International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 5, Issue 4
April 2018

Hydroponics Water Management Utilizing A streamlining Optimizer

Devvrat Akheriya
HMRITM, Delhi

Pallavi
GIET,Sonipat

Vijay Rohilla
HMRITM, Delhi

Abstract: *Hydroponics water management using adaptive scheduling with an on-line optimizer is the process measurement has a long time delay, and a feedforward (FF) control loop based on a model-based estimate of water losses is used. A long feedback loop, by which the FF model is adapted using output error feedback, is the mechanism used to minimize the control error. To read the output error, a drain measuring device, or soil moisture meter, is necessary. The optimization method used is a general tool developed for real-time application and is capable of optimizing linear and non-linear systems. The minimization algorithm used is based on a variant of the Powell direction set method in multiple dimensions. It compares favorably in speed of convergence and accuracy when compared with linear repressors for linear systems. It is therefore used as a generalized tool embedded in a modern greenhouse management system. The method allows on-site on-line identification of plant water needs. As an added benefit, the method provides information for the creation of crop transpiration models*

Index Terms—Optimization, Hydroponics, irrigation, on-line optimizer

I. INTRODUCTION

This work proposes a hybrid approach, where a simplified crop transpiration model is used to predict the necessary supply of water. At the same time, drain water flow from the crop is measured using an appropriate flow sensor. Using the error between drain measurement and the model estimate, the coefficients of the model are adapted iteratively. The adaptation process is continuous so that the model accounts for temporal variation of load (i.e. radiation) while it is also adapted for seasonal variations of crop growth.

With a good adaptive FFC, the system is inherently stable and is rapidly brought to the vicinity of the desired operating trajectory, and only incremental actions are left to the FBC. In such structures, the FFC must provide good nominal performance. A non-linear programming technique is used to optimize the dynamic performance of the system, based on a selected performance index.

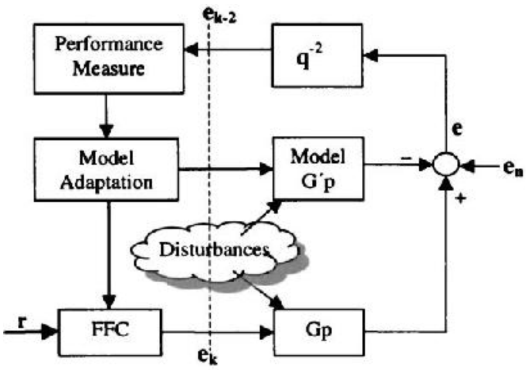
The adaptation process provides robust systems with improved performance. New understanding of the complexity of natural systems has been achieved recently in research on complex adaptive systems. Reduction of complex phenomena at a higher level to simpler problems at a lower level (Wildberger, 1997) is used. Systems in this new field of study share a common characteristic: adaptability. A complex system is considered to emerge from the interaction of multiple, autonomous, intelligent agents, competing and co-operating in the context of the overall system environment. In this view, autonomous intelligent agents can control a complex greenhouse system, one for each temperature (Goggos and King, 2000), CO_2, light, humidity and root environment control. These agents can utilize any well-known decision support methodology (maximum likelihood, fuzzy expert, etc.) and are best suited for the decision level control (optimized trajectory path, conflict resolution, control system configuration, etc.). Their autonomous nature promises to build co-operative systems of high maintainability, i.e. agent upgrade, or a new agent addition, as we learn more about the controlled plant. Other adaptive systems developed recently (Ferentinos, 1999) manage to accurately model the root environment of

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 5, Issue 4
April 2018

hydroponic systems and give useful predictions of major variables of this environment, using neural networks. These predictions can be used for further improvement and intelligent adaptation of the irrigation control process.

All these systems are more flexible in providing higher level management strategies, as they use multiple criteria for adjusting the performance index to include constraints reflecting financial or environmental issues. The system described provides the core for expanding to a multi-agent managerial system in the near future

The figure shown below is the model propsed in research paper.



