LAMM-MMA: Multiobjective Memetic Algorithm with Local Aggregate Meta-Model

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ABSTRACT

In this paper we describe a multiobjective memetic algorithm utilizing local distance based meta-models. This algorithm is evaluated and compared to standard multiobjective evolutionary algorithms (MOEA) as well as to a similar algorithm with a global meta-model.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*heuristic methods*; I.6.3 [**Simulation and Modeling**]: Applications

General Terms

Algorithms

Keywords

Multiobjective optimization, meta-model, evolutionary algorithm

1. INTRODUCTION

One of the approaches to make the MOEAs more usable by reducing their computation time is the use of so called meta-models. The meta-model is a simplified and cheaper approximation of the real objective function. This approximation is used instead of the complex and expensive original function. These models can be constructed in several ways, one of them is the use of models from the field of computational intelligence – including neural networks and support vector machines.

2. ALGORITHM DESCRIPTION

In this paper, we propose a new variant of ASM-MOMA [3] with local models used instead of a single global one, as we used in ASM-MOMA. We call this variant LAMM-MMA.

LAMM-MMA is a memetic multiobjective evolutionary algorithm. It uses a special memetic operator, which performs local search on some of the newly generated individuals. This operator uses the meta-model constructed based on previously evaluated points in the decision space. The meta-model is trained to predict the distance to the currently known Pareto front. In LAMM-MMA, the known points do not have the same weight, as those that are closer to the localy optimized one are considered more important.

The main idea is that points closer to the Pareto front are more interesting during the run of the algorithm, and the memetic operator moves the individuals towards the front. The meta-model provides a general direction in which the search should proceed. To obtain a training set for the meta-models we also added an external archive of individuals with known objective values.

The following sections detail the important parts of the algorithm.

2.1 Meta-model construction

We train a dedicated model for each individual I which shall be locally optimized by the memetic operator. For such an individual I we create a weighted training set

$$T_I = \{\langle(x_i, y_i), w_i\rangle | y_i = -d(x_i, P), w_i = \frac{1}{1 + \lambda d(x_i, I)}\},$$

where $d(x, y)$ is the Euclidean distance of x and y in the decision space, P is the set of non-dominated individuals in the archive and $d(x, P) = \min_{y \in P} d(x, y)$. λ is a parameter which controls the locality of the model.

The distance weighting adds some locality to the models trained for each individual. Note that individuals closer to the known Pareto front have larger target values.

2.2 Local search

In the local search phase we use another evolutionary algorithm to find better points in the surroundings of each individual. The algorithm runs only for a few generations and it uses only the meta-model evaluations. The newly found individuals are placed back to the population. During the initialization, the individual which should be optimized is inserted in the initial population and its variables are perturbed to create the rest of the population.

3. TEST SETUP

We tested our approach on the widely used ZDT [4] benchmark problems. These problems are all two dimensional, and we used 15 variables for each of them. In the local search phase we used various meta-models: namely multi-

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layer perceptron (MLP), support vector regression (SVM), and linear regression (LR). All the models use default parameters from the Weka framework [2] (which we used to run the experiments).

The main multiobjective algorithm (NSGA-II [1]) used a population of 50 individuals and stopped after 50,000 objective function evaluations. SBX crossover (probability 0.8) and polynomial mutation (probability 0.1) were used. The memetic operator was run on one quarter of the individuals in each generation.

The local search genetic algorithm ran for 30 generation with 50 individuals in the population. It used the same mutation (probability 0.2) and crossover (probability 0.8) operators as the main algorithm. The meta-model locality parameter λ was set to 1.

To compare the results we use a measure we call H_{ratio}, it is defined as the ratio of the hypervolume of the dominated space attained by the algorithm and the hypervolume of the global Pareto front.

4. RESULTS

Table 1 shows the results of our algorithm compared to original NSGA-II and ASM-MOMA. In the table NSGA means the original NSGA-II. LR, SVM, and MLP stands for the model used. G denotes the global model of ASM-MOMA and L stands for the local model of LAMM-MMA.

The numbers in the table represent the median number of objective function evaluations needed to reach the specified H_{ratio} value. Twenty runs for each configuration were made. A "-" symbol means that the particular configuration was not able to attain the specified H_{ratio}.

The results show that the local models further decrease the number of function evaluations compared to the global models. Generally, we can see that LR gives better results than SVM and MLP. It probably creates simpler, yet sufficient, models which indicate the right general direction in which the local search should proceed.

On ZDT1 the local model (LR) decreased the number of evaluations by another almost 8% compared to the global model, yielding a combined reduction factor of 8. The numbers for $H_{ratio} = 0.99$ are not that good, although the number of function evaluations dropped to approximately one half with both the local and global model.

Similar improvements can be seen on ZDT2 and ZDT3.

ZDT6 proved to be the most difficult problem among those we used for comparison. Although the number of evaluations dropped approximately to a third of the original for $H_{ratio} = 0.5$, this difference gets lower as the H_{ratio} grows, and the results for $H_{ratio} = 0.99$ are almost identical. In this case the results of local models are similar to those of a single global one.

5. CONCLUSIONS

In this paper we presented a memetic evolutionary algorithm for multiobjective optimization with local metamodels. We showed that local models give better results than a single global model, usually reducing the number of needed function evaluations by 10%. Although this difference may seem rather small it may greatly reduce the associated costs in practical tasks.

Table 1: Median number of function evaluations needed to reach the specified H_{ratio}

H_{ratio}	0.5	0.75	0.9	0.95	0.99
ZDT1					
NSGA	5600	18600	19850	20750	21850
NSGA-LR-G	1500	2000	2400	2800	**12750**
NSGA-SVM-G	1450	2050	2350	2850	13550
NSGA-MLP-G	2100	2800	3850	4500	15200
NSGA-LR-L	**1300**	1750	2250	2600	13100
NSGA-SVM-L	1350	**1650**	**2150**	**2450**	14150
NSGA-MLP-L	1600	2100	2700	3250	15700
ZDT2					
NSGA	650	1650	3550	5050	7900
NSGA-LR-G	**350**	550	750	950	1250
NSGA-SVM-G	**350**	**450**	700	1050	1750
NSGA-MLP-G	400	550	800	1000	1500
NSGA-LR-L	**350**	**450**	**600**	**850**	**1100**
NSGA-SVM-L	**350**	550	750	900	1250
NSGA-MLP-L	**350**	500	750	**850**	1250
ZDT3					
NSGA	600	1250	4150	7250	-
NSGA-LR-G	**300**	500	700	800	1150
NSGA-SVM-G	350	500	700	**750**	1100
NSGA-MLP-G	450	700	1000	1150	1750
NSGA-LR-L	**300**	**450**	**650**	800	1050
NSGA-SVM-L	350	550	700	850	**1000**
NSGA-MLP-L	350	550	850	950	1300
ZDT6					
NSGA	7950	10200	13950	17700	28650
NSGA-LR-G	2750	5950	11100	15750	30500
NSGA-SVM-G	**2500**	**4950**	**8650**	**12500**	**23500**
NSGA-MLP-G	3300	5850	10350	14650	26800
NSGA-LR-L	2850	5850	10550	15350	29200
NSGA-SVM-L	2600	**4950**	9100	12900	25300
NSGA-MLP-L	3350	6050	10300	13950	27150

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