REAL-TIME OPTIMIZATION FOR SMART AUTOMATION OF SURFACE IRRIGATION

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ABSTRACT

A system for the real-time optimization of furrow irrigation is described. The system estimates the soil infiltration characteristics in real-time and utilizes the data to control the same irrigation event to give optimum performance for the current soil conditions. The main features of the system are: the use of a model infiltration curve and a scaling process to describe the current soil infiltration characteristic; measurement of the inflow rate to the furrows; measurement of the water advance at a point approximately midway down the furrow; and a microcomputer running a hydraulic simulation program based on the full hydrodynamic model to predict the optimum time to cut-off.

The system was trialed on a furrow-irrigated commercial cotton property utilizing pipes through the bank (PTBs) to supply groups of furrows. The initial observations from these trials are presented in this paper and demonstrate that improvements in water use efficiency are potentially achievable through the use of the system.

Extensions to the system to improve its performance and to make it applicable to bay irrigation are described.

INTRODUCTION

Surface (bay and furrow) irrigation is one of the most commonly used methods for irrigating crops and pastures in Australia and around the world due to the low cost and low energy requirements. While well designed and managed surface irrigation systems may have application efficiencies of up to 95%, many commercial systems have been found to be operating with significantly lower and highly variable efficiencies. Previous research in Australia in the sugar and cotton industries (Raine and Bakker, 1996, Smith *et al.,* 2005) found application efficiencies for individual furrow irrigations ranging from 10 to 90%. Fewer data were available for bay irrigation of pasture and fodder crops but a similar performance is indicated (Smith *et al.*, 2009).

The efficiency of surface irrigation is influenced by the field design and the infiltration characteristics of the soil, but is primarily a function of the irrigation management.

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However, the complexity of the interactions makes it difficult for irrigators to identify optimal management practices. The infiltration characteristic of the soil is a dominant factor in determining the hydraulic behaviour of surface irrigation and both spatial and temporal variations in the infiltration characteristic are a major physical constraint to achieving high irrigation application efficiencies (Shafique and Skogerboe, 1983). The spatial and temporal variation commonly found in infiltration characteristics (Raine *et al*., 1997) within a field also limit the usefulness of generalised design and management guidelines for surface irrigation.

Real-time optimization of individual irrigations can help to overcome the effect of these spatial and temporal variations and provide a significant improvement in irrigation performance. Coupling this real-time optimisation with automation gives the ‘smart automation’ where the time to cut-off (and possibly flow rate) are varied automatically in response to the behavior of an irrigation to give the maximum performance for that irrigation. A number of simulation studies (e.g. Raine *et al.,* 1997, Smith *et al.,* 2005, Khatri and Smith, 2007, Gillies *et al*., 2010) have quantified the potential improvement in irrigation performance achievable through real-time optimization and control. When the management parameters were optimized to simulate perfect real-time control of individual irrigations, average application efficiencies in excess of 90% resulted along with storage efficiencies also greater than 90%.

Previous systems developed for real-time control (e.g. Azevedo *et al.,* 1992, Camacho *et al*., 1997) have not shown themselves to be commercially feasible. The major limitations are that they were excessively complex, too data intensive and too expensive. A viable system needs:

1. A simple control strategy,
2. Minimum sensing,
3. Robust and reliable simulation, and
4. Optimization to a simple user defined objective.

Extracting the best information on the soil infiltration characteristic from a minimum quantity of field data is central to the practical real-time control of surface irrigation (Oyonarte *et al*., 2002). The conundrum is that the quality of estimates is directly related to the quantity of data used. Current methods estimating infiltration tend to focus on advance data but infiltration (and Manning *n*) estimates can be improved greatly by inclusion of depth, recession and/or runoff data (Gillies and Smith 2005, Walker, 2005, Gillies *et al*., 2010). However, the cost and installation of the necessary sensors limits the use of these data in control systems. Further, many of these data occur too late in the irrigation to be of any use for control.

Khatri and Smith (2006) provided the basis for simple real-time optimization using a model infiltration curve for the field in question and an event-specific infiltration characteristic determined from a single advance measurement and a process of scaling. The method is based on the premise that for any field the shape of the infiltration characteristic remains the same but the magnitude varies spatially and temporally. A furrow is selected as the model furrow and extensive advance and run-off data are used to calculate the parameters in the Kostiakov-Lewis infiltration equation:

$$I = k\tau^{a} + f_{o}\tau \tag{1}$$

where I is the cumulative infiltration (m^3/m),
a, k, and f_o are the fitted parameters, and
τ is the infiltration time (min).

