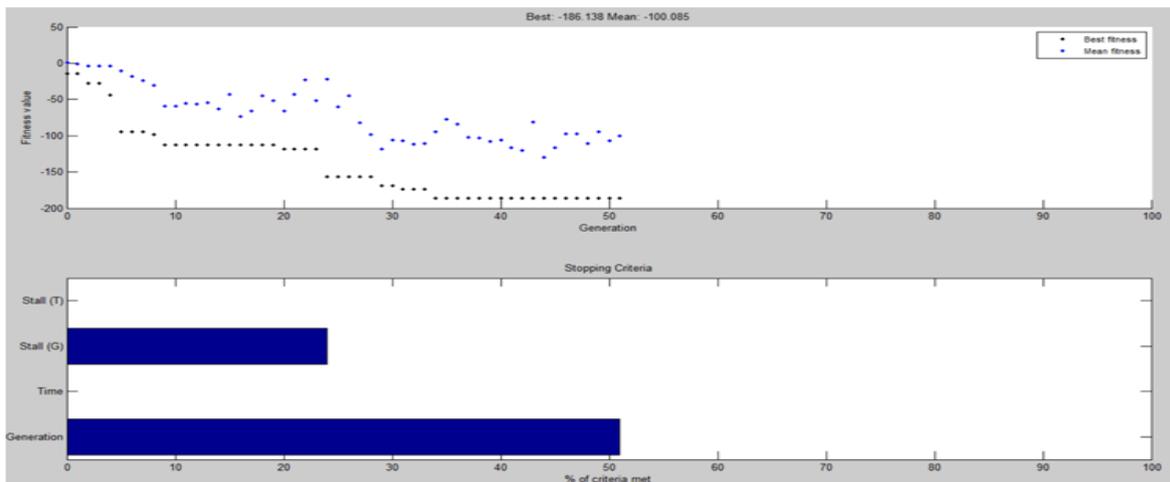


Figure1: Fitness values and stopping criteria for the optimized values recorded with six parameters X1 and X2 are the function outputs indicating the optimized responses for patterns under study. The values of X1 and X2 presented in Table1 and

Table 2 are observed at respective Fval presented in Tables. The different observations in the study are presented in Table 1

Table 1 Optimized values obtained using six parameters			
s.no	X1	X2	Fval
1	2.7431	131.1252	-36.5182
2	-1.4661	131.1196	-181.3107
3	-1.5385	131.1241	-157.7465
4	-0.1717	131.1635	-122.1162
5	-0.8235	130.4840	-182.2847
6	-1.5291	131.1450	-162.9514

In this simulation, number of generations =51, funccount=580, Function valuation=1040, Range set for optimization is [0 40], [0 40] and Fval is -183.9328, Best Fitness=-186.439, It's mean value is -99.3805 as presented in Figure 2.

