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Title: A Genetic Algorithm for Optimizing Off-Farm Irrigation Scheduling

Short Title: Irrigation Scheduling by Genetic Algorithm

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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 minimizing variations in the channel flow rate and maximizing the number of orders that are scheduled to be delivered at the requested time. If, however, an order is to be shifted, the irrigator preference for this to be by ± 24 hours rather than ± 12 hours is accounted for. Constraints include avoiding channel capacity exceedance. 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.

Keywords: genetic algorithms, irrigation networks, off-farm, open-channels, optimization, scheduling

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”; and
ϕ	fitness value.

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 order 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, however, is available to water planners to help them to balance these 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 exactly match the water requirements of the orders as requested. The second results from the fact that actual deliveries may not exactly match the scheduled deliveries (Schuurmans and Maherani, 1991). The present paper is concerned with the first aspect only.

Previous studies have shown that optimisation using evolutionary techniques such as genetic algorithms (GAs) has been more effective than traditional optimisation methods. Dandy and Connarty (1995) and Simpson et al. (1994) compared the performance of optimisation of water distribution systems using various techniques, including traditional optimisation techniques and GAs. The discrete nature of the decision variables favored the use of GAs over non-linear programming, where the outcome was continuous values of pipe diameter size. For small problems the ability of the optimisation techniques to find a known global optimum solution for the pipe network optimisation 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 optimisation technique. In summary, GAs are generally more effective than traditional optimisation techniques while offering a simplicity in implementation. It is relatively easy to add GAs to an existing simulation model rather than develop and implement the formulation of the optimisation problem to fit the more traditional optimisation techniques.

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 inputting weighting parameters. 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 is 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 the 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, 1996) 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.

Ihe proposed application of GA optimisation to water order scheduling will involve Goulburn–Murray Water (G–MW)—a major rural water authority in the mid-eastern area of Australia. G-MW serves 24,000 properties via 6,800 km of channels fed by 19 storages using 24,500 control structures with 7,000 GL p.a. It is intended to initially handle 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 hour period. A representative scheduling may involve approximately 170 orders for an area controlled by approximately 350 structures of which approximately 10% have capacity limitations (which by definition must apply to those on downstream spurs) and 5% of which might be routinely adjusted on a daily basis, resulting in approximately 35 flow rate time-series (at structures in the the union of these sets) which must be calculated. Thus, with hourly order shifts possible, a search space of 48^{170} (or 10^{280} approximately) possible solutions results.

Advance Notice Ordering Systems

An advance notice irrigation ordering system involves the following steps:

a) Irrigators place an order (using, for example, telephone keypad or internet browser).
b) 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.
c) The order is recorded in a computer database.
d) 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.
e) Irrigators can confirm when their request will be delivered (using, for example, telephone keypad or internet browser).
f) 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. The requested orders for a certain period of time, usually a single day, are then considered all 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 will be 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, 1989a; 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. (1993a) and Beasley et al. (1993b).

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/day). 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 Fig. 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 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, 1989a), 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 centralised control methods (requiring global information) proposed in the GA theory literature (Goldberg, 1989b).

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.

A. Minimize the number of orders shifted. (ϕ_1, ϕ_2, and ϕ_3)

B. Encourage particular sizes of order shifts and discourage others. (ϕ_4)

C. Avoid channel capacity exceedance. (ϕ_5)

D. 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 $\phi_f, f = 1,2,\ldots,6$.
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 to 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/day) versus time (in hours). At each control structure, a channel capacity (in ML/day) 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 to D, corresponding *fitness constituents* were developed. In the following sections the implementation of these fitness constituents—ϕ_1 to 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:

$$\phi_1 = 1 - \frac{o_1}{O} \tag{1}$$

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

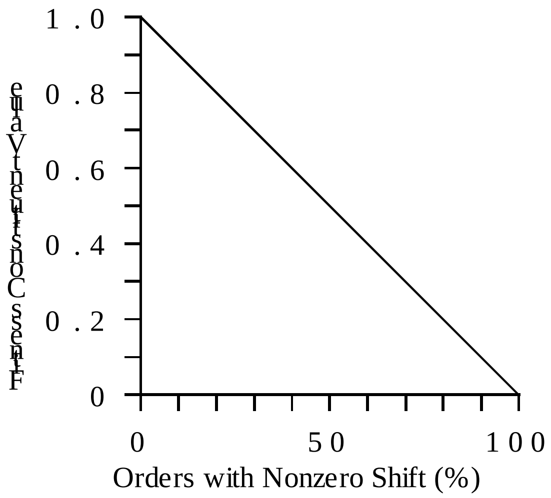


Figure 2: The Nonzero Order Shift Fitness Constituents: ϕ_1 and ϕ_2

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 Fig. 2.