The cumulative infiltration curve calculated from these parameters is the 'model infiltration curve'. Subsequently the model infiltration parameters can be used to estimate (by scaling) the cumulative infiltration curves for other furrows, and other irrigation events, using only one advance point for each of the remaining furrows or each subsequent irrigation event.

A scaling factor (F) is formulated for each furrow or event from a re-arrangement of the volume balance model as used by Elliot and Walker (1982) and McClymont and Smith (1996):

$$F = \frac{Q_{o}t - \sigma_{y} A_{o} x}{\sigma_{z} k t^{a} x + \frac{f_{o} t x}{1 + r}} \tag{2}$$

where Q_o is the inflow rate for the corresponding furrow (m^3/min),
A_o is the cross-sectional area of the flow at U/S end of furrow (m^2) (determined by any appropriate method),
a, k, f_o are the infiltration parameters of the model furrow,
σ_y is a surface shape factor taken to be a constant (0.77),
σ_z is the sub-surface shape factor for the model furrow,
r is the exponent from power curve advance function $x = p(t)^{r}$ for the model curve,
t (min) is the time for the advance to reach the distance x (m) for the irrigation event being controlled.

This scaling factor (F) is then applied in conjunction with the Kostiakov–Lewis infiltration model to scale the infiltration curve for the irrigation event being controlled:

$$I_{s} = F(k\tau^{a} + f_{o}\tau) \tag{3}$$

where I_s is the scaled infiltration (m^3/m), and
a, k, f_o are the infiltration parameters of the model furrow.

The major disadvantage with this approach is the use of the volume balance equation and the various empirical factors σ_y, σ_z, and r the values of which must be estimated. All have a significant effect on the outcome of the scaling.

Subsequent to this work a new surface irrigation simulation model (Gillies *et al*., 2010) was developed by the authors and which has provided the basis for the software required for real-time simulation. The model SISCO (*Surface Irrigation Simulation Calibration and Optimization*) is an application of the full hydrodynamic equations for spatially varied flow as described by McClymont (2007). In calibration mode, SISCO estimates the infiltration parameters and roughness parameter (Manning *n*) from the inflow hydrograph and any combination of the advance data, runoff hydrograph, water depth measurements and recession times. SISCO can accommodate variable inflow and variable slope in both calibration and simulation modes. The calibration screen of SISCO is shown in Figure 1, where the three infiltration parameters and Manning *n* are determined for an irrigation bay from depth measurements at 7 locations down the bay.

