A genetic algorithm for optimizing off-farm irrigation scheduling

J. B. Nixon, G. C. Dandy and A. R. Simpson

ABSTRACT

This paper examines the use of genetic algorithm (GA) optimization to identify water delivery schedules for an open-channel irrigation system. Significant objectives and important constraints are identified for this system, and suitable representations of these within the GA framework are developed. Objectives include maximizing the number of orders that are scheduled to be delivered at the requested time and minimizing variations in the channel flow rate. If, however, an order is to be shifted, the irrigator preference for this to be by ±24 h rather than ±12 h is accounted for. Constraints include avoiding exceedance of channel capacity. The GA approach is demonstrated for an idealized system of five irrigators on a channel spur. In this case study, the GA technique efficiently identified the optimal schedule that was independently verified using full enumeration of the entire search space of possible order schedules. Results have shown great promise in the ability of GA techniques to identify good irrigation order schedules.

Key words | genetic algorithms, irrigation networks, off-farm, open-channels, optimization, scheduling

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INTRODUCTION

Development of efficient scheduling systems for off-farm irrigation water delivery via open-channel networks is important to irrigation authorities and individual irrigators. There are increasing demands on irrigation authorities to be more efficient in their operations by making the best use of existing infrastructure, providing a high level of service to their customers, and minimizing water losses. Water ordering for open-channel delivery networks commonly uses an 'advance notice ordering' system. Many irrigation authorities use this system to record orders and schedule deliveries. Irrigation delivery schedules must be devised by water planners to deliver the orders, taking into account water availability, network capacity constraints, operating efficiency and customer satisfaction. Little computerized assistance (in the way of optimization algorithms), however, is currently available to water planners to help them balance these objectives, and many other requirements, in trying to identify efficient schedules for irrigation water deliveries. Thus, there is considerable scope for the development of decision support tools to aid planners in this complex scheduling activity.

Two aspects of irrigation water management can be distinguished. The first results from the fact that scheduled deliveries may not match the water requirements of the orders as requested. The second results from the fact that actual deliveries may not match the scheduled deliveries (Schuurmans and Maherani 1991). The present paper is concerned with the first aspect only.

In the following, significant objectives and important constraints are identified for an off-farm irrigation order scheduling system, and suitable representations of these within a genetic algorithm (GA) framework are developed. The relative importance of individual objectives and/or constraints may be adjusted by the use of weighting factors. This approach is then demonstrated for an idealized system of five irrigators, each with a single order request to be scheduled, on a channel spur. The GA technique efficiently identifies the optimal schedule that has been independently determined by full enumeration. Results in this study show great promise in the ability of GA techniques to identify optimal irrigation order schedules.

BACKGROUND

A vast body of literature exists on irrigation scheduling. This is, however, chiefly concerned with aspects of *on-farm* scheduling based on water moisture readings and crop application rates (Budikusuma 1994). In contrast, the present paper deals exclusively with *off-farm* irrigation scheduling. This is mostly concerned with the constraints associated with the irrigation channel network that delivers irrigation water from rivers and dams to the farm-gate, the scheduling objectives of the suppliers and consumers involved, and the hydraulic model used to approximate the channel network dynamics (Schuurmans 1991). In the case study presented in the present paper, a simple irrigation channel flow model is used, as questions of accuracy, reliability, stability, etc., associated with the use of any particular realistic hydraulic model are not the main thrust of this paper.

In the past, GAs have been applied to the scheduling of exam timetables (Fang 1992) and to job shop scheduling (Fang *et al*. 1993; Bierwirth and Mattfeld 1999; Norman and Bean 1999). Resource allocation and levelling in project planning and management (Hegazy 1999), optimizing the design of water distribution systems (Simpson *et al*. 1994), and optimal sequencing of water resource projects (Dandy and Connarty 1995) are other applications of GAs in engineering. The research discussed in the present paper is, to the authors' knowledge, the first published application of GAs to optimizing off-farm irrigation scheduling.

