Journal of Advanced Zoology

ISSN: 0253-7214

*Volume **44** Issue **S-2 Year 2023** Page **740**:**763***

Design and Implementation of Deep Learning Based Model Predictive Controller to Automatically Adjust Nutrient of Solution for Hydroponic Crop

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Article History

Received: 27 Aug 2023

Revised: 28 Sept 2023

Accepted: 06 Oct 2023

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Abstract — Smart farming is the future of agriculture sector and brings a new era in agriculture; it enables farmers to increase the production and quality of crops with minimal use of resources. In current scenario land availability decreases enormously, hence soilless hydroponic cultivation is considered as the fastest growing sector of agriculture. However, in hydroponic system it is a very challenging task to manage nutrient for crop. To solve these issues this study was conducted which could control robustly EC and pH of hydroponic solution with the help of deep learning model long short-term memory (LSTM). A model predictive controller (MPC) using LSTM was designed and simulated to control EC and pH in hydroponic farm. The predicted outcome of LSTM was operating time of pH buffer solution pump (T_{on}_pH) and nutrient solution pump (T_{on}_EC). The proposed MPC adjust these operating times to control EC and pH with an RMSE of 0.24 and 0.27s, respectively. Furthermore, proposed system improves the predicting accuracy of T_{on}_pH and T_{on}_EC of 77% and 61%, respectively, as compared to fuzzy logic controller. This study provides a smart and efficient way to predict and estimate the optimum value for robustly manage the nutrient as per crop requirements.

Keywords: Predict; Deep Learning; Soilless Cultivation; Hydroponic; Fuzzy Logic; Nutrient.

Introduction

Smart farming ushering a new era in agriculture sector and it is seen to be the future of this sector as it enhances farming practices and yield with the use of intelligent sensors, artificial intelligence (AI), Internet of Things (IoT), cloud computing, big data analysis, etc. Smart farming tools helps in minimizing the inputs (nutrient, water, land space, energy and labor), saving the crop from adverse weather, growing crop throughout the year, saving crop from abiotic and biotic stress, augmenting production and quality (Alipio et al., 2019). Different farming practices are included in smart faming, like greenhouse, hydroponic, aeroponic, aquaponic. Nowadays hydroponic is very popular in digital agriculture 4.0 era which helps in dealing with challenges like unmanageable soil degradation, restrained water sources, less availability of space, soil issues (soil fertility, weeds), environment pollution (due to excessive spraying of herbicides and pesticides) and unpredictable weather patterns (Verma & Gawade, 2021). Hydroponic is a soilless cultivation where nutrients required for plant growth are provided through a liquid nutrient solution instead of soil. Hydroponic farming can also be implemented indoor to efficiently utilize the space and fully supplies the exact amount and type of nutrients that the plants require at the right moment (Alipio et al., 2019). In such system artificial substrate like rock wool, coconut coir, carbonized rice husk, sawdust may or may not be used to support roots of plants. These systems are classified into two categories: open (nutrient solution used only one time) and closed (nutrient solution can be reused). In conventional farming, soil culture serves as a buffer to keep nutrients at appropriate level that promotes sustainable crop growth; however, with soilless cultivation, this buffer is absent, hence it is essential to effectively monitor and manage the nutrient levels in solution. The nutrient overdose causes ion toxicity, osmotic stress, and nutrient imbalance, while low values lead to nutrient deficiencies and reduced plant growth (Filho et al., 2018). There are two crucial factors in nutrient solution that should be controlled are hydrogen potential (pH) and electrical conductivity (EC). Since pH impacts photosynthesis and EC is a measure of a solution's salt concentration, they both have an impact on plant growth, quality, and yield. These factors may deviate from their optimum range that plant can withstand due to variation in environmental conditions (temperature and humidity).

