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Design a Soft Computing DECEL Model to Optimize Water Usage in Irrigation Management

Pradeep H.K.[1], Jasma Balasangameshwara[2], K.Rajan[3] and Archana B.K.[4]
[1]*Department of Computer Science & Engineering, JSS Academy of Technical Education, Bengaluru, Visvesvaraya Technological University, Belagavi, Karnataka, India.*
[2]*Department of Computer Science & Technology, Dayananda Sagar University, Bengaluru, Karnataka, India.*
[3]*ICAR - Indian Institute of Soil and Water Conservation, Ooty, India.*
[4]*Department of Electronics & Communication Engineering, JSS Academy of Technical Education, Bengaluru, Karnataka, India.*

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Abstract

Finite Automata (FA) and soft computing techniques have potential to improve agricultural water management practices. The existing irrigation systems suffer from low water productivity. This issue can be ameliorated through Dirt texture, Evapotranspiration and Crop Evolution based Land specific (DECEL) model. The soft computing models such as K-Nearest Neighbor (KNN) and linear regression prediction methods are used in the DECEL irrigation framework. The results exhibited that, the KNN algorithm obtained accuracy of 95.88% over dirt texture classification and 99.98% accuracy on crop coefficient prediction. The reference evapotranspiration is predicted using linear regression method.

Key words: Dirt texture; Evapotranspiration; Crop coefficient; Machine learning; Finite automata.

1. Introduction

The global food requirement increases about 60% by the year 2050 due to growing population (Alexandratos and Bruinsma, 2012). Currently irrigated land can only satisfy 40% of the expected global food requirement by the year 2050. Agriculture sector uses 70% of the available water (Provenzano and Sinobas, 2014). Currently only 16% of the cultivable area is irrigated due to adoption of conventional irrigation approaches (Alexandratos and Bruinsma, 2012; Playan *et al.*, 2014). The arid and semi-arid regions are currently expanded to 36% and global warming trend further expands the aridity area (Safriel *et al.*, 2005; Alcamo *et al.*, 2007; Arnell *et al.*, 2011). The efficiency and economic outcome is the vital concern of irrigation system (Burt *et al.*, 2005; Chartzoulakis *et al.*, 2015). The performance of irrigation system depends on timely supply of exactly required volume of water. The water transformation through soil and crop are expressed using the metrics such as evaporation, transpiration, infiltration, runoff and deep percolation. Evaporation is the process of water transformation from liquid to vapour. The transpiration is the process of water passed from crop stomata to atmosphere in the form of vapour. Evapotranspiration (ET) is the combined process of surface evaporation and crop transpiration. The infiltration is the process of water entry in the surface of soil. The deep percolation is the infiltrated water which moves beyond the root zone. The water moves out of the land is called runoff (Burt *et al.*, 1997). The dirt

Corresponding Author: Pradeep H.K.
Email: hkpradeep.research@gmail.com

properties, weather conditions and crop coefficient play crucial role in irrigation system (Dabach *et al.,* 2011; Soulis and Elmaloglou, 2018).

The rest of the paper is structured as follows. The Section 2 describes the evolution of various irrigation methods. The irrigation automation framework is outlined in Section 3. The soft computing approaches and their results are discussed in Section 4. Finally, the conclusions and future research directions are summarized in Section 5.

2. Related Work

The surface irrigation method is most extensively used technique and this approach is popular due to low initial cost and energy demand despite the low irrigation efficiency. Basin, border and furrow are generally practiced surface irrigation techniques (Raghuwanshi *et al.,* 2011). The sprinkler irrigation framework comprises of pipe network in which water flows with force through nozzles and it simulates precipitation with the help of overhead spraying. The solid set, linear and hand move, centre pivot, wheel line, gun type and hose-pull are various sprinkler irrigation techniques. In drip irrigation, water is supplied via pipe network in a fixed model and water is slowly emitted to each plant to the root zone (Tindula *et al.*, 2013). The evolution of first-generation irrigation technology was started with multi-client electronic hydrants for utilization at dispensation network. The second-generation irrigation technology was variable frequency pump. The micro irrigation method was the third generation in irrigation technology wherein WP was increased but marginally installed due to high initial investment (Pradeep *et al.,* 2021a). The sub surface drip irrigation (SDI) was the fourth generation in irrigation technology invented to solve the issues of surface drip irrigation specifically to eliminate emitter clogging issue. The fifth generation in irrigation technology was deficit irrigation invented to supply reduced amount of water without affecting the yield based on crop growth stage (Levidow *et al.,* 2014; Kang *et al.,* 2017). Intelligent irrigation is the emerging area which addresses the low water productivity issue (Pradeep *et al.,* 2019; Pradeep *et al.,* 2020; Krishnashetty *et al.,* 2021; Pradeep *et al.,* 2021b). The evolution of irrigation methods are presented in Table1.