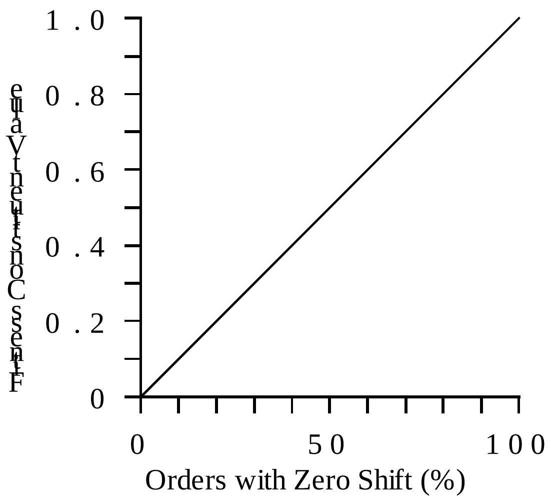


Figure 3: The Zero Order Shift Fitness Constituent: ϕ_3

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 Fig. 3 is defined by

$$\phi_3 = \frac{o_3}{O} \tag{2}$$

***Order Shift Magnitude Fitness Constituent:* ϕ_4**

For a single order, *o*, the fitness function for the order shift magnitude fitness values, $\phi_{4,o}$, illustrated in Fig. 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 hours. Shifts of around ± 12 hours are penalized.

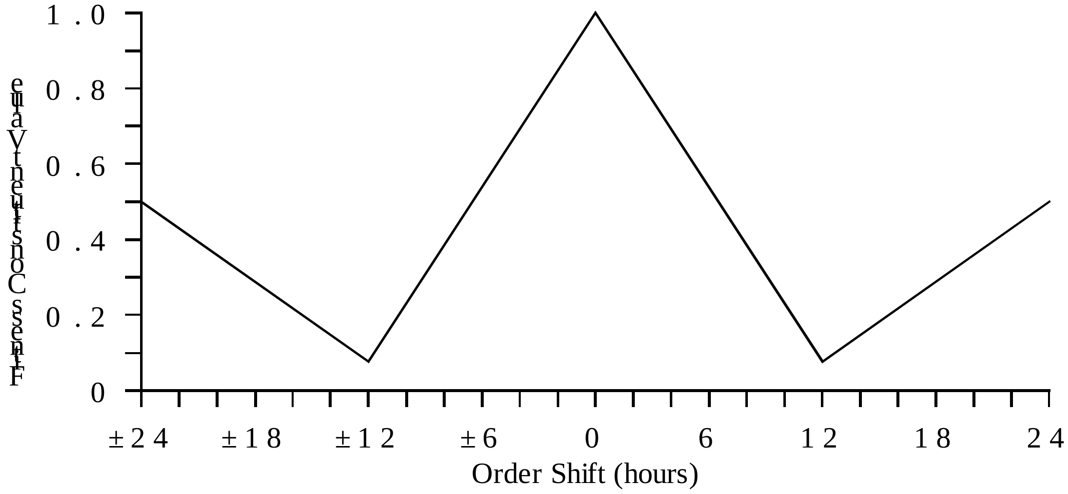


Figure 4: The Order Shift Magnitude Fitness Constituent: $\phi_{4,o}$

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

An assumption has been made that the GA is constrained such that no orders can be rescheduled for a start time greater than 24 hours 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.

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

$$\phi_4 = \frac{1}{O}\sum_{o=1}^{O}\phi_{4,o} \tag{3}$$

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 value, $\phi_{5,c}$, illustrated in Fig. 5.

