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An adaptive ant colony optimization framework for scheduling environmental flow management alternatives under varied environmental water availability conditions

J. M. Szemis[1], H. R. Maier[1], and G. C. Dandy[1]

[1]School of Civil, Environmental and Mining Engineering, University of Adelaide, Adelaide, South Australia, Australia

Abstract Human water use is increasing and, as such, water for the environment is limited and needs to be managed efficiently. One method for achieving this is the scheduling of environmental flow management alternatives (EFMAs) (e.g., releases, wetland regulators), with these schedules generally developed over a number of years. However, the availability of environmental water changes annually as a result of natural variability (e.g., drought, wet years). To incorporate this variation and schedule EFMAs in a operational setting, a previously formulated multiobjective optimization approach for EFMA schedule development used for long-term planning has been modified and incorporated into an adaptive framework. As part of this approach, optimal schedules are updated at regular intervals during the planning horizon based on environmental water allocation forecasts, which are obtained using artificial neural networks. In addition, the changes between current and updated schedules can be minimized to reduce any disruptions to long-term planning. The utility of the approach is assessed by applying it to an 89km section of the River Murray in South Australia. Results indicate that the approach is beneficial under a range of hydrological conditions and an improved ecological response is obtained in a operational setting compared with previous long-term approaches. Also, it successfully produces trade-offs between the number of disruptions to schedules and the ecological response, with results suggesting that ecological response increases with minimal alterations required to existing schedules. Overall, the results indicate that the information obtained using the proposed approach potentially aides managers in the efficient management of environmental water.

1. Introduction

Environmental flow management aims to ensure that ecological flow requirements of flora and fauna, which can be represented by the timing, duration, rate of change, and magnitude of flow [*Poff et al.*, 1997], are satisfied in regulated river systems [*Junk et al.*, 1989; *Poff et al.*, 1997]. However, due to the competing water demands for the environment and for human purposes (e.g., water supply, industrial, agricultural, and recreational), the water available for environmental purposes is generally insufficient to meet all ecological flow requirements [*Arthington et al.*, 2006; *Poff and Zimmerman*, 2010]. This conflict over water use is exacerbated by the rapid growth of the global population and by climate change [*Arthington et al.*, 2006; *Castelletti et al.*, 2010]. Given that there is limited water available for environmental purposes, there is a need to make best use of this water so as to achieve the best possible ecological outcomes.

This is not an easy task because the available environmental water: (i) has to be allocated not only within the river channel but also to the surrounding wetlands and floodplains, which accommodate a range of different species of flora and fauna; (ii) has to be scheduled at various times and released in various volumes and for various durations in order to maintain and restore the ecological integrity of different species, which generally have varying flow requirements [*Rogers*, 2011]; (iii) can be managed using a range of alternatives at different spatial scales, such as at the individual wetland scale (e.g., wetland regulators/pumps) or at a the landscape scale (e.g., flow releases and weir pool manipulation); and (iv) has to be managed over multiple years, since there are species that require dry periods over multiple years, such as the Black Box woodland (*Eucalyptus largiflorens*), or require the maintenance of a flood frequency of 1 in 2–5 years [*Rogers*, 2011], resulting in temporal dependencies between scheduling decisions.

In order to address this problem, optimization approaches have been used extensively to obtain optimal monthly reservoir flow releases or operating rule parameters for reservoirs/weirs [e.g., *Chang et al.*, 2010;

Chaves et al., 2003; *Higgins et al.*, 2011; *Homa et al.*, 2005; *Shiau and Wu*, 2004, 2007, 2013; *Suen and Eheart*, 2006; *Tilmant et al.*, 2010; *Yang*, 2011; *Yin et al.*, 2011; *Yin et al.*, 2010], or monthly schedules of optimal environmental flow management alternatives (EFMAs), such as wetland gate operations and reservoir releases [*Szemis et al.*, 2012; *Szemis et al.*, 2013]. However, all of the above approaches rely either on the *historical* natural flow hydrograph or an *assumed known volume* of available environmental water. While optimized schedules developed over extended time periods based on assumed water availabilities are useful for longer-term *planning* purposes (as in *Szemis et al.* [2013]), they are not suitable for use in an *operational* setting (e.g., determining optimal EFMA schedules under actual and predicted flow conditions), in which flows available for environmental purposes are likely to change from year to year as a result of natural hydrologic variability (e.g., droughts, floods). Consequently, there is a need to develop an optimal EFMA scheduling approach that takes changes in actual environmental water availability into account, and can therefore be used for *operational* purposes.

As has been demonstrated successfully in other areas of water resources management, such as irrigation scheduling, this can be achieved by updating schedules as new information becomes available [*Rao et al.*, 1992]. Alternatively, the development of optimal schedules can be based on forecasts of future conditions, rather than on historical or assumed future conditions, which can then be updated in an adaptive manner at regular time intervals [e.g., *Gowing and Ejieji*, 2001]. However, such approaches have not yet been applied to the optimal scheduling of EFMAs. Consequently, there is a need to develop an *adaptive* optimization approach that can be used for operational purposes, in which optimal EFMA schedules are (i) developed based on *forecasts* of available environmental water and (ii) *updated* at regular intervals throughout the planning horizon in order to take account of updated knowledge of hydrological conditions. However, in order to comply with practical requirements, any changes to existing EFMA schedules should be kept as small as possible during the adaptation process so as to minimize the negative impacts on related operational strategies and resource scheduling (e.g., human resources and equipment). Consequently, there is a need to develop a novel optimization formulation that enables an appropriate trade-off between ecological outcomes and practical considerations to be considered.

In order to address the research needs outlined above, the objectives of this paper are to (i) develop a novel *adaptive* approach to the optimal scheduling of EFMAs for rivers and their associated wetlands and floodplains that (a) is based on *forecasts* of available environmental water over the time period over which optimal EFMA schedules are developed, (b) enables *updated* hydrological information to be incorporated at regular intervals, and (c) is able to consider optimal trade-offs between the *minimization of changes to existing optimal schedules* and the maximization of ecological response; and (ii) to test the utility of the overall approach and its features for a real case study of a section of the River Murray in South Australia under various hydrological conditions over a 20 year period (1983–2003).

The remainder of this paper is organized as follows. The proposed adaptive optimization approach is introduced in section 2, with details of how the approach was applied to the case study given in section 3. The analyses performed to achieve the objectives are given in section 4, after which the results and discussion are presented in section 5. Concluding remarks are then presented in section 6.

2. Adaptive Optimization Approach for the Optimal Scheduling of Environmental Flow Management Alternatives

The main steps in the proposed framework are shown in Figure 1, which are based on the approaches introduced by *Szemis et al.* [2012, 2013]. The primary differences between this approach and those presented in *Szemis et al.* [2012, 2013] are:

1. Rather than assuming that the water that is available for environmental flow allocation purposes is *known* and *fixed* over the required planning horizon, optimal EFMA schedules over the planning horizon are (i) obtained initially based on *forecasts* of environmental water allocation over the planning horizon (i.e., at time step $ut = 1$) and (ii) *updated* at regular intervals (at time steps $ut = 2, 3, \ldots ft$), taking into account updated forecasts of environmental water allocation, as highlighted by the grey boxes in Figure 1. The forecast environmental water allocation is defined as $A_{max\_ni(pd)}$, where pd is the number of periods of estimated environmental water allocations, ranging from 1 to np. This general approach is similar to that adopted in other real-time water resources problems, such as in irrigation scheduling [*Gowing and Ejieji*,
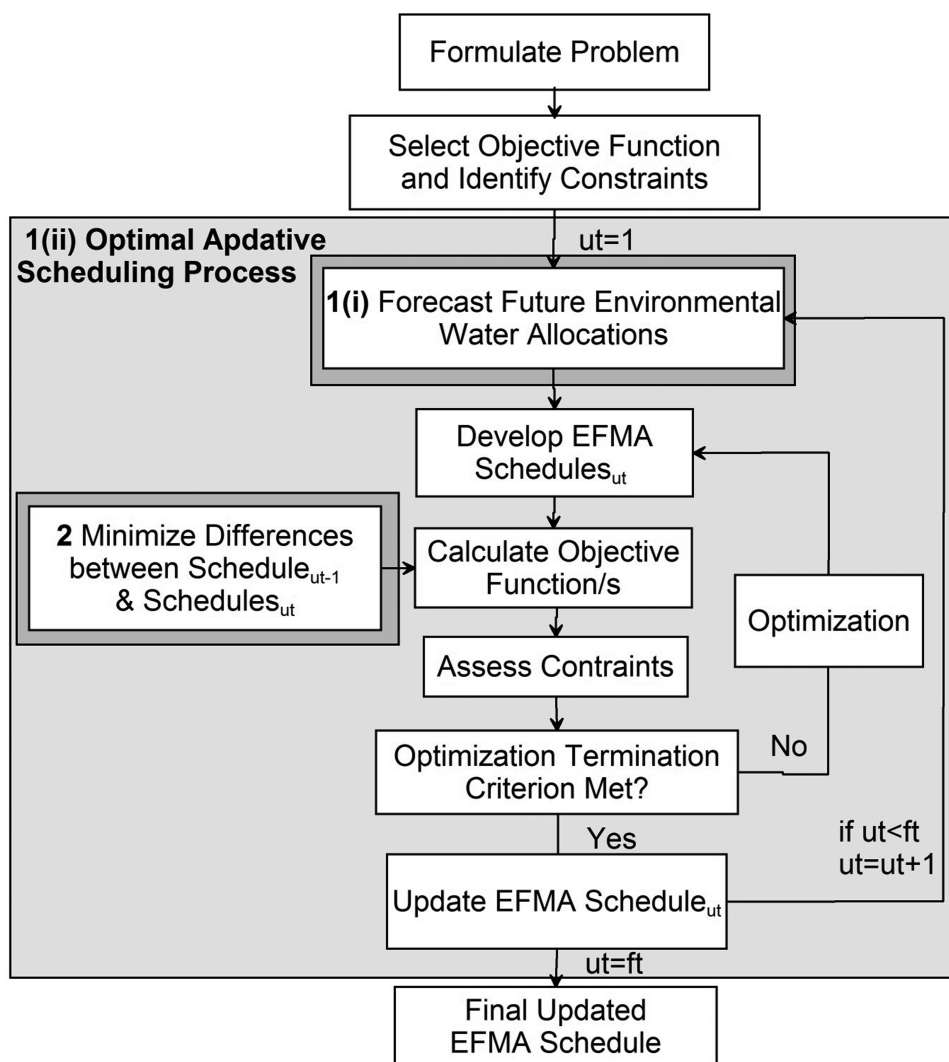
Figure 1. Steps in Proposed Adaptive Optimization Framework.