Table 1: Progress of irrigation techniques

Approach	Benefits	Implementation
Multi-client hydrants	Dispensation unit	Mostly used
Frequency pumps	Pumping plant	Mostly used
Drip & Sprinkler	Water control and irrigation scheduling	Marginally deployed
Sub surface drip	Water control and irrigation scheduling	Minimal
Deficit irrigation	Water control and irrigation scheduling	Minimal
Intelligent irrigation	High water productivity and economy	New era

3. Irrigation Automation Model

The Finite Automata (FA) is a core concept of intelligent computing. In this paper, the deterministic variant of FA (DFA) is used to design the automated irrigation framework provided with some rules that permit the automaton to handle the symbols, according to the rules to generate the output. There are only two possible outcomes over the input passed to the FA, “accept” or “reject”. In FA model the states are represented by circles. Arcs between the states are labeled by inputs. The States may have a self loop for some of the input symbols. In FA model one of the states is designated as start state, indicated by an arrow leading to that state without origin state and its necessary to have one or more states as final or accepting states, indicated by double circle. For all valid input string the FA should halt at one of the designated final state. In the present study an irrigation automation framework is proposed which is represented in Figure 1.

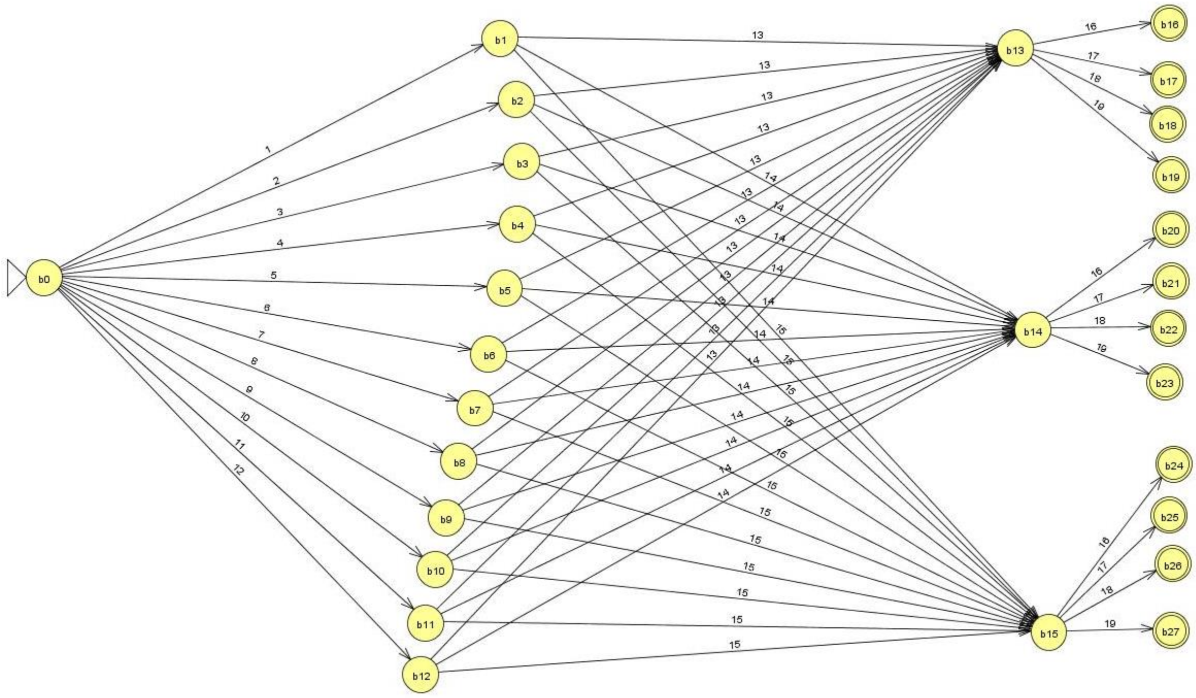

Figure 1: DFA model for irrigation automation

The input variables are dirt texture, evapotranspiration, and crop evolution coefficient data for specific land. The automated irrigation framework variables are reported in Table 2.The United States Department of Agriculture (USDA) has defined twelve major soil texture classes considering the combination of sand, silt and clay fractions, which are highlighted in Table 3. The set of soil texture input parameters are represented in the model as {1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12}. The weather data is classified as warm, temperate, and polar, reported in the Table 4 and also represented as input variables {13, 14, 15} in Figure 1. The crop evolution coefficient depends on the crop growth stage. They are represented in the model as {16, 17, 18, 19, 20} and reported in Table 5. The accepting states determine volume of water required for the given input pattern.

Table 2: Variables of automated irrigation framework

DFA Attributes	Description
