Reply to Paper: CYB-E-2021-01-0040
Reply to the Associate Editor

Associate Editor:
Comments to the Author:

A tremendous work on similar ideas has been done already in the literature, e. g. network function virtualization, for controlling and scheduling resources by using also machine learning training models. The authors should compare their work with these similar ideas and how their work outperforms the machine learning models for scheduling? The rationale behind the derivation of the problem statements for multiple DE algorithms should be further improved to reflect the potential of the proposed research work.

Thank you very much for your valuable suggestions.

We sincerely appreciate the time and effort that you and the referees dedicated to providing feedback on our manuscript and are grateful for the insightful comments on our paper. However, we are really sorry that some unclear contents and ambiguities in the previous manuscript may make the third referee misunderstand the scope and contribution of this paper.

We would like to mention that this paper focuses on how to improve the performance of distributed differential evolution (DDE) (i.e., help DDE find optimal solutions more efficiently) by allocating fitness evaluation (FE) budget resources. Therefore, we propose a three-layer framework together with three novel methods to enhance the DDE algorithm, which is far away from the field of task scheduling. That is, our algorithm is for solving optimization problems, but not task scheduling. In this sense, we think that the comparisons with work for task scheduling including those based on network function virtualization and machine learning models could be not appropriate for inclusion in this paper. Nevertheless, we have worked very hard to revise the manuscript with the best of care to further clarify the main scope and contribution of this paper. Also, we have given explanations in the reply to the third referee and answered his questions carefully, so as to address his issues and help him better understand the scope and contribution of this paper.

Except for the suggestion from the third referee about the comparisons with work for scheduling, we very much agree with your insightful comment that "*The rationale behind the derivation of the problem statements for multiple DE algorithms should be further improved to reflect the potential of the proposed research work*". Therefore, we have further re-considered the derivation of the problem statements in the abstract and Introduction of the manuscript and revised them carefully to reflect the contribution of this paper clearer.

Moreover, we have also taken the comments from the third referee about the organization of the paper into considerations and revised the manuscript accordingly, so as to improve the quality of the paper.

In the revised manuscript, all the revisions have been marked in blue color. We hope that the revised manuscript and this reply can address the issues raised by the third referee and help him better understand the scope and contribution of this paper. Thank you very much again for your effort in the quality improvement of this paper.

Reply to the Referee: 1

Recommendation: Accept

Comments:
Authors have addressed all comments properly.

Summary of Evaluation: Excellent
Organization: 5
Clarity: 5
Length: 4
References: 5
Correctness: 5
Significance: 5
Originality: 5
Attachments: 5
If Survey Coverage: 5
Contribution: 5

What are the contributions of the paper?:
This paper is efficiently contributed in the field of resource allocation.

What are the additional ways in which the paper could be improved?:
Try for human neuroscience basis optimization for getting better results.

Thank you very much for your very positive recommendation and comments and suggestions.

Reply to the Referee: 2

Recommendation: Accept

Comments:
(There are no comments. Please check to see if comments were included as a file attachment with this e-mail or as an attachment in your Author Center.).

Summary of Evaluation: Excellent
Organization: 4
Clarity: 4
Length: 4
References: 4
Correctness: 5
Significance: 5
Originality: 5
Attachments: 5
If Survey Coverage: 4
Contribution: 5

What are the contributions of the paper?: no comments.

What are the additional ways in which the paper could be improved?: no comments.

Thank you very much for your very positive recommendations.

Reply to the Referee: 3

Recommendation: Prepare A Major Revision

1. Thanks for your reply to my previous concerns. With a better understanding of the main contribution of this research work, I have additional comments as follows.

Thank you for your positive comments on our effort in enhancing the quality of the paper.

We have carefully considered your additional comments and revised the manuscript accordingly. Furthermore, we have provided more descriptions and explanations in the reply. We sincerely hope that the revised manuscript and the reply can address your issues and help you better understand the contribution of this paper.

- The paper should be revised to be more clear and organized. Examples of the poor presentation of the paper are as follows,
1). The second paragraph in Section 1. It starts with However. It is better to be combined with the first paragraph.

Thank you for your suggestion.

We have combined the second paragraph with the first paragraph in the revised manuscript.

2). The second paragraph in page 2, These DDEs have shown their efficiency in some complex and time-consuming optimization problems. Which DDEs do the author mean?

Thank you for your question.