Hydroponic cultivation has some drawbacks such as inappropriate management or abrupt changes in EC and pH of the nutrient solution can damage the roots of the plants and stunt their growth. Also, required regularly monitoring and replenish of nutrient solution, which adds labour cost, lengthen and complicated the process (Chang et al., 2018). To address these issues many researchers efficiently integrated a fuzzy logic controller (FLC) into the hydroponic system (Bacalla & Vinluan, 2019; Chen et al., 2022; Fuangthong & Pramokchon, 2018). The fuzzy logic (FL) was applied in the hydroponic system for decision-making purposes to maintain EC and pH within desired limit as per crop requirement. However, the effectiveness of FLC depends on human knowledge and expertise. To design a FL requires expert knowledge for selecting values of membership functions (MFs) (input and output). Hence, machine learning (ML) models like bayesian networks, adaptive neuro fuzzy inference system (ANFIS) were applied which automatically predicts the optimum value of actuators to autonomously control the hydroponics farm. These ML models were trained on real dataset of hydroponic farm. These models simplify the hydroponic farm management practices and helps in increasing the productivity (Vincentdo & Surantha, 2023). However, the effectiveness of ML model depends on the accuracy of extracting features manually

from the input dataset. This manual feature extraction approach is one of the difficult task in ML model. This complexity is reduces by deep learning (DL) model, since it can extract the features automatically and precisely. Thus DL model can efficiently and effortlessly use in regression (Chandel et al., 2022), forecasting (Dubey et al., 2022; Mohanraj et al., 2023), voice recognition (Kinkar & Jain, 2021) and classification problems (Chandel et al., 2021). A DL based time series model long short-term memory (LSTM) is used in soilless cultures to predict root-zone EC (Moon et al., 2018). Currently DL models are only applied for predicting nutrients in hydroponic systems, yet there is a lack of research in the application of DL model to control nutrients of hydroponic farms in real time. The main objective of this study is to use DL model for controlling the EC and pH of lettuce (Lactuca Sativa) and Chinese cabbage (Brassica Rapa) cultivated in hydroponic farm.
The main contributions of this paper are as follows:

(1) This study designs and simulates a DL model based predictive controller for adjusting the EC and pH of nutrient solution within in a defined range for lettuce and Chinese cabbage in a hydroponic system.
(2) The performance of model predictive controller (MPC) and conventional FLC for automatically controlling the nutrients in hydroponic farms is evaluated and compared.

Related work

There have been several previous researches were conducted on the monitoring and controlling of EC and pH of hydroponic system using AI based ML models. A FL and data fusion system was designed and simulated in MATLAB to control water temperature, EC and pH of hydroponic system (Bacalla & Vinluan, 2019). Similar study was conducted using micro-controller board, sensors, exhaust fan and pump with FL to monitor and control humidity and pH level of solution for hydroponic system in real-time (Fakhrurroja et al., 2019). Another study was conducted in which working time of different solution pumps (acid pH solution, alkaline pH solution and EC solution) were regulated by FL system to adjust EC and pH at specific values (Chen et al., 2022). Thus, earlier studies revealed that FLC was one of the most effective systems for hydroponic cultivation to automatically managing the nutrients or environmental parameters. However, the FL system has some major drawbacks including: difficulty in deciding the shape and position of MFs for each fuzzy variable, repeatedly update the rules and dependence on estimation of the premise and its ramifications. Moreover, there is no unique solution for employing FL to solve problems. Thus, multiple solutions of a specific issue, causes confusion and produces unintended results (Zheng et al., 2021). To overcome these shortcomings neural network (NN) based AI models were incorporated in controlling systems. NNs learned from training data and accordingly predict outcomes for new dataset. It solves the problem with high computational power and less complexity and provides arbitrary approximate solutions. Artificial neural network (ANN) was used to predict EC, pH, total dissolved solids (TDS) and sodium to determine quality of water of river for irrigation purposes (Ubah et al., 2021). A similar study was conducted by Moon et al. (2018) in which recurrent neural network (RNN) was used to predict the EC of root-zone nutrient uptake solution in a closed-loop soilless culture (Moon et al., 2018). The predicting capability of NN combined with controlling capability of FL to produce a robust processing tool known as ANFIS. This hybrid approach applies NN based learning algorithm to determine the shape and location of MFs of FL. Compared to prevalent FLC, ANFIS accurately adjusts the pH and TDS of nutrient solution by 67% in nutrient film technique (NFT) based hydroponic system (Vincentdo & Surantha, 2023).