Previous studies have shown that GAs are more effective than traditional optimization methods for problems involving discrete decision variables. Simpson *et al*. (1994) compared the performance of the optimization of water distribution systems using various techniques, including traditional optimization techniques and GAs. The discrete nature of the decision variables favored the use of GAs over nonlinear programming, which gave continuous values of pipe diameter size. For small problems the ability of alternative optimization techniques to find a known global optimum solution for the pipe network optimization problem is similar. However, for larger problems this is not the case. Dandy *et al*. (1996) showed that, for the New York City tunnels problem, the GA was able to find lower cost solutions to the problem than any other previously used traditional optimization technique. Dandy and Connarty (1995) applied GAs to the problem of finding the optimal size and sequence of new water resources projects in south-east Queensland, Australia. They found that the GA approach required much less computer time than integer linear programming (ILP) and gave better results. In addition, the GA approach allowed projects to start in any year, whereas ILP only worked, within a reasonable time, with discrete five-year blocks. In summary, GAs are generally more effective than traditional optimization techniques while offering simplicity in implementation. It is relatively easy to add GAs to an existing simulation model rather than develop and implement the formulation of the optimization problem to fit the more traditional optimization techniques.

The proposed application of GA optimization to water order scheduling will involve Goulburn–Murray Water (G–MW) – a major rural water authority in the south-eastern area of Australia. G-MW serves 24,000 properties via 6800 km of channels fed by 19 storages using 24,500 control structures with 7000 GL p.a. It is intended to initially optimize a scheduling task equivalent to what is achieved by a human planner in approximately four hours. Typically one planner is required to schedule the orders for one 'area' of a district within G–MW's jurisdiction, which are requested to start over a 48 h period. A representative scheduling task may involve approximately 170 orders for an area controlled by approximately 350 structures. Approximately 10% of the structures might have capacity limitations and 5% might be routinely adjusted on a daily basis. This typically results in approximately 35 flow rate time-series which must be calculated. Thus, with hourly order shifts possible, a search space could consist of 48^{170} (or approximately 10^{280}) possible solutions.

ADVANCE NOTICE ORDERING SYSTEMS

An advance notice irrigation ordering system involves the following steps:

(1) Irrigators place an order (using, for example, telephone keypad or internet browser).
(2) In placing an order, they are required to specify:
 - their offtake point number;
 - the date they request the delivery to commence;
 - the time they request the delivery to commence;
 - the requested duration of the delivery; and
 - the requested flow rate of the delivery.
(3) The order is recorded in a computer database.
(4) Each day, irrigation planners schedule the irrigation orders stored in the database that are requested to start within the next 2 to 3 days. This may involve moving some orders backwards or forwards in time. In doing so, the irrigation planners try to ensure that channel capacities are not exceeded, that flows in the channels are relatively smooth throughout the day, and that other constraints are satisfied and/or objectives are met. The schedule is then fixed for the next day.
(5) Irrigators can confirm when their request will be delivered.
(6) Each day, irrigation operators adjust network channel control structures and check offtake points to ensure that the orders are delivered as planned.

Irrigators are usually required to place their orders a specified number of days in advance. All requested orders for a certain period of time, usually a single day, are then considered together by an irrigation planner. The scheduling of orders for a particular day is usually performed by a planner one day in advance. An advance notice ordering system is designed to schedule a set of orders for a given irrigation day in such a way that maximizes the use of the water available in the system. It is during periods of peak demand that such a system is most beneficial. One such peak demand period occurs after a heavy fall of rain, followed by a prolonged dry period, when many irrigators require water almost simultaneously. The scheduling of orders in this manner allows for the greatest number of orders to be satisfied.

GENETIC ALGORITHMS

A GA is a search procedure, based on natural selection and the mechanisms of population genetics (Goldberg 1989*a*; Michalewicz 1996). The GA technique has its roots in the biological processes of 'survival of the fittest' and adaptation. Overviews of the theoretical fundamentals and successful applications, and research topics in the GA field can be found, respectively, in Beasley *et al*. (1993*a*) and Beasley *et al*. (1993*b*).

It has been proven that, under certain assumptions, the GA is guaranteed to find a global optimum (Bäck 1991) and, furthermore, to find it in finite time (Holland 1992). These theoretical results, however, are of little practical worth in most GA applications, which frequently introduce additional domain-specific heuristics that violate the required assumptions. Nevertheless the GA technique has been successfully applied to many engineering problems (Willis *et al*. 1997).

Irrigation delivery schedule genetic algorithm representation

Each irrigator places an order for a requested starting time with a desired duration (in hours) and a specified flow rate in megalitres per day (ML d^{-1}). In this research, each order to be scheduled for a plan day has been encoded in the GA as a string of numbers. Each position in this string represents the order number, and the integer value represents the number of hours the requested order is scheduled to be shifted. A negative order shift corresponds to 'bringing forward' an order (i.e. starting it earlier), while a positive order shift corresponds to 'holding off' an order (i.e. delaying its start).

