A Novel Cultural Evolution-Based Nomadic Pastoralist Optimization Algorithm (NPOA): The Mathematical Models

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***Abstract*—In this paper, the mathematical models for a proposed novel modified Pastoralist Optimization Algorithm (POA) called the Nomadic Pastoralist Optimization Algorithm (NPOA) inspired by the nomadic pastoralists herding strategies and cultural evolution strategy is presented. The nomadic pastoralist herding strategies which are scouting, camping, herding, splitting and merging were mathematically modeled. The mathematical models will be used to develop the proposed algorithm. The algorithm when developed will be tested on several benchmark functions to ascertain the algorithms exploration and exploitative ability. The performance will also be validated by comparing with POA and other popular and similar metaheuristic algorithms such as GOA, PSO, ABC, BBO and ICA**

Keywords— Optimization; Nature Inspiration; Metaheuristics; Cultural Algorithm, Pastoralist Optimization Algorithm (POA); Nomadic Pastoralist Herding Strategy (NPHS);

I. INTRODUCTION

The rapid growth in technology has brought about faster and more accurate solutions to emerging real world problems. At the heart of this technological advancement and optimal solution seeking is optimization. Optimization is basically a search for optimal solution using the right procedures and mathematical representations [1]. [2] defined optimization (or mathematical programming) as a systematic selection of variable values within some allowed limits whose aim is to minimize or maximize an objective function of a decision problem. Optimization is viewed as optimal seeking in nature in which problem dependent objectives (performance index) must be evaluated or achieved and constraints must be satisfied [3]. Optimization problems (OP) are problems that contains several solutions, variables, constraints and a function or performance measure to measure the optimality of a chosen solution. The general approaches for solving OP can be analytical, experimental, graphical or numerical. [4].

Real world OPs are complex and difficult to solve because of their large number variables and constraints, non-linear and multi-modal objective function and are computational expensive, hence, the need for innovative optimization techniques in solving them [5, 6]. This innovative Nature Inspired (NI) optimization techniques which are mostly population based and metaheuristic Optimization Algorithms (OA) have proven to be very efficient in solving most real world problems. Novel nature-inspired metaheuristic OA are being developed because according to the no free lunch theorem, no OA can optimally solve all Op's, even though they are capable of solving most OP.s [7].

NI-OA are inspired by natural phenomenon, and they are classified as either swarm-based, human-based, evolutionary-based, chemistry-based, physics-based and mathematics-based [8]. Example of some of these algorithms include Particle Swarm Optimization (PSO) [9], Ant Colony Optimization (ACO) [10], Artificial Bee Colony (ABC) [11], Biogeography-based Optimization (BBO) [12], Ant Lion Optimization (ALO) [13], Whale Optimization Algorithm (WOA) [14], Lion Optimization Algorithm (LOA) [15] and Grasshopper Optimization Algorithm (GOA) [16], Pastoralist Optimization Algorithm (POA) [17].

Most of the listed algorithms deploy mostly the biological evolution strategy through mutation or crossover or both and agents share information with a narrow temporal and spatial scale. Cultural evolution strategies on the other hand allows agents to evolve share information through a well-structured belief space. Cultural Algorithm (CA) allows agents to learn from a global knowledge domain rather than local as in the case of most OA. This allows culture to evolve faster than biological and other social evolution strategies. CA have been applied for evolution and modification of some algorithms [18].

In this paper, the cultural evolution strategy was adopted for the evolution of the Nomadic Pastoralist Herding Strategy (NPHS). The strategy has been used to develop a novel POA using the biological (genetic) evolution strategy [17]. Although the algorithm show promising results, there is still need for improvement especially in convergence speed and accuracy.

The remainder of this paper is structured as follows: In Section 2.1, cultural evolution framework is presented, section 2.2, Pastoralist herding strategy is presented, by the mathematical models of NPOA using cultural algorithm evolution strategy and lastly, conclusion and recommendation in Section 4.

II." CULTURAL EVOLUTION FRAMEWORK

A. Cultural Algorithm (CA)

Cultural Algorithm (CA) is a group of computational models that are characterized by three major components; the population space, the belief space and the procedure that describes the knowledge sharing approach between the belief and population space [19]. These models are derivative of the cultural evolution process in nature as shown in the CA framework in Fig. (1).