Furthermore, another ML model such as bayesian network was used to implement IoT based smart hydroponic farm, where data gathered from sensors on server using IoT protocol was used to generate BNs. This approach predict decisions to automatically regulate the actuators and better control the environment and nutrients of hydroponic farm from manual approach by 20-60% (Alipio et al., 2019). To study the nutrient balance in the closed-loop soilless culture, the DL model LSTM was utilized to interpret macronutrient ion concentrations using environmental and growth parameters recorded in greenhouses (Moon et al., 2019). A study was conducted by Escorcia-Gutierrez et al. (2022) in which three DL models were successfully applied to predict and classify nutrients and pH levels present in soil (Escorcia-Gutierrez et al., 2022).

Materials and Methods

This study focused on integrating deep learning algorithm in hydroponic system to generate appropriate controlling actions based on real-time of data gathered from EC, pH sensors. LSTM was used to design MPC which predicts operating time (T_{on}) of two pumps: one for providing nutrient solution and other for pH adjusting buffer solution. The prevalent FL approach was also applied on the similar system to make a fare comparison between LSTM and FL. The pipeline of complete procedure was shown in Figure 1.

Experimental setup

The experiment was designed for hydroponic system having frame length 3.9 m, width 2.4 m and height 2.0 m. The data used during simulation was collected from hydroponic farm situated at the experimental site of VR International Organic Farming Solution in Bhopal, M.P., India (longitude 23.148°N and latitude 77.494°E). The hydroponic system was equipped with PVC pipes, nutrient solution tank, fresh water tank, buffer solution tank, mixing tank, foggers, cooling fan and pumps. NFT based hydroponic system was incorporated, where nutrient solution with narrow stream and slow rate is repeatedly circulating in pipes and roots of plants are dipped in solution (Figure 2 a and b). In proposed system coconut coir was used to hold the roots and 18 watt submersible pump was employed to supply water in channels/pipes. The hydroponic system was equipped with UV plastic roofing to minimize the abrupt changes occurred due to extreme weather and covered with net to protect the produce from pests. The lettuce and Chinese cabbage was cultivated in the experimental set up simultaneously, for two years

2019-2020 and 2020-2021 during winter season (December to February), both crop require similar amount of nutrients (EC and pH). The crop was cultivated in soilless culture; hence it consumed nutrients from solution. The optimum EC and pH required for proper growth of lettuce and Chinese cabbage was 1200-1800 µs/cm and 6-7, respectively (Singh & Dunn, 2016).