Suppose a set of five irrigation orders needs to be scheduled. The string illustrated in Figure 1 represents one particular solution. For this string, order 1 has been delayed 2 hours from the requested time, order 2 will be supplied as requested, order 3 has been scheduled to start 3 hours earlier than requested, while the start times for orders 4 and 5 have been delayed 24 and 6 hours, respectively.

Order number (#)	1	2	3	4	5
Order shift (hours)	+2	0	–3	+24	+6

Figure 1 | A typical GA string for a scheduling problem with five orders.

SCHEDULING CONSTRAINTS

A count of the number of orders for which the start times were requested within a *planning period* determines the number of orders to be scheduled, O, and hence the length of the GA strings. The orders are allowed to be shifted by the GA process such that the scheduled start times always remain within the planning period.

Genetic algorithm operators

The GA operates on a *population* of alternative schedules for irrigation water delivery. Initially, the population of solutions is generated randomly. An improved population is then produced in the next *generation* by using the three GA operators of *selection*, *crossover* and *mutation*. Selection is a 'survival of the fittest' process and involves the choice of which *parent* strings of 'high' fitness that will form a 'mating pool' are used to provide the characteristics of subsequent *child* strings. Crossover is a partial exchange of order shift values between parent strings that produces child strings that, in this instance, are guaranteed to satisfy the imposed constraints discussed above. Mutation occasionally alters the order shift value at a randomly selected position of a randomly selected string to a different value, that is allowable for that order. The reproduction process is terminated after a maximum number of generations, predetermined by the operator. The individual steps in the evolutionary process of the GA are discussed below.

Given two feasible schedules as parents, the problem of guaranteeing that the offspring resulting from crossover are also feasible may be approached using penalty functions to relax troublesome constraints and penalize the objective for violating them (Goldberg 1989*a*), or using random keys (Bean *et al.* 1995). In the present paper, the schedule representation used is a robust method of encoding the problem that enables general crossover operators to lead to feasible solutions, thus requiring neither of these or other centralized control methods (requiring global information) proposed in the GA theory literature (Goldberg 1989*b*).

A poor choice of representation, whereby an optimal or near-optimal solution cannot be formed by the simple GA process, can also result in what is termed *deception* (Deb 1991). Deception, however, is a property of a particular representation of a problem, rather than of the problem itself (Forrest and Mitchell 1993). In principle, a deceptive representation could be transformed into a non-deceptive one, but in practice finding the appropriate transformation can range from a trivial activity to a highly creative one, or may even be intractable (De Jong 1985). The potential for deception in the problem at hand using the representation presented has, however, not been investigated in the present study.

OPTIMIZATION OBJECTIVES

Many *scheduling objectives* may be considered to be important in delivering irrigation water to irrigators in an appropriate manner. The following *optimization objectives* were considered to apply to 'desirable' schedules:

(1) Minimize the number of orders shifted (φ_1, φ_2, and φ_3).
(2) Encourage particular sizes of order shifts and discourage others (φ_4).
(3) Avoid channel capacity exceedance (φ_5).
(4) Minimize channel flow rate variations (φ_6).

In a particular case, some of these are of relatively greater importance and some may be relatively unimportant. The relative importance can be taken into account by weighting the optimization objectives (using w_f, $f = 1, 2, \ldots, 6$ values) appropriately.

THE EVOLUTIONARY PROCESS

The steps of a GA for irrigation order schedule optimization have been developed as follows:

(1) Randomly generate an initial population of P_0 order shift strings.
(2) Decode each string and compute a number of performance measures φ_f, $f = 1, 2, \ldots, 6$.
(3) For each string, multiply each of the measures by an appropriate weight w_f, $f = 1, 2, \ldots, 6$ and sum these to obtain an overall fitness measure φ.
(4) Randomly divide the population of strings into pairs of strings and allow the better of each pair (in terms of fitness) to become a parent for the next generation (tournament selection).
(5) Repeat Step 4 to complete the creation of the mating pool.
(6) Randomly divide the mating pool into pairs of strings. Perform a crossover operation, with specified probability p_c, on each pair of strings. For *one-point crossover*, this operation involves cutting each parent string at the same point along their length (determined randomly) and switching the right-hand tails with each other to produce two offspring. If crossover is not to occur, the two offspring are identical to their parents.
(7) Perform a mutation operation, with specified probability p_m, of the value at each position of the offspring strings produced in Step 6. This mutation operation involves changing the existing order shift value to another feasible choice (chosen randomly).
(8) Repeat Steps 2–7 for a specified number of generations G.

