



**Optimal Water Allocation and Scheduling for Irrigation  
Using Ant Colony Algorithms**

by

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## Abstract

In most regions of the world, irrigation is vital for food production. However, under increased water demands due to population growth, economic development, and climate change in recent decades, there is likely to be a significant reduction in the amount of water available for irrigation. Therefore, it is imperative to make the best use of water that is available for irrigation. This applies to: 1) the optimal allocation of land and water resources for irrigation management to achieve maximum net return, subject to constraints on area and water allocations at the district or regional scale; and 2) the optimal irrigation scheduling of available water, as well as fertilizer, in order to maximise net return at the farm scale. In order to rigorously address these problems, metaheuristic optimization algorithms have been used extensively due to their abilities in terms of finding globally optimal or near-globally optimal solutions and relative ease of linkage with complex simulation models. However, the application of these algorithms to real-world problems has been challenging due to the generally large size of the search space and the computational effort associated with realistic long-term simulation of crop growth and associated soil-water processes.

In this thesis, general simulation-optimization frameworks for optimal irrigation management (including optimal crop and water allocation, and optimal irrigation water and fertilizer application scheduling) have been developed in order to make the application of metaheuristic optimization methods to the above problems more computationally efficient. As part of this approach the problems are represented in the form of decision graphs which are solved using ant colony optimization (ACO) as the optimization engine. The frameworks enable dynamic reduction of the size of the search space by using dynamic decision variable option (DDVO) adjustment during solution construction. This also ensures only feasible solutions are obtained as part of the stepwise solution generation process. In addition, the computational efficiency of the ACO algorithms within the framework for optimal crop and water allocation has been increased by biasing the options at each node in the decision-tree graph based on domain knowledge

(represented by a visibility factor, VF). Furthermore, the framework for optimal irrigation scheduling was linked with a process-based crop growth model to enable optimal or near-optimal irrigation water and fertilizer application schedules to be identified.

This thesis is arranged as a series of three publications that present the main research contributions. The first paper introduces a generic simulation-optimization framework for optimal crop and water allocation at the regional or district scale using decision-tree graphs, ACO and the search space reduction technique based on dynamically adjusting decision variable options during stepwise solution construction. The performance of this technique in terms of finding feasible solutions, solution quality, computational efficiency and convergence speed was compared with that of linear programming (LP) and a “standard” ACO approach using static decision variable options (SDVO) on a benchmark case study from the literature. The second paper extends the ACO formulation for optimal crop selection and irrigation water allocation in the first paper by incorporating domain knowledge through VFs to bias the search towards selecting crops that maximize net returns and water allocations that result in the largest net return for the selected crop, given a fixed total volume of water. This improvement enables locally optimal solutions related to the factors (i.e., crops and water) affecting net return to be identified, and enables promising regions of the search space to be explored. The benefits of this improved formulation were tested on the benchmark case study used in the first paper and a real-world case study based on an irrigation district located in Loxton, South Australia near the River Murray. In the final paper, the formulation for detailed optimal irrigation water and fertilizer application scheduling at the farm scale is introduced and applied to a case study considering corn production under center pivot irrigation in Colorado, USA. The Root Zone Water Quality Model 2 (RZWQM2) was used for this case study to simulate the detailed impacts of irrigation water and fertilizer application scheduling on crop growth at a fixed time step. The utility of the proposed framework was demonstrated in terms of finding better net returns while using less fertilizer and similar amounts of water, or similar net returns while using



less water and fertilizer, compared with the Microsoft Excel spreadsheet-based Colorado Irrigation Scheduler (CIS) tool for annual crops.



## Statement of Originality

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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