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Data-Driven Surrogate-Assisted Multiobjective Evolutionary Optimization of a Trauma System

Data-driven optimization is solving an optimization problem solely based on data and not requiring analytical models of objective and constraint functions of the problem. Usually data-driven optimization requires a lot of computation power so for reducing the need for the huge amount of computation power surrogates are develop and used. Surrogates are used to replace the need for exact function evaluations in optimization. Surrogate management plays a major role in surrogate-assisted optimization on when to use and update the surrogate.

The article divides data-driven optimization problems into two different categories, offline and online data-driven optimization. In offline data-driven optimization data is acquired before evolutionary optimization and no new data will be able to have during the optimization. In online data-driven optimization new data can be acquired during the evolutionary optimization. The experiment shown in the article shows the use of an offline data-driven optimization on trauma system design.

Machine learning models can be used as a surrogate, like Kriging or neural networks. Because surrogate models are subject to errors there is a need for managing the trade-off between the surrogate accuracy over the exact function evaluation. The main challenges to data-driven optimization are computational cost, data quantity, data quality and heterogeneity of data which are all related to surrogate construction.

The article uses data-driven optimization to optimize trauma system. Trauma system is a network of hospitals. The goal of a trauma system is to reduce death and disability from injury. The optimal trauma system is efficient by having right care at right time at right place, but also being very cost effective. The problem objectives are to minimize the travel time of all the patients and to minimize the number of exceptions made during the selection to which hospital to take the patient to. The problem constraint is the cost of transportation. Should the patient transport by air or land and what is the distance to correct hospital to patient to have a right treatment.

The article used clustering algorithm as a surrogate to reduce the computation time. To handle the balance between computation time and solution quality they used a regression model to estimate the number of clusters required.

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Offline Data-Driven Evolutionary Optimization Using Selective Surrogate Ensembles

The article focuses on offline data-driven optimization where no data are acquired during the actual optimization process. This means that surrogate models are constructed beforehand and won't be update during optimization. Therefore, the article proposes an adaptive selective ensemble as a surrogate management strategy.

The proposed algorithm builds a large number of surrogate models before the optimization starts. The algorithm uses probability-dependent sampling to determine the number of surrogate models needed and adaptively selects a small subset of models built offline, so-called bagging algorithm.

By using this technique during the optimization, they can achieve the local approximation accuracy and reduce the computational cost. As shown in their experimental they managed to maintain the same or even better fitness and minimum variance with surrogate models (DDEA-SE and DDEA-RBF) as without them (DDEA-E). They also managed to beat the online data-driven optimization algorithms (CAL-SAPSO and GPEME).

The experimental results show that the proposed algorithm can deal with various problems with up to 100 decision variables.