Flow rate time-series

As part of the performance measure computation of Step 2 above, a number of flow rate time-series are calculated, based on water mass balance in the open-channel network, to determine the flow regime for the irrigation order schedule corresponding to an order shift string. Each time-series represents the flow past a specific control structure in the irrigation network as a series of values for flow rate (in ML d^{-1}) versus time (in hours). At each control structure, a channel capacity (in ML d^{-1}) specifies a maximum flow rate that should not be exceeded. Each flow rate time-series takes into account the requested order times and the scheduled order shifts. Conceptually, at the end of an irrigation water delivery order at a 'finishing' offtake point, water is made available for the beginning of a 'following' order at a 'starting' offtake point. These lags for water in the system, known as *travel times*, are taken into account in the calculation of the time-series. An example of a time-series calculation is given in the case study below.

FITNESS CONSTITUENTS

For each of the optimization objectives A–D, corresponding *fitness constituents* were developed. In the following sections the implementation of these fitness constituents – φ_1–φ_6 – is discussed in detail. Typical functional forms are given below.

Order shift sign fitness constituents: φ_1, φ_2, and φ_3

The GA has been developed such that it 'rewards' irrigation water delivery schedules for which the majority of orders are scheduled to be delivered at the requested times. Similarly, it 'penalizes' schedules for which orders are brought forward or held back in time. Three fitness constituents—φ_1, φ_2 and φ_3—have been based on these concepts.

A count, o_1, is made of the number of order shifts that are negative, i.e. those for which irrigators' orders are scheduled earlier than they were requested, to give a fitness measure of

$$\varphi_1 = 1 - \frac{o_1}{O} \tag{1}$$

referred to as the *negative order shift fitness constituent* value. The function defined by Equation (1) is illustrated in Figure 2.

A count, o_2, is also made of the number of order shifts that are positive, i.e. those for which irrigators' orders are scheduled later than they were requested. The *positive order shift fitness constituent* value, φ_2, is then defined analogously to the negative order shift fitness constituent value φ_1. This function is also illustrated in Figure 2.

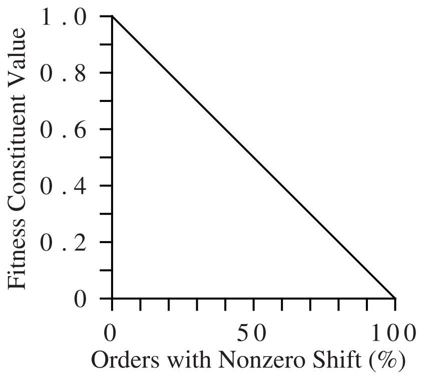

Figure 2 | The nonzero order shift fitness constituents: φ_1 and φ_2.

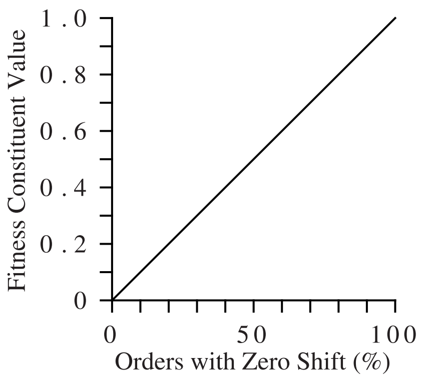

Figure 3 | The zero order shift fitness constituent: φ_3.

The number of irrigators' orders that are scheduled exactly when they were requested is given by $o_3 = O - (o_1 + o_2)$. The *zero order shift fitness constituent* illustrated in Figure 3 is defined by

$$\varphi_3 = \frac{o_3}{O} \tag{2}$$

Order shift magnitude fitness constituent: φ_4

For a single order, o, the fitness function for the order shift magnitude fitness values, $\varphi_{4,o}$, illustrated in Figure 4 is designed to lead the GA to schedules that satisfy optimization objective B: schedules that involve order shifts approaching 0 hours are rewarded as are, to a lesser degree, those involving shifts approaching ± 24 h. Shifts of around ± 12 h are penalized.