2001], multipurpose reservoir operation [*Galelli et al.*, 2012], flood control [*Niewiadomska-Szynkiewicz et al.*, 1996] and the management of large water resource systems [*Giuliani and Castelletti*, 2013]. It should be noted that the approach has elements in common with model-predictive control methods used in other areas of water resources management [e.g., *Bakker et al.*, 2013; *Park et al.*, 2009; *Prasad et al.*, 2013; *Xu et al.*, 2013], where a desired system state is assumed and the difference between actual and desired system response is minimized. However, as part of the proposed approach the aim is not to control the system to achieve a desired state, but rather to optimize system response.

2. In order to ensure that any changes to the EFMA schedules due to the updating process (i.e., from *ut-1* to *ut*) are minimized, while still maximizing ecological response, a novel *multiobjective* optimization *formulation* is introduced. It should be noted that the specific changes that are minimized are case study dependent (e.g., which of the resources affected by potential changes to an EFMA schedule are constrained, what the dependencies between different operational strategies are) and need to be selected by the relevant authorities (e.g., water manager or river operator).

As can be seen in Figure 1, the proposed approach begins with the formulation of the problem, which includes identifying: (i) the wetlands, floodplains and river reaches that are to be managed; (ii) appropriate ecological indicators (e.g., vegetation or fish species); (iii) the planning horizon over which the schedule for the EFMAs is to be developed (e.g., 5 years), as well as the planning period (e.g., 20 years); (iv) the time

interval, t, at which schedules are to be developed (e.g., monthly), which ranges from 1 to T intervals; and (v) the EFMAs, M_a that are available for achieving the desired ecological response (e.g., flow release options, regulator settings, pumping schedule), where a ranges from 1 to h. EFMAs, as well as the suboptions associated with each of these alternatives (e.g., magnitude, duration), are discussed in *Szemis et al.* [2012, 2013]. In order to cater to the adaptive elements of the approach, additional variables that control the number of updates within the planning horizon, ut ranging between 1 and ft, where ft is the maximum number of updates and the update interval, xu, (i.e., annual, quarterly), are also defined.

Once the problem has been formulated, the objectives (i.e., maximize ecological response and minimize differences between schedules) and constraints (e.g., environmental allocation constraints) need to be defined. Next, the optimal scheduling process can commence. The first step of this process involves the forecasting of the water allocation that will be available for environmental purposes over the planning horizon with the aid of a forecasting model. The selection and development of an appropriate forecasting model is dependent on the problem at hand, as well as the previous and current hydrological data that are available within the case study area.

Next, a number of potential EFMA schedules are developed and their utility is assessed via the objective functions and constraints. This is undertaken by linking a multiobjective ant colony optimization algorithm (ACOA) with appropriate hydrological and ecological models. For a discussion on the justification of the use of ACOAs in preference to other optimization approaches, such as dynamic programming (which would require the reformulation of the EFMA scheduling problem) or genetic algorithms, the reader is referred to *Szemis et al.* [2012]. The optimization process continues until certain stopping criteria, such as achieving the maximum number of iterations have been met. The outcome of this process is an optimal EFMA schedule over the selected planning horizon at time step $ut = 1$, based on the forecasts of future environmental water allocations at this time step.

At time step $ut = 2$, the forecasts of the water allocation that will be available for environmental purposes over the planning horizon are updated based on the latest available information and the process of obtaining optimal EFMA schedules is repeated. In order to minimize the differences between the existing optimal schedule and the new optimal schedule based on updated water availability estimates (Figure 1), the following objective, F_D, should be used in addition to the objective of maximizing ecological response:

$$F_D = \sum_{mc=nc(1)}^{nc(f_{nc})} \sum_{v=1}^{K} w_{D,v} \sum_{t=ti(v)}^{tf(v)} D_{mc,t} \tag{1}$$

with

$$D_{mc,t} = 1 \text{ when } M_{mc,ut,t} \neq M_{mc,ut-1,t}$$

$$D_{mc,t} = 0 \text{ when } M_{mc,ut,t} = M_{mc,ut-1,t}$$

where the number of differences between the initial schedule at ut-1 and the new schedule at ut is defined as $D_{mc,t}$ for the mcth management alternative scheduled over K years and $ti(v)$ to $tf(v)$ time intervals. The number of management alternatives (M_a) that will be compared, mc ranges from $nc(1)$ to $nc(f_{nc})$, while $w_{D,v}$ specifies the weight value that indicates the relative importance of minimizing the difference between subsequent schedules for year v. The inclusion of $w_{D,v}$ enables the minimization of the differences between schedules at different stages of the planning horizon to be prioritized. For example, it might be desirable to minimize differences at the earlier stages of the planning horizon, in which case larger values of the weights corresponding to these time periods would be used. In contrast, if no such preferences exist, the same value would be used for all weights. A value of 1 for $D_{mc,t}$ is given when the option selected for the mcth management alternative at time step ut and at time interval t is not the same as the corresponding option for the EFMA schedule at $ut-1$. In contrast, a value of 0 is assigned to $D_{mc,t}$ when the selected options are the same. For example, if a regulator is open as part of the optimal schedule developed at ut-1, at the tth time step, and the regulator is closed at the tth time step as part of the optimal schedule at ut, then the corresponding value of $D_{mc,t}$ is 1. As can be seen from equation (1), the values of D_{mc} are summed over the time intervals at which schedules are to be developed, as well as the f_{nc} user-defined management alternatives for which the minimization of differences between management options is considered important.

The process of updating the forecasts of the available environmental water allocations and reoptimizing the EFMA schedules in light of this information, while ensuring that any changes to updated schedules are limited, is repeated for $ut=3, 4, \ldots, ft$.

3. Methodology

In this section, the utility of the approach introduced in section 2 is assessed by applying it to a section of the River Murray in South Australia under various hydrological conditions. Details of the case study, which were adapted from *Szemis et al.* [2013], are given in section 3.1, followed by details of how the proposed adaptive optimal EFMA scheduling approach (Figure 1) is applied to the case study in sections 3.2–3.8.

3.1. Case Study

The case study area under investigation is a reach of the South Australian River Murray between Locks 1 and 2 (Figure 2). In this figure, the River flows from Lock 2 to Lock 1. The South Australian River Murray is part of a larger river system (the Murray-Darling Basin (MDB)) that is located in south eastern Australia and includes portions of four states, namely Victoria, Queensland, New South Wales and South Australia (see Figure 2) [*Reid and Brooks*, 2000]. Over the years, it has become highly regulated due to the construction of six locks along the river channel, as well as a number of upstream structures, such as Hume Dam, located on the border between Victoria and New South Wales [*George et al.*, 2005]. As result of this regulation and the overallocation of water, the flow variability within the river section in Figure 2 has reduced and caused much of the biota in the river and adjacent wetlands and floodplains to be stressed or altered [*Overton et al.*, 2010]. In response, a basin-wide plan developed by the Murray Darling Basin Authority and approved by the Government of Australia now recognizes the environment as a key stakeholder within the MDB. However, how any environmental water allocations should be prioritized to maximize ecological response is unclear, particularly given that the environmental allocation is not constant from 1 year to the next, but is reduced during times of drought and increased during times of flooding [*GSA*, 2013].