States	Q = {b_0, b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9, b_{10}, b_{11}, b_{12}, b_{13}, b_{14}, b_{15}, b_{16}, b_{17}, b_{18}, b_{19}, b_{20}, b_{21}, b_{22}, b_{23}, b_{24}, b_{25}, b_{26}, b_{27}}

Input symbols	Soil texture variables = {1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12} Evapotranspiration data variables = { 13, 14, 15} Crop evolution input parameters = {16, 17, 18, 19, 20}
Start state	b_0
Final states	F = {b_{16}, b_{17}, b_{18}, b_{19}, b_{20}, b_{21}, b_{22}, b_{23}, b_{24}, b_{25}, b_{26}, b_{27}}

Table 3: Dirt classification transitions

Current State	Input	Next State	Soil texture
b_0	1	b_1	Sand
b_0	2	b_2	Loamy sand
b_0	3	b_3	Sandy loam
b_0	4	b_4	Loam
b_0	5	b_5	Silty loam
b_0	6	b_6	Silt
b_0	7	b_7	Clay loam
b_0	8	b_8	Sandy clay loam
b_0	9	b_9	Silty clay loam
b_0	10	b_{10}	Sandy clay
b_0	11	b_{11}	Silty clay
b_0	12	b_{12}	Clay

3.1. Reference evapotranspiration

The reference evapotranspiration is an important metric to understand the crop water requirements to obtain satisfactory yield. The reference evapotranspirationplays vital role to compute irrigation water requirements. To estimate reference evapotranspirationthe weather data such as temperature (T), wind speed (WS), solar radiation (SR), sunshine hours (SS), relative humidity (RH), rainfall (RF) and vapour pressure (VP) are key input variables (Allen and Pruitt, 1991). The most widely used model for estimation of reference evapotranspirationis FAO-56 Penman-Monteith method (Allen *et al.*, 1998).

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} U_2 (e_s - e_a)}{\Delta + \gamma (1+0.34U_2)} \quad (1)$$

where,

ET_0 = Reference ET (mm day $^{-1}$),

e_s = Saturation vapor stress (kPa),

e_a = Actual vapor stress (kPa),

Δ = Incline of the saturation vapor stress function (kPa °C^{-1}),

G = Dirt heat flux density (MJm^{-2} day^{-1}),

γ = Psychometric constant (kPa °C^{-1})

R_n = Net radiation (MJm^{-2} day^{-1}),

T = Average air temperature (°C)

U_2 = Mean wind speed at 2 m height for 24-h (m s^{-1}) and

$e_s - e_a$ = Vapor stress loss (kPa).

3.2. Dataset

The observed weather dataset of metrological station, University of Agriculture Sciences, GKVK, Bengaluru is used for prediction of reference evapotranspiration. The Colorado Maize crop evolution water requirement data set is used for prediction of crop coefficient. The soil texture classification dataset is created using USDA triangle soil texture classification reference model.

