reality which is useful and also essential for further developments.

Friday, 2008-03-28	10:45–12:15	Parallel Session F

DEH - Room 341 — Data Estimation and Heuristics

Chair — *Istvan Maros*

DEH.1 **A New Metaheuristic for the Multidimensional 0-1 Knapsack Problem**

Presenter: Gyorgy Csebfalvi (University of Pecs)

Coauthors: Aniko Csebfalvi

The multidimensional 0-1 knapsack problem (MKP) is one of the most well-known NP-hard problems and has received wide attention from the operational research community during the last four decades. MKP arises in several practical problems such as the capital budgeting problem, cargo loading, cutting stock problem, and computing processors allocation in huge distributed systems. Several different techniques have been proposed to solve this problem. However, due to its NP-hard nature, exact methods are unable to find optimal solutions for larger problem instances. Heuristic methods have become the alternative, and the last generation of them, the metaheuristics, are being successfully applied to this problem. Hence, in practise, heuristic algorithms to generate near-optimal solutions for larger problem instances are of special interest. One of the best heuristic approaches for MKP is the genetic algorithm (GA) developed by Chu and Beasley (1998). In this GA the candidate solutions are directly represented by their 0-1 vectors, therefore standard crossover and mutation operators are applied. In this paper we propose a harmony search metaheuristic called Sounds of Silence (SoS) for MKP. The presented algorithm is an adaptation of the original SoS algorithm developed by Csebfalvi (2007) for the resource-constrained project scheduling problem (RCPSP). The SoS for RCPSP gives nearly three times better results for large 'academic' instances then the recently best state-of-the-art heuristics with significantly shorter run-times. The harmony search (HS) algorithm was developed by Lee and Geem (2004) in an analogy with music improvisation process where music players improvise the sounds of their instruments to obtain better harmony. In this approach, the variable values form a melody, which aesthetic value is represented by the objective function value. Namely, the higher the value, the higher the quality of the melody is. In the original HS, the improvisation is a random modification of randomly selected sounds. In our approach, the improvisation means a random perturbation of a promising melody. In MKP the items form polyphonic sounds according to their resource consumptions, and the left side of the knapsack constraints forms a polyphonic melody. So, assuming that in every phrase only the 'high sounds' are audible, the transformed problem will be the following: find the most aesthetic 'Sounds of Silence' melody by improvisation! Naturally, the 'high sound' in music is analogous to the overloading (infeasibility) in MKP, and the aesthetic value means profitability (utility). In our band each musician is responsible for exactly one polyphonic sound (item). The melody selection as a task is connected to the conductor (the higher the aesthetic value of a melody the higher the chance, that it will be selected by the conductor). The algorithm starts with a 'more or less random' repertoire uploading phase, after that, the band begins to improvise. In each repertoire uploading (improvisation) step, each musician has the right to present (modify) an idea (a value between zero and one) about the importance of his/here sound (item). In the repertoire uploading phase 'more or less random' means a random perturbation of the relaxed solution of the problem. It is a crucial point of the algorithm, because we have to balance between the diversity and quality. In our approach we used a simple but effective trick to resolve this problem. When a relaxed variable value is one (zero) then we replace it with a random value next to one (zero) from a truncated gaussian distribution with mean one (zero). In every other case we replace the relaxed variable value with a randomly generated truncated gaussian distribution value, which is spreading around the relaxed value. Naturally, the quality of the starting repertoire is highly affected by the spreading range. According to the given importance order, the conductor generates a feasible solution using a simple but effective replacement (improvement) operator without 'pseudo-utility' computation. In the improvisation phase, when a new melody is better than the worst in the repertoire, the worst will be replaced by the better one. Naturally, the two most important parameters of the SoS algorithm are the repertoire size and the number of improvisations. In the improvisation phase the diversity is decreasing step by step, which is controlled by a decreasing standard deviation value. The higher the standard deviation, the higher the variability (diversity) of the searching process is. Numerical results show that the adapted SoS is an efficient, robust and very fast algorithm that is competitive with all state-of-the-art algorithms (Chu and Beslay (1998), Raidl (1998), Vasquez and Vimont (2005)) for MKP known by the authors of this paper for instance sets MKNAPCB1-9 (OR-Library). The algorithm was run 30 times on each problem instance with the number of function evaluations limited to 100

(1000). Since the optimal solution values for most of these problems are not known, the quality of a solution is measured by the percentage gap of the SoS's solution value with respect to the optimal value of the LP-relaxed problem. Results show that most of the time the new algorithm converges much faster to better solutions, in particular for large instances. Using SoS the overall average of percentage gap for 100 evaluations was 0.95 %, which is nearly two times better than the same measure given by the Chu and Beasley's genetic algorithm (1.81 %) for 1000 evaluations.