II. Methods Used

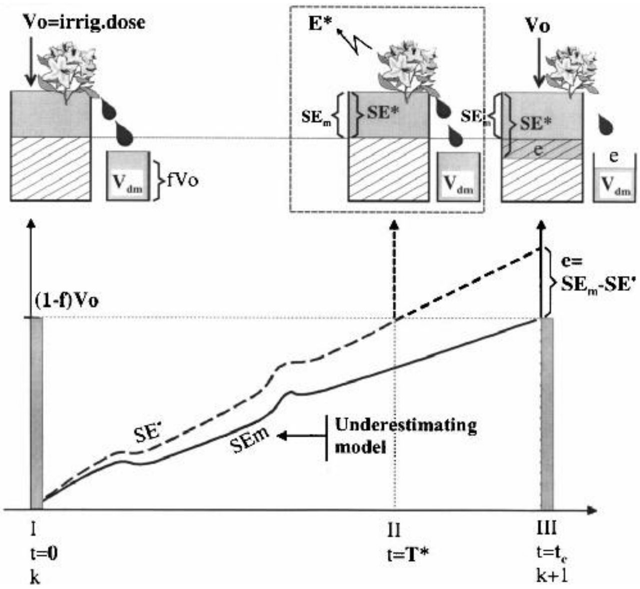
A. Model building

In irrigation systems, the objective is to supply water at a rate V_o to cover the plant water needs $(1-f)V_o$ while ensuring a certain bleed (fV_o) on the system. This bleed is necessary to 'clear out the contamination' and to maintain favourable conditions in the root environment. The percentage f depends upon the purity of the water source and on the contamination rate, which may depend on the temperature of the root environment and other factors. In this regard, f could be set as a function that can vary with weather conditions for a better tuning of irrigation and additional savings in water, nutrients and environment.

The latter is a common greenhouse-growing practice and the irrigation water is supplied in specified time cycles. In each cycle, the amount of water supplied, V_o, is determined by the grower in order to satisfy crop requirements. This simply represents a non-adaptive FF model estimate implicitly used by the grower, usually to set a fixed scheduler. Defining the fraction of drain water as f, the real crop evapotranspiration as E^* and its integral as SE*, the current growing practice can be expressed by:

$$SE^*_{T^*}=\& \; E^*\,dt=(1-f)V_o$$

Below is the concept of model prediction of irrigation needs and its error appearance in measured drain.



III. Automatic Optimization Algorithm

1. Setup a virtual function for P.M.: $J=f(N)$
2. Setup Optimizer X
3. Define V_o, f
4. Apply V_o, $k=k+1$, $t_c=0$
5. Do Loop

Calculate SE_m (from Eq. (4)), clock t_c

Measure drain and integrate V_{dm}

While $SE_m B(1-f)V_o$

6. Compute SE* (from Eq. (3)) and e_k (from Eq. (6))
7. Compute J
8. Call OPTIMIZER X to update [a,b,g] using J
9. Go To step 4

IV. Optimizer

The optimizer module is an iterative search algorithm that can adjust the model parameters in

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 5, Issue 4
April 2018

order to minimize the specified error metric. The algorithm is a variant of the 'Powell direction set method in multiple dimensions' minimization algorithm (Press et al., 1992). This algorithm does not need any process model or gradient information to conduct the parameter search and can therefore accommodate any user-defined performance criterion. Instead, it explores the parameter space performing line minimization along the way, always searching for the best (conjugate) directions. In this case, the search for better parameters never stops in order for the algorithm to detect drifts of the system characteristics (i.e. plant growth, etc.) (Fig. 5). In order to achieve a better fit of the search parameters and shorter search times, the parameter space is separated into two regions of environmental conditions as determined by solar radiation (i.e. regions with low or high solar radiation with a boundary at 100 W/m^2). A separate set of parameters (a, b, g) is created for each of these regions, resulting in the formation of a parameter dictionary. Each time the environmental conditions shift to a different region, the

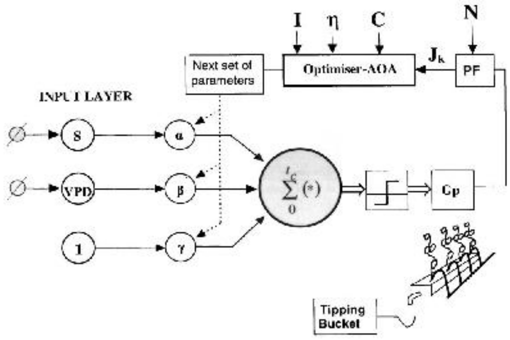
Operator steps to set-up the AOA of Table 1

