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Atomistic Mathematical Theory for Metaheuristic Structures of Global Optimization Algorithms in Evolutionary Machine Learning for Power Systems

Jonah Lissner

Abstract

Global Optimization in the 4D nonlinear landscape generates kinds and types of particles, waves and extremals of power sets and singletons. In this chapter these are demonstrated for ranges of optimal problem-solving solution algorithms. Here, *onts*, particles, or atoms, of the ontological blueprint are generated inherently from the fractional optimization algorithms in Metaheuristic structures of computational evolutionary development. These stigmergetics are applicable to incremental machine learning regimes for computational power generation and relay, and information management systems.

Keywords: metaheuristic, particle swarm optimization, global optimization, machine learning, evolutionary algorithms, stigmergetics, arrow's paradox, atomistics, Fermat's last theorem, network theory, Hensellian mathematics

1. Introduction

The evolution of Algorithms from a simple route, to complexified paths requires maps from zones of optimal utilization, to be solved sufficiently, in a given amount of time.

These algorithms are constructed for the purpose of building and advancing a continuity for the next location of optimal utilization, in order to realize the importance to form workable nodes and circuits, that are discrete and exact algorithm criteria in a time-basis. Therefore, a complete network on a nonlinear surface and related machine learning epochs is built.

These criteria are based on Fermat's Theorem proving global extrema locations either at stationary or bounding points, based ultimately upon the Pythagorean Theorem, where:

Let $\mathbf{N}$ be the set of natural numbers 1, 2, 3, ..., let $\mathbf{Z}$ be the set of integers 0, ± 1 , ± 2 , ..., and let $\mathbf{Q}$ be the set of rational numbers a/b , where a and b are in $\mathbf{Z}$ with $b \neq 0$. In what follows we will call a solution to $x^n + y^n = z^n$ where one or more of x , y , or z is zero a *trivial solution*. A solution where all three are non-zero will be called a *non-trivial solution* [1].

2. Materials and methods

2.1 Metaheuristic structural rules for the algorithm building

It is a rule of No Unreasonable Effectiveness of Mathematics in any Science [Wigner] [2], and therefore a notion that No Unreasonable Effectiveness of Axiomation in any Science, that 3 Rules of Information Physics [3IP] by Jonah Lissner exist:

I. Problem of Demarcation.

II. Rule of Information Dichotomy [*Gestalt-Inverse Gestalt*], and thereby requiring a kind of.

III. Context-Restricted Deep Structure [CRDS] for the given topology.

Therefore hypothesized to be commutable terms within this 3IP rulebase, The Three Thermodynamic Rules of Macrodynamics by Jonah Lissner. The 3 General Rules of Macrodynamics [3GRM] which are established to define Global Optimization Algorithm [GOA] challenges:

1. The Rule of the Continuity of Primaries
2. The Rule of Perpetuation of Information Inequalities of Primaries
3. The Rule of Unprovable Ideals, Cardinals or Delimitations of Complex Adaptive Evolutionary Systems [CAES].

3. Algorithm definition

The **Metaheuristic Algorithm** is defined by the Author [Jonah Lissner] as.

An ontological mechanism to generate or activate decision paths [algorithms] and make decision potential to solve [essentially two-state] paradoxes, a computational physical network and topos, for practical effort or application. Therefore can be constructed a theoretical or hypothetical guideway from objects and particles to advance ontological gradations of relevance and value, through a logical progression.

