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Mimicking the collective intelligence of human groups as an optimization tool for complex problems

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ABSTRACT

A large number of optimization algorithms have been developed by researchers to solve a variety of complex problems in operations management area. We present a novel optimization algorithm belonging to the class of swarm intelligence optimization methods. The algorithm mimics the decision making process of human groups and exploits the dynamics of such a process as a tool for complex combinatorial problems. In order to achieve this aim, we employ a properly modified version of a recently published decision making model [64,65], to model how humans in a group modify their opinions driven by self-interest and consensus seeking. The dynamics of such a system is governed by three parameters: (i) the reduced temperature βJ, (ii) the self-confidence of each agent β', (iii) the cognitive level $0 \leq p \leq 1$ of each agent. Depending on the value of the aforementioned parameters a critical phase transition may occur, which triggers the emergence of a superior collective intelligence of the population. Our algorithm exploits such peculiar state of the system to propose a novel tool for discrete combinatorial optimization problems. The benchmark suite consists of the NK - Kauffman complex landscape, with various sizes and complexities, which is chosen as an exemplar case of classical NP-complete optimization problem.

A comparison with genetic algorithms (GA), simulated annealing (SA) as well as with a multiagent version of SA is presented in terms of efficacy in finding optimal solutions. In all cases our method outperforms the others, particularly in presence of limited knowledge of the agent.

1. Introduction

Human groups are proven to outperform single individuals in solving a variety of complex tasks in many different fields, including new product development, organizational design, strategy planning, research and development. Their superior ability originates from the collective decision making: individuals make choices, pursuing their individual goals on the basis of their own knowledge/expertise and adapting their behavior to the actions of the other agents. Social interactions, indeed, promote a mechanism of consensus seeking within the group, but also provide a useful tool for knowledge and information sharing [1–4,40]. This type of decision making dynamics is common to many social systems in Nature, e.g., flocks of birds, herds of animals, ant colonies, school of fish [40–50], as well as bacterial colonies [5–7], and even to artificial systems [8–11].

Even though the single agent possesses a limited knowledge, and the actions it performs are usually very simple, the collective behavior leads to the emergence of a superior intelligence known as swarm or collective intelligence [12–15,29], which in the last years have seen a huge growth of applications in the field of optimization swarm-based algorithms in operations management context [30–33]. The swarm algorithms exploit the collective intelligence of the social groups, such as flock of birds, ant colonies, and schools of fish, in accomplishing different tasks. They include the Ant Colony Optimization (ACO) [17–19], the Particle Swarm Optimization [20], the Differential Evolution [21], the Artificial Bee Colony [22,23], the Glowworm Swarm Optimization [24,25], the Cuckoo Search Algorithm [26], and very recently the

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Grey Wolf Optimizer [27] and the Ant Lion Optimizer [28]. These algorithms share remarkable features, such as decentralization, self-organization, autonomy, flexibility, and robustness, which have been proven very useful to solve complex operational tasks [34,35]. Applications of ACO algorithm mainly concern the traveling salesman problem, scheduling, vehicle routing, and sequential ordering [36]. More recently, they have been also employed in supply chain contexts to solve production-inventory problems [37,38] and network design [39].

In this paper we propose a novel swarm intelligence optimization algorithm to solve complex combinatorial problems. The proposed algorithm is inspired by the behavior of human groups and their ability to solve a very large variety of complex problems, even when the individuals may be characterized by cognitive limitations. Although it is widely recognized that human groups, such as organizational teams, outperform single individuals in solving many different tasks including new product development, R&D activities, production and marketing issues, literature is still lacking of optimization algorithms inspired by the problem solving process of human groups. Similarly to other social groups, human groups are collectively able, by exploiting the potential of social interactions, to achieve much better performance than single individuals can do. This specific ability of human groups has been defined as group collective intelligence [51,52] that recently is receiving a growing attention in the literature as to its antecedents and proper measures [51,52].

The proposed algorithm, hereafter referred to as Human Group Optimization (HGO) algorithm, is developed within the methodological framework recently proposed by CG [53,54] to model the collective decision making of human groups. This model captures the main drivers of the individual behavior in groups, i.e., self-interest and consensus seeking, leading to the emergence of collective intelligence. The group is conceived as a set of individuals making choices based on rational calculation and self-interested motivations. However, any decision made by the individual is also influenced by the social relationships he/she has with the other group members. This social influence pushes the individual to modify the choice he/she made, for the natural tendency of humans to seek consensus and avoid conflict with people they interact with [55]. As a consequence, effective group decisions spontaneously emerge as the result of the choices of multiple interacting individuals.

To test the ability of HGO algorithm, we compare its performance with those of some benchmarks chosen among trajectory-based and population-based algorithms. In particular, the HGO is compared with the Simulated Annealing (SA), a Multi Agent version of the Simulated Annealing (MASA) and with genetic algorithms (GA).