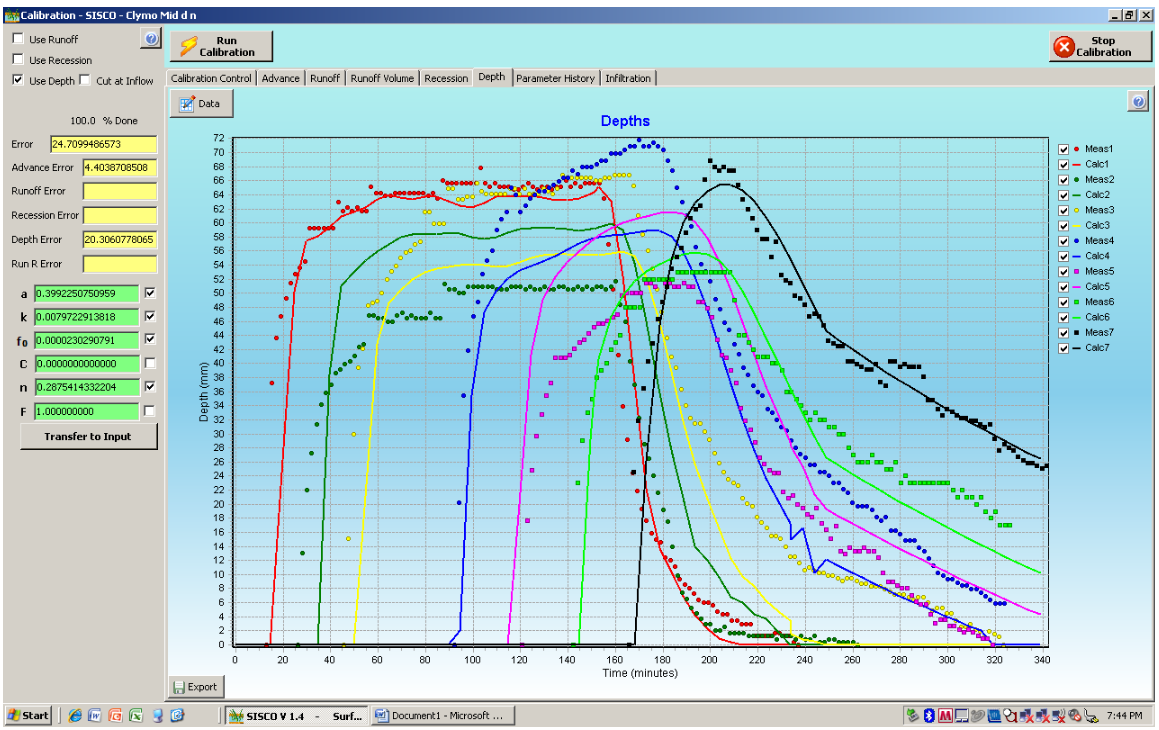


Figure 1. Calibration Screen of SISCO Showing Measured and Calculated Depths at Various Locations down an Irrigation Bay

In this paper, the results of preliminary trials of the real-time optimization are presented and improvements are proposed to the approach developed by Khatri and Smith (2006). It is extended to include bay as well as furrow irrigation, to use SISCO to perform the scaling as well as the simulation and optimization, to accommodate the spatial variability of infiltration between furrows, and to include a self learning capability that progressively refines the model curve.

THE BASIC REAL-TIME OPTIMIZATION SYSTEM

The system follows directly from that proposed by Khatri and Smith (2006) and uses their concept of the model infiltration curve. In its simplest form it uses a predetermined inflow rate and maximizes performance by varying the time to cut-off. This is justifiable because experience has shown that if the flow rate is selected appropriately to begin with then varying it gives little improvement in performance, although if the physical control hardware allows inflow to be varied the system can accommodate it.

Field Characterization

Before the system is implemented in any bay or set of furrows, the initial model infiltration curve must be established. The best estimate comes from the usual process of inverse solution by SISCO in calibration mode from advance and other measurements taken during an irrigation. However, in the absence of such measurements it can be estimated from soil texture or experience. The inflow rate to be used is also set at this time from trial simulations performed using the model infiltration curve in SISCO.

The physical characteristics of the furrows or bay such as length, slope and cross section shape are also required.

Optimization and Control

The optimization and selection of the preferred time to cut-off during each irrigation event, in each set of furrows, involves the following steps.

1. *Soil moisture deficit*. This can be determined from soil moisture measurements or from a soil moisture balance based on estimates of crop water use since the last irrigation.

2. *Measurement of inflow*. The system can use either a constant inflow or a continuous inflow hydrograph. To avoid the expense of flow metering, inflow is inferred from water depth or pressure depending on the inflow system. For example, for a set of furrows supplied by flexible gated fluming, the inflow to each furrow can be calculated from the pressure in the fluming using the gated pipe program of Smith (1990). This information is implemented in the system as a look-up table of pressure versus flow specifically prepared for that set of furrows. Similarly, for other inlet configurations the look-up table would be developed from the head-discharge relationship for the particular structure.

3. *Advance*. A single advance measurement (time for the known distance) is taken at a point approximately mid-way down the field. This measurement triggers the commencement of the simulation modelling and optimization.

4. *Infiltration scaling*. The model uses the measured inflow and the advance time to the known point to calculate the scaling factor (equation 2) and hence the infiltration

characteristic (equation 3) for that particular irrigation. This is then used in the optimization.

5. *Optimization*. The optimization employs a derivative of the SISCO model which selects the time to cut-off that gives the best performance according to a user defined objective function. For example, one simple objective that satisfies the requirement of many growers is to maximize the application efficiency E_a while ensuring that at least 90% of the soil moisture deficit is satisfied and a minimum depth is applied at the downstream end of the field (ensures that the advance reaches the end of the field). However more complex objectives specifying uniformity, deep drainage and runoff targets can be used but might serve to reduce the robustness of the system.

6. *Control*. Finally, the inflow is cut-off at the designated time and the process is repeated for subsequent sets.