Table 4: Weather data classification transitions

Current state	Input	Next state	Weather classification
b_1	13	b_{13}	Warm
b_1	14	b_{14}	Temperate
b_1	15	b_{15}	Polar
b_2	13	b_{13}	Warm
b_2	14	b_{14}	Temperate
b_2	15	b_{15}	Polar
b_3	13	b_{13}	Warm

b_3	14	b_{14}	Temperate
b_3	15	b_{15}	Polar
b_4	13	b_{13}	Warm
b_4	14	b_{14}	Temperate
b_4	15	b_{15}	Polar
b_5	13	b_{13}	Warm
b_5	14	b_{14}	Temperate
b_5	15	b_{15}	Polar
b_6	13	b_{13}	Warm
b_6	14	b_{14}	Temperate
b_6	15	b_{15}	Polar
b_7	13	b_{13}	Warm
b_7	14	b_{14}	Temperate
b_7	15	b_{15}	Polar
b_8	13	b_{13}	Warm
b_8	14	b_{14}	Temperate
b_8	15	b_{15}	Polar
b_9	13	b_{13}	Warm
b_9	14	b_{14}	Temperate
b_9	15	b_{15}	Polar
b_{10}	13	b_{13}	Warm
b_{10}	14	b_{14}	Temperate
b_{10}	15	b_{15}	Polar
b_{11}	13	b_{13}	Warm
b_{11}	14	b_{14}	Temperate
b_{11}	15	b_{15}	Polar

b_{12}	13	b_{13}	Warm
b_{12}	14	b_{14}	Temperate
b_{12}	15	b_{15}	Polar

Table 5: Transition table represents crop growth evolution classification

Current state	Input	Next state	Crop evolution
q13	16	q16	initial stage
q13	17	q17	development stage
q13	18	q18	mid-season
q13	19	q19	late season
q14	16	q16	initial stage
q14	17	q17	development stage
q14	18	q18	mid-season
q14	19	q19	late season
q15	16	q16	initial stage
q15	17	q17	development stage
q15	18	q18	mid-season
q15	19	q19	late season

4. Results and Discussions

The DFA irrigation framework is reviewed using Java Formal Languages and Automata Package (JFLAP) tool. (Rodger *et al.*, 2006). The model is validated for the pattern "11316". The variable '1' indicates sandy soil texture, '13' indicates warm weather and '16' indicates initial stage of crop. The tracing of sample pattern amp is represented in Figure 2. The pattern "11316", demands high water supply because of sandy soil texture, warm weather and initial stage of crop. Hence for pattern 1, the model halts at state q16, which indicates high crop-water requirement for the given input condition.