The river reach under investigation spans 89.0 kilometers and currently accommodates two regulated wetlands and a large number of high lying floodplains along the river channel. As a result of the construction of the locks, the wetlands closer to Lock 1 have become permanently inundated (i.e., continual connection to the river) and experience no drying, whereas, wetlands closer to Lock 2 are temporary and rarely inundated due to upstream system constraints [*Overton et al.*, 2010]. Each wetland and surrounding floodplain houses a variety of flora and fauna, ranging from high-lying black box woodland (*Eucalyptus largiflorens*) to water birds and fish (e.g., ibis and carp gudgeon) [*Turner*, 2007].

In order to preserve and maintain the ecological integrity of the wetlands within this river section, it has been suggested to not only release environmental water upstream at the South Australian border, but to also operate gates at the wetland inlets, with two wetlands within the case study area currently falling into this category [*Schultz*, 2007; *Turner*, 2007].

3.2. Problem Formulation
3.2.1. Specification of Ecological Assets and Indicators

The first step of the problem formulation stage involves identifying the ecological assets (i.e., wetlands, floodplains, river) to be managed, H_i, where i ranges from 1 to q. In this case study, the management of two wetlands, Morgan Lagoon and Brenda Park, is considered (i.e., $q=2$) (Table 1). This includes the wetlands themselves, the high-lying floodplain areas surrounding the wetlands, and the adjacent main river channel. These wetlands have been selected because they are the only wetlands within the case study area that currently have operational regulators. The vegetation areas within the wetland and floodplain, as well as the location of the fish and water bird species within the wetlands themselves, are identified with the aid of existing wetland management plans [*Schultz*, 2007; *Turner*, 2007].

Next, the ecological response indicator, $E_{i,n}$ is identified, which is the Murray Flow Assessment Tool (MFAT) developed by *Young et al.* [2003]. This was also used by *Szemis et al.* [2012, 2013]. This indicator quantifies the ecological response of each species (including vegetation, waterbird and fish) within the river, and adjacent wetlands and floodplains (Table 1). MFAT was developed specifically for the River Murray and can be used to investigate the impact of different flow scenarios on the ecological response of flora and fauna in terms of two ecological processes, that is, recruitment (e.g., promoting seed germination) and maintenance (e.g., preserving
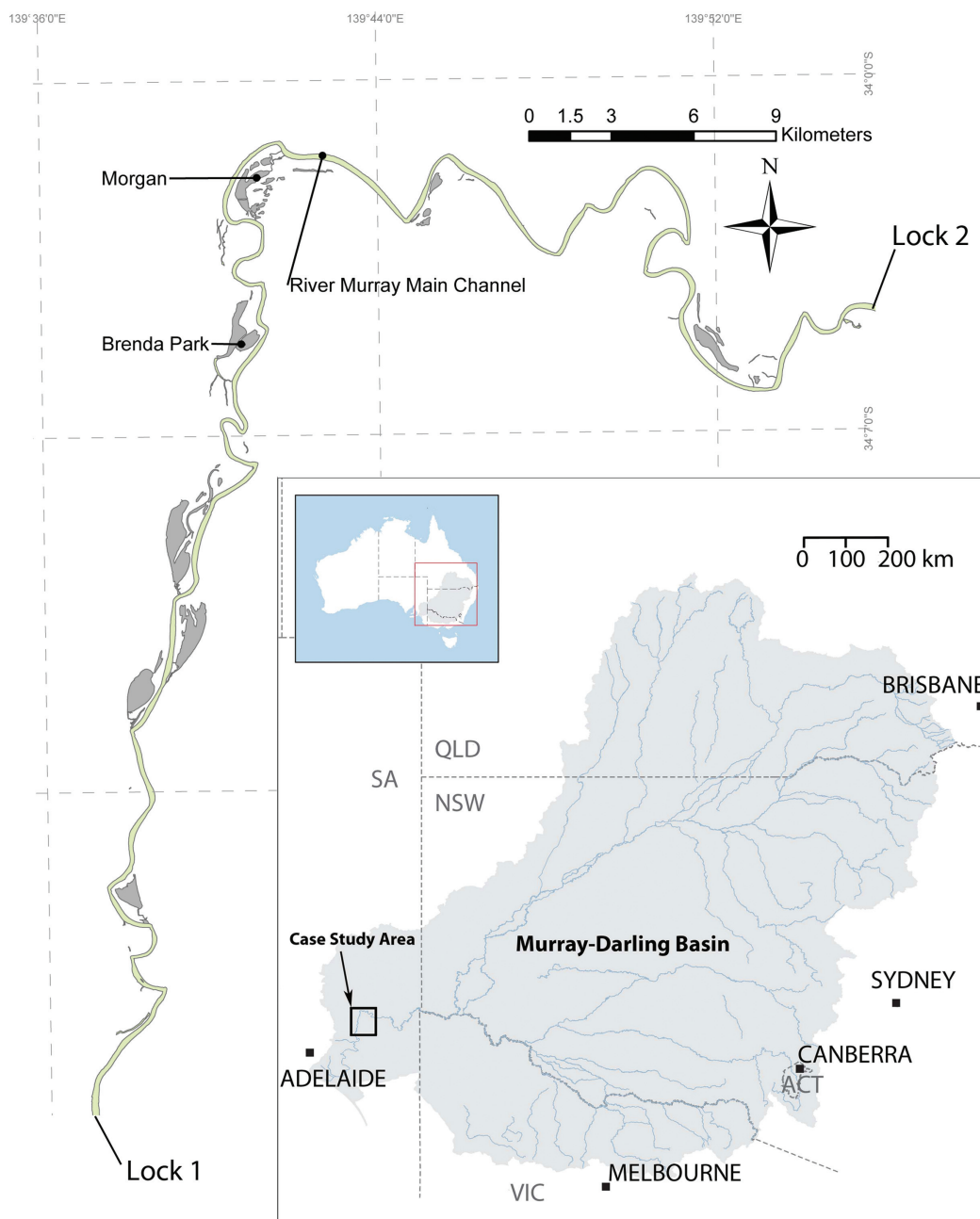
Figure 2. Map of case study area (adapted from Murray-Darling Basin Authority website, http://www.mdba.gov.au/river-data/spatial-data-services/spatial-information).

adult habitat) [*Young et al.*, 2003]. In order to determine the ecological response using MFAT, response curves are used, which are based on five flow components, that is frequency, duration, timing, rate of change and magnitude. The response curves used for the case study area are those given in *CRCFW* [2003] and *Overton et al.* [2010], and include species such as river red gum (*Eucalyptus camaldulensis*), wetland specialists (e.g., carp gudgeons) and waterbirds (e.g., grebes). In addition, weights for the recruitment and maintenance processes need to be selected and are chosen based on literature or expert knowledge. A total of 10 species are defined for the case study area and the proportions of each species type per wetland are given in Table 2.

3.2.2. Identification of Planning Horizon, Time and Update Intervals

The planning horizon, Yv (v = 1, K years), time interval, t, where t ranges from 1 to the final interval, T and the variables introduced as part of the proposed adaptive optimization approach, that is, the update

Table 1. Details of Problem Formulation for Case Study

Problem Formulation Steps		Specification
1	Managed ecological assets	$q = 2$
	H_i, $i = 1$ to q	(Morgan Lagoon and Brenda Park)
2	Ecological indicator	Murray Flow Assessment Tool (MFAT)
	$E_{i,r}$, $r = 1$ to $s(i)$	[*Young et al.*, 2003]
		Total number of species types = 10
3	Planning horizon and period	
	Y_v, $v = 1$ to K	$K = 5$ years
	$Y_p = 1$ to P	$_P = 20$ years
	Time interval	
	t, $t = 1$ to T	Monthly, $T = 60$ months
	Update interval, xu	
	Number of updates	$xu = 1$ (i.e., year), $ft = 20$
	ut, $ut = 1$ to ft	
4	Management alternatives	$h = 3$
	M_a, $a = 1$ to h	(1 reach and 2 asset scale)
5	Management alternative suboptions	Reach——magnitude and duration
	(i.e., magnitude, $M_{a,m}$, and/or duration, $M_{a,d}$)	Asset——duration
6	Number of management alternatives compared	$fn = 3$
	mc, $mc = 1$ to fn.	

interval, xu, and the number of updates, ut, (which ranges from 1 to ft) need to be selected (see Table 1). In this case, a planning horizon of 5 years is chosen, as wetland management plans in the study area are generally developed over 5 years [*EA*, 2007; *Schultz*, 2007], while a monthly time step is selected, since wetland gate operations are set on a month by month basis [*Schultz*, 2007; *Turner*, 2007], with the total number of time intervals, T, being 60. Finally, the update interval, xu, is set to 1 year given that environmental allocation within the case study area is specified on an annual basis [*DEWNR*, 2013], while the EFMA schedule will be updated along a 20 year planning period (Y_p) from 1983 to 2003, thus ft, equals 20.

