



Optimization of irrigation scheduling using ant colony algorithms and an advanced cropping system model



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ARTICLE INFO

Article history:

Received 24 March 2017

Accepted 4 July 2017

Available online 25 July 2017

Keywords:

Optimization

Irrigation scheduling

Ant colony optimization

Crop growth modeling

ABSTRACT

A generic simulation–optimization framework for optimal irrigation and fertilizer scheduling is developed, where the problem is represented in the form of decision–tree graphs, ant colony optimization (ACO) is used as the optimization engine and a process–based crop growth model is applied to evaluate the objective function. Dynamic decision variable option (DDVO) adjustment is used in the framework to reduce the search space size during the generation of trial solutions. The framework is applied for corn production under various levels of water availability and rates of fertilizer application in eastern Colorado, USA. The results indicate that ACO–DDVO is able to identify irrigation and fertilizer schedules that result in better net returns while using less irrigation water and fertilizer than those obtained using the Microsoft Excel spreadsheet–based Colorado Irrigation Scheduler (CIS) tool for annual crops. Another advantage of ACO–DDVO compared to CIS is the identification of both optimal irrigation and fertilizer schedules.

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1. Introduction

In many regions of the world, irrigation is vital for food production. While the importance of irrigation should increase in the near future as a result of population growth (Dyson, 1999), economic development (Schneider et al., 2011) and climate change (Döll, 2002), there will most likely be a reduction in the amount of water available for irrigation due to increased domestic (Rosegrant and Ringler, 2000), industrial, commercial (Malla and Gopalakrishnan, 1999) and environmental (Burke et al., 2004; Szemis et al., 2013) demands, as well as over-allocation of existing resources (Jury and Vaux, 2005) and the impact of climate change (Arnell, 1999; Liu et al., 2010). Consequently, there is a need to identify irrigation management strategies (e.g., sequential irrigation scheduling) that maximize economic return for a given water allocation. However, this is not a trivial task due to the typically large search space for this type of problem (Nguyen et al., 2016b). This is because the development of an irrigation

management strategy involves a number of associated choices to be made in relation to various components, including crops (type, rotation, area planted), irrigation method and scheduling (magnitude, duration, and timing), as well as fertilizer application method and scheduling (magnitude and timing).

In order to address the irrigation management strategy problem as described above, various approaches including optimization, simulation, and combined simulation–optimization approaches have been employed. For the optimization approach (Singh, 2012, 2014), irrigation has been scheduled using dynamic programming (Rao et al., 1988; Naadimuthu et al., 1999), nonlinear programming (Ghahraman and Sepaskhah, 2004) and multi-objective programming (Lalehzari et al., 2015) to maximize crop yield or economic profit. Although these “conventional algorithms” (CAs) for optimization have the advantage of being simple and efficient to apply, they are somewhat limited in terms of handling nonlinear problems as well as the “curse of dimensionality” (i.e., the search space size grows exponentially with the number of state variables), such as those that occur in irrigation management (Singh, 2014). In the past decade, metaheuristic algorithms, such as evolutionary algorithms (EAs), have been used extensively to overcome the shortcomings of CAs for solving computationally demanding (i.e., NP-hard) sequential irrigation scheduling problems. For example,

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development and evaluation of genetic algorithms (GAs) for the irrigation scheduling problem have been presented by Nixon et al., (2001), Wardlaw and Bhaktikul (2004), Haq et al., (2008), Haq and Anwar (2010), Anwar and Haq (2013), and Sadati et al., (2014).

The simulation approach for solving irrigation management problems varies widely in the level of model complexity and soil-water-plant process representation. Simplistic crop models used for irrigation management include: 1) those based on crop-water production functions (Jensen, 1968; Doorenbos and Kassam, 1979) to calculate crop yield response to irrigation water (Reca et al., 2001; Evans et al., 2003; Azamathulla et al., 2008; Georgiou and Papamichail, 2008; Brown et al., 2010; Prasad et al., 2011; Nguyen et al., 2016a; Nguyen et al., 2016b); and 2) the FAO Penman-Monteith method for crop evapotranspiration (ET) and the crop growth coefficient approach of Doorenbos and Pruitt (1977) to estimate crop water requirements (Shyam et al., 1994; Sethi et al., 2006; Khare et al., 2007). While these quasi-empirical modeling approaches are computationally efficient, they are unable to represent the underlying physical processes affecting crop water requirements and crop growth in a realistic manner. This limits the usefulness of the results obtained and prevents investigation of certain management strategies (i.e., fertilizer application timing and rate) on the optimal trade-offs between water allocation and net return. To assess the impact of different irrigation management strategies in a more realistic manner (i.e., through a detailed description of ET and/or crop growth), a number of process-based soil water balance/dynamics (George et al., 2000; Shang et al., 2004; Shang and Mao, 2006) and crop growth (Ma et al., 2012b; Foster et al., 2014; Sun and Ren, 2014; Seidel et al., 2015; Linker et al., 2016) modeling studies have been conducted. These have utilized well-known cropping and agroecosystem models, including CERES-Maize (Jones et al., 1986), CROPGRO (Boote et al., 1998), RZQWM2 (Ma et al., 2012a), AquaCrop (Vanuytrecht et al., 2014), EPIC (Zhang et al., 2015), STICS (Coucheney et al., 2015), and SWAT (Arnold et al., 2012).