We would like to mention that "these DDEs" refer to the DDEs for solving non-decomposable problems. We are sorry that this sentence in the previous manuscript makes you confused. Therefore, we have revised "These DDEs" to be "The DDEs for solving non-decomposable problems" to make the paper easier to understand, which has been marked in blue color in the revised manuscript.

3). In page 2 also, However, as different problems favor different strategies and parameters. Which problems and strategies do the author mean? Examples might be required.

Thank you for your question and suggestion.

We would like to mention that the "different problems" means different optimization problems and the "strategies" means mutation strategies in DEs and DDEs. For example, "DE/rand/1" and "DE/best/1" mutation strategies can be suitable for different optimization problems. This can be supported by the experimental results provided in this paper. For instance, as can be seen in Table S. I of the supplementary material, "DE/best/0.1" (i.e., the DE with "DE/best/1" mutation strategy and with crossover parameter *CR*=0.1) obtains the best results on F07, F09, and F11, while "DE/rand/0.9" (i.e., the DE with "DE/rand/1" mutation strategy and with crossover parameter *CR*=0.9) produces the best results on F01-F03. Similarly, the results in Table S. II to Table S. IV of supplementary material also show the examples that DEs with different strategies and parameters obtain the best results on different optimization problems. To make the paper easier to understand, we have revised related contents and provided further descriptions and examples in the Introduction part of the revised manuscript, where the revised contents are as "*However, optimization problems with different characteristics may favor algorithms with different configurations such as the mutation strategies and parameters. For example, algorithms with different mutation strategies and crossover parameters can result in different optimization results on different optimization problems.*".

Herein, the Table S. I in the supplementary material is also given below for your reference.