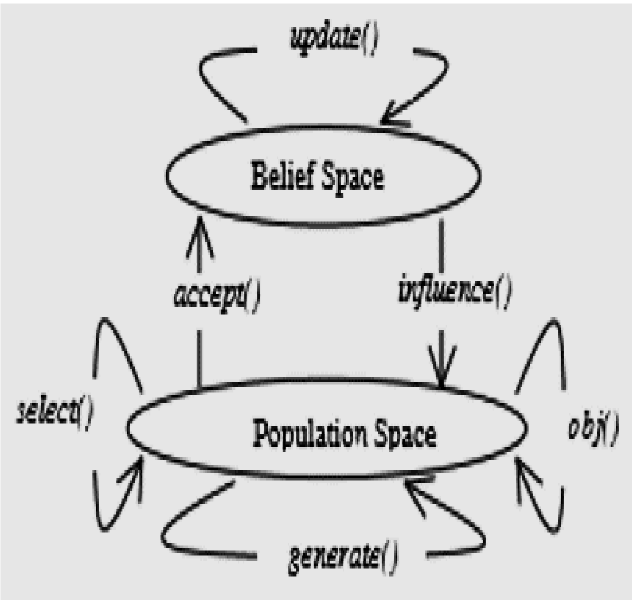

Fig. 1. Cultural algorithm framework [18]

CA is a dual inheritance system that describes evolution in human culture at macro-evolutionary level and micro-evolutionary level which occur in the belief and population space respectively [18]. That is, both the belief and population spaces are updated after each time step based on each other's feedback. As shown in Figure 1, the fitness of each individual is first evaluated using the *obj()* objective function in the population space, after which accepted individuals from the population space are used to update the belief space using the *accept()* function for selecting the individuals. Using the *influence()* function, the individuals to form the population of the next generation are selected using the knowledge from the belief space [20]. For each generation, this processes are repeated until a pre-specified termination condition is met. Fig. (2) shows the cultural algorithm pseudocode.

```
Start
    Initialize
        t=0; B^t; P^t
    Repeat;
        Evaluate Fitness of P^t: ⟹ obj(P^t)
        Select Accepted Individuals: ⟹ Accept(P^t)
        Update Belief Space B^t: ⟹ Update(B^t)
        Generate New Population P^(t+1): ⟹ Influence (B^t)
        Update Time: ⟹ t=t+1
        Until Termination Condition Is Met
end
```

Fig. 2. Cultural algorithm pseudocode [20]

B. Knowledge Sources of CA

CA is built There are five knowledge sources; Situational. Normative, Domain, Historical and Topological.

i. Situational Knowledge (SK): this knowledge source stores the best found exemplars or solution throughout the evolutionary process and is used to lead or guide other individuals on the direction of search, that is towards the exemplars [21, 20, 22].

ii. Normative Knowledge (NK): this knowledge source stores the minimum and maximum values of numeric attributes or a lists of all possible nominal attributes [22]. Normally used during mutation, it guides the adjustment behavior of individuals by determining the step size of search [20].

iii. Domain Knowledge (DK): This knowledge source keeps information about the problem domain used in guiding a search [20]. It also keeps the accepted rules of each generation that are used to guide search for subsequent generations [21].

iv. Topographical Knowledge (TK): This knowledge source is used to diversify the set of rules generated by individual agents in order to prevent local optima entrapment [22]. It was proposed originally to explain region-based functional landscape patterns.

v. Historical Knowledge (HK): is used to store significant events during the search process such as moves, fitness and landscape change in order to guide future moves [20].

These five knowledge sources play different roles in a search process with diverse problem solving capability. The Mathematical representation of the SK and NK knowledge sources which are represented in the belief space, the acceptance function and belief space adjustment, the influence function and all its updating strategies can be found in [23].

III. NOMADIC PASTORALISM

Pastoralism is a livestock production system characterized by extensive movement of animals in search of water and quality pasture [24]. The traditional knowledge of pastoralism allows the pastoralists to manage all entities efficiently using some highly flexible strategies. These strategies help the nomadic pastoralists to survive the unpredictable and potentially hazardous pastoral life [25, 26].