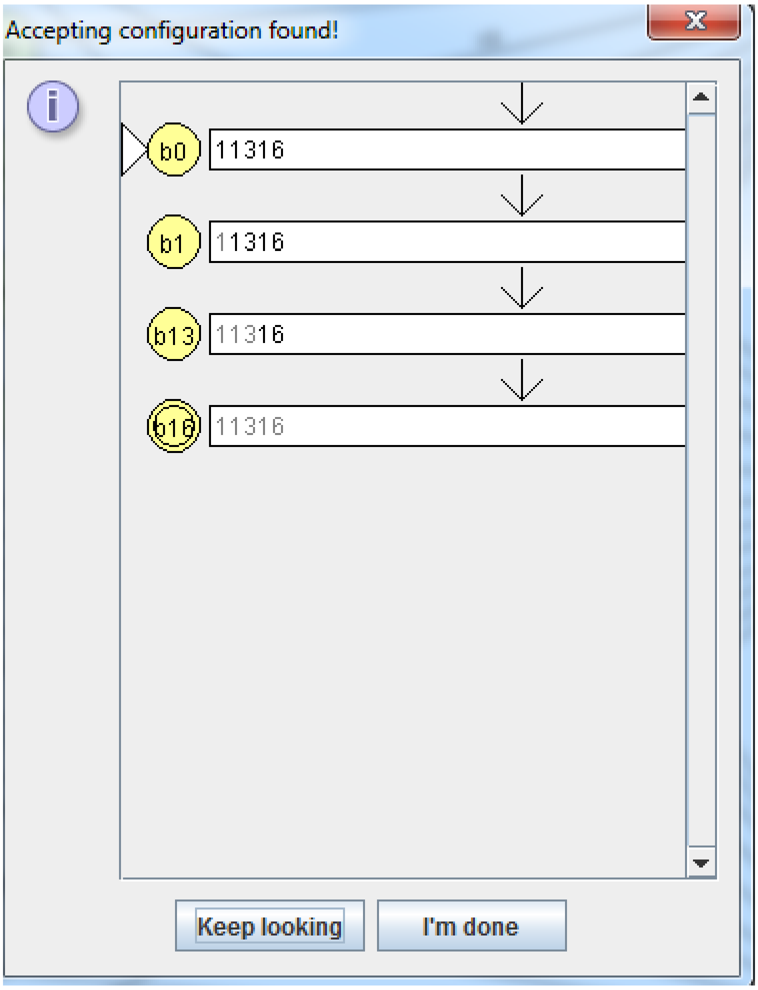

Figure 2: Tracing over input pattern "1 13 16"

4.1. Evapotranspiration prediction

The evapotranspiration is an important metric to understand the crop water requirements to obtain satisfactory yield. The linear regression method is used for prediction of evapotranspiration, which determines water requirement considering weather data. The relevant data instances are reported in Table 6. The models are analyzed using statistical performance measures such as Mean Absolute Error (MAE) and coefficient of correlation (R). The different weather input variable combinations are reported in Table 7. The prediction accuracy is highlighted in Figure 3.

Table 6: Evapotranspiration estimation sample instances

Maximum temperature	Minimum Temperature	Vapor Pressure	Relative Humidity	Wind Speed	Bright Sun Shine Hours	Evapotranspiration
32.4	21.8	17.8	80	4.4	2.6	3.5

32.6	22.0	16.5	84	4.0	7.6	3.9
33.6	22.4	19.1	85	3.8	8.8	4.2
34.2	20.8	19.4	87	4.8	8.0	4.3
31.8	21.2	17.7	82	9.0	9.7	4.5
34.2	21.2	18.8	85	7.7	8.7	4.7

Table 7: Statistical analysis of linear regression model over different input combination

Input combination No.	Input Variables	Statistical Analysis	
		MAE	R^2
1	Max.Temp, Min.Temp, Vapor pressure, Relative humidity, Wind speed, Bright sunshine hours	0.16	0.90
2	Max.temp, Min.Temp, Vapor pressure, Relative humidity, Wind speed	0.27	0.82
3	Max. Temp, Min.Temp, Vapor pressure, Relative humidity	0.27	0.82
4	Max. Temp, Min.Temp, Vapor pressure	0.32	0.74
5	Max. Temp, Min.Temp	0.32	0.73