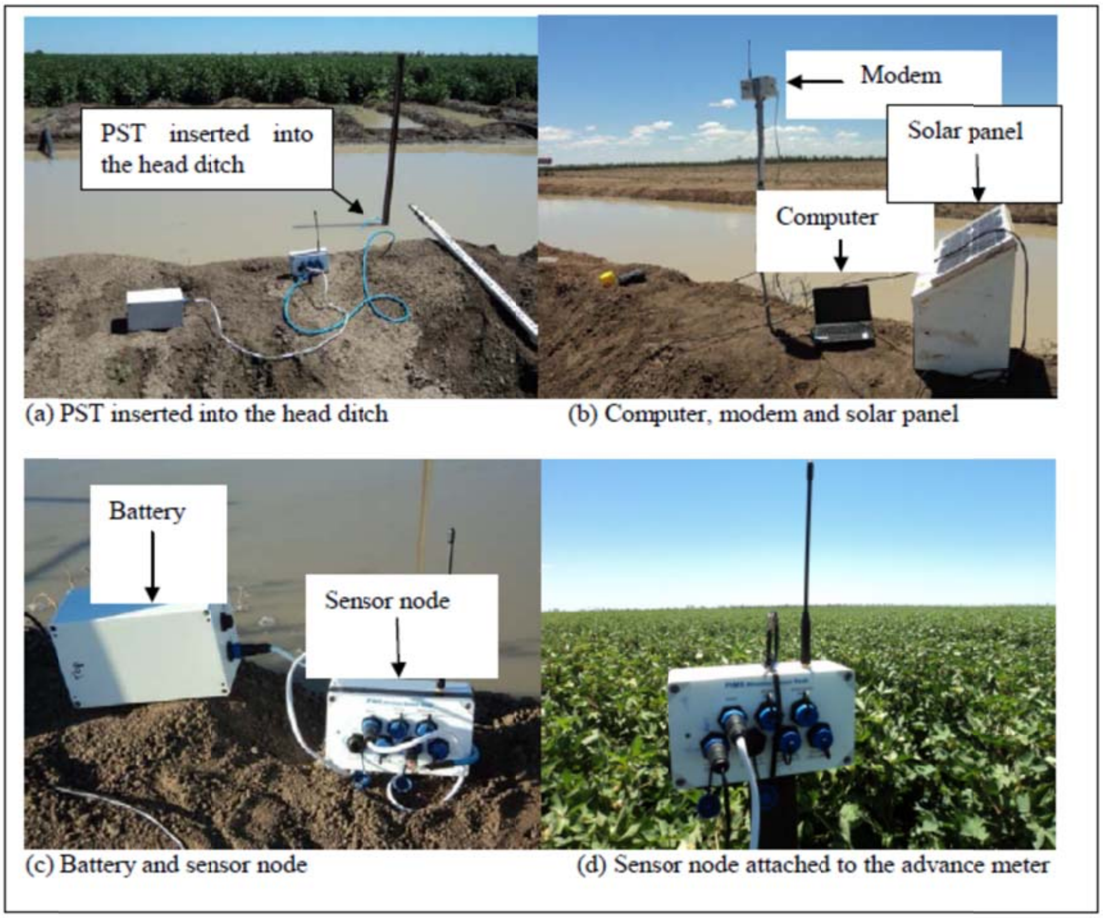
PRELIMINARY TRIALS

Trials were undertaken on a commercial furrow-irrigated cotton property at St George in south-western Queensland, Australia. Four irrigations in the summer season 2010/11 were monitored in a section of the field that used pipes-through-the-bank (PTB) to supply groups of 11 furrows (Figure 2). The furrows were 970 m long and spaced at 1 m apart.

The flow rate was inferred using head measurements in the supply channel and a calibration equation for the PTB. The model curve used in the software for each irrigation was obtained from the actual infiltration curve from the immediately preceding irrigation. The advance sensor (with the associated components) was placed 500 m from the inlet. Communication between the various components was via radio telemetry. The inflow was terminated manually at the predicted time to cut off.

A significant outcome from the trials was that the real-time optimization model (sensing, infiltration scaling, simulation and optimization) performed robustly and reliably without user intervention.

