A Comparative Study of Intelligent Techniques for Modern Portfolio Management

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Abstract: In this paper we present a wide range of intelligent technologies applied to the solution of the portfolio selection problem. We also provide a classification of the available intelligent technologies, according to the methodological framework followed. Finally, we provide a comparative study of the different intelligent technologies applied for constructing efficient portfolios and we suggest potential paths for future work that lie at the intersection of the presented techniques.

1 INTRODUCTION

Computer Science not only provided a fast and reliable way of calculating computationally demanding financial models but also revolutionized the financial modeling research field itself by developing innovative algorithmic approaches for solving difficult financial problems that in many cases cannot be solved using exact methods. The computational approaches dealing with financial modeling can be clustered into four different groups depending on the applied methodology.

2 INTELLIGENT TECHNIQUES FOR OPTIMAL PORTFOLIO SELECTION

2.1 Evolutionary Algorithms

The first classification concerns the so called Evolutionary algorithms (EAs). EAs are population based stochastic optimization heuristics inspired by Darwin's Theory of Evolution. An EA searches through a solution space in parallel by evaluating a set of possible solutions. Genetic Algorithms (GAs) which belong to the family of EAs have been proved very effective for solving constrained portfolio optimization problems (Shoef and Foster, 1996); (Chang et al., 2009) that cannot be solved with exact methods. Genetic and Evolutionary Programming (EP) and Evolutionary Strategy (ES) belong as well to EAs.

2.2 Swarm Intelligence

The second classification of algorithmic approaches for the construction of efficient portfolios concerns the Swarm Algorithms. Swarm Intelligence (SI) is inspired from the biological examples provided by social insects. SI is a decentralized, self-organized system in which the agents through their collective behavior find coherent solutions to the arisen problems. Ant Colony Optimization (ACO) is an optimization procedure inspired by ants' ability to identify optimal paths by depositing pheromone on the ground.

Another popular SI technique is the Particle Swarm Optimization (PSO). The particle exchanges information with the neighboring members, in order to adjust its trajectory towards the best attained position. Both ACO and PSO techniques have been applied to solve the constrained portfolio selection problem (Deng and Lin, 2010); (Doerner et al., 2004); (Armananzas and Lozano, 2005); (Golmakani and Fazel, 2011); (Zhu et al., 2011).

2.3 Local Search Algorithms

The third classification of computational approaches for the solution of the portfolio selection problem concerns the Local Search Algorithms techniques.

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These algorithms try to improve an initial solution by applying iteration in order to create the neighborhood of the current solution. Then the best solution of the neighborhood is selected for the next iteration. The process continues until a solution considered optimum is found.

Simulated Annealing (SA) is a well known local search technique developed to deal with highly nonlinear problems. SA techniques have been applied extensively for the solution of the portfolio selection problem (Chang et al., 2000); (Crama and Schyns, 2003); (Maringer and Kellerer, 2003); (Ehrgott et al., 2004); (Armananzas and Lozano, 2005). Hill Climbing and Tabu Search (TS) are as well known local search techniques applied to the portfolio optimization problem.

2.4 Multiobjective Evolutionary Algorithms

Finally the last classification of computational approaches for the solution of the portfolio selection problem concerns the Multiobjective Evolutionary Algorithms (MOEAs). Multiobjective optimization (MO) is the problem of maximizing / minimizing a set of conflicting objective functions subject to a set of constraints. In MO there is not a single solution that maximizes / minimizes each objective to its fullest. This happens because the various objective functions in the problem are usually in conflict with each other. Therefore, the objective in MO is to find the Pareto front of efficient solutions that provide a tradeoff between the various objectives. MOEAs can be useful in the solution of complex problems for which no efficient deterministic algorithm exists (Metaxiotis and Liagkouras, 2012). In finance there are several NP-hard problems for which the use of a heuristic is clearly justified (Schlottmann and Seese, 2004). Portfolio Selection belongs to this category of problems, because of the simultaneous optimization of several conflicting objectives subject to a set of constraints imposed to the problem.