3.2.3. Selection of Management Alternatives and Suboptions
This step of the problem formulation stage involves the determination of the management alternatives, M_a, where a is between 1 and h, and the corresponding suboptions. The environmental flow releases at the South Australia border are selected as the only reach scale management alternative, while the operations of gates at the two wetlands (i.e., Morgan and Brenda Park, see Figure 2) constitute the chosen asset scale management alternatives. As a result, there are three management alternatives (i.e., $h = 3$) that can be considered in the development of the optimal EFMA schedules. The suboptions for the reach scale management alternative include magnitude, $M_{a,m}$, and duration $M_{a,d}$ suboptions, while only the duration suboption is required for asset scale management alternatives (i.e., regulators open or closed), as shown in Table 1. The selection of the maximum number of magnitude suboptions, n, is dependent on the case study area and system constraints, where the number of potential duration suboptions at each time step equals p, where p varies between 12 in July and 1 in June the following year.

Finally, the management alternatives for which changes between current (i.e., at $ut-1$) and updated (i.e., at ut) schedules are to be limited, M_{mc}, need to be selected, where mc ranges from 1 to fn management alternatives. For the case study, fn is set to three (Table 1), since the differences are compared for all selected management alternatives.

3.3. Specification of Objective Function and Constraints
Once the problem has been formulated, the objective functions and constraints are defined (see Figure 1). As per the methodology introduced in section 2, the two objectives include the maximization of ecological response and the minimization of changes to optimized EFMA schedules. Details of the formulation of these

Table 2. Species Composition in Case Study Area

		Species Composition (% Per Asset)			
Asset	Wetland Name	Floodplain Flora	Wetland Flora	Waterbird	Fish
1	Morgan Lagoon	50.0	11.0	25.0	14.0
2	Brenda Park	53.0	0.0	29.0	18.0

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objectives for the case study are given below. As described in *Szemis et al.* [2013], the ecological response can be composed of a number of different components, including different types of assets (e.g., wetland or floodplain) and different ecological processes (e.g., recruitment or maintenance). As a result, the number of assets, species and years considered need to be defined as sets, where the number of assets in set H ranges from 1 to q, while the number of species per ith asset is identified as the R_i set, with each ith asset accommodating $s(i)$ species. Finally, the total year set, V, ranging from 1 to a maximum year of Y_K is also defined, with the sets shown below.

$$i \in H = \{1, 2, \ldots, q\} \tag{2}$$

$$R_i = \{1, 2, \ldots, s(i)\} \tag{3}$$

$$V = \{1, 2, \ldots, Y_K\} \tag{4}$$

The ecological components (e.g., fauna species or recruitment process) that are to be investigated as part of the gth ecological response objective, where g ranges from 1 to fg, are then defined in the form of g subsets, which also range from 1 to fg. In this study, the aim is to maximize the overall ecological response within the case study area, which results in a single ecological objective ($F_{E,1}$), where $fg=1$. The corresponding equation is as follows:

$$F_{E,1} = \sum_{i \in H_1} w_{1i} \sum_{r \in R_{i,1}} w_{2r} \sum_{v \in V_1} \frac{w_{3v} E_{i,r,v}}{Y_{K,1}}, \quad g=1 \tag{5}$$

where $E_{i,v,r}$ is the ecological indicator value for asset i, for indicator type r, in the vth yearly time interval. The subset H_1 contains the number of assets that enable the assessment of the river, wetland and floodplain ecological response, which in this case is three (including two regulated wetlands and their surrounding floodplains, as well as the river channel). On the other hand, $R_{i,1}$ contains information about which species (e.g., waterbirds) are incorporated in the ecological response objective ($F_{E,1}$). The number of species per ith asset can be seen in Table 3. Finally, V_1 specifies the number of years for which the ecological response objective is calculated, which is five in this study (i.e., $K=5$). Weights, w_{1i}, w_{2r} and, w_{3v} place emphasis on the ith wetlands, floodplains or river reaches, rth ecological indicator and Y_Kth year, respectively. For this case study, the values of the weights are set equal to one to give equal preference to each asset, species and year.

The objective function used for the minimization of differences between EFMA schedules at subsequent time steps is given in equation (1). Preliminary testing, which involved visually comparing the trade-off curves developed for a range of weights, indicated that increasing the weighting for differences in the early years produced the best trade-offs (i.e., a set of schedules that was nondominated). Thus, the weight values used in this case study are, $w_{D,1}$ equals 5, $w_{D,2}$ equals 2, and $w_{D,3}$ to $w_{D,5}$ equal 1.

The constraints considered include the number of suboptions available for each management alternative (i.e., equations (6) and (7)), and the annual environmental water allocation available (i.e., equation (8)). The constraints on the number of magnitude and duration suboptions per management alternative, M_a, are as follows:

$$M_{a,m\_min} \leq M_{a,m} < M_{a,m\_max}, \quad m = 1 \text{ to } n \tag{6}$$

$$M_{a,d\_min} \leq M_{a,d} < M_{a,d\_max}, \quad d = 1 \text{ to } p \tag{7}$$

where the magnitude suboptions ($M_{a,m}$) are constrained by minimum and maximum values of M_{a,m_min} and M_{a,m_max}, respectively, and the duration suboptions ($M_{a,d}$) are constrained by minimum and maximum values of M_{a,d_min} and M_{a,d_max}, respectively, for each management alternative. The specification of M_{a,m_min}, M_{a,m_max}, M_{a,d_min} and M_{a,d_max} is user-defined, based on the requirements of the case study area under consideration (e.g., M_{a,m_max} could be selected based on a maximum achievable flow in the case study area). In this case, the minimum magnitude option for the environmental flow releases at the border, M_{1,m_min}, is set to 0 GL/month, while the maximum value, M_{1,m_max}, is dependent on the forecasted annual environmental water allocation each year. If the asset scale management alternative (i.e., $a=2,3$), M_{a,m_min} equals 1, the gate is closed, whereas if M_{a,m_max} equals 2, the gate is open. In addition, M_{a,d_min} is set to 1,

Table 3. Details of the Number of Species Per Asset in the Total Ecological Response Objective ($g=1$) for All Investigations

Asset Set $i \in H$	Number of Species $(s(i))$ in $R_{i,1}$ $(g=1)$
1	28
2	17

Table 4. Details of Candidate Inputs and Selected Inputs for All Five ANNs

Candidate Inputs	Selected Inputs				
	Environmental Allocation (t+1)	Environmental Allocation (t+2)	Environmental Allocation (t+3)	Environmental Allocation (t+4)	Environmental Allocation (t+5)
Inflows (t, t-1, t-2, t-3, t-4)	t, t-1	t, t-1, t-2	t	t-4	t-2, t-4
Storage (t, t-1, t-2, t-3, t-4)	t, t-3	t-2	t-1, t-2, t-3	t, t-2, t-4	t-1, t-3, t-4
Environmental allocations (t, t-1, t-2, t-3, t-4)	t	t	t-1, t-4	t, t-2, t-3	t-2, t-3

while the maximum number of duration suboptions, M_{a,d_max}, is set to 12 to correspond to the number of months in a given water year.

The second constraint considered is associated with the environmental water allocation, which can vary over a set planning horizon (e.g., annually) due to the forecasts of environmental water made each year, $A_{max\_ni(pd)}$) (see section 2). This information is then used to update the schedule at regular times in the planning horizon. The constraint is given as:

$$\sum_{t=i\_ni(pd)}^{f\_ni(pd)} A_t \leq A_{\max\_ni(pd)} \tag{8}$$

where, A_t is the environmental water allocation at the tth time step, pd is the number of periods of constrained environmental water allocations, ranging from 1 to np, while the number of increments in each period, $ni(p)$ ranges from 1 to Vp, and $i\_ni(pd)$ and $f\_ni(pd)$ are the corresponding initial and final time steps for pd, over which a particular water allocation is released. The duration of each increment is defined as $d_{ni(p)}$, and the summation of all duration increments for each period must equal the total duration interval, T_d. In this case, the environmental water allocation varies annually making the number of periods, pd, five, whereas the number of increments in each period equals 12, corresponding to the number of months in a year.

3.4. Forecasting of Future Environmental Water Allocation

In order to obtain forecasts of environmental water allocations over the planning horizon of 5 years, five artificial neural networks (ANNs) are developed to obtain forecasts at t+1, t+2, t+3, t+4 and t+5. ANNs are used as they have been used successfully for water resources modeling in a variety of applications [*Abrahart et al.*, 2012; *Maier et al.*, 2010; *Wu et al.*, 2014]. The ANNs are developed using the procedure outlined in *Wu et al.* [2014], including input selection, data splitting, architecture selection, structure selection, calibration and validation. In total, 106 years of reconstructed environmental water allocation and inflow storage data from 1897 to 2003 are available for model development [see *MDBA*, 2012a].

Input selection is performed using a combination of system understanding and the partial mutual information (PMI) algorithm, which accounts for both input significance and independence and has been applied successfully in other water resources studies [*Bowden et al.*, 2005; *May et al.*, 2008a; 2008b]. The candidate inputs considered before application of the PMI algorithm are shown in Table 4 and have been selected based on the assumption that the past 5 years of inflows, storages and environmental allocation in the Murray Darling Basin can influence future environmental allocations. The final inputs selected are summarized in Table 4, which indicate that future environmental flow allocations are a function of environmental flow allocations, system storage and system inflows in current and previous years.