Sample results from the trials are provided in Table 1. They show that with the exception of Trial 4, the irrigation times predicted were shorter than those used by the farmer in irrigating the remainder of the field. This translated to reduced runoff and deep percolation and higher application efficiencies as a direct result of the real-time optimization. It is also apparent from this table that the farmer was utilizing the knowledge gained from preceding irrigations to modify his future management practices. He progressively reduced both the inflow rate and irrigation times throughout the season. It is for this reason that the final irrigation of the season (Trial 4) had a shorter cut-off time than that predicted by the real-time optimization. In this case the farmer controlled irrigation failed to reach the end of the field.



(a) PST inserted into the head ditch (b) Computer, modem and solar panel
(c) Battery and sensor node (d) Sensor node attached to the advance meter

Figure 2. Equipment used in the Preliminary Trials

Table 1. Trial Results

	Irrigation number			
	1	2	3	4
Inflow (l/s)	6	5	3.8	3.3
Soil moisture deficit (mm)	80	80	82	90
Predicted performance[2]				
Time to cut-off[1] (min)	280 (565)	392 (489)	408 (484)	568 (480)
Application Efficiency E_a (%)	72	66	83	73
Requirement Efficiency E_s (%)	93	100	98	94
Potential performance[3]				
Application Efficiency E_a (%)	99	72	91	100

[1] Farmer's time to cut-off shown in brackets.
[2] Predicted by the real-time optimization.
[3] Based on optimization using the actual infiltration curve.

Despite the evident gains from using the real-time optimization, none of the controlled irrigations reached their full potential, as shown by the potential efficiencies listed in Table 1. One contributor to this was the failure of the scaling process to provide an accurate estimate of the actual infiltration characteristic. The two causes of this were identified as the use of the volume balance model for the scaling and a less permeable soil in the lower half of the field. Typically the scaled infiltration was higher than the actual average infiltration characteristic and hence the times to cut-off predicted were greater than actually required.

THE NEW REAL-TIME OPTIMIZATION SYSTEM

Extension to Bay Irrigation

Bay irrigation of pasture or fodder crops differs from furrow irrigation in some ways that influence the real-time optimization significantly. In Australia bays are typically very much shorter than irrigated furrows (200 to 600 m c.f. 600 to 1500 m). The surface roughness is also very much greater (Manning n values typically 0.2 to 0.4 c.f. 0.04 for bare furrows) and varies with time (pasture condition). This means a much greater volume of water is temporarily stored on the surface of the bay in the irrigation flow and the hence inflow can be cut-off earlier in the irrigation, in some cases before the advance has reached the half way distance down the bay. These factors combine to make the real-time optimization more difficult in bay irrigation.

For furrow systems a single advance measurement approximately mid-way down the field is sufficient to perform the infiltration scaling (assuming the Manning n is known or can be estimated from the furrow characteristics), and allows sufficient time to make the control decision on optimum time to cut-off. For bay irrigation, the need to estimate the Manning n as well as the scaling factor requires either two advance points or multiple depth measurements at a single point. Because of the shorter times to cut-off for bay irrigation, the measurements need to take place within the first third of the field. Even so there is less time to undertake the optimization and make the control decisions. A depth sensor that continuously records flow depth is best used in lieu of the advance sensor (the depth data can be used later in the self learning feature).

Scaling the Model Infiltration Curve with SISCO

The preliminary trials showed that the infiltration scaling using the volume balance model was too dependent on the three shape parameters σ_y, σ_z, and r. Subsequently the optimization model (based on the SISCO model) which does not use these parameters has been modified to undertake this task. It uses the measured inflow and the model infiltration curve in a series of simulations and simply varies the scaling factor F (and Manning n) until the simulated advance (or depths) match the measured values.

Self Learning

Conducting an evaluation of an irrigation for each bay or set of furrows to obtain the model curve for each is expensive, time consuming and requires specialized equipment. An alternative is to introduce a self learning capability into the system whereby an initial estimate of the model curve is improved with each subsequent irrigation. For this self learning, the flow and depth measurements (taken early in the irrigation for use in the control loop) are continued throughout the entire irrigation. These data are then used to revise the model infiltration curve and check the adequacy of the inflow rate used in the irrigation, as follows.

Firstly, in calibration mode the modelling software can use the inflow and depth data to calculate the actual infiltration characteristic for the irrigation just completed. This can then be averaged with the characteristics from any previous irrigations to give the updated model curve. In this way the model curve is refined to ensure that its shape is truly representative of the soils in the particular field.