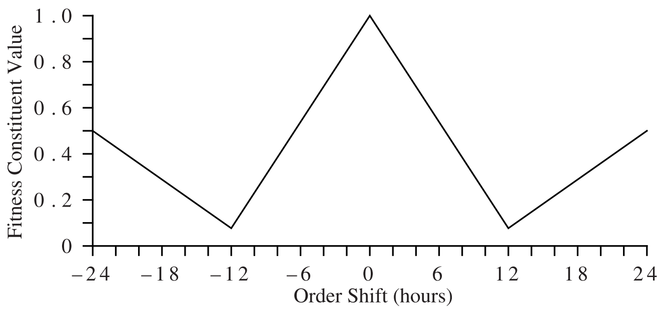

Figure 4 | The order shift magnitude fitness constituent: $\varphi_{4,o}$.

This functional form assumes that, from an irrigator's perspective, it is preferable to be shifted by approximately 24 h than by approximately 12 h, since the latter would involve a major timetable disruption on any given day, while the former would only involve interchanging the timetables for the two days.

An assumption has been made that the GA is constrained such that no orders can be rescheduled for a start time greater than 24 h from that which was requested. This constraint was imposed to enable full enumeration of all possible solutions to the problem. It is possible to relax this constraint if desired.

The *orders shift magnitude fitness constituent* value is then defined by

$$\varphi_4 = \frac{1}{O} \sum_{o=1}^{O} \varphi_{4,o} \tag{3}$$

Channel capacity exceedances fitness constituent: φ_5

The exceedance of channel capacity at each control structure c is penalized. The manner in which this occurs is determined by the function for the channel capacity exceedance fitness values, $\varphi_{5,c}$, illustrated in Figure 5.

A weight $w_{5,c}$ is determined, for each control structure that applies, so as to represent the relative importance of the amount of channel capacity exceedance as defined by $\varphi_{5,c}$. Although other weightings may be used, in this instance the weight is simply set to 1.0 for the M control structures at which a capacity (ML d^{-1}) is set, and to 0.0

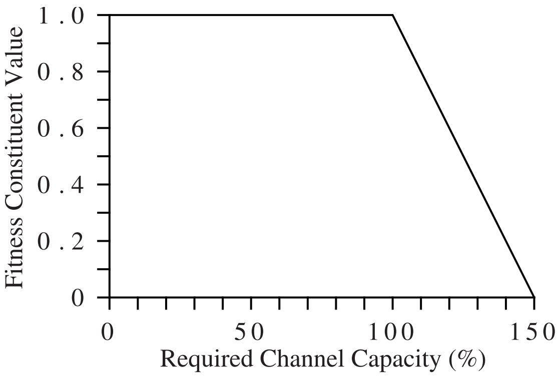

Figure 5 | The channel capacity exceedance fitness constituent: $\varphi_{5,c}$.

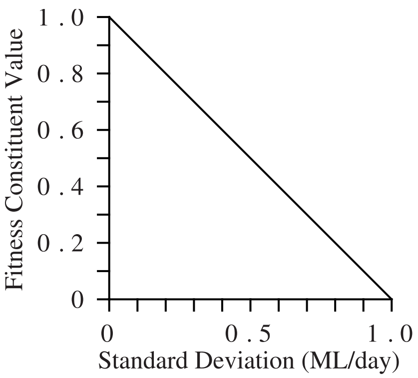

Figure 6 | The flow rate standard deviation fitness constituent: $\varphi_{6,c}$.

otherwise. The *channel capacity exceedances fitness constituent* value for the channel network is then defined by

$$\varphi_5 = \frac{1}{M}\sum_{c=1}^{M} w_{5,c}\varphi_{5,c} \qquad \text{where} \qquad \sum_{c=1}^{M} w_{5,c} = 1\,. \tag{4}$$

Flow rate standard deviations fitness constituent: φ_6

For each of the S control structures in the network that are chosen to be included in the analysis, the standard deviation of the flow rate time-series (ML d^{-1}) is calculated. Time-series points between the first non-zero flow rate value and the last non-zero value, inclusively, are used to calculate the deviation. The flow rate standard deviation fitness value, $\varphi_{6,c}$, for a particular structure is then given by the function illustrated in Figure 6. Thus schedules that correspond to a time-series at a particular control structure that has standard deviation approaching zero are deemed increasingly more fit while a large standard deviation is assigned a low fitness value.