1. Specify a virtual variable computing the Performance Measure (P.M.)
2. Setup generalized optimizer X

–number of parameters and first estimates *I*
–learning rate h
–safety constraints *C*

3. Setup (step 3 of Table 1) Irrigation Program Y, and Start
4. Assign GO-X to Irrigation program Y, enable GO-X

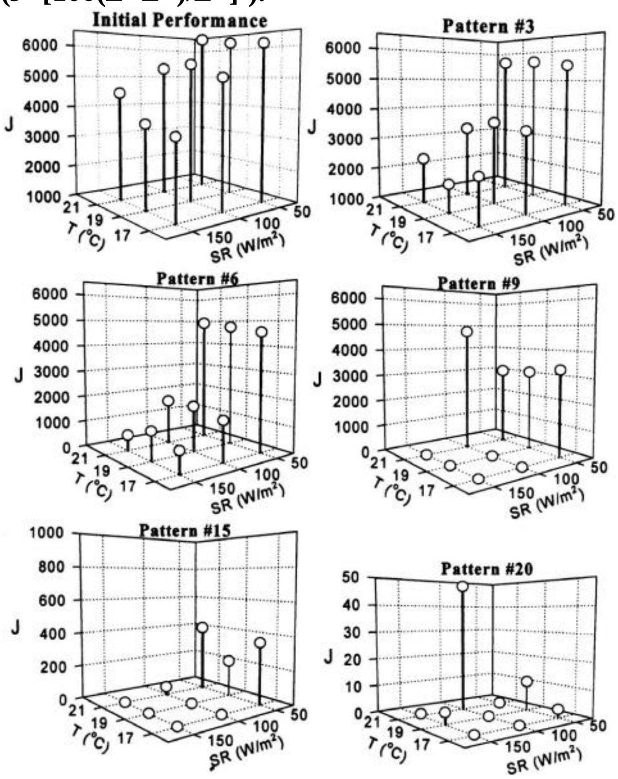
A simple linear perceptron for learning of the crop transpiration model.



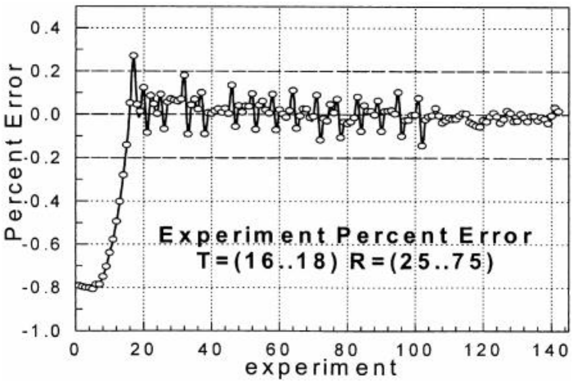
A. Simulation

Preliminary results have been produced with simulated transpiration data on a plant linear model, which was explicit on solar radiation, relative humidity and temperature, instead of radiation and VPD. This simulated learning used an enhanced variation of the Hooke–Jeeves (Shoup, 1979) algorithm (Rerras et al., 1998). This algorithm explores the parameter space by modifying one parameter at a time while searching for a gradient. After all parameters have been explored, the algorithm moves in the direction of steepest descent until no further progress is attained. Thus, the algorithm cycles between exploration and pattern searches until a local minimum is reached. The results can be summarised in the charts of Fig. 6, showing the performance progress with regards to two of the three inputs, the temperature and the radiation. In each chart, the dot-headed grid represents the performance map after a certain number of experiments represented by the number of successive pattern searches. Each pattern search is preceded by a maximum of three explorations. Each exploration demands evaluation of the performance (one irrigation cycle that lasts approximately 1 h).

Global performance map at different stages of optimization in simulation. Performance is defined as the percent relative error squared (J=[100(E−E*)/E*]^2).



Estimation error versus experiment number (simulation) for a single set of parameters.



