**Title: Physics-Informed Evolutionary Learning and Optimization**

**Background**

Physics, as a foundational framework for describing the natural world, has been pivotal to scientific inquiry throughout human history. Physical information has long been integrated into various research domains, including evolutionary computation. Over the past two decades, such information has frequently been applied in data-driven contexts within evolutionary computing [1]. By utilizing data from classical physics simulators—such as the finite element method [2], finite difference method [3], and finite volume method [4]— researchers have developed surrogate models to approximate real-world physical indicators. These models guide evolutionary algorithms, enabling optimal solutions in engineering optimization problems. Recently, the significance of physical information has been increasingly recognized within artificial intelligence, with a growing body of research dedicated to integrating physical data into learning and optimization processes [5]. Notably, evolutionary computation has demonstrated substantial promise in physics-informed machine learning and optimization applications, where physical information extends beyond traditional data-driven surrogate models. In specific application areas, embedding physical prior knowledge directly into optimization processes has enhanced convergence efficiency and accuracy [6, 7]. Moreover, evolutionary algorithms, renowned for their ability to manage multimodal optimization problems, have shown distinct potential in addressing the complex landscapes inherent to physics-based machine learning [8]. Additionally, evolutionary algorithms are broadening the scope of physics-informed machine learning, effectively tackling challenges that traditional optimization methods, such as evolutionary transfer [9], meta-learning [10] and architecture search [11], often find difficult to overcome. Collectively, these advancements highlight the promising role of evolutionary computation in physics - informed learning and optimization.

**Aims and Scope**

The theme of this special section is *Physics-Informed* *Evolutionary* *Learning* *andOptimization*, which aims to advance the development of evolutionary computation within the realm of physics-informed learning and optimization. This special section welcomes submissions on traditional physical data-driven optimization techniques, applications of evolutionary algorithms in physics-informed machine learning, and evolutionary optimization methods that incorporate physical priors, information, or ordinary/partial differential equations. We invite submissions that explore theories, algorithms, and applications at the intersection of physics and evolutionary computation.

Authors are encouraged to submit original, unpublished work to this special section. Topics of interest include, but are not limited to:

 Evolutionary computation on physics-simulator-based engineering optimization

 Evolutionary computation with physics prior

 Neural evolution for physics-informed machine learning

 State-of-the-art evolutionary computation techniques (e.g., evolutionary transfer,

evolutionary multiobjective optimization, evolutionary multitasking) for physics - informed machine learning

 Evolutionary neural architecture search for physics-informed neural networks

 Evolutionary computation in physics-informed inverse design

 Evolutionary computation for ordinary\partial differential equations

 Evolutionary computation for reduced order models of dynamical systems.

 Evolutionary computation for scientific discovery

 Evolutionary computation for physics-informed applications (e.g., structure design, lithium battery, and electrochemistry, etc)

**Workshops** **keywords:**

Physics-Informed Machine Learning;

Physics-Informed Evolutionary Optimization; Evolutionary Computation;

**References**

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Yew-Soon Ong received the Ph.D. degree in artificial intelligence in complex design from the University of Southampton, U.K., in 2003. He is President’s Chair Professor in Computer Science at Nanyang Technological University (NTU), and holds the position of Chief Artificial Intelligence Scientist of the Agency for Science, Technology and Research Singapore. At NTU, he serves as Director of the Data Science and Artificial Intelligence Research and co-Director of the Singtel-NTU Cognitive & Artificial Intelligence Joint Lab. His research interest is in artificial and computational intelligence. He is founding Editor-in-Chief of the IEEE Transactions on Emerging Topics in Computational Intelligence and AE of IEEE Transactions on Neural Networks & Learning Systems, IEEE on Transactions on Cybernetics, IEEE Transactions on Artificial Intelligence and others. He has received several IEEE outstanding paper awards and was listed as a Thomson Reuters highly cited researcher and among the World's Most Influential Scientific Minds.

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Kalyanmoy Deb received a bachelor’s degree from the Indian Institute of Technology, Kharagpur, India, in 1985. and the master’s and Doctoral degrees in engineering mechanics from the University of Alabama, Tuscaloosa, AL, USA, in 1989 and 1991, respectively. He is a University Distinguished Professor and a Koenig Endowed Chair Professor with the Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI, USA. He has written more than 620 research papers with 199,000+ Google Scholar citations. His research interests are in evolutionary optimization algorithms and their application in optimization and machine learning. Prof. Deb received many awards, including the Infosys Prize and the Edgeworth Pareto Award. He is a Fellow of ACM and ASME.

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