The available data are split into training (50%), testing (30%) and validation (20%) subsets using a modified version of the DUPLEX algorithm [see *May et al.*, 2008a]. This data splitting algorithm is used as it is deterministic and suitable for data that are skewed and peaked and have low to medium variability [see *May et al.*, 2010; *Wu et al.*, 2013], which is the case here (Table 5). Both input selection and data splitting approaches are implemented using a Neural Network Excel Add-in (http://www.ecms.adelaide.edu.au/civeng/research/water/software/).

Multilayer perceptrons (MLPs) are used for the model architecture, as they are the most commonly used form of ANN in water resources and have been used successfully in many applications [*Maier et al.*, 2010; *Wu et al.*, 2014]. A single hidden layer is used, as MLPs with a single hidden layer have been proven to be

Table 5. Statistical Properties of the Data[a]

Variables	Mean	Standard Deviation	Skewness	Kurtosis
Inflows	18348.4	8183.7	1.54	3.69
Storage	11731.2	2803.5	−0.75	0.33
Environmental allocations	2229.0	288.6	−1.73	4.96

[a]Number of observations = 106.

universal function approximators [*Hornik et al.*, 1989]. The number of hidden nodes is determined by trial and error based on model performance on the testing set, which has also been used effectively in a large number of studies [*Wu et al.*, 2014]. The number of hidden nodes tried varied from 1 to 7 and the optimal number of hidden nodes for each ANN model is given in Table 6.

The back-propagation (BP) algorithm is employed for calibration, since it is the most frequently used method for calibrating MLPs [*Maier et al.*, 2010; *Wu et al.*, 2014]. The optimal values of the parameters controlling BP searching behavior (i.e., momentum and learning rate) are determined by trial and error based on model performance on the testing set, with the parameter ranges tested and the optimal values given in Table 6. It should be noted that each calibration run is repeated 10 times using a different random seeds.

To check the replicative validity of the ANN models, the residuals of the training data are examined, with the standardized residuals for the ANN 1 model shown in Figure 3. The fact that the residuals are approximately white noise and the auto-correlation coefficient is 0.3 suggests that the selected model is able to adequately capture the relationships contained in the data. In addition, almost all of the residuals are within the 95% confidence intervals. Similar results are obtained for the remaining ANN models. Predictive validity is checked with the aid of the validation set and a number of performance metrics, including Root Mean Square Error (RMSE), Mean Average Error (MAE) and Mean Absolute Percentage Error (MAPE) [*Bennett et al.*, 2013; *Dawson et al.*, 2007], with the resulting values shown in Table 7. As can be seen, all models performed well, with MAPEs of the validation data varying between 7.3 and 9.6%.

3.5. Development of Environmental Flow Management Schedules

Once the problem is formulated and the environmental water allocations are forecast for each period for the EFMA schedule at ut, trial EFMA schedules can be developed. As the decision variables chosen at one time period, such as the duration of an environmental flow release, potentially have an impact on options available at subsequent time steps, trial schedules are developed with the aid of a decision tree graph consisting of the management alternatives and suboptions, which can be adjusted dynamically based on selected options [*Foong et al.*, 2008a; 2008b; *Szemis et al.*, 2012; *Szemis et al.*, 2013].

An example decision tree graph that considers environmental flow release, as well as magnitude and duration suboptions, is given in Figure 4. The example considers four magnitude options (i.e., 0, 100, 200, and 300 gigalitres (GL)) and three duration suboptions, and is constructed over three time steps. If the maximum duration (i.e., 3 time intervals) is chosen at the first time step, the graph is adjusted dynamically so that no other decision paths are made available at subsequent time steps (decision points), as shown by the bottom path in Figure 4. On the other hand, if a duration option of one is chosen at the first time step (top path), then the number of available options decreases from three to two, as there are only two more time steps remaining. This results in a reduced search space, increasing the likelihood that optimal and near optimal schedules can be found [*Szemis et al.*, 2013]. A detailed discussion of this approach for the development of EFMA schedules is given in *Szemis et al.* [2012, 2013].

3.6. Calculation of Objective Function and Assessment of Constraints

Once an EFMA schedule has been developed, its utility needs to be assessed, which is done via the objective function and constraints. In order to enable calculation of the objective function and constraint values,

Table 6. Parameter Values Ranges Tested and Final Selected Parameters for Each ANN

Parameter	Parameter Value Ranges	Selected Parameter Values				
		ANN 1 (t+1)	ANN 2 (t+2)	ANN 3 (t+3)	ANN 4 (t+4)	ANN 5 (t+5)
Number of hidden layer nodes	1–7	3	5	4	6	5
Learning rate	0.05–0.75	0.05	0.05	0.05	0.05	0.05
Momentum	0.0−0.90	0.0	0.1	0.1	0.0	0.1
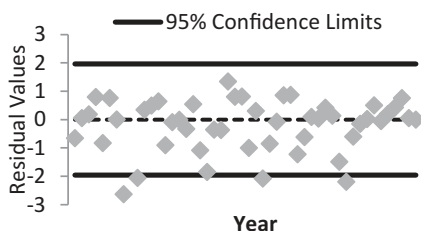
Figure 3. Graph of training data standardized residuals for the ANN 1 model.

a hydrological model of the river system is developed so that the ecological response of the river system to changes in the flow regime can be determined with the aid of MFAT.

The hydrological model is based on backwater curves that relate flows at the South Australian border to the corresponding river height (T. Bjornsson, South Australian Department of Water, personal communication, 2010) and is used to develop relationships between the flow at the South Australian border and river height at the Brenda Park and Morgan Lagoon wetlands. Fill values, that is, the river height at which a particular wetland or floodplain is inundated, as well as area versus average depth curves for each specified vegetation area, are determined using ArcGIS and a range of data sources that include a Digital Elevation Model (DEM) obtained from the Department of Environment, Water and Natural Resources baseline surveys [*SKM*, 2004*; Smith and Fleer*, 2006; *Waanders*, 2007] and wetland management plans [*Schultz*, 2007; *Turner*, 2007]. Once this is completed, the hydrological models for the wetlands and floodplains are developed using the water balance equations described in *Szemis et al.* [2013].

Average monthly evaporation data are obtained from the Australian Bureau of Meteorology website (http://www.bom.gov.au/climate/data/). A value of 0.7 is chosen as the pan coefficient, as this is a commonly used value in the Murray Darling Basin [*Gippel*, 2006]. To account for rainfall, average monthly rainfall data for the case study area are used, which are also obtained from the Australian Bureau of Meteorology website (http://www.bom.gov.au/climate/data/). It should be noted that both models are subject to a number of assumptions, including (i) water seepage is negligible since it is small compared with evaporation loss, and (ii) the rate of river level rise and fall occurs gradually over each month. The storage capacity of the wetlands is very small compared with the magnitude of streamflow, and thus has a negligible effect on downstream flow. Further details on the models are provided in *Szemis et al.* [2013].

3.7. Optimization and Updating of EFMA Schedule

The Pareto Ant Colony Optimisation Algorithm (PACOA) [*Doerner et al.*, 2004] is used, as it has been used successfully for this problem and achieved better result than alternative multiobjective ACO variants in *Szemis et al.* [2013]. To account for multiple objectives, this algorithm uses multiple pheromone matrices and updates the pheromone for each matrix based on the first and second best solution achieved for each objective. The steps in the optimization procedure are given in Figure 5. The first step is the initialization of the PACOA control parameters, after which the optimization process takes place. As part of this process, *b* ants generate *b* trial EFMA schedules by selecting a management alternative and associated suboptions (i.e., magnitude and/or duration) at each time step, as illustrated in the example in Figure 4. This is repeated for a large number of iterations (*its*).

Once a complete trial EFMA schedule has been developed by an ant, the utility of this schedule is assessed using a fitness function, which utilizes objective function and constraint values. Fitness functions are used to drive the optimization process because ACO algorithms do not explicitly consider the constraints apart from upper and lower bounds on the decision variables, making it necessary to include penalties within the fitness function. A number of different fitness function formulations are investigated for the case study, with the fitness function that performs best and is hence used in this study given below:

Table 7. Error Measures for All Forecasting ANN Models

| Model	Data Set	MAE	RMSE	MAPE
ANN 1 (t+1)	Training	122.7	171.8	5.8%
	Testing	139.7	198.7	6.7%
	Validation	151.6	204.7	7.3%
ANN 2 (t+2)	Training	123.7	163.3	5.7%
	Testing	176.7	228.5	8.5%
	Validation	202.4	250.3	9.6%
ANN 3 (t+3)	Training	157.8	195.9	6.9%
	Testing	183.0	221.4	8.8%
	Validation	165.8	201.4	8.0%
ANN 4 (t+4)	Training	125.8	166.2	6.0%
	Testing	177.0	226.2	7.9%
	Validation	186.1	241.0	8.5%
ANN 5 (t+5)	Training	138.0	179.8	6.4%
	Testing	222.9	291.8	10.6%
	Validation	187.3	242.2	8.9%
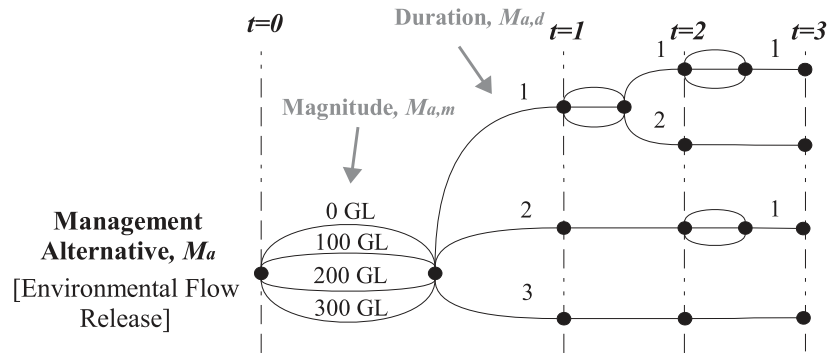
Figure 4. Example of an EFMA schedule graph for environmental flow releases (in gigalitres (GL)) incorporating dynamic constraints.