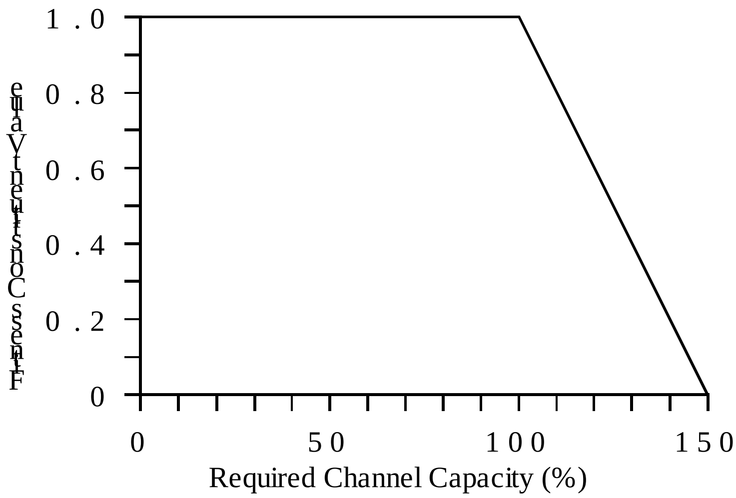


Figure 5: The Channel Capacity Exceedance Fitness Constituent: $\phi_{5,c}$

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 $\phi_{5,c}$. 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/day) is set, and to 0.0 otherwise. The *channel capacity exceedances fitness constituent* value for the channel network is then defined by

$$\phi_5 = \frac{1}{M}\sum_{c=1}^{M} w_{5,c}\phi_{5,c} \qquad \text{where} \qquad \sum_{c=1}^{M} w_{5,c} = 1 \tag{4}$$

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/day) 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, $\phi_{6,c}$, for a particular structure c is then given by the function illustrated in Fig. 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.

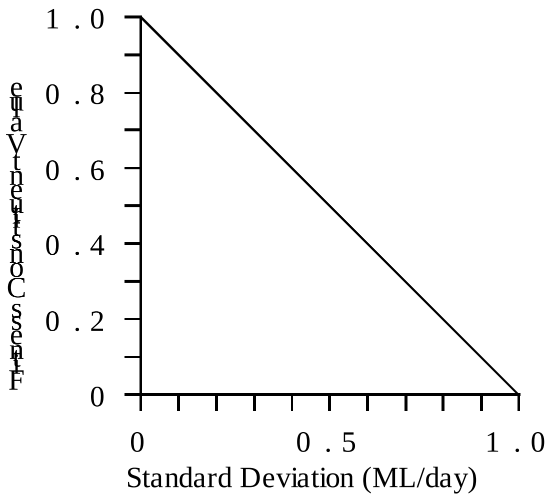


Figure 6: The Flow Rate Standard Deviation Fitness Constituent: $\phi_{6,c}$

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

$$\phi_6 = \frac{1}{S}\sum_{c=1}^{S} w_{6,c}\phi_{6,c} \qquad \text{where} \qquad \sum_{c=1}^{S} w_{6,c} = 1 \tag{5}$$

The function illustrated in Fig. 6 assigns negative fitness constituent values to time-series of standard deviation less than 1 ML/day. 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 to 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 to 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:

$$\phi = \frac{1}{6}\sum_{f=1}^{6} w_f\phi_f \qquad \text{where} \qquad \sum_{f=1}^{6} w_f = 1 \tag{6}$$

The total is multiplied by a factor of 100 so that

$$\Phi = 100\phi \tag{7}$$

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 hours, wherein only shifts in exact multiples of one hour were allowed. Details of the channel network topology are illustrated in Fig. 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 resulting in a scheduling scenario in which some orders require shifting to satisfy flow variation or other objectives and/or constraints.