3 COMPARATIVE STUDY OF INTELLIGENT TECHNIQUES APPLIED FOR EFFICIENT PORTFOLIO CONSTRUCTION

Below the table displays the most popular intelligent techniques among the authors in the portfolio selection research field. According to the table the most popular artificial intelligence technique among the authors in the field of portfolio selection is the MOEAs with 33% of the total publications. EAs come second with 29%. On the other hand, Local Search Algorithms (LSAs) techniques are less popular among the authors in the field as they count for the 15% of all publications in the field.

Table 1: Artificial intelligence techniques for the solution of the Portfolio Selection problem.

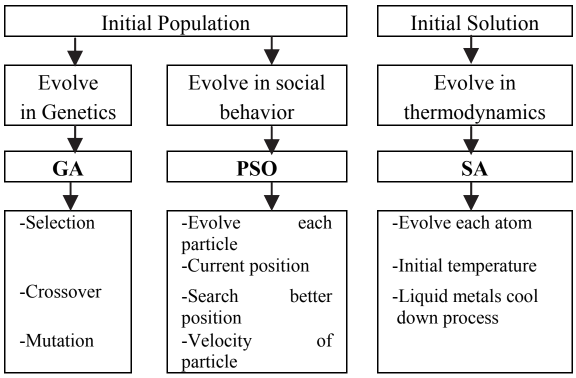
Multiobjective Evolutionary Algorithms	33%
Evolutionary Algorithms	29%
Local Search Algorithms	15%
Swarm Intelligence	23%

3.1 Theoretical Comparison of Artificial Intelligence Techniques

Below we compare four well known intelligent techniques that belong correspondently to the fields of EAs, SI, LSAs and MOEAs.

Specifically the representatives of the four fields are the following: GAs, PSO, SA and Non-dominated Sorting Genetic Algorithms II (NSGA-II). The four aforementioned techniques are evaluated with regard to their ability to solve efficiently portfolio selection problems. The Table below highlights the main features of the examined techniques.

Table 2: Comparison of artificial intelligence techniques.



As the graph above reveals the GAs and PSO share more in common compared to SA. We notice that GA has a population of alternative solutions (chromosomes) while SA has only one individual (the current solution). Additionally, there are differences in terminology between the two intelligent techniques that reflect the different approaches for finding the optimal solution to the problem. For instance in GA are used the terms: chromosomes or individuals, fitness evaluation, selection, crossover and mutation. On the other hand in SA the dominant terminology is: temperature, costs, neighbourhood, and moves.

If we want to find common ground between the two optimization techniques we would say that SA can be considered a GA where the population size is one. Since there is only one solution in the population (the current solution) there is no crossover but only mutation.

This is the key difference between GA and SA. GA can create new solutions by combining existing solutions (crossover), whereas SA creates a new solution by modifying the current solution with a local move. Which intelligent technique is better able to find optimal solutions depends mainly on the problem and representation used. Additionally, we should highlight that both GA and SA techniques share the assumption that good solutions are more probable to be found near already known good solutions rather than randomly selecting from the whole selection space.

Table 3: Genetic algorithms vs simulated annealing.

Genetic Algorithms	Simulated Annealing
chromosomes	one individual - current solution
fitness evaluation	calculate the energy of the system
Selection	neighbourhood
Crossover	modify current solution
mutation	local move

Finally, it is clear that the performance of a GA is seriously affected by the relative weights of mutation and crossover respectively. For instance if mutation defined to be the principal way for creating new solutions then the GA tend to follow the way it function a SA, as the solutions are being at large independently improved.

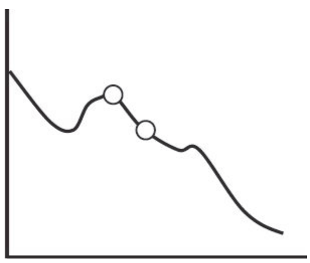


Figure 1: Both GA and SA techniques share the assumption that good solutions are more probable to be found near already known good solutions.