DEH.2 **Heuristic Portfolio Optimization Using the Omega Performance Measure and Real World Transaction Costs**

Presenter: Chris Parker (London Business School)

One of the major problems with many performance measures is that they assume a returns distribution can be sufficiently described using only mean and variance. It is widely known in finance that returns distributions exhibit characteristics which do not conform to the normal distribution assumption often used. Another issue with these measures is that they assume that all investors have the same views as to what is a loss and what is a gain and also that the mean return is the loss threshold. However, one investor may believe that a return at the mean is a gain while a second investor believes that this is a loss. A final problem is that they assume investors view the risk of a return much greater than the mean exactly the same as they view the risk of a return much smaller than the mean. These assumptions make the portfolio optimization problem much simpler, but do not present a realistic view of the financial markets. As a result, investors of all investment levels have been taking on unnecessary risk in their portfolios. We present an argument to use a more complete but still intuitive performance measure, Omega, as the optimization criteria. Omega has been suggested by Keating and Shadwick (2002) as what they call a 'universal performance measure'. Keating and Shadwick argue that assuming that returns can be fully described using mean and variance and that the mean return is the only return level needed to describe the risk and reward within a portfolio has oversimplified risk measurement. They propose Omega as a performance measure because it contains all higher moments of returns distributions without the need to estimate them and allows for a loss reference other than the mean return. The Omega performance measure does not suffer from the detrimental effects brought on by relying upon these assumptions. It is mathematically equivalent to the returns distribution and therefore includes all higher moments of the returns distribution. This means it does not rely on the assumption that a returns distribution can be fully described using only its mean and variance. Furthermore, it does not require the need to estimate these moments and makes no assumption as to the shape of an investor's utility function. The only assumption needed in order to use the Omega performance measure is that investors prefer more over less. This means that Omega does not assume investors view the risk associated with a large gain in the way they view the risk associated with a large loss. Finally, Omega allows for different loss thresholds. This removes the need for the final assumption that all investors have the same beliefs as to what is a gain and what is a loss. Together these characteristics of Omega provide a different picture of the portfolio optimization problem. It can be interpreted as a likelihood ratio for the investment or simply as a measure for second-order stochastic dominance of a portfolio over a risk-free rate equal to the loss threshold and we are attempting to find the portfolio with the greatest second-order stochastic dominance. Unlike mean-variance optimization and the Sharpe Ratio, optimizing a portfolio based on its Omega value does not result in a unimodal function. This means deterministic algorithms such as quadratic programming will find sub-optimal and inconsistent portfolios in a continuous framework. In addition, these methods do not work when entering the discrete framework that is inherent when only integer numbers of shares can be purchased. A third issue that cannot be resolved by deterministic algorithms is the formulation of transaction cost constraints. The addition of transaction costs in the optimization process has been shown to have an impact on portfolio structure and performance and is therefore a necessary consideration for the optimization problem. The inability of deterministic algorithms to find globally optimal solutions leads to the need for heuristic optimization techniques. Particle Swarm Optimization (PSO) is one such technique based on the Adaptive Cultural Model. This is the process by which cultural norms are propagated through society by people's natural desire to evaluate their surroundings, compare themselves to others around them, and imitate the successful people. Our parameterization results indicate that PSO finds consistent optimal portfolios for the loss threshold used in terms of the Omega value obtained and the portfolio structure. The consistency and efficiency of different parameterizations for PSO are compared to a benchmark Monte Carlo simulation. In all of thee parameterization cases, PSO outperforms the Monte Carlo simulation. The study compares optimal portfolio structure and Omega values 6 different cost structures (including no costs) and 6 investment levels ranging from $5,000 to $1,000,000 using the constituent stocks of the Dow Jones Industrial Average. Optimized results are compared to the index, market value weighted, and naive portfolios. The empirical study confirms that transaction costs and integer constraints have an impact on optimal portfolio structure.