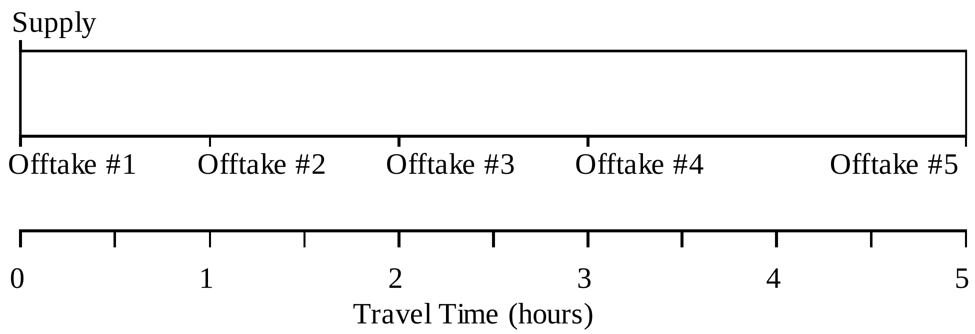


Figure 7: Irrigation Channel for the Case Study

Table 1: Irrigator Order Requests for the Case Study

Order Request (#) (1)	Offtake Point (#) (2)	Order Start (hours) (3)	Order Duration (hours) (4)	Order Rate (ML/day) (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

Table 2: Fitness Constituent Weights for the Case Study

Fitness Constituent (name)	Constituent Symbol (ϕ_f)	Constituent Weight (w_f)	Optimization Objective	Equation Reference (Eq.)	Figure Reference (Fig.)
(1)	(2)	(3)	(4)	(5)	(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

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 $w_{5,1} = 1$ in Eq. (4) and $w_{6,1} = 1$ in Eq. (5). Other parameters defining this problem are the number of orders $O = 5$ and the weights w_f, $f = 1,2,\cdots,6$ listed in Table 2.

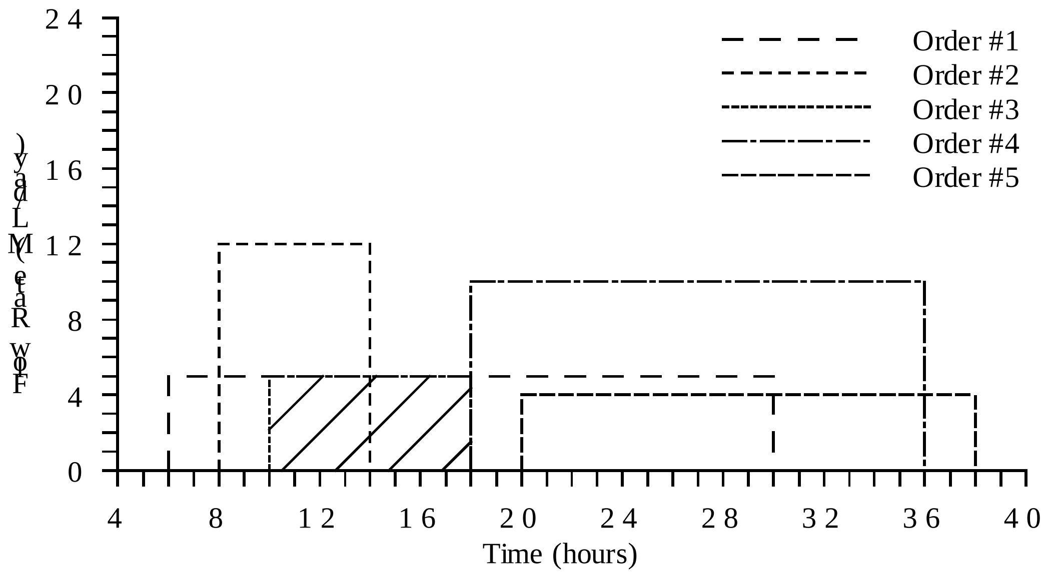


Figure 8: Irrigator Order Requests for the Case Study, without Travel Times

The irrigators' requested orders are illustrated in Fig. 8. No account has been taken of the time lag between the offtakes, i.e., the horizontal axis represents the times at which the irrigators would prefer to start and finish their orders. The irrigators' requested orders are again illustrated in Fig. 9. In this case 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.