Second, the model can use the actual infiltration characteristic in optimization mode to determine the inflow that would give the best possible irrigation performance. If the calculated inflow rate is markedly different from that used in the irrigation, the user can be given the option to alter the flow rate for the next irrigation.

Accommodating Spatial Variability in Furrow Irrigation

For furrow irrigation all of the above measurement, simulation and optimization take place in a single furrow. However it is well known that there is considerable variation in the infiltration characteristics between furrows and hence in the irrigation performance between furrows in the same field or set (e.g. Gillies *et al*., 2008 & 2011). This is illustrated in Figure 3 which shows the variation in completion times for a set of 80 furrows on a cotton farm in central Queensland. The irrigation illustrated in Figure 3 was relatively well managed with an application efficiency of 78%. Runoff was 8.9% but varied from 0 to 24% for the individual furrows. Deep drainage averaged 14 mm (range 0 to 27 mm).

Given this knowledge of the statistical variation between furrows (from the variation of completion times across the set), SISCO can perform a whole set optimization and determine the flow rate and time to cut-off that gives best performance for the set as a whole. For example, for the field in Fig 3, optimization increased the application efficiency to 84%, reducing deep drainage to 6.5 mm but increasing runoff to 10%.

The consequence for the real-time optimization system is that the time to cut-off for best performance in the control furrow may not correspond to that which gives best performance for the entire set (Gillies *et al*., 2008). However if the statistical variation between furrows is known, SISCO can provide the relationship between the control furrow and the whole set. This can then be used to adjust the scaling factor to allow the control furrow to better represent the set.

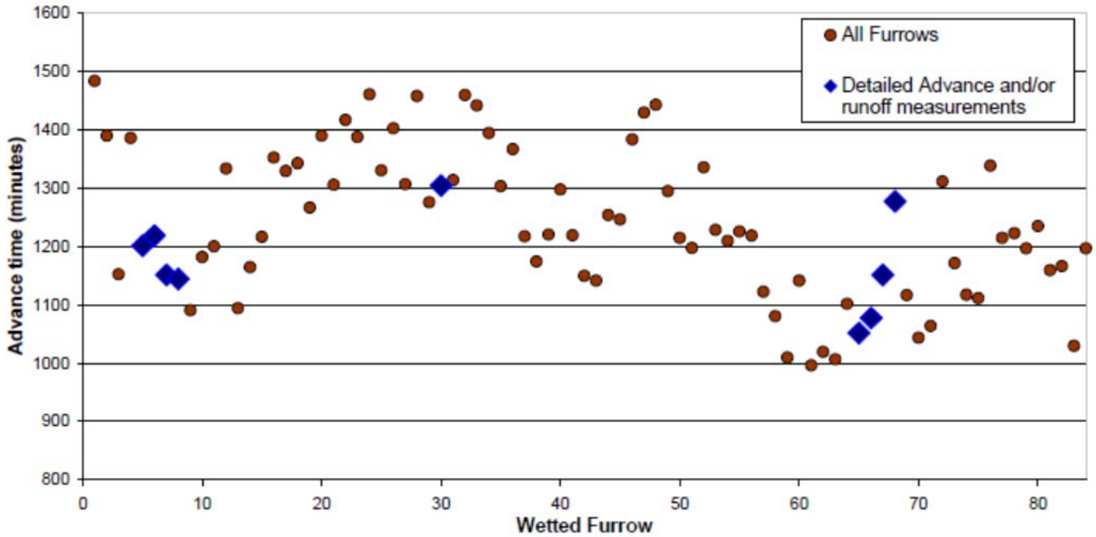


Figure 3. Variation in completion times for a furrow irrigated field of 80 furrows (from Gillies *et al*., 2008)

Figure 4. Automated Bay Outlet and Water Depth Sensor for the FarmConnect® System (Rubicon Water publicity brochure)

Automation and control

While the real-time optimization can be operated as a manual system the greatest benefits occur when it is integrated with automation. The desired time to cut-off is transmitted to the control hardware. The development of this hardware is outside the scope of the current project. The intention is to use a commercially available system such as the Rubicon Water FarmConnect® system (Figure 4). Work on extending the system as described above has commenced and is due to be trialled on two properties in the coming 2011/12 irrigation season.

CONCLUSIONS

A system for the real-time optimization of furrow irrigation has been developed and tested. It has been shown to give improved irrigation performance although it fell short of delivering the maximum performance. Improvements to the system have been described along with its extension to bay irrigation.

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