Diversity and Convergence Issues in Evolutionary Multiobjective Optimization: Application to Agriculture Science

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Abstract

Evolutionary Algorithms are the stochastic optimization methods, simulating the behavior of natural evolution. These algorithms are basically population based search procedures efficiently dealing with complex search spaces having robust and powerful search mechanism. EAs are highly applicable in multiobjective optimization problem which are having conflicting objectives. This paper reviews the work carried out for diversity and convergence issues in EMO.

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1. Introduction
Many conflicting objectives are handled by multi objective optimization. In this situation, one cannot derive one solution which is optimizing all the objectives simultaneously. Now, it is required to find multiple trade-off solutions. Evolutionary Algorithms are well suited for solving multiobjective optimization problem and it leads to a burning research area called “Evolutionary Multiobjective Optimization” [1,2]. The first development in the area of EMO has been started with the development of algorithm VEGA (Vector Evaluated Genetic Algorithm) [3] by Schaffer in 1984.

![Fig. 1. Diversity and Convergence in Evolutionary Multiobjective Optimization](image)

Several issues have been proposed in EMO, like non-dominated sorting, niching mechanism, elitism, diversity and convergence.

This paper is an effort of receiving the work carried out related to diversity and convergence issues in EMO. In section II and III, the basic concepts of EMO are discussed. Burning research issues are discussed in section IV. Section V is the conclusion and future scope.

2. Evolutionary multiobjective optimization

Population based search procedure is the major strength of Evolutionary Algorithms (EAs) and it makes us capable to get multiple solutions a single run. EAs are perfect with very large and complicated search spaces and highly applicable in multiobjective optimization problems. Evolutionary approaches, including genetic algorithms [4], genetic programming [5], evolutionary strategies [6] and evolutionary programming [7] are used to solve multiobjective optimization problem. It will be generating the research area called Evolutionary Multi-objective Optimization [8-11].

Different EAs have been developed for the purpose of multiobjective optimization. First generation of the algorithms is including NSGA (Non-dominated Sorting Genetic Algorithm) [12], NPGA (Nitched Pareto Genetic Algorithm) [13], Multi-Objective Genetic Algorithm (MOGA) [14]. The major focus was on fitness sharing and niching integrated with Pareto Ranking. The second generation includes following EMO algorithms, Strength Pareto Evolutionary Approaches(SPEA) [15], SPEA2 [16], PAES [17], NSGA-II [18], NPGA-II [19], PESA [20] and Micro Genetic Algorithm [21, 22].
3. Diversity and Convergence Issues In EMO

During multiobjective optimization of conflicting objectives two major requirements are: diversity and convergence towards the approximate true pareto front. It is based on “jumping genes” (JG) phenomenon. There are basically multiple approaches but out of them the two most popular approaches were diversity handling and its impact on overall solution[24].

4. A Case of EMO on Agriculture Science

We extend the above problem in sugar manufacturing process. The main objectives identified in sugar manufacturing process involve, Firing control of boilers → ‘C_B’, Sugarcane recovery → ‘S_r’ and Transportation and delivery mechanism→ ‘TD_m’

4.1. Firing control of boilers (C_B)

It consist of all the parameters required to control the speed of boiler thereby eliminating the waste of firing material like bagasse. The signals are being sent from Central Mill Control through SCADA. SCADA gets the signal from the Main Control Center which is a block receiving signals from sensor Mesh and Raster Scan images. Signal control is being achieved by DN3 protocol of SCADA to computing relay which governs the steam fire.

4.2. Sugarcane recovery (S_r)

Sugarcane recovery depends on several small parameters like Method of Planting, Seed Rate, Spacing between sugarcane, Organic Measures, Maturity and Harvesting.

4.3. Transportation and delivery mechanism (TD_m)

5. Fig. 2. IMO Learning Cycle (Adapted from V. Belton et al., 2008)

TD_m refers to delivery of sugarcane without waiting, as more is the waiting time more will be drying of sugarcane, hence less will be recovery. During start of the production process boiler is run at maximum speed,
Therefore sugarcane arriving at the mill should be thick and should have high juice value so that boiler energy is full converted into juice.

In order to achieve higher quality sugar we need to have all these parameters optimised. Since it is a continuous process we use Interactive Multiobjective Optimisation and apply it on Learning perspective. Learning here relates to ‘Farmer Learning’ and ‘Machine Learning’ relating to sensor networks and SCADA control system. The learning cycle of IMO (V. Belton et al., 2008) has Decision Maker (DM) which provides information about the preferences needed from the point of view of generating a reference model and plurality of value functions are generated. The Decision Maker uses the User Knowledge and process it on the basis of three basic parameters: Inference Engine, Preference Model, Optimization of knowledge rules based on these parameters $C_B$, $S_r$, $TD_m$ respectively.
In order to develop a mathematical model consider a decision ‘D’ consisting of decision classes Cl= {Cl1, Cl2, …, Clm}. In case of sugar industry we have three basic classes {CB, Sr, TDM}.

In order to apply interactive learning to the above classes we need to apply multi-criteria sorting and learning. Under these three basic classes we have three subclasses. The condition attributes are criteria and decision classes arranged in upward or downward manner depending on the current situation. If the dominance of these classes is to be identified we use “if-then” rules as described by the maximization function below:

\[
\max f_{o/p}(x) ; o/p = (1, 2, \ldots, M)
\]

subject to

\[
TD_m \geq 0 ; TD_{m \min} < TD_m < TD_{\max}
\]

\[
CB \geq 0 ; CB_{\min} < CB < CB_{\max}
\]

In order to proceed with the process the classes needs to be iterated and randomly combined by changing by changing their values from “min” to “max”. The two values of classes are then mutated to generate a good solution.

6. Conclusion And Future Scope

Diversity (maintain the diverse set approximation) and convergence (guiding the population towards the pareto set) are the important research issues in EMO. Several proposals for enhancing the diversity and convergence in EMO have been reviewed in this paper supported by an example on Agriculture Science.

References

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