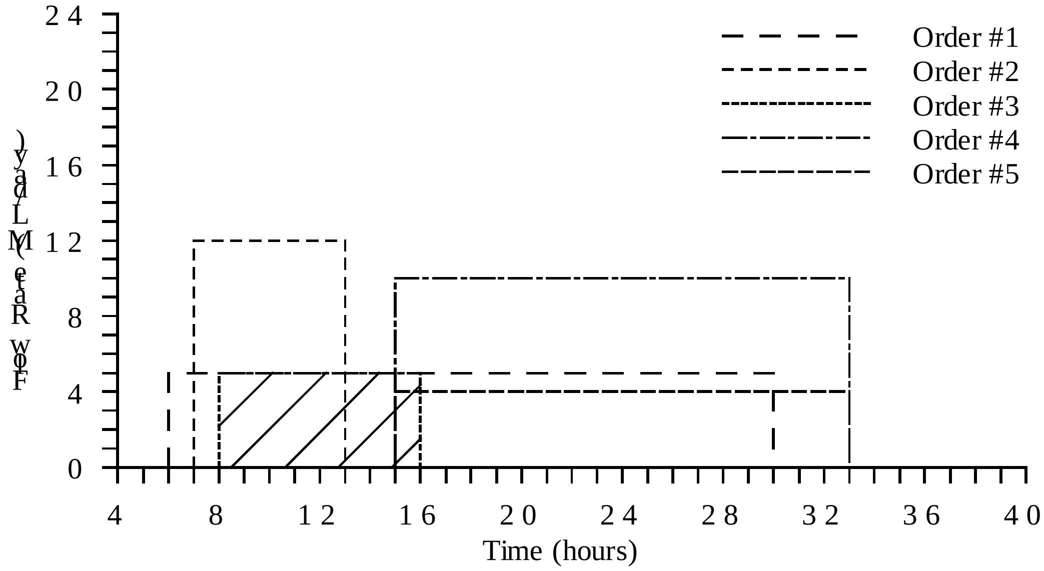
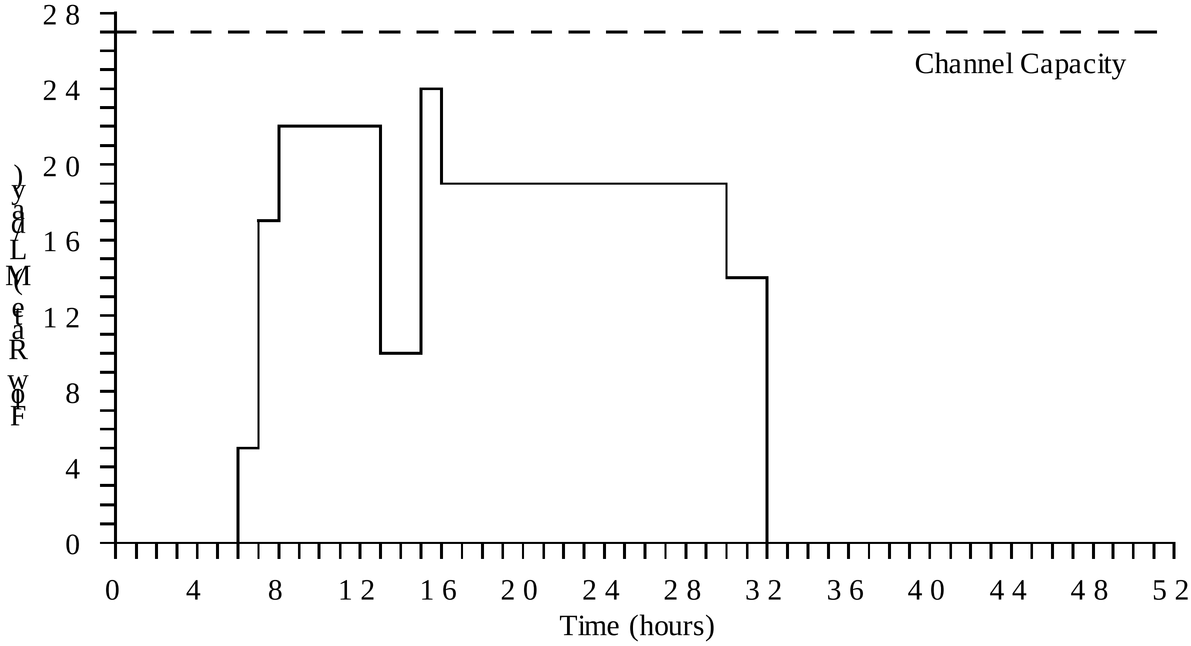