A weight $w_{6,c}$ is determined, for each control structure c, to apply to the flow rate standard deviation fitness so as to represent the relative importance of time-series flow rate variations at individual control structures. For the entire channel network, the *flow rate standard deviations fitness constituent* value is defined by

$$\varphi_6 = \frac{1}{S}\sum_{c=1}^{S} w_{6,c}\varphi_{6,c} \qquad \text{where} \qquad \sum_{c=1}^{S} w_{6,c} = 1\,. \tag{5}$$

The function illustrated in Figure 6 assigns negative fitness constituent values to time-series of standard deviation greater than 1 ML d^{-1}. Although this function is used in the case study below, it could be argued that a more suitable function—bounded by 0 and 1—would avert the possibility of large negative values of this constituent dominating the weighted constituent sum and thus resulting in a negative total fitness value for any schedule under evaluation.

COMBINING SCHEDULING OBJECTIVES

The individual fitness constituents φ_1–φ_5 are bounded by 0 and 1. The use of such a scaling retains a string's relative performance and also attempts to bias the selective pressure towards better strings, although still allowing relatively unfit strings the potential to reproduce (Chipperfield 1998). The corresponding optimization objectives can thus be given various operator-specified weightings w_1–w_6, depending on their importance. Wall (1996) suggested that the fitness constituent weights be scaled so that their total is unity.

The total fitness of any order schedule is hence given by

$$\varphi = \frac{1}{6}\sum_{f=1}^{6} w_f\varphi_f \qquad \text{where} \qquad \sum_{f=1}^{6} w_f = 1\,. \tag{6}$$

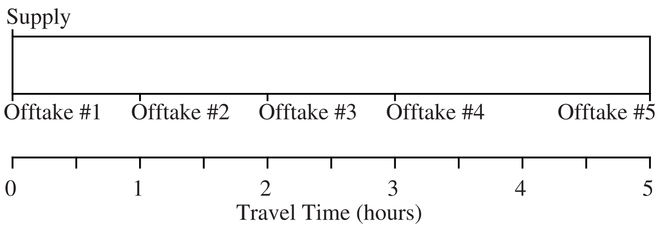

Figure 7 | Irrigation channel for the case study.

The total is multiplied by a factor of 100 so that

$$\Phi = 100\varphi \qquad (7)$$

represents the 'pseudo-percentage' of the theoretical maximum achievable value.

CASE STUDY

A problem involving scheduling irrigation water deliveries in a single channel spur was constructed for which the set of all possible solutions in the search space could be fully enumerated, and hence the optimal schedule determined by an exhaustive search. This case study consists of five irrigators with one order each, constrained by a maximum order shift magnitude of 24 h, wherein only shifts in exact multiples of 1 h were allowed. Details of the channel network topology are illustrated in Figure 7. The irrigators' order requests and the fitness function weightings used are listed in Tables 1 and 2, respectively. The travel times, order rates and order times have been chosen such that some orders require shifting to satisfy flow variation or other objectives and/or constraints.

In this case study there is only one control structure, at the head of the only channel, and its flow rate time-series is used in determining both fitness constituents φ_5 and φ_6. Thus $M=1$, $S=1$, and $w_{5,1}$ in Equation (4) and $w_{6,1}=1$ in Equation (5). Other parameters defining this problem are the number of orders $O=5$ and the weights w_f, $f=1, 2, \ldots, 6$, listed in Table 2.

The irrigators' requested orders are illustrated in Figure 8. In this figure, no account has been taken of the time lag between the offtakes, i.e. the horizontal axis

Table 1 | Irrigator order requests for the case study

Order request (#) (1)	Offtake point (#) (2)	Order start (h) (3)	Order duration (h) (4)	Order rate (ML d^{-1}) (5)
1	1	6.0	24.0	5.0
2	2	8.0	6.0	12.0
3	3	10.0	8.0	5.0
4	4	18.0	18.0	10.0
5	5	20.0	18.0	4.0

represents the times at which the irrigators would prefer to start and finish their orders. The irrigators' requested orders are again illustrated in Figure 9. In this figure the time lag between the offtakes has been accounted for, i.e. the horizontal axis represents the times at which the water authority must supply the irrigators' orders past the supply control structure at the upstream end of the channel spur.