The above modeling studies have generally focused on a small number of irrigation management strategy combinations from among the large number that are available (e.g., Camp et al., 1997; Rinaldi, 2001; Arora, 2006; Ma et al., 2012b). Consequently, there is a need to combine detailed process-based crop growth simulation models with optimization approaches so that better irrigation management solutions resulting in maximum net returns can be identified more efficiently. The majority of simulation-optimization studies in the literature have employed conventional optimization algorithms (Cai et al., 2010; Karamouz et al., 2012; Hejazi et al., 2013). An exception to this is the work of Kloss et al., (2012), who developed a stochastic simulation framework combining the CropWat (Smith, 1992), PILOTE (Mailhol et al., 1997), Daisy (Abrahamsen and Hansen, 2000), and APSIM (Keating et al., 2003) cropping system models with an evolutionary algorithm to optimize irrigation management and water productivity. In general, simulation-optimization approaches utilizing CAs have been somewhat restricted due to the generally large size of the search space, which may limit the ability to find globally optimal or near-globally optimal solutions in an acceptable time frame.

In addition to evolutionary algorithms such as GAs, other metaheuristic search algorithms such as ant colony optimization (ACO) algorithms, have contributed significantly to solving a range of water resources problems (Afshar et al., 2015), including irrigation management problems (Nguyen et al., 2016a; Nguyen et al., 2016b). In ACO, the problems are represented in the form of a decision-tree graph which artificial ants have to traverse in a stepwise fashion in order to generate trial solutions. Therefore, use of ACO can increase the probability of finding globally optimal or near-globally optimal solutions and improve computational efficiency through reduction in the size of the search space and incorporation of domain

knowledge during the optimization process. In a similar way to other metaheuristic algorithms, another advantage of ACO for irrigation management problems is the ability to easily connect to simulation models (Maier et al., 2014; Maier et al., 2015).

Nguyen et al., (2016b) developed a general optimization framework for the crop and water allocation problem that utilized a dynamic decision tree graph and ACO as the optimization engine. The framework was subsequently extended (Nguyen et al., 2016a) to include the use of domain knowledge to bias the selection of crops and water allocations at each node in the decision-tree graph in order to increase computational efficiency. However, these studies only focused on the annual optimal crop and water allocation problem (i.e., each sub-area of the total area in the studied region required decisions on which crop should be planted and how much water should be supplied to the selected crop), but did not consider irrigation water scheduling throughout the year (i.e., timing and magnitude of water allocation) for each crop in a sub-area. In addition, both studies used crop water production functions to calculate yield (instead of a physically-based and more computationally expensive crop growth simulation model) and did not consider the application of fertilizer, which can have a significant influence on achieving maximum net return.

As evidenced from the above discussion, many existing simulation-optimization approaches for solving the irrigation management problem have either used simplified representations of crop growth processes (which have a number of disadvantages for irrigation scheduling problems) or mathematical optimization algorithms that are not especially amenable to linkage with process-based crop growth models. Furthermore, while metaheuristic algorithms can be linked to detailed crop growth models, there are often inherent issues with simulation run-times and size of search space (Loucks and Van Beek, 2005; Nguyen et al., 2016b). Despite the potential advantages of ACO with respect to search space size reduction, to the authors' knowledge, ACO has not previously been combined with process-based crop simulation models to identify realistic irrigation and fertilization schedules that maximize net return for a given water allocation. This type of approach is needed to rigorously assess the large number of combinations associated with the different components of the irrigation scheduling problem. Consequently, the specific objectives of this paper are:

1. To develop an innovative metaheuristic simulation-optimization framework that links ant colony optimization (ACO) with a process-based crop growth model, enabling optimal or near-optimal irrigation water and fertilizer application schedules to be identified.
2. To demonstrate the proposed optimization framework for an irrigation management case study in eastern Colorado, USA.

The remainder of this paper is organized as follows. A brief introduction to ACO is given in Section 2. The generic simulation-optimization framework for irrigation and fertilizer scheduling is introduced in Section 3, followed by a case study description and methodology for evaluating the proposed framework with the case study in Section 4. The results and discussion are presented in Section 5 before a summary and conclusions are given in Section 6.

2. Ant colony optimization (ACO)

ACO is a metaheuristic optimization algorithm inspired by the foraging behavior of ants to identify the shortest path from their nest to a food source using pheromone trails (Dorigo et al., 1996). In ACO, the decision space of the optimization problem is represented by a graph, the nodes and edges of which represent decision variables and decision variable options, respectively. A solution is constructed

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