3.1.1 Comparison of PSO with GAs

PSO and GAs on the other hand share many similarities. First of all, both techniques start with a population of random solutions and search for the optimal solution by updating generations. However, a striking difference between the two techniques is that PSO does not have evolution processes such as mutation and crossover. Instead in PSO the potential solutions (particle) moves through the search space by following the current best particles.

Table 4: GA vs PSO.

GA	PSO
chromosomes	population of solutions - particles
fitness evaluation	evaluate fitness of each particle
Selection	update particle's velocity and position based on the best objective value found so far by the particle and the entire population
Crossover	
Mutation	

Analytically, in PSO the particles are randomly initialised and freely move through the search space. During movement each particle updates its own velocity and position based on the best objective value found so far by the particle and the entire population respectively. The updating policy drives the particle to move towards the region of the higher objective function. Finally, all particle gather around the position with the highest objective function.

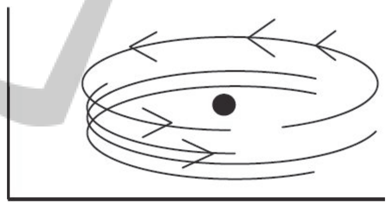


Figure 2: In PSO the updating policy drives the particles to move towards the region of the higher objective function.

3.1.2 Comparison of TS with GAs

TS uses a local search procedure to move from a current solution to a neighbor solution, until a stopping criterion has been satisfied. The search process starts with an initial solution and moves from neighbor to neighbor as long as possible while improving the objective function value.

Table 5: GA vs TS.

GA	Tabu Search
chromosomes	current solution
fitness evaluation	best known solution
Selection	objective function value
Crossover	neighbourhood of current solution
Mutation	Subset of the neighbourhood of current solution - Allowed by the aspiration.
	Tabu list

TS allows hill climbing to overcome local optima. A key property of tabu search is to pursue the search whenever a local optimum is encountered by allowing non improving moves. Additionally, the use of memory (tabu list) prevents the cycling back to previously visited positions.

3.1.3 Comparison of NSGA-II with GAs

NSGA-II is a popular non-domination based genetic algorithm for MO. The algorithm creates a population of initial solutions. After the initialization of the population, the population is sorted based on non domination into each front. The first front consisted by the non-dominated set in the current population. The second front is only dominated by individuals of the first front, and so on.

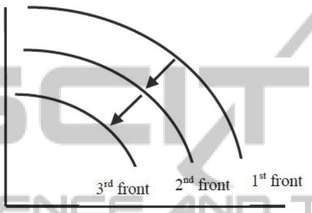


Figure 3: NSGA-II, population is sorted based on non domination into each front.

Each individual in each front is assigned a rank value based on the front in which it belongs to. Thus, individuals in the first front are assigned fitness value of 1, and individuals in the second front are given a value of 2 and so on.

Additionally a parameter called crowding distance is calculated for each individual. Crowding distance measures how close an individual is to its neighbours. The greater the average crowding distance the better, as indicates better population diversity. Parents are selected from the population, by using binary tournament selection based on the rank and the crowding distance. The selected population generates offsprings from crossover and mutation operators.

Table 6: GA vs NSGA-II.

GA	NSGA-II
chromosomes	population of solutions
fitness evaluation	population is sorted based on non domination into fronts
Selection	crowding distance is calculated for each individual
Crossover	Parents are selected
Mutation	Offsprings generated from crossover and mutation operators
	Population sorted again based on non-domination

The population including now the initial population and the offsprings is sorted again based on non-domination and only the N individuals are selected. The selection is based as before on rank and crowding distance on the last front. NSGA-II technique has been applied extensively for the solution of the constrained portfolio selection problem (Deb et al., 2002); (Lin and Wang, 2002); (Anagnostopoulos and Mamanis, 2009); (Deb et al., 2011).

4 CONCLUSIONS

In it only since 1990s that artificial intelligence techniques have been applied to the constrained portfolio optimization problem. Yet in that short space of time, they have had remarkable success in this particular research field. Given the initial success we can reasonably expect in the future a growing number of powerful artificial intelligence techniques applied to the solution of the constrained portfolio optimization problem.

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