A. Nomadic Pastoralist Herding Strategy (NPHS)

The strategies adopted by the nomadic pastoralist include: Scouting for exploration and search for suitable camp site [27] , camp selection and camping for temporary settlements and daily exploitation [28], herding, which include splitting or herd dispersal for daily herding, risk minimization and trap avoidance [29], finally, merging for camp fitness evaluation and the search for a new camp depending on the quality assessment [30]. The pastoralist herding strategy is shown in Fig. (3).

These strategies have been modelled mathematically using the biological evolution strategy and used to develop a novel POA. The algorithm has been tested on standard benchmark unimodal and multimodal functions and its result were very competitive in terms of its exploration and exploitation capability [17]. However, it suffers from slow convergence which inspires the evolution of NPHS using cultural evolution strategy.

B. Mathematical Models of the Cultural Evolution of NPHS

a) Initialization

The first step in developing the NPOA is to generate the population of pastoralist (nP) randomly because NPOA is a population-based metaheuristic algorithm. In NPOA, a solution is called a pastoralist which is represented in the search space as:

$$P = [P_1, P_2, P_3, \dots, P_D] \quad (1)$$

where, P is the pastoralist and D is the dimension or number of variables of the optimization problem. The second step is to select (25%) of the pastoralist as scout pastoralist (S) represented as;

$$S = [S_1,\ S_2,\ S_3,\ \dots,\ S_D] \quad (2)$$

where, S is the scout pastoralist.

Next, the belief space at time t ($B(t)$) which comprises the situational, normative and domain knowledge component is initialized as shown in Equation (3).

$$B(t) = \{\{\varsigma(t)\},\ \{N(t)\},\ \{\delta(t)\}\} \quad (3)$$

where,

$$\varsigma(t) = \{\hat{y}_i(t)\},\ i = 1{:}n \quad (4)$$

$$N(t) = \left\{X_j(t): X_j(t) = \left(I_j(t), L_j(t), U_j(t)\right)\right\},\ j = 1{:}D \quad (5)$$