$$Y_{E,1} = \frac{1}{Y_{E,1}} + Penalty_{a1} \tag{9}$$

where $F_{E,1}$ is the ecological response score calculated using MFAT (Equation 5) (which is inversed to ensure that the score is maximized), and $Penalty_{a1}$ is a penalty function that ensures the water allocation constraints for each period are adhered to, as given by:

$$Penalty_{a1} = \begin{cases} 0 & \text{if } \sum_{t=i_{ni(pd)}}^{f_{ni(pd)}} A_t \leq A_{\max_{ni(pd)}} \\ \left\{ \sum_{t=i_{ni(pd)}}^{f_{ni(pd)}} (A_t) - A_{\max_{ni(pd)}} \right\} \times 1,00 & \text{if } \sum_{t=i_{ni(pd)}}^{f_{ni(pd)}} A_t > A_{\max_{ni(pd)}} \\ 1,000 & \text{if } \quad F_{E,1} = 0.0 \end{cases} \tag{10}$$

where the variables in equation (10) are defined in equation (5). In this case, there is only one period (i.e., $pd=1$), where $i_{in(pd)}=1$ and $f_{in(pd)}=60$. It should be noted that the second objective, the minimization of differences between subsequent schedules, does not need to be transformed into a fitness function and as a result, equation (1) is used within the optimization process. After each iteration, the b trial schedules generated by the b ants undergo a nondominated sorting process in order to determine the schedules that are on the Pareto front for that particular iteration and are subsequently stored in an offline storage matrix. As mentioned earlier, the first and second best solution for each j objective (i.e., in equations (1) and (9)) are used to update the j-pheromone matrices as part of the global update, using the following equation.

$$\tau_t^j = (1-\rho) \cdot \tau_t^j + \rho \cdot \Delta \tau_t^j \tag{11}$$

$$\Delta \tau_t^j = \begin{cases} 15 & \text{if suboption is in best and second best solution,} \\ 10 & \text{if suboption is in best and solution,} \\ 5 & \text{if suboption is in second best solution,} \\ 0 & \text{otherwise.} \end{cases}$$

where the pheromone value for each tth suboption and jth objective (τ_t^j) is reduced by pheromone evaporation, ρ, and increased by a pheromone value ($\Delta \tau^j$), which is based on whether a given suboption is within the best and/or second best solution. Pheromone evaporation is applied to suboptions of schedules that perform poorly, which deters the algorithm from selecting these suboptions again. In this manner, the environment is modified to guide the ants into regions of the search space that contain nondominated schedules. The process of developing, assessing and updating the pheromone trails to guide the PACOA to near-optimal trade-offs continues until the specified stopping criterion has been satisfied, which corresponds to convergence of the hypervolume indicator [*Fonseca et al.*, 2006] in this case. The reference point required for the hypervolume calculations is determined as part of preliminary testing of the PACOA to lie outside the range of the extreme points of the Pareto front.
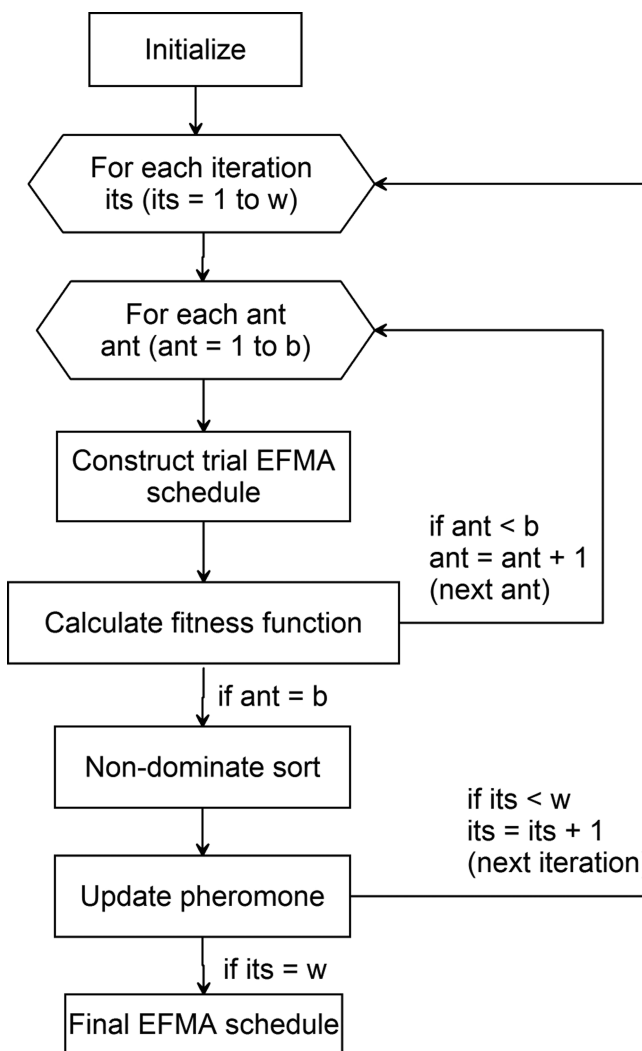
Figure 5. Pareto ant colony optimization algorithm procedure.

Before the PACOA is applied, an extensive sensitivity analysis is conducted such that optimal values of the parameters that control the searching behavior of the algorithm are identified and to maximize the chances that the best possible approximation to the optimal trade-offs are developed. The ranges of parameter values tested and the final parameters selected are given in Table 8.

An update interval, *xu*, of 1 year is the selected (see Table 1). Consequently, 20 updates of estimates of future environmental water allocations and optimal EFMA schedules are performed over the 5 year planning horizon over a 20 year period (1982–2002).

4. Analyses Conducted

In order to assess the utility of the proposed adaptive multiobjective optimization approach for the optimal scheduling of EFMA alternatives in an operational setting, its performance in terms of overall ecological response is compared with that of a number of alternative approaches over a 20 year period from 1982 to 2002, as detailed below. In all tests (Methods 1–4, Table 9), the number of magnitude options (n) is set to 37, while the maximum number of durations equals 12. The details of each asset subset (H_g), the number of species subsets in each asset ($R_{i,g}$), the number of years subset V (i.e., Y_K) and the allocation constraint period are given in Tables 1 and 3. It should be noted that minimum monthly flows within the river channel are set to South Australian entitlement flows [*MDBA*, 2012b], while weights for recruitment and maintenance within MFAT are set to 0.5 each, with the exception of the weight for the wetland flora species, which is set to 0.25 for recruitment and 0.75 for maintenance [*CRCFW*, 2003]. An equal preference is given to all species and assets, and each optimization run is repeated 10 times with different starting positions in the solution space.

Table 8. Range of PACOA Parameters Investigated and Values Selected

PACOA Parameter	Range of Values Tested	Selected Value
Number of ants (*ant*)	20, 200, 300,500	500
Initial pheromone (τ_o)	0.5, 1.0, 10.0	0.5
Evaporation rate (ρ)	0.5, 0.1, 0.15, 0.2, 0.5	0.1
Evaluations	90,000	90,000

4.1. Effectiveness of Using Optimal EFMA Scheduling

In order to test the effectiveness of using optimal EFMA scheduling as a means of maximizing ecological response for a given environmental water allocation, the performance of the proposed approach is compared with that of a benchmark

Table 9. Details of Methods Used

Method	Method for Obtaining Environmental Water Allocations	Annual Updating of Optimal Schedules	Minimization of Changes to Schedules
1	Fixed (570 GL/yr)	No	No
2	ANN models	Yes	Yes
3	ANN models	Yes	No
4	Actual	Yes	No

approach that does not include any management of environmental water allocations (i.e., using the actual flows with no wetland regulators). It should be noted that as part of the proposed approach (Method 2, Table 9), the ANN models are used to obtain forecasts of environmental water availability over the next 5 years, optimal EFMA schedules are obtained over a 5 year period and these schedules are updated annually by reoptimizing using the multiobjective ACO approach that trades-off maximizing ecological response with minimizing changes to existing schedules. It should also be noted that optimal updated schedules selected from the Pareto fronts correspond to an inflection point on the trade-off curve (i.e., an EFMA schedule that determines a good balance between minimization of differences between subsequent schedules and maximizing the MFAT score).