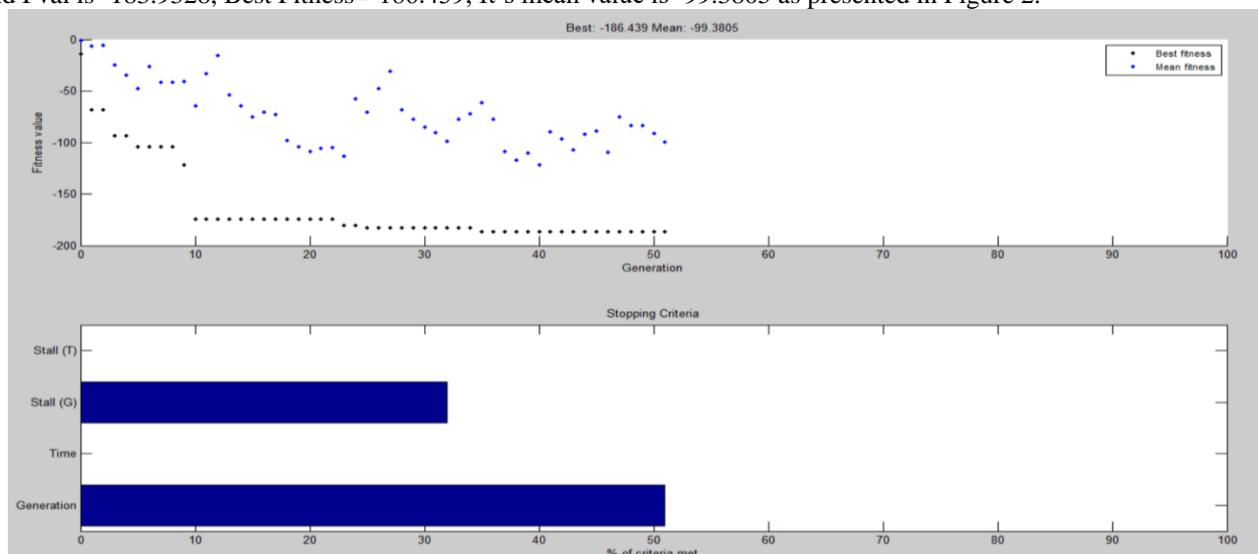


Figure2: Fitness values and stopping criteria for the optimized values recorded with nine parameters.



The observations in the simulation are recorded in Table 2. The nine parameters in the two patterns are showing optimized values. The range set for plot objective for achieving optimization is [0 40] and [0 40]

Table 2	Optimized values obtained using nine parameters		
S.No	X1	X2	Fval
1	4.8844	43.1589	-183.9328
2	5.5048	42.5781	-184.6536
3	5.5047	42.5570	-185.6836
4	5.4952	42.5511	-186.3098
5	0.7802	43.1464	-51.8159

III. CONCLUSION & FUTURE SCOPE

Optimization approach can be applied to more than two patterns with multiple parameters in various studies involving soil data, agricultural studies and such studies involved in other similar fields. The optimized parameter in current study is near optimizing parameters in second pattern as shown in Table1 for a number of readings with respective Fvals and with six parameters used in the work. Both the parameters in patterns are optimized while using all nine parameters in the work presented in Table 2. Results are obtained using Matlab2013a. Data was used from [12].

IV. REFERENCES

- [1]. Amir, I. and Fisher, F.M., 1999. Analyzing agricultural demand for water with an optimizing model. *Agricultural systems*, 61(1), pp.45-56.
- [2]. Utamima, A., Reiners, T. and Ansari-poor, A.H., 2019. Optimisation of agricultural routing planning in field logistics with Evolutionary Hybrid Neighbourhood Search. *Biosystems Engineering*, 184, pp.166-180.
- [3]. Kropp, I., Nejadhashemi, A.P., Jha, P. and Hernandez-Suarez, J.S., 2022. Agricultural innovization: an optimization-driven solution for sustainable agricultural intensification in Michigan. *Computers and Electronics in Agriculture*, 199, p.107143..
- [4]. Gao, F., Li, Z., Zhang, P. and Wu, Y., 2024. The evaluation and optimization of the agricultural sustainable development based on a data-driven approach: A case from Northern Anhui. *Heliyon*, 10(12).
- [5]. Talaviya, T., Shah, D., Patel, N., Yagnik, H. and Shah, M., 2020. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial intelligence in agriculture*, 4, pp.58-73.
- [6]. Capitanescu, F., Marvuglia, A., Gutiérrez, T.N. and Benetto, E., 2017. Multi-stage farm management optimization under environmental and crop rotation constraints. *Journal of Cleaner Production*, 147, pp.197-205.
- [7]. Pei, W., Guo, X., Ren, Y. and Liu, H., 2021. Study on the optimization of staple crops spatial distribution in China under the influence of natural disasters. *Journal of Cleaner Production*, 278, p.123548.
- [8]. Padhiary, M., Saha, D., Kumar, R., Sethi, L.N. and Kumar, A., 2024. Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. *Smart Agricultural Technology*, 8, p.100483.
- [9]. Dembani, R., Karvelas, I., Akbar, N.A., Rizou, S., Tegolo, D. and Fountas, S., 2025. Agricultural data privacy and federated learning: A review of challenges and opportunities. *Computers and Electronics in Agriculture*, 232, p.110048.
- [10]. Padhiary, M., Saha, D., Kumar, R., Sethi, L.N. and Kumar, A., 2024. Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. *Smart Agricultural Technology*, 8, p.100483.
- [11]. Welekar, R. and Dadiyala, C., 2023, May. Optimizing Crop Yield in Agriculture using Data Mining and Machine Learning Techniques. In 2023 4th International Conference for Emerging Technology (INCET) (pp. 1-7). IEEE.
- [12]. r3trovision (2023) 'Soil moisture, temp and nutritions'. Available at: <https://www.kaggle.com/datasets/r3trovision/soil-moisture-temp-and-nutritions>