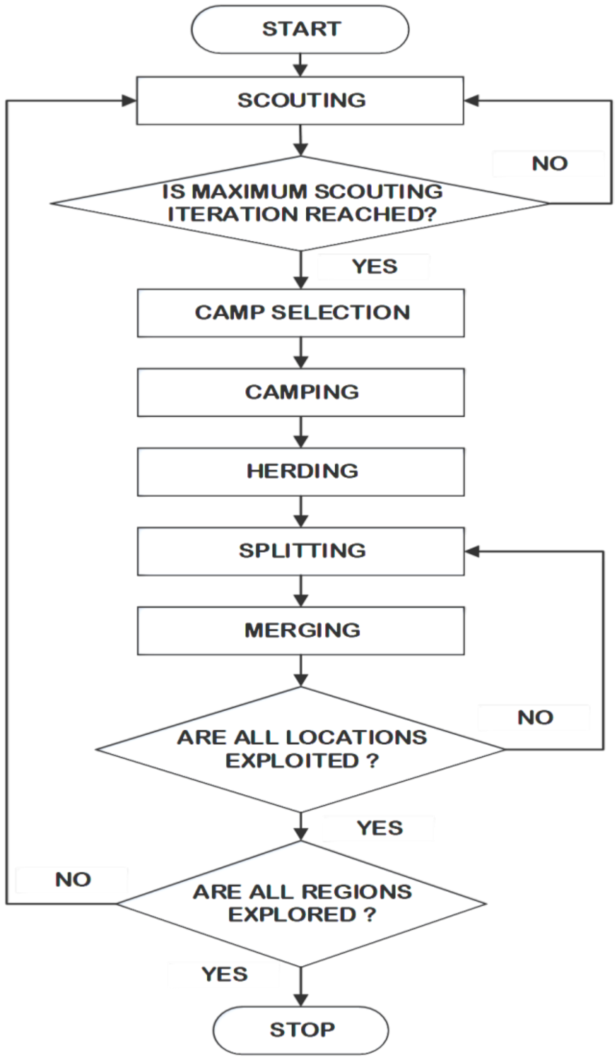

Fig. 3. Nomadic pastoralist herding strategy

$\varsigma(t)$ which is the SK component comprise of the scouters situational knowledge component $\varsigma_S(t)$ and the herders situational knowledge component $\varsigma_H(t)$: $\varsigma(t)\epsilon\{\varsigma_S(t), \varsigma_H(t)\}$. $\hat{y}_i(t)$ is the optimal solution and n is the number of solutions. Similarly, the normative knowledge component is also divided into the Scouters NK and herders NK represented as $N_S(t)\ and\ N_H(t)$ respectively, where $N(t)\epsilon\{N_S(t), N_H(t)\}$.

The closed interval $I_j(t) = [x_{max,j}(t) - x_{min,j}(t)]$, $x\epsilon\{s, p\}$, $U_j(t)$ and $L_j(t)$ are the upper and lower bound score respectively and D is the dimension of the search problem. $\delta(t)$ represents the domain knowledge component at time *t* which stores the rules in the splitting stage.

b) Scouting

After selecting the number of scout pastoralist, their locations are initialized randomly within the search space using Equation (6) and followed by evaluation of fitness of each scout. The fitness of scout i is evaluated using Equation (7).

$$S_{i,j} = rand([L_b, U_b]^D) \quad (6)$$

$$F(S_{i,j}) = FF\ (S_j) \quad (7)$$

where $rand([L_b, U_b]^D$ is a D-dimensional random vector between the lower bound and upper bound of the search space and FF is the fitness function which is problem dependent. Next, the finesses of all scouts were sorted based on their fitness values in ascending order. The best 20% of scout population whose behaviour are acceptable are selected for the belief space adjustment using the pseudocode in Equation (8).

$$S_{accept} = S_{sorted}(1{:}\,nAccept){:}\,(nAccept = round(0.2 * nS)) \quad (8)$$

- Situational Knowledge Update: The situational knowledge component is updated using Equation (9).

$$\varsigma_S(t+1) = \begin{cases} F(S_i(t)), & if\ F(S_i(t)) < \hat{y}(t) \\ \hat{y}(t), & \text{otherwise} \end{cases} \quad (9)$$

Where $\{F(S_i(t))\}$ is the minimum fitness of scout i, and $\hat{y}(t)$ is the initial global optimum solution of all scouts at time t.

- Normative Knowledge Update**:** The normative component determines the step size of the search, hence, controls the algorithms exploration and exploitation. The rules of updating the normative knowledge components are given as follows;

$$S_{min,j}(t+1) = \begin{cases} S_{i,j}(t), & if\ S_{i,j}(t) \leq S_{min,j} \text{ or } F(S_i(t)) < L_j(t) \\ S_{min,j}(t), & \text{otherwise} \end{cases} \quad (10)$$

$$S_{max,j}(t+1) = \begin{cases} S_{i,j}(t), & if\ S_{i,j}(t) \geq S_{max,j} \text{ or } F(S_i(t)) < U_j(t) \\ S_{max,j}(t), & \text{otherwise} \end{cases} \quad (11)$$

$$L_j(t+1) = \begin{cases} F(S_i(t)), & if\ S_{i,j}(t) \leq S_{min,j} \text{ or } F(S_i(t)) < L_j(t) \\ L_j(t), & \text{otherwise} \end{cases} \quad (12)$$

$$U_j(t+1) = \begin{cases} F(S_i(t)), & if\ S_{i,j}(t) \geq S_{max,j} \text{ or } F(S_i(t)) < U_j(t) \\ L_j(t), & \text{otherwise} \end{cases} \quad (13)$$

$$I_j(t+1) = [S_{max,j}(t+1) - S_{min,j}(t+1)] \quad (14)$$

$I_j(t+1)$ is the size of the normative component at time t + 1.

Due to the diversity of scouters during searching, the step size (that is the normative component size of scout j (I_j)) is high which guarantees effective exploration of scout pastoralists.