A relevant algorithm to solve for discrete stigmergetics in nonlinear optimization challenges for graphing algorithms of power systems has been demonstrated in Ant Colony Optimization [ACO]:

Here in general formula where

$$p_{xy}^k = \frac{(\tau_{xy}^\alpha)(\eta_{xy}^\beta)}{\sum_{z \in \text{allowed}_x} (\tau_{xz}^\alpha)(\eta_{xz}^\beta)}$$

by trail update action $\tau_{xy} \leftarrow (1 - \rho)\tau_{xy} + \sum_k \Delta\tau_{xy}^k$.

for given function sets

$$f(x) = \lambda x, \text{ for } x \geq 0; \quad (1)$$

$$f(x) = \lambda x^2, \text{ for } x \geq 0; \quad (2)$$

$$f(x) = \begin{cases} \sin\left(\frac{\pi x}{2\lambda}\right), & \text{for } 0 \leq x \leq \lambda; \\ 0, & \text{else} \end{cases} \quad (3)$$

$$f(x) = \begin{cases} \pi x \sin\left(\frac{\pi x}{2\lambda}\right), & \text{for } 0 \leq x \leq \lambda; \\ 0, & \text{else} \end{cases} \quad (4)$$

Evolutionary Game Theory [EGT] challenges in optimization schedules are therein linked to Ant Colony Optimization [ACO], e.g. Eigenvector centrality formula

Where for $G := (E, V)$ with V vertices let $A = (av, t)$, e.g. $av, t = 1$ or $av, t = 0$. Therefore $xv = 1/1$

$$\text{SigsetM}(v)xt = 1/1 \text{ SigsetG } av, t \text{ xt}[\textit{ibid}]. \quad (5)$$

It is a basis for optimization schedules that there is an asymmetrical velocity, mass and gravity of said scope of systems. At various times in the computational history, particle optimization on the manifolds evolve at a faster rate [or slower rate] than before. Hence the given incremental and discrete rate of increase, in valleys and peaks accelerates and stabilizes at a higher positive, null or negative value and result in extremal mechanics and nonlinear dynamics. An example can be demonstrated utilizing power faults and extremals on the electrical circuits [3].

These problems of prediction for probability of choice of one object or particle of a set, for pariwise sets and in algorithms, have been demonstrated in Arrow's Impossibility Theorem and for Algorithmic Information Theory [AIT] whence we can replace *voter* for global optimization *particle* and replace *group* with *set*:

1. If every voter prefers alternative X over alternative Y, then the group prefers X over Y.
2. If every voter's preference between X and Y remains unchanged, then the group's preference between X and Y will also remain unchanged (even if voters' preferences between other pairs like X and Z, Y and Z, or Z and W change).
3. There is no "dictator": no single voter possesses the power to always determine the group's preference [4].

Important is Criteria 3, from whence adaptive and efficient algorithms have space to be constructed as particles on the run-time, for a given Global Optimization Algorithm [GOA].

4. Building the algorithm

In a praexological theory [5] this is proposed because of the inherent general inaccuracy of specific problems, learning rubrics, and Macrodynamic properties of a given performance landscape, and ultimately inefficient of any algorithmic system, given isomorphic [atomistic or non-atomistic] qualities of rulebase, algorithmic structure, weights, and variables [6]. These in turn can be represented as information sets, materiel, work, and symbolic representation and/or power in specific *qualia* of *Historical Rule of Perpetuation of Information Inequalities* set to various scales and models.