TABLE S.I.
COMPARISONS AMONG DDE-ARA AND CONVENTIONAL DEs ON 10-D FUNCTIONS

Func.	DDE-ARA	DE/best/0.1	DE/best/0.9	DE/rand/0.1	DE/rand/0.9
F01	**0.00E+00±0.00E+00**	1.08E+04±2.35E+04(+)	1.50E+05±5.06E+05(+)	3.76E+04±1.62E+04(+)	**0.00E+00±0.00E+00(≈)**
F02	**0.00E+00±0.00E+00**	1.06E+00±9.77E-01(+)	1.97E+02±1.39E+03(+)	2.77E+01±2.61E+01(+)	**0.00E+00±0.00E+00(≈)**
F03	**0.00E+00±0.00E+00**	3.50E+00±2.79E+00(+)	7.25E+02±3.32E+03(+)	4.60E+01±3.36E+01(+)	**0.00E+00±0.00E+00(≈)**
F04	**1.07E+00±3.15E+00**	1.11E+01±1.39E+01(+)	2.29E+01±1.56E+01(+)	3.81E+00±3.62E+00(+)	1.84E+01±1.67E+01(+)
F05	**1.89E+01±2.55E+00**	1.95E+01±2.48E+00(≈)	2.03E+01±1.28E-01(+)	1.98E+01±1.38E+00(+)	2.02E+01±7.87E-02(+)
F06	**2.26E-01±3.75E-01**	2.82E-01±4.53E-01(+)	2.83E+00±1.88E+00(+)	1.76E+00±5.27E-01(+)	1.15E+00±1.52E+00(+)
F07	9.79E-02±4.05E-02	**3.21E-02±1.43E-02(-)**	2.57E-01±6.42E-01(+)	4.75E-02±1.58E-02(-)	1.99E-01±1.49E-01(+)
F08	**0.00E+00±0.00E+00**	6.04E-01±8.98E-01(+)	1.24E+01±5.84E+00(+)	**0.00E+00±0.00E+00(≈)**	5.30E+00±4.97E+00(+)
F09	8.83E+00±2.31E+00	**4.53E+00±1.18E+00(-)**	1.61E+01±7.61E+00(+)	6.01E+00±1.27E+00(-)	1.78E+01±9.20E+00(+)
F10	**5.57E-02±6.55E-02**	2.84E+01±2.60E+01(+)	3.90E+02±2.34E+02(+)	5.50E+00±6.21E+00(+)	6.28E+01±3.01E+01(+)
F11	3.05E+02±1.08E+02	**2.02E+02±8.86E+01(-)**	7.42E+02±3.36E+02(+)	2.96E+02±9.38E+01(≈)	4.04E+02±3.05E+02(+)
F12	3.76E-01±1.37E-01	3.10E-01±7.86E-02(-)	3.85E-01±3.01E-01(+)	3.47E-01±6.75E-02(-)	**2.87E-01±1.70E-01(-)**
F13	**1.57E-01±4.52E-02**	1.75E-01±3.65E-02(+)	2.20E-01±9.37E-02(+)	1.95E-01±3.82E-02(+)	1.68E-01±7.08E-02(+)
F14	1.49E-01±4.09E-02	**1.22E-01±3.05E-02(-)**	2.75E-01±1.49E-01(+)	1.63E-01±4.30E-02(+)	1.51E-01±4.85E-02(≈)
F15	1.18E+00±2.90E-01	**8.80E-01±1.61E-01(-)**	1.61E+00±8.51E-01(+)	1.01E+00±1.87E-01(-)	1.98E+00±6.10E-01(+)
F16	2.15E+00±2.91E-01	**2.02E+00±2.70E-01(-)**	2.86E+00±5.34E-01(+)	2.29E+00±2.40E-01(+)	2.44E+00±7.19E-01(+)
F17	4.67E+01±4.96E+01	1.06E+04±8.61E+03(+)	1.23E+03±5.94E+03(+)	3.00E+04±1.95E+04(+)	**8.16E+00±2.15E+01(-)**
F18	1.46E+00±1.23E+00	3.48E+01±2.95E+01(+)	6.20E+01±5.67E+01(+)	3.20E+02±2.13E+02(+)	**1.28E+00±8.28E-01(-)**
F19	**2.11E-01±1.22E-01**	5.30E-01±4.34E-01(+)	2.98E+00±1.72E+00(+)	4.04E-01±1.32E-01(+)	4.27E-01±4.80E-01(+)
F20	8.71E-01±3.75E-01	2.80E-01±3.97E-01(+)	6.72E+02±4.58E+03(+)	**2.47E-01±1.39E-01(-)**	2.69E-01±4.10E-01(-)
F21	**3.74E-01±2.37E-01**	4.51E+01±4.74E+01(+)	6.76E+04±4.77E+05(+)	5.38E+02±4.74E+02(+)	1.08E+00±3.31E+00(+)
F22	**3.06E-01±2.42E-01**	4.07E+00±7.06E+00(+)	7.40E+01±8.20E+01(+)	7.32E-01±1.02E+00(+)	6.70E+00±9.39E+00(+)
F23	3.29E+02±1.72E-13	3.29E+02±1.72E-13(≈)	3.30E+02±3.73E+00(+)	**3.27E+02±1.67E+01(-)**	3.29E+02±1.72E-13(≈)
F24	1.15E+02±2.99E+00	**1.13E+02±2.09E+00(≈)**	1.29E+02±1.95E+01(+)	1.14E+02±2.12E+00(≈)	1.23E+02±1.02E+01(+)
F25	1.39E+02±9.82E+00	**1.34E+02±9.51E+00(-)**	1.93E+02±2.17E+01(+)	1.46E+02±9.59E+00(+)	1.97E+02±1.83E+01(+)
F26	**1.00E+02±5.22E-02**	**1.00E+02±3.59E-02(≈)**	**1.00E+02**±9.97E-02(≈)	**1.00E+02±3.54E-02(≈)**	**1.00E+02±5.74E-02(≈)**
F27	**3.31E+00±1.70E+00**	1.69E+02±1.81E+02(+)	2.93E+02±1.61E+02(+)	1.47E+02±1.64E+02(+)	1.63E+02±1.72E+02(+)
F28	**3.68E+02±1.24E+01**	4.03E+02±4.44E+01(+)	4.68E+02±9.75E+05(+)	3.72E+02±5.40E+00(+)	3.85E+02±2.26E+01(+)
F29	**1.44E+02±2.63E+01**	5.83E+02±7.37E+02(+)	4.00E+05±9.75E+05(+)	5.44E+02±8.68E+01(+)	2.34E+02±6.04E+01(+)
F30	4.77E+02±3.27E+01	5.31E+02±1.07E+02(+)	7.54E+02±3.49E+02(+)	5.21E+02±3.18E+01(+)	**4.75E+02±2.34E+01(≈)**
+/≈/-		18/4/8	29/1/0	20/4/6	19/7/4

According to the Wilcoxon's rank sum test (significant level of α=0.05), the symbols "+", "≈", or "-" are adopted to indicate that the proposed algorithm is significantly better (+), similar (≈), or significantly worse (-) than the compared algorithms, respectively.

4). The motivation and research problem in Section 1 should be re-edited.

Thank you for your suggestion.

We have further revised the motivation and research problem in Section I carefully with consideration of your valuable comments. We hope that the revised manuscript can meet with your approval.