Figure 10(a) illustrates the flow rate time-series, calculated at the supply control structure at the 'upstream' end of the channel spur, for the orders as requested, taking travel times into account. This time-series is calculated by summing the orders illustrated in Figure 9. The horizontal line in Figure 10 indicates the channel capacity of 27 ML d^{-1}.

Exhaustive search enumeration

Figure 10(b) illustrates the scheduled time-series, calculated at the same point on the channel spur, for the optimal order schedule as determined by exhaustive search. Since there are 49 possible order shift values for each of the 5 orders, there is a total of $49^5=282{,}475{,}249$ possible scheduling solutions. The enumeration to determine the fitness of all of these solutions took approximately 6 h 5 min of central processor unit (CPU) time on a Hewlett–Packard B160L Unix work-

Table 2 | Fitness constituent weights for the case study

Fitness constituent (name) (1)	Constituent symbol (φ_f) (2)	Constituent weight (w_f) (3)	Optimization objective (4)	Equation reference (equation) (5)	Figure reference (figure) (6)
Negative order shift	φ_1	1/12	A	(1)	2
Positive order shift	φ_2	1/12	A	(1)	2
Zero order shift	φ_3	1/12	A	(2)	3
Order shift magnitude	φ_4	1/4	B	(3)	4
Channel capacity exceedances	φ_5	1/4	C	(4)	5
Flow rate standard deviations	φ_6	1/4	D	(5)	6

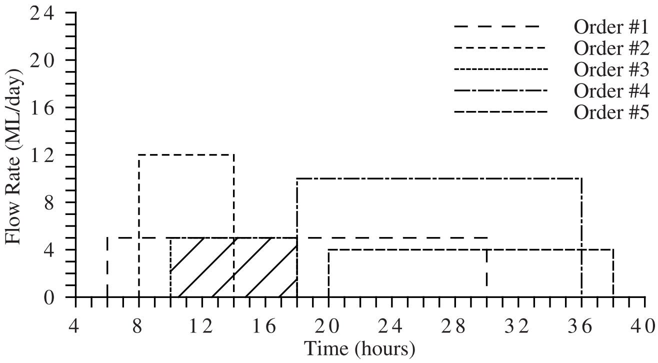

Figure 8 | Irrigator order requests for the case study, without travel times.

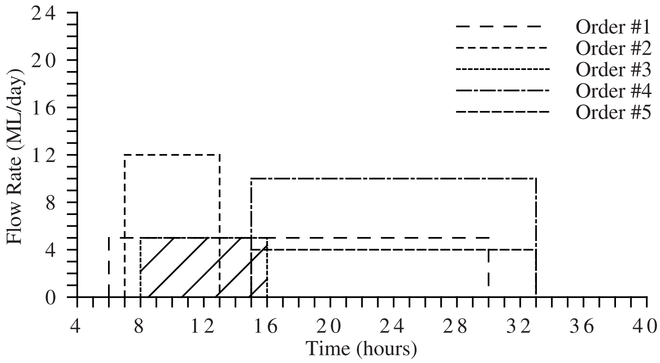

Figure 9 | Irrigator order requests for the case study, with travel times.

station. All programming was in Fortran 90 (Metcalf and Reid 1996).

Genetic algorithm optimization of irrigation schedules

The optimal solution illustrated in Figure 10(b) was also identified by GA scheduling. Parameters used in the GA were: $P_0 = 1000$, $p_c = 0.8$, $p_m = 0.0$ and $G = 53$. Also implemented was a procedure by which, at each generation, the members of the population were forced to be unique. This was achieved by replacing each duplicated string with one generated randomly. This process was repeated until the proposed replacement was, in fact, different to all other population members.

The GA took approximately 26.2 s to execute 53 generations, and the total number of solutions simulated was thus 53,000. From this it can be seen that the GA is efficient with respect to finding the optimal solution, in terms of both the number of solutions evaluated (0.019% of the total search space) and CPU time executed (0.12% of the time required for full enumeration). The optimal solution was first found after only 46 generations (equivalent to 46,000 evaluations). Also, the GA was able to find five of the top six 'fittest' solutions (determined by enumeration).