4.2. Effectiveness of Adaptive Optimization Approach

In order to test the effectiveness of the proposed adaptive optimization approach (Method 2, Table 9) in improving ecological response, its performance is compared with that of the approach used in *Szemis et al.* [2013] (Method 1, Table 9), in which a known, constant environmental flow allocation of 570 GL/yr is assumed each year and hence the updating of optimal schedules is not required.

4.3. Effectiveness of Minimization of Differences Between Successive Schedules

In order to test the effectiveness of the proposed multiobjective formulation in being able minimize changes to existing schedules while maximizing ecological response, the performance of the proposed approach (Method 2, Table 9) is compared with that of an approach that only maximizes ecological response, without consideration of minimizing changes to subsequent schedules (Method 3, Table 9). It should be noted that the solutions for Method 3 are extracted from the same Pareto front as the solutions for Method 2, but correspond to the solutions that result in the highest MFAT score.

4.4. Effectiveness of ANN Forecasting Model

In order to test the effectiveness of the ANN models in producing forecasts of environmental water availability that maximize ecological response, the performance of Method 3 (Table 9), which utilizes the ANN forecasts but only maximizes ecological response, is compared with that of an approach that is identical, apart from using perfect knowledge of future environmental water allocations, instead of those produced by the ANN models (Method 4, Table 9).

5. Results and Discussion

5.1. Effectiveness of Using Optimal EFMA Scheduling

As can be seen from Figure 6 by comparing the MFAT scores obtained using the benchmark (Actual) and the proposed (Method 2) approaches, there is significant benefit in optimal EFMA scheduling, as indicated by the substantial increases in ecological response. This indicates that it is worthwhile to operate regulators at the Morgan Lagoon and Brenda Park wetlands, particularly at times when there are lower flows, as is the case for the water years of 1994–1995, 1997–1998, and 2002–2003 (see Figure 7).

5.2. Effectiveness of Adaptive Optimization Approach

When the proposed approach (i.e., Method 2) is used, annual MFAT scores are generally higher than those obtained using known, constant environmental water allocations (Method 1), as shown in Figure 6. This is particularly evident at higher flows (see years 1990–1991, 1992–1993, 1995–1996, and 1996–1997 in Figure 7), where the ANN models are able to forecast above average environmental water allocations, enabling releases and regulator operations to be altered. In contrast, when an average environmental allocation is assumed and higher flows are actually released, the EFMA schedule developed is suboptimal, producing lower ecological response.

In order to better understand the reasons for the differences in MFAT scores, it is worthwhile to compare the MFAT scores for different wetlands, species and ecological processes (Figure 8), as these are aggregated
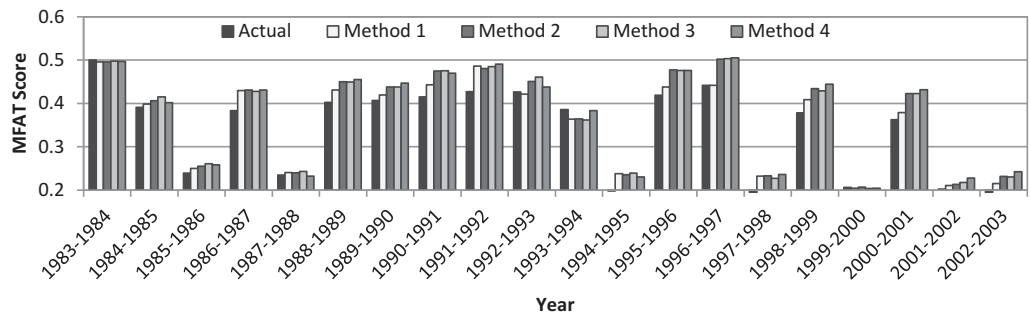
Figure 6. Average annual MFAT scores achieved for each method and actual data between the years 1983–2003.

to produce the annual scores presented in Figure 6. As can be seen in Figure 8a, there are generally only small differences in MFAT scores for Morgan Lagoon. However, the differences are more pronounced in water years 1990–1991 and 1996–1997, which is due primarily to the increased maintenance ecological response that could be achieved for river red gums by using the adaptive scheduling approach (Method 2––Figure 8c). This is because when Method 1 is used, it is assumed that an average environmental allocation is available, which is not enough to overtop the regulator and inundate the higher lying vegetation, such as river red gums. Because of this, in 1990–1991, the regulator is opened for 8 months (i.e., July to January) to promote a response for lower lying vegetation. However, when higher environmental allocations are released, as is the case in 1990–1991, the Morgan Lagoon regulator is opened when it would normally be closed in order to obtain an ideal dry period. In comparison, Method 2, taking into consideration predicted higher environmental allocation, was able to adjust the schedule to open the gate in December, thereby achieving the required dry period.

While the MFAT scores obtained using Methods 1 and 2 are different for Morgan Lagoon (Figure 8a), this is not the case for Brenda Park (Figure 8b), suggesting that there is much more benefit in using the proposed adaptive scheduling approach for the former wetland. The only differences in the MFAT scores for Brenda Park (i.e., 1995–1996 and 1996–1997) when using the deterministic and adaptive approaches are primarily due to the maintenance MFAT scores achieved for the floodplain flora, as shown in Figure 8d. The largest difference occurs in 1996–1997, where a score of 0.17 is obtained when Method 1 is used, whereas a score of 0.39 is obtained when Method 2 is used. This increase in MFAT score for Brenda Park when Method 2 is used is due to the ability of this method to update the optimal EFMA schedule at the beginning of 1996–1997 using improved environmental water allocation estimates. In order to achieve a maintenance response for floodplain flora, the flora must undergo a dry phase. However, prior to 1996–1997, for the EFMA schedule developed using Method 1, the gate is closed and the wetland is allowed to dry. However, closing the gate for greater than 15 months has a negative impact on the floodplain flora. In contrast, in Method 2, the gate is closed from July to August, thereby providing sufficient time for the ideal dry period for the floodplain flora and achieve an overall maintenance score of 0.39.
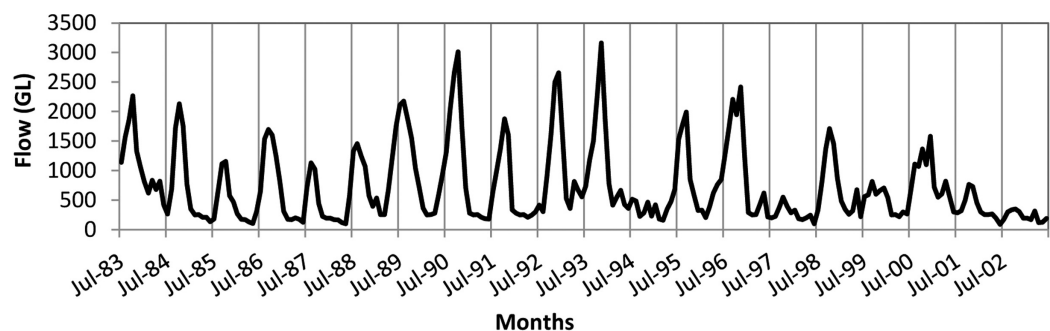