Clerc has demonstrated a general Metaheuristic algorithm where for $f: \mathbb{R}^n \rightarrow \mathbb{R}$ essentially $f(\mathbf{a}) \leq f(\mathbf{b})$. S includes the number of particles in the swarm having specific position and velocity in the search—space:

```

for each particle  $i = 1, \dots, S$  do
  Initialize the particle's position with a uniformly distributed random vector:  $\mathbf{x}_i \sim U(\mathbf{b}_{lo}, \mathbf{b}_{up})$ 
  Initialize the particle's best known position to its initial position:  $\mathbf{p}_i \leftarrow \mathbf{x}_i$ 
  if  $f(\mathbf{p}_i) < f(\mathbf{g})$  then
    update the swarm's best known position:  $\mathbf{g} \leftarrow \mathbf{p}_i$ 
  Initialize the particle's velocity:  $\mathbf{v}_i \sim U(-|\mathbf{b}_{up}-\mathbf{b}_{lo}|, |\mathbf{b}_{up}-\mathbf{b}_{lo}|)$ 
while a termination criterion is not met do:
  for each particle  $i = 1, \dots, S$  do
    for each dimension  $d = 1, \dots, n$  do
      Pick random numbers:  $r_p, r_g \sim U(0,1)$ 
      Update the particle's velocity:  $v_{i,d} \leftarrow \omega v_{i,d} + \phi_p r_p (\mathbf{p}_{i,d} - \mathbf{x}_{i,d}) + \phi_g r_g (\mathbf{g}_d - \mathbf{x}_{i,d})$ 
      Update the particle's position:  $\mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i$ 
      if  $f(\mathbf{x}_i) < f(\mathbf{p}_i)$  then
        Update the particle's best known position:  $\mathbf{p}_i \leftarrow \mathbf{x}_i$ 
      if  $f(\mathbf{p}_i) < f(\mathbf{g})$  then
        Update the swarm's best known position:
           $\mathbf{g} \leftarrow \mathbf{p}_i$ 

```

(6)

5. Results and discussion

5.1 Complex adaptive evolutionary system: thermodynamic landscape

For the purpose of evaluating algorithmic fitness on the given landscape the following ansatz can be utilized for Particle Swarm Optimization [PSO] for a decision tree:

$$\text{For } f: M_n \rightarrow M \text{ and where } M = KH_-(t, h) \text{ } \mathbf{x} \in M \quad (7)$$

Where
 M = Manifold
 M' = Algorithmic Landscape/Manifold, for
 KH = potentiated Knowledge History of the Algorithm
 t = tradition or procedural process structure [word, string, grammar, memory mapping, rulebase, database] of the algorithm
 h = computational multiplicatives and inequalities of the $\mathbf{x} \in M$ = Adaptive Landscape History of the [Numerical] Object(s) or Particle(s) on the Network.

Lovbjerg and Krink demonstrate for the thermodynamic variables on the Particle Swarm Optimization [PSO]:

$$\rightarrow v_i = \chi(w \rightarrow v_i + \phi \rightarrow 1i(p \rightarrow i- \rightarrow x_i) + \phi \rightarrow 2i(p \rightarrow g- \rightarrow x_i)) \quad (8)$$

where χ is the constriction coefficient.

Here the Three General Rules of Macrodynamics [3GRM] Macrodynamic Automata Rules [MAR] are applied to Information Natural Dynamics [IND] criteria:

Natural Sets, Natural Kinds, Natural Procedures, Natural Strings, Natural Radicals, Natural Binaries, Natural Radices, in Complex Adaptive Evolutionary System [CAES]-Multiagent System [MAS] for 4D model variables.

These variables should each contain criteria:

Time-Complexity, Particle-Value, Particle-Weighting in Fuzzy set theory, Gravity of System, $\langle \rangle$ Nanodynamics of System variables [TC-PV-PW-GS-NDS]

Set approximate to

$f : \Omega \subset \mathbb{R}^n \rightarrow \mathbb{R}$ with the global minima f^* and the set of all global minimizers X^* in Ω to find the minimum best set in the function series of (x)

(9)

for system conditions, system boundaries, number and density of particles in the total Information Natural Dynamics [IND] of the Global Optimization Algorithm [GOA]. These are applied to algorithmic manifold for the candidate solution on the given search spaces. It can be argued that given the extremes of information disequilibrium applied to macrodynamic disequilibrium models, there are inevitably generated extremals of various degrees of power, in the incremental Information Dynamics.