- Considering mentioning that on page 2, The algorithm layer employs multiple DE algorithms to satisfy the requirements of various problems.
1). Why does the paper limit the contribution of the algorithm layer into the family of DE algorithms only?

Thank you for your question.

We would like to mention that this paper focuses on how to improve the performance of DDEs (i.e., help DDEs find optimal solutions more efficiently) by allocating fitness evaluation (FE) budget resources among the DE populations. Therefore, the algorithm layer only considers the family of DE algorithms in this paper because we want to enhance the performance of DE algorithm. Although it can be interesting to consider other algorithms, this could be not suitable for this paper because improving the optimization performance of other algorithms is beyond the scope of this paper.

Nevertheless, your comment indeed reminds us that the fitness evaluation budget resources adaptive allocation framework can be applied to other distributed evolutionary computation algorithms as future work, which has been added in the revised manuscript to enhance the quality of the paper.

2). Why it doesn't consider other optimization algorithms that might optimize the computation resources for other problems based on their demands of quality of service?

Thank you for your question.

We would like to mention that optimizing the scheduling of computational resources based on the demand of quality of service is not the focus of this paper. Therefore, we do not need to consider this.

3). Is the algorithm layer will be a central unit for all the machines and resources in the infrastructure layer or it will be a distributed unit on each machine? In the case of centralized architecture, communication and computation topologies are required.

Thank you for your question.

We would like to answer that the algorithm layer is not a central unit for the scheduling of the machines. The algorithm layer contains multiple DE populations for solving the optimization problems. Therefore, we do not need to consider the communication and computation topologies about the infrastructure layer.

4). A tremendous work on similar ideas has been done already in the literature, e.g., network function virtualization, for controlling and scheduling resources by using also machine learning training models. What is your contribution in comparison with these similar ideas and how does your work outperform the machine learning models for scheduling?

Thank you for your comments and questions.

We would like to mention that the major focus of this paper is to improve the performance of DDEs (i.e., help DDEs find optimal solutions more efficiently) for optimization problems, but not the task scheduling for improving the quality of service. Herein, the "adaptive resource allocation" in our work means to adaptively allocate the fitness evaluation budget resources among the multiple DE populations, but not the scheduling of hardware resources or the virtualized computational resources. Therefore, the ideas like those based on network function virtualization and machine learning models for controlling and scheduling resources are very different from the scope and contribution of this paper. With this concern, we have revised the manuscript carefully to better clarify the scope and contribution of this paper (refer to the reply to your next comment). Also, due to the above reasons, it could be not suitable to compare the algorithm proposed in this paper with network function virtualization or machine learning models.

5. The related research works section and references are very poor because they do not include sufficient references or similar related works on scheduling.

Thank you for your comments.

Sincerely, we would like to mention that the major focus of this paper is to improve DDEs by allocating fitness evaluation (FE) budget resources among multiple populations, so that it can find the optimal solution more efficiently, i.e., have better optimization performance, which has no relationship with task scheduling.

In addition, we have noticed that the terms like "schedule computational tasks" and "schedule layer" in the previous manuscript may result in ambiguity and make you confused, for which we are really sorry. We would like to mention that the term "schedule computational tasks" does not mean the proposed algorithm is for task scheduling. In fact, the term "computational tasks" in the previous manuscript only refers to the fitness evaluations of individuals in multiple populations in DDEs. Therefore, to avoid such ambiguity, we have replaced all the "computational tasks" with "fitness evaluations" in the revised manuscript. Furthermore, the term "schedule layer" (i.e., the name of the second layer in the proposed framework) is not for the task scheduling for quality of service. Actually, it is to dispatch individuals to different distributed machines to perform fitness evaluations efficiently. Therefore, we have also changed the term "schedule layer" to "dispatch layer" and revised related contents and figures in the revised manuscript. We hope that these revisions can help better clarify the scope of this paper.

Nevertheless, as we use the distributed computing techniques (DCTs) to run the DDE algorithm, it would be interesting to make a review of existing work for task scheduling. Therefore, we do review some related works about the DCTs like the references [21] to [24] with the descriptions like "*Besides, some researches studied better task scheduling and load balance in distributing computing systems [49]-[51]. For example, as wireless distributed computing has various benefits for applications [21]-[23], Alfaqawi et al. [24] proposed an efficient load balancing algorithm for wireless distributed computing networks.*".

[21] M. Alfaqawi, M. H. Habaebi, M. R. Islam, and M. U. Siddiqi, "Energy harvesting network with wireless distributed computing," *IEEE Syst. J.*, vol. 13, no. 3, pp. 2605-2616, 2019.