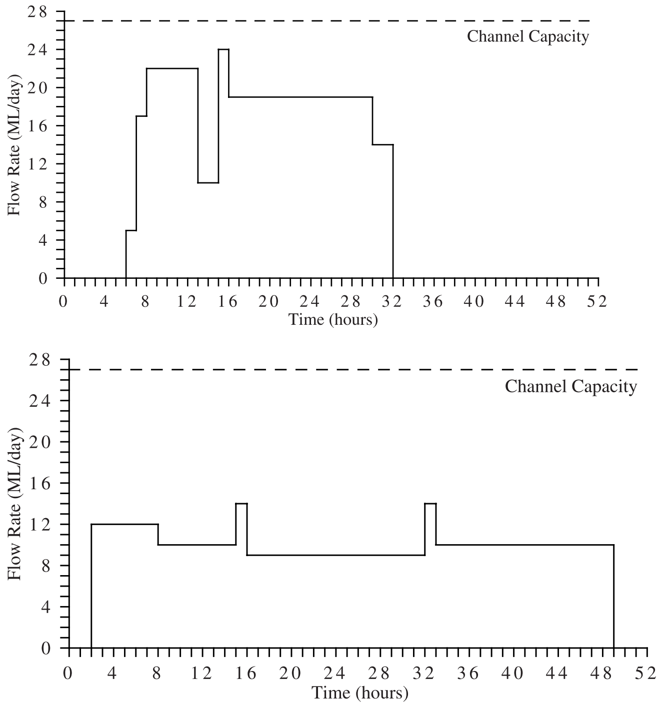

Figure 10 | Case study flow rate time-series, for schedules: (a) requested by the irrigators; and (b) determined optimal by both exhaustive search and the GA. (a) string=[0,0,0,0,0], $\Phi=-6.95$, (b) string=[2,-5,0,17,0], $\Phi=+52.7$.

Clearly, in this case study, exceedance of channel capacity is not an issue for a planner, but must nevertheless be taken account of by the GA when evaluating possible solutions. Using the chosen set of objectives and corresponding weights, it seems desirable to shift some orders so that a smoother flow is obtained at the control structure.

Alteration of the relative weightings for the fitness constituents, from those of Table 2, results in changes to the set of schedules that are determined to be the fittest. Experiments using the unequal weightings to the six constituents of fitness listed in Table 2 and an equal weighting resulted in the same strings ([2,-5,0,17,0], [3,-5,0,18,0], [3,-22,0,-24,0], [2,-5,0,18,0]), in the same order, as members of the top four fittest schedules. The fitness values changed, but the strings representing the schedules found did not. The top three strings correspond to the top three schedules determined by enumeration, using both unequal and equal weightings. Experiments have indicated that, even with idealized small size example problems, such as those discussed in this paper, some of the fittest solutions can also be some of the hardest for the GA technique to find.

CONCLUSIONS

This paper has examined the use of genetic algorithm optimization to identify off-farm irrigation water delivery schedules that achieve the best possible outcomes for a set of objectives, while satisfying a set of constraints. Significant objectives and important constraints have been identified and suitable representations of these within the GA framework have been developed. The most significant research outcome is the development of a methodology for applying GA techniques to the optimal scheduling of irrigation orders in off-farm open-channel systems.

For a relatively simple irrigation order optimization problem of an idealized system of five irrigators on a channel spur, the GA efficiently identified the known globally optimal schedule. The results have shown great promise in the ability of GA techniques to identify optimal irrigation order schedules. The results of this evaluation of the applicability of GA technology to flow management of open-channel gravity systems have thus shown that the technology can efficiently schedule irrigation order requests.

ACKNOWLEDGEMENTS

The research team gratefully acknowledges the funding and/or in-kind support received from:

- (Australian) Land and Water Resources Research and Development Corporation/National Program for Irrigation Research and Development;
- Goulburn–Murray Water (Australia);
- Rubicon Systems Australia Pty Ltd.

ACRONYMS AND ABBREVIATIONS

CPU	central processor unit
GA	genetic algorithm
ILP	integer linear programming

NOTATION

The following symbols are used in this paper:

c	control structure number;
f	fitness constituent;
G	number of generations;
M	number of structures considering channel capacity exceedance;
O	number of irrigation orders;
o	irrigation order number;
P_0	(initial) population size;
p_c	crossover probability;
p_m	mutation probability;
S	number of structures considering time-series flow rate standard deviations;
w	fitness constituent weight;
Φ	overall fitness 'percentage';
φ	fitness value.

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