

## Chapter IX

# Evolving Solutions for Multiobjective Problems and Hierarchical AI

## Introduction

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Multiobjective problems (MOP) are a class of problems for which different, competing objectives are to be satisfied and for which there is generally no single best solution, but rather for which a set of solutions may exist which are all equally as good. In commercial real-time strategy (RTS) games, designers put a lot of effort into trying to create games where a variety of strategies and tactics can be employed and where (ideally) no single simple optimal strategy exists. Indeed, a great deal of effort may be spent in ‘balancing’ the game to ensure that the main strategies and units all have effective counters (Rollings & Morris, 1999). It may be the case, then, that RTS games may be considered as MOP. If not in terms of the overall goal of winning the game, which is clearly a single overriding objective, then in terms of the many different objectives that must be met in order to achieve victory. There may be a number of strong, potentially *winning* strategies, each of which is formed from the combination of a large number of tactical and strategic decisions and where improvement in one area will lead to increasing a weakness elsewhere.

Due to the obviously combative nature of RTS, it has also been seen as an ideal area for attempting to evolve strategies using competitive coevolution. The nature of the problem—which combines individual unit control, localised tactical behaviour, and global strategies—also promotes the development of hierarchical AI systems. The use of coevolution and hierarchical AI both have potential hidden problems, which experimenters and game developers should be aware of should they plan to use this approach. We begin this chapter looking at MOP before considering the specific issues relating to the use of coevolving hierarchical AI methods.

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## Multiobjective Problems

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MOP are a distinct class of problem from those presented in Chapter VII where a single solution is better than all other possible solutions. The different objectives in a MOP might entail some degree of conflict such as an airplane attempting to maximise both the number of passengers and the distance that can be travelled on a load of fuel. A more detailed example will highlight the problem.

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### The Multiobjective Knapsack Problem

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In the last chapter, the knapsack problem was presented. There also exists a multiobjective version of this problem where the second objective is to minimise the weight of the knapsack (Steuer, 1986). Obviously the most valuable load would simply include one of every item, while the lightest would not include any. Thus the two objectives clearly conflict. Rather than a single solution, we need to find a set of solutions where improvements for one objective cannot be achieved without impairing performance in the second. This set of solutions is known as the pareto-optimal set, or simply the pareto-set.

For the MOP knapsack problem, fitness can be evaluated on the basis of whether a solution is dominated or not (Zitzler, 1999). A solution is dominated if there exists another solution of the same (or lesser weight) and is of greater value, or if there exists another solution of the same value but of lesser weight. The set of *nondominated* solutions forms the pareto-set.

This is clearly related to the situation desired in RTS games, where designers try to design games which support a number of nondominated strategies.

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