



SDI Review Form 1.6

PART 1:

Journal Name:	British Journal of Mathematics & Computer Science
Manuscript Number:	2013_BJMCS_3381
Title of the Manuscript:	Pseudorandomness in Central Force Optimization

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- This form has total 9 parts. Kindly note that you should use all the parts of this review form.



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PART 2: Review Comments

	Reviewer's comment	Author's comment (if agreed with reviewer, correct the manuscript and highlight that part in the manuscript. It is mandatory that authors should write his/her feedback here)
Compulsory REVISION comments	1. The optimization method described in the manuscript looks similar to the well known method of gradient descend, especially the equation 2 (acceleration is an analogue of the gradient, which is estimated via Eq. 1, meaning that the method can be called quasi-gradient descend). Therefore, an explicit comparison with gradient descend-type methods is required to show advantages of the proposed method constructively. The "gravity" analogy seems more confusing than helping, especially given the fact that the space is multidimensional, there is no velocity concept, and the notion of "mass" in the proposed optimization method is quite different from that in mechanics (as the author himself admits). 2. It looks like the author rediscovers what is very well known in the field of numerical optimization methods, namely, that the convergence strongly depends on the quality of initial approximation. This is exactly why the distribution of starting points makes a big difference. There is no need to discuss this well-known fact at length. Random number generators are often used for generating starting point sets as a	1. The reviewer astutely points out that CFO is similar in some ways to classical "gradient" optimization methods, which indeed is the case. Because it is important, this similarity is, in fact, the subject of a previously published paper, viz, "Formato RA. Central force optimisation: a new <i>gradient-like</i> metaheuristic for multidimensional search and optimisation. Int. J. Bio-Inspired Comp. 2009;1(4):217-238" (emphasis added), to wit, "This paper raises the question of what CFO really is by describing it as a 'gradient-like' metaheuristic. With the values $\alpha = 2$, $\beta = 2$, for example, and the difference of fitnesses in the definition of CFO 'mass' used here, the ratio of mass to the distance between probes looks very much like the square of a directional derivative in the decision space. Of course, it is not one because of the unit step function needed to keep the 'mass' positive. But it certainly is similar to a derivative, and, in that sense, CFO may be thought of as a <i>gradient-like</i> deterministic optimiser. This characterisation may be useful as a catalyst for the development of a multidimensional 'generalised gradient' as a new mathematical construct. This expanded concept of derivative might include the unit step as an integral part, for example, in order to implement effective CFO searches." This paper also discusses at length the notion of "mass" and "gravity" in CFO space. It provides specific examples of "positive" and "negative" gravity and mass, and it explains the



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	strategy in the “game against nature”, i.e., to increase chances that at least a few would work well on the objective function’s landscape. Instead of attempting to explain how “pseudo-random” or “arbitrarily chosen” variables differ from “true” random ones, the author should better discuss the task of selecting the set of initial approximations in the framework of Monte-Carlo approach that has substantial advantages over using regular procedures, especially for multi-dimensional spaces. 3. The quality of the illustration material does not seem acceptable for publication in a respectable journal. The Figures 10 or 11 do not look good at all. A detailed description (legend) should be provided for each figure and each table. Instead of tables such as Table 1, results of a statistical analysis are more appropriate (e.g., a histogram of the number objective function computations across runs). Statistical results presented in a compact form should be provided not just for one, but for all (or most) benchmark objective functions.	use of the Unit Step function in the mass definition as a requirement for creating positive-definite masses. The paper also highlights the differences between metaphorical “CFO space” and our physical Universe by addressing specifically the kinematics of gravitational trapping in the context of energy-conserving close encounters. The author believes that the modifications to the paper 3381 more than adequately address all of the reviewer’s concerns because, in fact, all the issues raised are the subject of previously published work. 2. The reviewer’s second comment fails to address the fact that CFO is essentially a deterministic metaheuristic that provides the <i>option</i>, at the algorithm designer’s discretion, of including a measure of “pseudorandomness,” which is not at all the same as “true randomness.” CFO thus offers “the best of both worlds” because it can be implemented purely deterministically, purely randomly, pseudorandomly, or in a hybrid manner. No other algorithm provides this flexibility, and the very point of the paper is that the designer may advantageously create pseudorandom implementations that perform better than purely deterministic ones. The paper provides specific examples of this benefit, and, in fact, additional material has been added to better demonstrate this effect (CFO-alone data in Table 2 and accompanying discussion). In addition, the original CFO paper, “Formato RA. Central Force Optimization: A New Metaheuristic with Applications in Applied
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		Electromagnetics. Prog. Electromagnetics Research. 2007;77:425–491," addresses all of the other points brought up in the reviewer's comment #2, so that there is no need to repeat this material. 3. In order to improve the quality of the illustrations, all figures have been recomputed or redrawn, printed at "best photo" quality on photo paper, and scanned at 400 dpi to JPG files, which then were inserted into the paper (JPG's available as separate files if required). As to "statistical results," CFO is deterministic, even when a pseudorandom element is added, which is the very point of the paper. Because CFO is deterministic, a <i>single run</i> provides <i>all</i> the data that can possibly be obtained because every run with the same setup returns precisely the same results. This characteristic, in fact, is one of CFO's major advantages, and it is discussed extensively in the paper. By contrast, the other algorithms used for comparison, viz, GSO/GA/PSO, are inherently stochastic and, as a consequence, do require a statistical description, which is included in Table 2. To address the question of how many function calculations these algorithms required, Table 3 has been added that includes the number of function calls per run as reported in the original GSO paper "He S, Wu QH, Saunders JR. Group Search Optimizer: An Optimization Algorithm Inspired by Animal Searching Behavior. IEEE Trans. Evol. Computation, 2009;13(5):973-990," which has been added as a reference. In addition, the paper that initially introduced the 23-function
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		benchmark suite used for GSO, "Yao X, Liu Y, Lin G. Evolutionary Programming Made Faster. IEEE Trans. Evol. Comp. 1999;3(2):82-102," has been added to the references because it discusses the benchmarks in detail (functional form, locations/magnitude of optima, decision space, general attributes), so that it is not appropriate to repeat this information.
<u>Minor</u> REVISION comments	What abbreviations GSO and GA stand for is not immediately clear. It should not be assumed that every reader knows that GA stands for "genetic algorithm", let alone that GSO means "glowworm swarm optimization". Besides, GA is a rather wide and large set of algorithms (it is an approach to optimization), so it is not clear based on what reasons the author is comparing his method to that whole set.	Additional discussion has been added to define the terms "GSO," "GA," and "PSO," as well as discussion of the setup parameters for these algorithms. The original GSO paper has been added to the list of references.
<u>Optional/General</u> comments		The author thanks Professor Shimansky for his time and consideration in reviewing this paper.