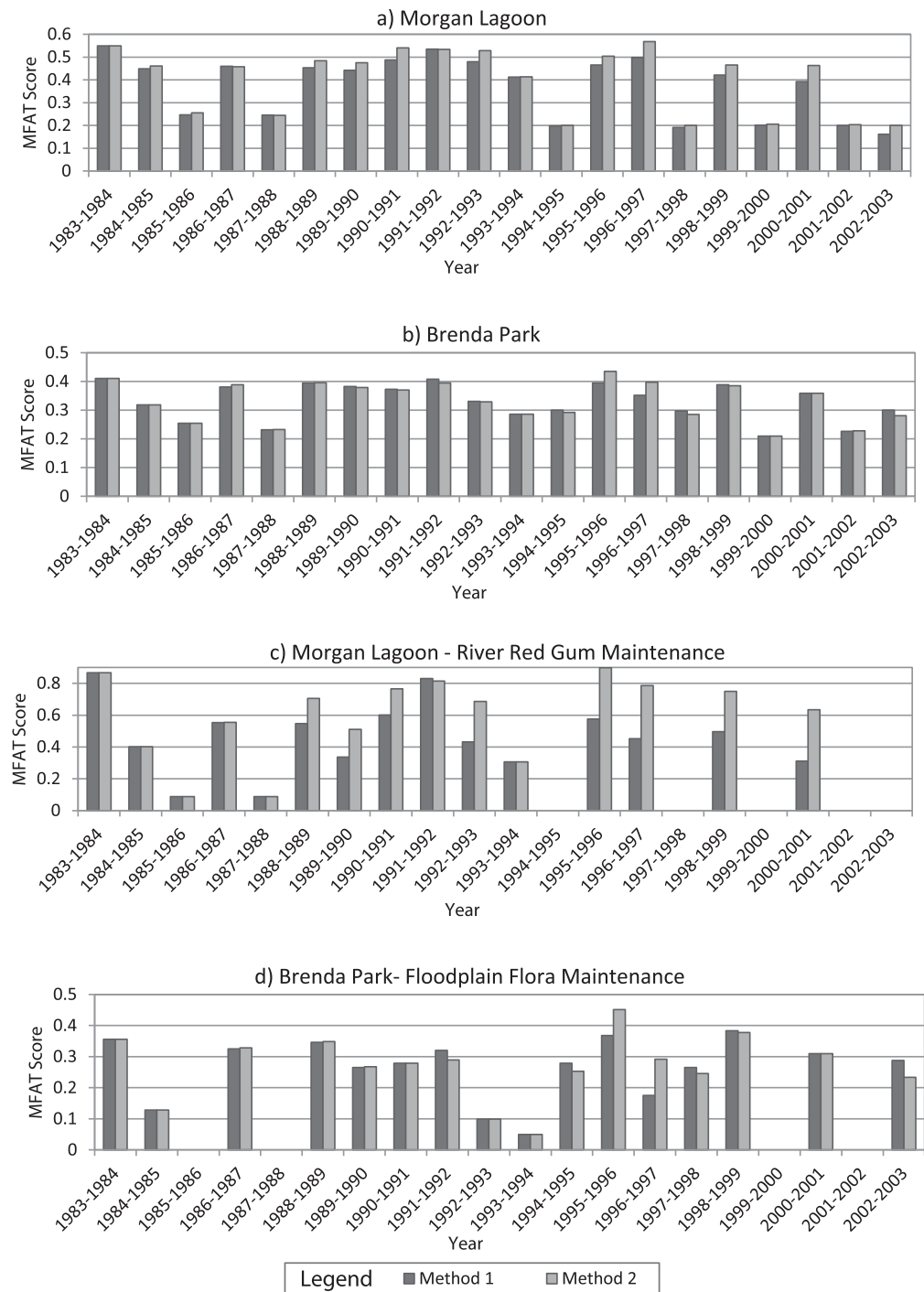**Figure 7.** Actual flows at the South Australian Border.

Figure 8. Average annual MFAT scores achieved for Methods 1 and 2 for the years 1983–2003.

The average MFAT score for the wetland and floodplain species within the case study area obtained using Methods 1 and 2 are shown in Figure 9. In the first 4 years, both methods achieve similar results, with wetland flora scores higher than those for floodplain flora. However, in the water year of 1987–1988, a higher wetland score is achieved for Method 1 than Method 2 because a higher environmental allocation is predicted using the latter method, and as such the EFMA schedule is adapted to suit higher lying vegetation. In reality, average flows were released and consequently, Method 1 achieves better results than Method 2.
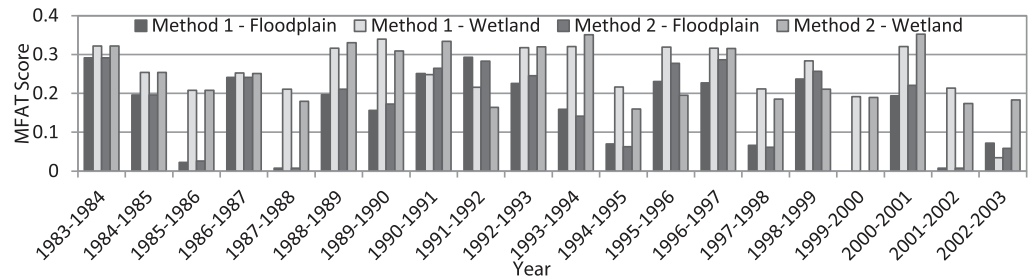
Figure 9. Average annual MFAT scores for floodplain and wetland flora achieved for Methods 1 and 2 between the years 1983–2003.

In 1991–1992, the floodplain flora scores for both Methods outperform the wetland flora scores, due to higher flow within the South Australian River Murray. This suggests that irrespective of the method used, when high flows are available, the floodplain flora will benefit more than the wetland flora, given that the latter will not experience ideal ecological conditions since it is flooded for a longer period. Finally, in 1995–1996 and 1998–1999, it can be seen that for Method 1, the wetland score achieved is higher than that achieved for Method 2. However, this is the reverse for the floodplain score. This is because in Method 1, lower allocations are assumed, and as such, the EFMA schedule developed favors wetland flora, whereas higher allocations forecast in Method 2 place more emphasis on the floodplain flora. As a result, when low flows are released, as is the case in 1995–1996 and 1998–1999, the predicted environmental allocations have an impact on which species should be favored. This suggests that at times of low flows, such as drought, managers should be aware of the impact the volume of environmental allocation has on these species, and as such should favor the species in need of improvement of ecological health.

5.3. Effectiveness of Minimization of Differences Between Successive Schedules

In general, the performances of Methods 2 (trade-off between maximizing ecological response and minimizing disruptions to optimal schedules) and 3 (best possible ecological response) are very similar (Figure 6). In order to obtain a better understanding of the trade-offs between maximizing ecological response and minimizing changes to optimized EFMA schedules, the trade-off curves for the water years 1983–1984, 1992–1993, and 2002–2003 are shown in Figure 10. As can be seen, in all 3 years, substantial reductions in the number of changes to the optimal schedules can be achieved with very small reductions in MFAT score. These results indicate that the proposed multiobjective formulation is successful in reducing disruptions to existing schedules with minimal impact on ecological response, which is important from a practical management perspective. However, the exact nature of the changes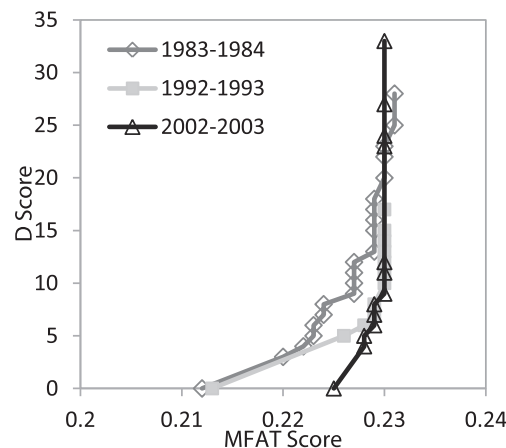 from one schedule to the next would have to be examined by the appropriate authorities in order to determine the significance of the changes.

5.4. Effectiveness of ANN Forecasting Model

As can be seen from Figure 6, the MFAT scores obtained using Methods 3 (using forecasts of future environmental water allocations using the ANN models) and 4 (using actual future environmental water allocations) are very similar. This suggests that the ANN models are performing well, as their use enables MFAT scores to be obtained that are close

Figure 10. Trade-off curves developed using Method 2 for the 1st year (1983–1984), 10th year (1992–1993), and 20th year (2002–2003).

to the maximum scores that could be obtained with the aid of perfect knowledge of environmental water allocations over the next 5 years.

6. Conclusions and Recommendations

Overall, the results suggest that the use of optimal EFMA scheduling can result in substantial increases in ecological response and that the proposed adaptive scheduling approach is able to improve ecological response further in an operational setting, compared with approaches used previously. This is achieved by forecasting environmental water allocations over the next 5 years with the aid of artificial neural network models and updating schedules on an annual basis. From a practical perspective, the proposed multiobjective optimization formulation is able to reduce the number of changes to existing optimized schedules during the updating process at a very small reduction in ecological response.

Even though the results demonstrate the utility of the proposed adaptive optimization approach, improvements could be made by considering uncertainties, such as those associated with the estimation of ecological response and the forecasting of future environmental flow availability. For example, the Murray Flow Assessment Tool (MFAT) uses response curves that are based on imperfect knowledge [*Baihua and Merritt*, 2012], thus introducing uncertainties in the objective function. In order to address this issue, comprehensive sensitivity analysis could be used to assess the impact of the uncertainties of MFAT, as suggested by *Norton and Andrews* [2006] and *Baihua and Merritt* [2012]. There is also uncertainty in the ANN forecasting models, which could be taken into account by considering more sophisticated ANN model development approaches [e.g., *Kingston et al.*, 2005; *Kingston et al.*, 2008; *Zhang et al.*, 2011] or by updating the ANN forecasting models as new data become available to extend their range of applicability [*Bowden et al.*, 2012]. In addition, it is difficult to physically interpret the inputs selected for the forecasting model, however, as more data become available, a critical examination of the selected inputs might provide fruitful in order to increase system understanding. Finally, an investigation on the update interval would also be beneficial, as the interval step may affect the optimal EFMA schedule development, as well as provide a means to account for system failures (e.g., broken wetland regulators).

Overall, the results demonstrate the utility and benefit of the proposed adaptive optimal EFMA scheduling approach in an operational setting. The approach has the potential to aid wetland managers in making informed decisions on how to best schedule EFMAs in an operational setting at times when environmental water allocations are likely to vary from year to year and when there is a limited amount of water available for the environment, which needs to be efficiently used to achieve the best possible ecological outcomes. In addition, the ability to assess the number of differences between schedules and understand the resulting impact on the ecological health of the system is likely to minimize any disruptions to the long term planning of EFMAs, as well reduce the resources required to make these changes.

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