

Editorial

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Real-life scenarios and problems tend to be dynamic in nature. As such, the concept of a fixed or static optimum solution is no longer meaningful. From a solution formulation point of view, the techniques to derive the solutions have to adapt to react to the time-varying or uncertain landscape. Befittingly, the theme of this issue is therefore adaptation and we have 5 excellent papers to demonstrate the importance of dealing with the complexity of a dynamic solution landscape.

The first paper featured in this issue by Jin et al. deals with issue of finding robust solutions over time. It is clear that with dynamic optimization problems, it has become less meaningful to find optimal solutions. Rather what is more meaningful is to find solutions that are robust, in the light of time-varying design specifications. Instead of a conventional tracking of moving optima approach which forms the backbone of how dynamic optimization problems are dealt with, Jin and his co-authors presented a new problem formulation approach which they refer to as ROOT, or robust optimization over time. The main idea behind ROOT is to derive acceptable solutions that change slowly over time, rather than putting emphasis on a moving global optimum. They demonstrated convincingly the advantages of their approach on several test problems.

The second paper by Terrazas and Krasnogor is on self-assembly of structures; using an approach that allows the dynamic fitness function to be measured more quickly as the system evolves. Their work is based on the computational model of self-assembly, namely the self-assembly Wang tiles system. With any evolutionary approach, fitness evaluation is a crucial component. In this case the complexity of fitness evaluation with regards to mapping from a genotype to

phenotype is clearly evident. They reasoned that the fitness comparison of experimental sampling of configurations is time-consuming and tend to be inaccurate. To overcome this shortcoming, they presented a complementary dual assessment protocol which relies on morphological image analyses as fitness function. They introduced the concept of fitness distance correlation to correlate genotypic distance to known optimum and clustering to verify the discerning capability of an objective function for dissimilar phenotypes.

As with the second paper in this issue, the third paper also deals with self-organizing systems. The work by Li and McDonald pertains to self-organization on dynamic vehicle routing problem. Their case study is on Barclay Cycle Hire truck dispatch. Through self-organization, they observed the emerging behavior of trucks that self-organize. The authors noted that self-organization approach has not been studied or applied to vehicle routing problem. Since vehicle routing is important in the fields of transportation, logistics and distribution networks, the work described offers a nice alternative to conventional centralized control approaches in dealing with dynamic problems.

The fourth paper by Zhu and Yan proposed an adaptive variable space differential evolution algorithm. In their approach, they relied on global population distribution to dictate the adaptive variable space. The operators for the differential evolution are configured based on local information on distance and direction. They demonstrated the efficacy of their approach by comparing it against two well-tuned conventional differential evolution and several state-of-the-art parameter adaptive differential evolution variants on scalable benchmark functions.

The final paper in this issue is by Ni et al. Its focus is on data clustering using a novel memetic algorithm. Their work is relevant in the context of harnessing the problem-solving capacity of particle swarm optimization and a simulated

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annealing-based local search, a key feature of memetic computation approaches. It clearly demonstrates the need to track how data evolves over time in dynamic optimization problems, and the large scale data clustering approach is one viable option. An important issue dealt with is to know when input data go “out of control” and splitting or evolving into very different clusters. The work clearly shows the need for synergistic marriage of optimization techniques, and they demonstrated its applicability in data clustering. Especially with the emerging field of big data analytics, we see this as an excellent prelude of one possible approach of how memetic computational approaches can play a role.

Finally, we take the chance to include an erratum to an earlier published paper by Kadlec and Gabrys to complete this issue. We thank all authors for their excellent contributions for this issue and the reviewers who have diligently offered their behind-the-scene support to ensure the publication worthiness of the manuscripts submitted for consideration, and not forgetting the effort of the Editors who managed the review of the papers.