5.2 Complex adaptive evolutionary system: weighting

These differentiable functions can be further defined c.f. Dense heterarchy in Complex Systems Algorithms of a coupled oscillators, where in general formula.

$$\frac{dx}{dt} = (P(t) + \mu Q(t, \mu))x + f(t), \quad (10)$$

Here in a differential equation we can demonstrate.

$$u^{(n)} = f(t, u, u', \dots, u^{(n-1)}), n \geq 2, \quad (11)$$

These can be demonstrated in Particle Swarm Optimization [PSO], and Macrodynamic models of Meta-optimization of Particle Swarm Optimization [PSO] [7], c.f.

$$\mathbf{v}_i(t+1) = w \cdot \mathbf{v}_i(t) + n_1 r_1 (\mathbf{p}_i - \mathbf{x}_i(t)) + n_2 r_2 (\mathbf{p}_{best} - \mathbf{x}_i(t)) \quad (12)$$

for each set of given epoch or evolutionary landscape scenario prediction in analytical and expectation weighting parameter formula algorithm optimization [Meissner, et al., *ibid*].

5.3 Complex adaptive evolutionary system: thermodynamics

Regarding bounding definitions, Chaitin demonstrated in Algorithmic Information Theory [AIT] algorithmic decomposition given Boltzmann-Shannon entropy, where in general formula to set the integral.

$$H(X) = \sum_i P(x_i) I(x_i) = - \sum_i P(x_i) \log_b P(x_i),$$

and

$$\lim_{p \rightarrow 0^+} p \log(p) = 0.$$

For Information Natural Dynamics [IND] pairwise comparison, the genesis and stigmergetic evolutionary dynamics of the A-group agent $\mathbf{H_A}$ c.f. for

$$f : \mathbb{R}^n \rightarrow \mathbb{R} \text{ for } \mathbf{x}_i \in \mathbb{R}^n \text{ and } \mathbf{v}_i \in \mathbb{R}^n \quad (13)$$

in Particle Swarm Optimization [PSO].

The variables include function space, gradient, vector and weighting and additionally the stigmergy of the given Macrosystem and subsystem autonomies such as in a Pairwise Breakout Model [PBM].

In associated Fuzzy set logic to determine power externals and singleton mechanics in atomistic Natural Dynamic System [NDS] operations, are often utilized border-pairs or extremals for multi-pair Multilayer Perception-Learning Classification Algorithms [MLP-LCM] [7].

Examples of particle Monadicity in Algorithmic Information Theory [AIT] whence the formula

$$\mathbf{F} : \mathbf{L}(\mathbf{A})^N \rightarrow \mathbf{L}(\mathbf{A}) \text{ where the } n\text{-tuple } (\mathbf{R}_1, \dots, \mathbf{R}_N) \in \mathbf{L}(\mathbf{A})^N \quad (14)$$

indicate the possibilities and types of information physical mechanics for possible variables of the landscape extremals as particles within the min-max parameters [8]. A particle-discrete control function of the node degrees on the evolutionary landscape can therefore be defined where essentially

$$f(\mathbf{t}(\mathbf{i}) : \mathbf{P}(\mathbf{k})^n \rightarrow \mathbf{K} \int \mathbf{P}(\mathbf{k}) \mathbf{d} \mathbf{k}(\mathbf{t}') \mathbf{K} \mathbf{P} \mathbf{d} \mathbf{j}(\mathbf{t}) / \mathbf{d} \mathbf{t}. \quad (15)$$

To quantify, *Primary extrema* of n -arity or n -Adicity [Jonah Lissner] are therefore defined by the Author [Jonah Lissner] for alternatives of pair choices [as monoidal algorithmic circuits in the Complex Adaptive Evolutionary System [CAES]] which can be fractional off the prime polynomial root modulus, from the initial power conditions and therefore generate the discrete information inequalities. These can be demonstrated in Henselian numbers, and secondly, derivable fractional functions, inherent in any given complex *topos* of an complex adaptive evolutionary system [9].

Nagata defined thusly: A local ring R with maximal ideal m is called **Henselian** if Hensel's lemma holds. This means that if P is a monic polynomial in $R[x]$, then any factorization of its image P in $(R/m)[x]$ into a product of coprime monic polynomials can be lifted to a factorization in $R[x]$ [10].