B. Learning experiments

Experiments with the new optimizer were performed in a greenhouse at the Agricultural University of Athens where a rose crop was grown in channels of perlite substrate using an open loop irrigation–hydroponic system. In one of the growth channels, the irrigation was adjusted using the optimization method. At the end of the channel, the drain water flow was measured using a tipping bucket sensor. The irrigation dose was fixed at 6 l per application and the model was used to determine the irrigation application timing. At the same time the model parameters were tuned using the optimizer. The initial values for the model parameters were assigned using rough estimates of evapotranspiration versus solar radiation and air vapor pressure deficit. Even so the initial algorithm errors were not excessive and, in any case, they were reduced quickly by the process of optimization.

Fig. 8 shows measured evapotranspiration versus model predictions during 3 days of experiments. Significant reduction of prediction errors can be observed, especially in the third day of experiments where the errors do not exceed 10% at any time. The graph in Fig. 9 shows the accuracy of the irrigation program proposed by the model after 3 days of learning. The set point for the drain was set to 600 ml (10% of the irrigation dose, V_o=6000 ml). During daytime, there was virtually no error in the draining achieved, while early in the morning and late in the night the errors were +3 and −1%, respectively. It is worth noting that a big source of noise (e_n) existed during the experimental period shown in Figs. 8 and 9. This was caused by drain water absorption by trash accumulated in the drain duct ahead of the drain meter.

V. Conclusion

The current practice on perlite or pumice and other natural substrates is mostly using the grower's estimation capabilities and the 24 h total drain measurement, to adjust the daily fixed-time irrigation schedule. The method of model adaptation based on a drain-measuring device provides high accuracy and, more importantly, 'weather following'. Compared with model-based control techniques, it offers the ability of on-site on-line tuning that removes the need for exact knowledge of a plant transpiration model. Another significant advantage over advanced control techniques is its simplicity and transparency to the user. Thus, the method achieves the same accuracy with other methods that directly monitor the water level, i.e. in rock-wool substrates. Furthermore, it provides higher safety as the measurement of the drain reflects to a large sample or even the total population of plants instead a single plant measurement.

Splitting the day in two or more regions involving different levels of the prime factor of evaporation, which is the radiant energy, proves to be useful for many reasons. The experimental runs for separate high and low radiation have given model parameters that are extremely accurate for the low radiation regime and especially for the night hours. Under low process noise conditions, high accuracy can be achieved in all operating regimes. A sudden large error in expected drain or a sharp change in the model parameters can be attributed to faults in the hydro-mechanical gear or the plant physiology itself and run fault diagnosis.

Currently, the development is applied on commercial production sites to evaluate growers' responses and operational data from different crops.

References

[1] Ferentinos, K.P., 1999. Artificial neural network modeling of pH and electrical conductivity of hydroponic systems.

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 5, Issue 4
April 2018

[2] Gates, R.S., Zolnier, S., Buxton, J., 1998. Vapor pressure deficit control strategies for plant production..
[3] Gieling, T., Janssen, H.J.J., Van Straten, G., Suurmond, M., 2000. Identification and simulated control of greenhouse closed water supply systems
[4] Goggos, V., King, R. E., 2000. Qualitative-evolutionary design of greenhouse environment control agents.
[5] Hamer, P., 1997. Optimization of irrigation and nutrition
[6] DGVI.F2.3, Rue de la Loi 200, Brussels.
[7] Hashimoto, Y., 1989. Recent strategies of optimal growth regulation by the speaking plant concept.
[8] Monteith, J.L., Unsworth, M., 1990. Principles of Environmental Physics.
[9] Devvrat, Rajeev Ratan, Ajay Kumar.2017 Automated Hydroponics System to deliver nutrients directly to the root of plants.
[10] Lenord Melvix J.S.M, Sridevi C.2014 Design of Efficient HydroponicNutrient Solution Control System using Soft Computing based Solution Grading.
[11] Press, W.H., Teukolsky, S.A., Vetterling, W.T., Flannery, B.P., 1992. Numerical Recipes in C: The Art of Scientific Computing.
[12] Rerras, N., Anastasiou, A., Ferentinos, K., Sigrimis, N., 1998. An adaptive optimizer for process control.
[13] N. Sigrimis [a,*], K.G. Arvanitis [b], G.D. Pasgianos [c], K. Ferentinos [d] Hydroponics water management using adaptive scheduling with an on-line optimizer.