Figure 9: Irrigator Order Requests for the Case Study, with Travel Times

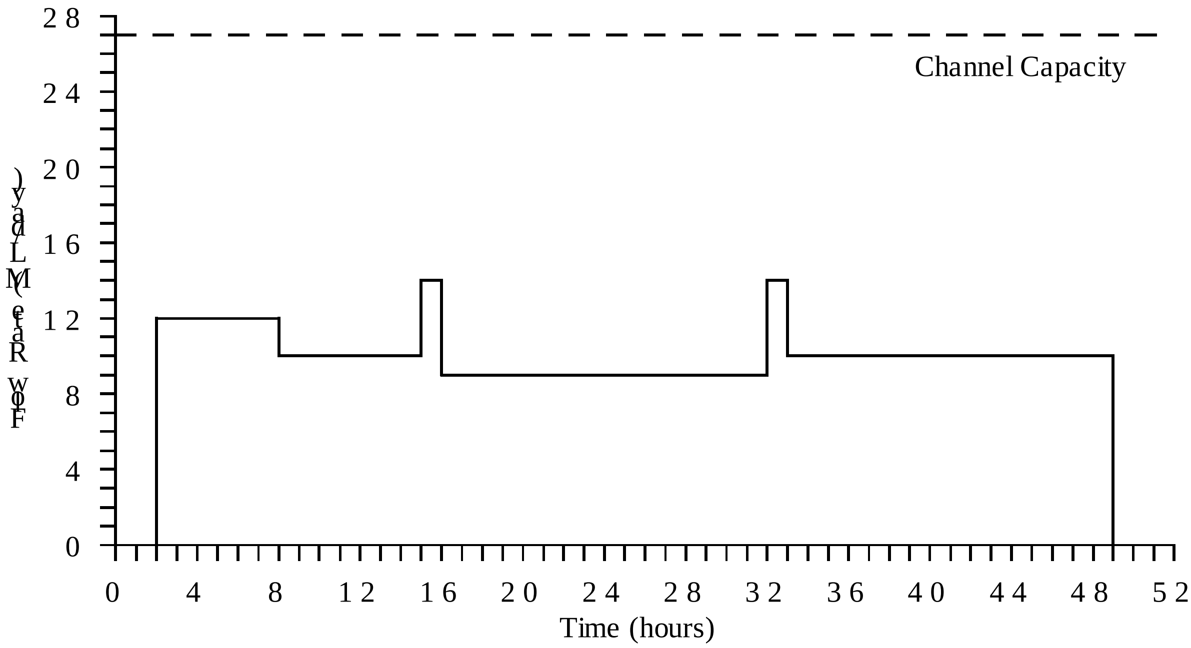
Fig. 10(a) illustrates the flow rate time-series, calculated at the supply control structure at the "upstream" end of the channel spur, for the orders as requested, taking travel times into account. This time-series is calculated by summing the orders illustrated in Fig. 9. The horizontal line in Fig.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

Exhaustive Search Enumeration

Fig. 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 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 hours and 5 minutes of central processor unit (CPU) time on a Hewlett–Packard B160L Unix workstation. All programming was in Fortran 90 (Metcalf and Reid, 1996).



(a) string = $[0, 0, 0, 0, 0]$, $\Phi = -6.95$



(b) string = $[2, -5, 0, 17, 0]$, $\Phi = +52.7$

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

Genetic Algorithm Optimization of Irrigation Schedules

The optimal solution illustrated in Fig. 10(b) also was also identified by GA scheduling. Parameters used in the GA were: $P_0 = 1{,}000$, $p_c = 0.8$, $p_m = 0.0$, 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 seconds 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 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).

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 he nonuniform weightings to the six constituents of fitness listed in Table 2 and a uniform 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 change, but the strings representing the schedules found do not. The top three strings correspond to the top three schedules determined by enumeration, using both nonuniform and uniform 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.

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Acronyms and Abbreviations

CPU central processor unit
GA genetic algorithm

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