[22] M. Alfaqawi, J. Chebil, M. H. Habaebi, and D. Datla, "Wireless distributed computing for cyclostationary feature detection," *Digital Commun. Netw.* vol. 2, no. 1, pp. 47-56, 2016.

[23] M. Alfaqawi, J. Chebil, M. H. Habaebi, N. Ramli, and H. Mohamad, "A novel scheme for performing wireless distributed computing with strip spectral correlation algorithm," in *Proc. Asia-Pacific Conf. Commun.*, 2013, pp. 387-392.

[24] M. Alfaqawi, M. H. Habaebi, M. U. Siddiqi, M. R. Islam, S. Khan, and D. Datla, "Adaptive load balancing algorithm for wireless distributed computing networks," in *Proc. Int. Conf. Intell. Syst. Eng.* 2016, pp. 256-261.

[49] Z. H. Zhan, X. F. Liu, Y. J. Gong, J. Zhang, H. S. H. Chung, and Y. Li, "Cloud computing resource scheduling and a survey of its evolutionary approaches," *ACM Comput. Surveys*, vol. 47, no. 4, Article 63, pp. 1-33, Jul. 2015.

[50] S. M. Ghaleb, S. Subramaniam, Z. A. Zukarnain, and A. Muhammed, "Load balancing mechanism for clustered PMIPv6 protocol.," *EURASIP J. Wirel. Commun. Netw.*, vol. 135, pp. 1-23, 2018.

[51] J. K. Konjaang, F. H. Ayob, and A. Muhammed, "Cost effective Expa-Max-Min scientific workflow allocation and load balancing strategy in cloud computing," *J. Comput. Sci.*, vol. 14, no. 5, pp. 623-638, 2018.

6. This type of algorithms creates new challenges such as the placement of the three layers algorithm, orchestraization and management.

Thank you for your comment.

We would like to mention that this paper proposes a DDE-ARA framework together with three novel methods to allocate fitness evaluation (FE) budget resources among different DE populations. Moreover, only the algorithm layer will have DE algorithms while the second and third layer do not contain algorithms. Therefore, the proposed algorithm does not have the challenges as you pointed out.

What are the contributions of the paper?: Various algorithms have been proposed for non-decomposition distributed differential evolution (DDE). It proposes a framework that classifies the DDE problem into three main layers, i.e. algorithm, scheduling and resources. For the algorithm layer two algorithms have been proposed, GPI and FEA while LBS for the scheduling layer.

Thank you for your comment.

We would like to mention that this paper proposes a non-decomposition distributed differential evolution (DDE) algorithm named DDE-ARA for solving optimization problems, where DDE mentioned in this paper refers to "a kind of algorithm" but not "problem". Besides, to make the paper easier to understand and to avoid ambiguity, we have changed the name of the second and third layer in DDE-ARA to be "dispatch layer" and "machine layer", respectively.

What are the additional ways in which the paper could be improved?: Consider and compare this work with similar research works done in the domain of virtualization to schedule and optimize resources considering machine learning.

Thank you for your suggestion.

We would like to sincerely mention that this could be not reasonable because this paper has no relationship with the domain of virtualization. Furthermore, we would like to mention that this work has already been compared with conventional and state-of-the-art similar research works on all the 30 optimization problems of CEC 2014 competitions at 10, 30, 50, and 100 dimensions, which can be seen in Section IV-B and Section IV-C of the revised manuscript.

Indeed, we really appreciate your time and effort very much in providing potential suggestions on the quality improvements of our manuscript. Thank you very much.

Reply to the Referee: 4

Recommendation: Accept

Comments:
Correction done.

Summary of Evaluation: Good
Organization: 4
Clarity: 4
Length: 4
References: 4
Correctness: 4
Significance: 4
Originality: 4
Attachments: 5
If Survey Coverage: 4
Contribution: 4

What are the contributions of the paper?:
Authors have proposed a new DDE-ARA framework that comprises three novel methods; GPI, FEA and LBS, aiming to enhance the search efficiency and the computational speed up of distributed differential evolution (DDE) that is very significant in solving complex optimization problems. The proposed framework is able to produce good quality solutions; improve the search and computational speed up performance better when compared with the benchmark approach results. The produced results are far promising when compared with top-performing algorithms from the CEC2014 competition.

What are the additional ways in which the paper could be improved?:
None - authors has done the correction.

Thank you very much for your very positive recommendation and comments.