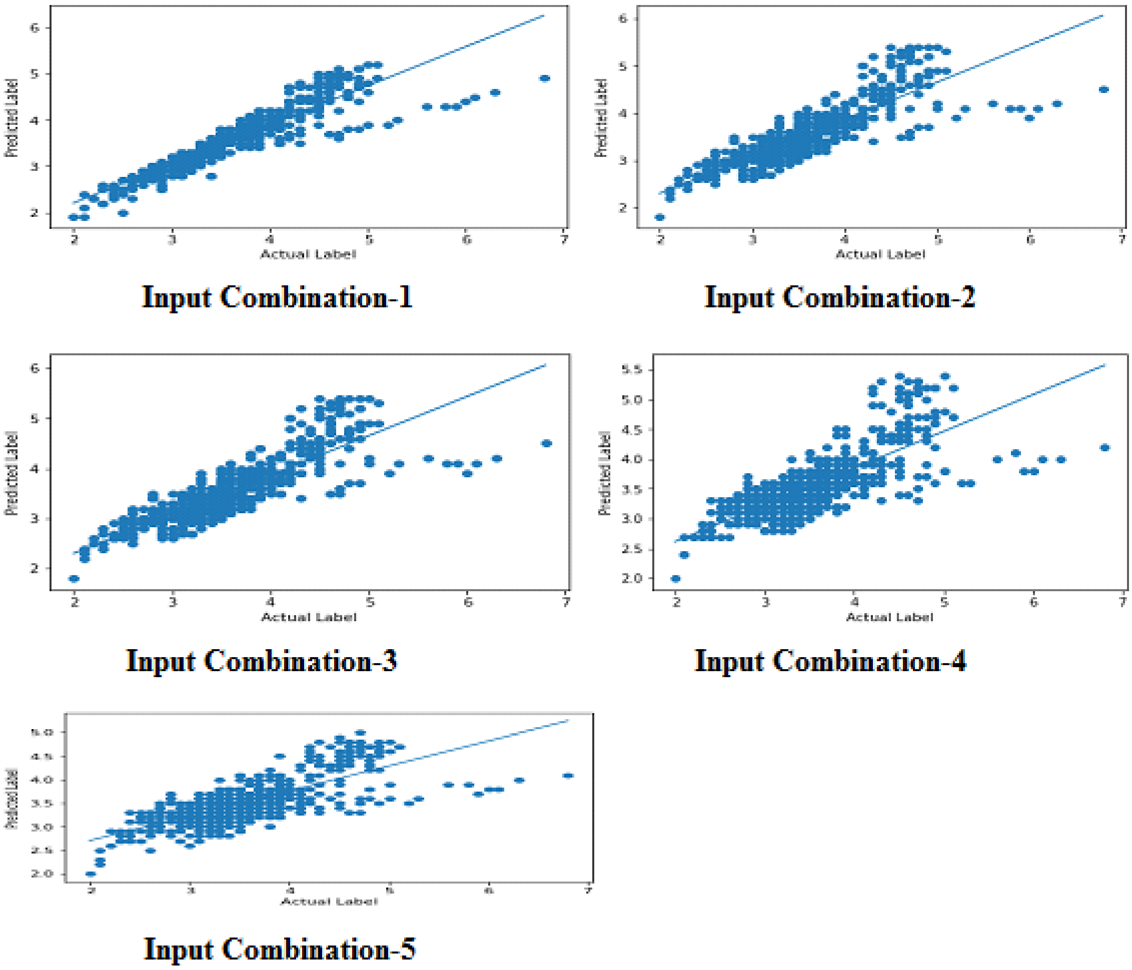

Figure 3: Linear regression model prediction analysis over different input combinations

4.2. Dirt texture and crop-evolution coefficient prediction using K-NN algorithm

The dirt texture determines the water holding capacity of soil and which helps to increase the water productivity of irrigation system. The crop evolution-based coefficient indicates the crop water requirement based on the plant growth stage and it supports for computing water budget in irrigation automation. The K-NN algorithm is applied to predict dirt texture and crop coefficient. The sand, silt and clay fraction are input variables for soil texture classification, which are reported in Table 8. The Maize crop growth stage water requirement is input for crop coefficient prediction. The experimental results exhibited the accuracy of 95.88% over soil texture prediction and 99.98% accuracy over crop coefficient prediction and reported in Table 9.

Table 8: Dirt texture classification sample instances

Sand	Silt	Clay	Type
91	6	3	Sand
50	20	30	Sandy clay loam
15	55	30	Silty clay loam
40	10	50	Clay

Table 9: Dirt texture and crop coefficient estimation accuracy

Algorithm	Prediction	Input	Accuracy
K-NN	Dirt texture	Sand, silt and clay fraction	95.88%
K-NN	Crop-coefficient	Crop growth stage and crop species	99.98%

5. Conclusion

In the proposed research work the finite automata and soft computing concepts are integrated to design a DECEL model to optimize water usage in irrigation management. The automated irrigation framework is proposed using deterministic finite state machine, linear regression and K-NN algorithm. The proposed irrigation automation framework predicts the water requirement considering soil texture, evapotranspiration and weather data. The linear regression model experimental results proved that the best input features combination for prediction of reference evapotranspiration are Max.Temp, Min.Temp, vapor pressure, relative humidity, wind speed and bright sunshine hours. The soil texture class and crop coefficient values are predicted using K-NN algorithm and results exhibited the 95.88% and 99.98% accuracy respectively. As far as we know, the proposed DECEL model is a novel idea, which is designed to increase water productivity in irrigation system. The proposed research work opens the future research on development of efficient intelligent irrigation system and also deployment in the field.

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