- Scout Population Influence: The updated SK and NK components were used to influence the scout population if the maximum scouting rate is not exceeded. The scouts move into a new location guided by normative and situational knowledge component as shown in Equation (15).

$$S'_{i,j} = \begin{cases} S_{i,j} + |\alpha * I_j(t+1) * N_{ij}(0,1)| & if\ S_{i,j} < \hat{S}_j \\ S_{i,j} - |\alpha * I_j(t+1) * N_{ij}(0,1)|, & otherwise \end{cases} \quad (15)$$

where, $S'_{i,j}$ and $S_{i,j}$ is the next and current position of scout i for variable j, $\hat{S}_j$ is the best scout position so far. The fitnesses of the new scouters are re-evaluated using Equation (7).

c) Camp Selection and Camping

Selection of the best location for camping is obtained by selecting the best scout in terms of their fitness after completing the maximum scouting iteration. The roles of the scout pastoralist are reversed to herders after scouting and they are joined with other pastoralists. The k[th] pastoralist P_K is initialized at a camp using Equation (16).

$$P_{k,j} = \begin{cases} \hat{S}_j & if\ k = 1 \\ \hat{S}_j + rand([-r, r]^D) & if\ k > 1 \end{cases} \quad (16)$$

where $\hat{S}_j$ is the best scout position, r is the camp radius and D is the variable size (j ϵ [1:D]).

d) Herding

The fitness of the k[th] pastoralist is evaluated using Equation (17) during herding. This is followed by sorting and selection of the best 20% of pastoralist or herders' population whose behaviour are acceptable are selected for the belief space using Equation (18).

$$F(P_K) = FF\ (P_K) \quad (17)$$

$$P_{accept} = P_{sorted}(1{:}\,nAccept){:}\,(nAccept = round(0.2 * nP)) \quad (18)$$

- Situational Knowledge Update**:** The situational knowledge component of herders is updated using Equation (9).

$$\varsigma_H(t+1) = \begin{cases} F(P_k(t)), & if\ F(P_k(t)) < \varsigma_S(t+1) \\ \varsigma_S(t+1), & \text{otherwise} \end{cases} \quad (19)$$

where $F(P_k(t))$ is the fitness of pastoralist k, and $\varsigma_H(t+1)$ is the situational best fitness of the herders at time t+1, while $\varsigma_S(t+1)$ is the situational best fitness of the scouters.

- Normative Knowledge Update: The normative components of herders were updated as follows;

$$P_{min,j}(t+1) = \begin{cases} P_{k,j}(t), \ \boldsymbol{if}\ P_{k,j}(t) \leq P_{min,j} \text{ or } F(P_k(t)) < L_j(t) \\ P_{min,j}(t), \quad \text{otherwise} \end{cases} \tag{20}$$

$$P_{max,j}(t+1) = \begin{cases} P_{k,j}(t), \ \boldsymbol{if}\ P_{k,j}(t) \geq P_{max,j} \text{ or } F(P_k(t)) < U_j(t) \\ P_{max,j}(t), \quad \text{otherwise} \end{cases} \tag{21}$$

$$L_j(t+1) = \begin{cases} F(P_k(t)), \ \boldsymbol{if}\ P_{k,j}(t) \leq P_{min,j} \text{ or } F(P_k(t)) < L_j(t) \\ L_j(t), \quad \text{otherwise} \end{cases} \tag{22}$$

$$U_j(t+1) = \begin{cases} F(P_k(t)), \ \boldsymbol{if}\ P_{k,j}(t) \geq P_{max,j} \text{ or } F(P_k(t)) < U_j(t) \\ L_j(t), \quad \text{otherwise} \end{cases} \tag{23}$$

$$I_j(t+1) = \left[P_{max,j}(t+1) - P_{min,j}(t+1)\right] \tag{24}$$

$I_j(t+1)$ is the size of the normative component at time t + 1.