2. The decision making model of human groups

Here we briefly summarize the decision making model presented in Ref. [53,54]. We consider a human group made of M socially interacting members, which is assigned to accomplish a complex task. The task is modelled in terms of N binary decisions and the problem consists in solving a combinatorial decision making problem by identifying the set of choices (configuration) with the highest fitness, out of 2^N configurations.

As an example of application of the method, the fitness landscape, i.e., the map of all configurations and associated fitness values, is generated following the classical *NK* procedure (see Appendix A for more details), where N are the decisions and K the interactions among them. Each decision d_i of the vector $\mathbf{d}$ is a binary variable $d_i = \pm 1,\ i = 1, 2, \ldots, N$. Each vector $\mathbf{d}$ is associated with a certain fitness value $V(\mathbf{d})$ computed as the weighted sum of N stochastic contributions $W_j\left(d_j, d_1^j, d_2^j, \ldots, d_K^j\right)$ that each decision leads to the total fitness. The contributions $W_j\left(d_j, d_1^j, d_2^j, \ldots, d_K^j\right)$ depend on the value of the decision d_j itself and the values of other K decisions $d_i^j,\ i = 1, 2, \ldots, K$, and are determined following the classical *NK* procedure [56–58]. The fitness function is then defined as

$$V(\mathbf{d}) = \frac{1}{N}\sum_{j=1}^{N} W_j\left(d_j, d_1^j, d_2^j, \ldots, d_K^j\right) \tag{1}$$

The integer index $K = 0, 1, 2, \ldots, N-1$ corresponds to the number of interacting decision variables, and tunes the complexity of the problem: increasing K increases the complexity of the problem. Individuals are characterized by cognitive limits, i.e. they posses a limited knowledge. The level of knowledge of the kth member of the group is identified by the parameter $p \in [0,\ 1]$, which is the probability that each single member knows the contribution of the decision to the total fitness.

Based on the level of knowledge, each member k computes his/her own perceived fitness (self-interest) as follows:

$$V_k(\mathbf{d}) = \frac{\sum_{j=1}^{N} D_{kj} W_j\left(d_j, d_1^j, d_2^j, \ldots, d_K^j\right)}{\sum_{j=1}^{N} D_{kj}}. \tag{2}$$

where $\mathbf{D}$ is the matrix whose elements D_{kj} take the value 1 with probability p and 0 probability $1-p$.

During the decision making process, each member of the group makes his/her choices to improve the perceived fitness (self-interest) and to seek consensus within the group. The dynamics is modelled by means of a continuos-time Markov process where the state vector $\mathbf{s}$ of the system has $M \times N$ components $\mathbf{s} = (s_1, s_2, \ldots, s_n) = \left(\sigma_1^1, \sigma_1^2, \ldots \sigma_1^N, \sigma_2^1, \sigma_2^2, \ldots \sigma_2^N, \ldots, \sigma_M^1, \sigma_M^2, \ldots \sigma_M^N\right)$. The variable $\sigma_k^j = \pm 1$ is a binary variable representing the opinion of the member k on the decision j. The probability $P(\mathbf{s},\ t)$ that at time t, the state vector takes the value $\mathbf{s}$ out of 2^N possible states, satisfies the master equation

$$\frac{dP}{dt} = -\sum_l w\left(\mathbf{s}_l \to \mathbf{s}_l'\right) P(\mathbf{s}_l, t) + \sum_l w\left(\mathbf{s}_l' \to \mathbf{s}_l\right) P\left(\mathbf{s}_l', t\right) \tag{3}$$

where $\mathbf{s}_l = (s_1, s_2, .., s_l., s_n)$ and $\mathbf{s}_l' = (s_1, s_2, ., -s_l., s_n)$. The transition rate of the Markov chain (i.e. the probability per unit time that the opinion s_l flips to $-s_l$ while the others remain temporarily fixed) is defined so as to be the product of the transition rate of the Ising–Glauber dynamics [59], which models the process of consensus seeking to minimize the conflict level, and the Weidlich exponential rate [60,61], which models the self-interest behavior of the agents:

$$w\left(\mathbf{s}_l \to \mathbf{s}_l'\right) = \frac{1}{2}\left[1 - s_l \tanh\left(\beta \frac{J}{< \kappa >} \sum_h A_{lh} s_h\right)\right] \times \exp\left\{\beta'\left[\Delta V\left(\mathbf{s}_l', \mathbf{s}_l\right)\right]\right\} \tag{4}$$

In Eq. (4) A_{lh} are the elements of the adjacency matrix, $J/\langle\kappa\rangle$ is the social interaction strength and $\langle\kappa\rangle$ the mean degree of the network of social interactions. The quantity β is the inverse of the social temperature that is a measure of the degree of confidence the members have in the other judgement/opinion. Similarly, the quantity β' is related to the level of confidence the members have about their perceived fitness (the higher β', the higher the confidence).