5.4 Complex adaptive evolutionary system: networks

The network of circuits then form the basis for Complex Network Systems [CNS] from Simple networks $L \propto \log N$ and adaptive complex or dynamic systems and increasingly complex or quantum probability mechanics.

Scale-free or Barabasi-Albert Models are utilized to advance the mechanics and hypotheses for Complex Network Systems [CNS] e.g. for

$$P(k) \sim k^{-3}$$

and

$$p_i = \frac{k_i}{\sum_j k_j},$$

exist for give node degree correlations and links at network computations for a generic clustering law of

$$C(k) = k^{-1}. \quad (16)$$

It can be determined in scale-free network nodes.

$$L \propto \log \log N \text{ for } P(k) \sim k^{-\gamma}.$$

where

$$s(G) = \sum_{(u,v) \in E} \deg(u) \cdot \deg(v),$$

and dynamically

$$P(k) \sim k^{-\gamma} \text{ with } \gamma = 1 + \frac{\mu}{a_{\infty}}.$$

where.

$$p(x_i, x_j) = \frac{\delta x_i x_j}{1 + \delta x_i x_j}.$$

6. Conclusion

These Metaheuristics for Global Optimization Algorithms [GOA] are for purpose of achievement of the theoretical completion between two and more nodes on the network landscape, and ultimately the given requirements for the applied electrical grid. This theory can be utilized to derive, add, multiply, subtract, or divide units designated as necessary to accurately define the parameters for control of the electrical grid, and for control of network extremals.

Some theoretical requirements for Power System applications and machine learning algorithm libraries for solving heuristic challenge for power requirements and control on manifolds have been demonstrated:

1. In the definition for innovation in Global Optimization Algorithms [GOA] for Machine Learning in Power Systems the Path-decision or Algorithm is the activated object [ontesis] and Algorithmic network is the kind or type of systemic algorithmic operation of object-getting and technology-building [telesis], due to computational physical plasticity conditions and relevant criteria.
2. Furthermore the network theory meaning of Path-decision or Algorithm and the computational landscape itself as a network, can be defined discretely in terms of multiple avenues and nodes for algorithms of Boolean systems, [e.g. *st-connectivity*] whence it has progressed in weight, mass and velocity of the defined Ontology.
3. Path-decision or *Algorithm programmes* in Computational Sciences, by modules of Alphanumeric Symbols/Characters as *Power Systems of Algorithms*, [PSA]-Information Natural Dynamics [IND] or in a macrodynamic method, *Systems*

of Utilization may develop, for the purpose of heuristic advancements based on computational physical references, functions and operations on specific topologies and as treated as given *Computational sequences*.

It is proposed from 3 Rules of Information Physics [3IP] and The 3 General Rules of Macrodynamics [3GRM] for *Unprovable Ideals, Cardinals or Delimitations of Optimization* from origins in *The Rule of Perpetuation of Information Inequalities of Primaries*. These criteria are the basis to utilize previous methodologies of reasoning for contemporary and future new evolutionary algorithmic landscapes in the accretive methods.

This Metatheory develops theoretical agreement for the computational physical basis for a General Global Optimization Field Theory [GGOFT], given the algorithmic requirements of minima and maxima of a set of functions for a given computational surface, to determine roots, stationary and turning points, points of inflection, convexity, and concavity for atomistic qualities of evolutionary landscape extremals and their subsequent geometric values and derivations [11].

Therefore in this dialectic, the *Onts* or Particles in Complex Adaptive Evolutionary System [CAES] and Dynamic Global Workspace Theory-Intelligent Computational System Organization [DGWT-ICSO], can be understood as network gateways in conjunction with nonlinear surfaces, described by *Epistemes*, or Semantical value for given Formulae, Algorithms, Landscape. Their purpose is to build and attempt to game-solve more complex and efficient, workable algorithmic structures for the machine learning algorithm challenges to incremental Global Optimization Algorithm [GOA] regimes [12].

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