I_j (the normative component size) is very small during herding because of the closeness of pastoralist in the camps. This allows the algorithm to effectively exploit the camping area.

e) Splitting

Each pastoralist (herders) split to different locations within the camp using the normative, situational and domain knowledge components given as:

$$P'_{k,j} = \begin{cases} \widehat{P}_{k,j} + \left|\alpha * I_j(t+1) * N_{ij}(0,1)\right| & if\ P_{k,j} < \widehat{P}_j \\ \widehat{P}_{k,j} - \left|\alpha * I_j(t+1) * N_{ij}(0,1)\right| & if\ P_{k,j} \geq \widehat{P}_j \\ round\left(\widehat{P}_{k,j}\right) & if\ t > 1\ \&\&\ \delta(t) > \phi \end{cases} \tag{25}$$

where, $P'_{k,j}$ is the next position of k[th] pastoralist, $\widehat{P}_{k,j}$ is the previous best position of herders and $P_{k,j}$ is the current pastoralist location. The domain knowledge rule $\delta(t)$ is given as:

$$\delta(t) = \left(\frac{\varsigma_S(t+1) - \varsigma_H(t+1)}{\varsigma_S(t+1)}\right) * 100 \tag{26}$$

where $\varsigma_S(t+1)$ and $\varsigma_H(t+1)$ scouters and herders situational best fitness, ϕ is a constant representing the branching threshold set as a percentage.

The fitness of the new herders positions $P'_{k,j}$ were evaluated using Equation (17) where P_K is replaced with $P'_{k,j}$, followed by acceptance population selection (Equation (18)). Next, the situational knowledge component is updated using Equation (27) followed by update of the normative knowledge components using Equations (20 to 24).

$$\varsigma_H(t+2) = \begin{cases} F(P'_k), \ \boldsymbol{if}\ F(P'_k) < \varsigma_H(t+1) \\ \varsigma_H(t+1), \quad \text{otherwise} \end{cases} \tag{27}$$

where $F(P'_k)$ is the minimum fitness of k[th] pastoralist, and $\varsigma_H(t+2)$ is the new situational best fitness of the herders at time t+2, while $\varsigma_H(t+1)$ is the situational global best fitness of the herders at time t+1.

f) Merging

During merging, the fitness of the best location within the camp (C_{best}) is updated by comparing the situational best at t+2 and at t+1 as shown in Equation (28).

$$C_{best} = \begin{cases} \varsigma_H(t+2), \text{ if } \varsigma_H(t+2) < \varsigma_H(t+1) \\ \varsigma_H(t+1), \text{ otherwise} \end{cases} \tag{28}$$

where, $C_{best,}$ is the camp best location (that is the best pastoralist within the camp). If all locations in the camp have not been exploited (β not exceeded), the pastoralist splits again to new locations by repeating the steps in section (v).

If all regions have not been explored (maximum iteration not reached), the new regions to be explored by scouters were obtained using the situational knowledge components only and is given as:

$$S''_{i,j} = \begin{cases} S_{i,j} + \left|\alpha * (Vmax_j - Vmin_j) * N_{ij}(0,1)\right|, & if\ S_{i,j} < \dot{S}_j \\ S_{i,j} - \left|\alpha * (Vmax_j - Vmin_j) * N_{ij}(0,1)\right|, & if\ S_{i,j} \geq \dot{S}_j \end{cases} \tag{29}$$

where, $S'_{i,j}$ *and* $S_{i,j}$ is the next and current position of scout i, $\dot{S}_j$ is the previous best position of scouters, $Vmax_j$ and $Vmin_j$ are the upper and lower bound of variable j. The processes in sections (i to vi) are repeated until the stopping criteria (maximum generation is reached). The Global best solution G_{best} is obtained as the last updated situational fitness and position.

Using these mathematical models, a modified POA called the Nomadic Pastoralist Optimization Algorithm (NPOA) will be developed. The algorithm when developed will be applied to solve various combinatorial and numerical optimization problems with the view of obtaining a competitive or better results will be obtained.

IV. CONCLUSION

This paper presents the mathematical models of the evolution from nomadic pastoralist herding strategy to Nomadic Pastoralist Optimization Algorithm (NPOA). The background of cultural algorithm framework and pastoralist herding strategies were first presented followed by the mathematical models of each herding strategy. This models will be used to develop the NPOA and the algorithm will be applied on some standard benchmark test functions. The performance of the algorithm will be compared with existing pastoralist optimization algorithm and some similar and popular metaheuristic optimization algorithms like PSO, GOA, BBO, ABC and ICA.

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