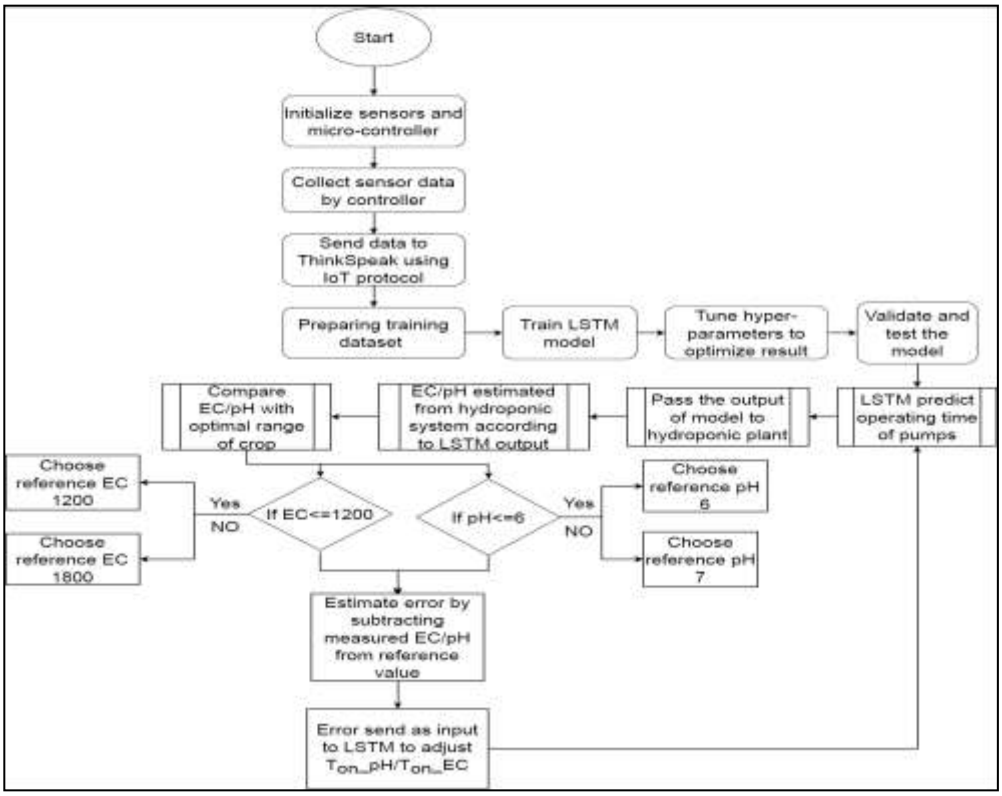


Figure 1. Pipeline of LSTM based model predictive controller to maintain EC and pH of hydroponic system

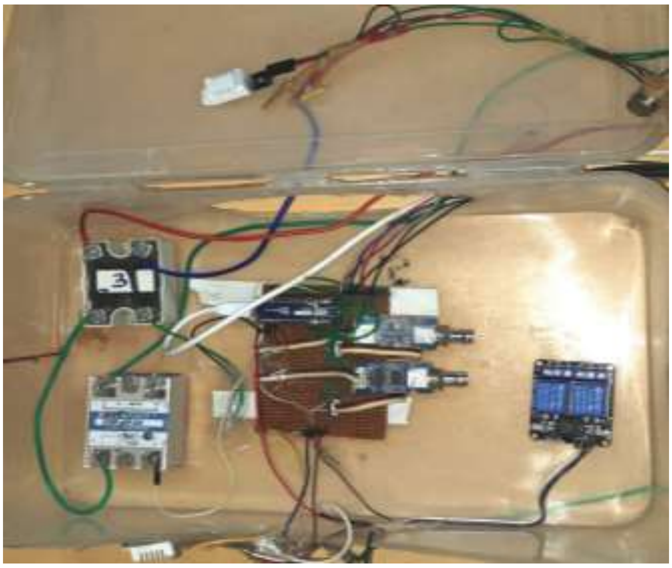
In order to monitor the nutrients of solution continuously, probes of EC and pH sensors were dipped in mixing tank. The pumps of the nutrient/buffer solution activated when the EC/pH range deviates from threshold and combining the solution with fresh water in a mixing tank before supplying it to gullies. In this setup three pumps were installed one for supplying fresh water in mixing tank and other two for nutrient reservoir and buffer solution, respectively. Also, the data accumulated from sensors was transmitted and stored in server using micro-controller Arduino nano 33 IoT. The data was deposited on ThinkSpeak platform, which is an open source IoT service to aggregate, visualize, and analyze the data. The data accessed by ThinkSpeak server used for preparing the training dataset for DL model and simulating the design of FLC and MPC based hydroponic system. The output decision predicted by controller was further sent back to Arduino in activating the appropriate pumps to control EC and pH of solution. The solid state relays (SSRs) were used as a mediator between micro-controller and pump, Arduino activates relay which finally actuates pump (Figure 2c). The detail specifications of electronic components used to develop nutrient controller for hydroponic farm is shown in Table 1.

Table1. Specification of electronic components used in hydroponic setup

Component	Specification	Manufacture
EC sensor	Operating voltage 3.3 or 5 V DC, Measuring range of EC = 0 -2000µs/cm, Resolution = ± 5%	Seeed Studio, Shenzhen, China
pH sensor	Operating voltage 3.3 or 5 V DC, Measuring range of pH = 0 -14, Resolution = ± 0.15%	Seeed Studio, Shenzhen, China
Pump for fresh water supply	Operating voltage: 230V AC, 18 Watt submersible pump, 1.85 meter water lifting capacity	Generic, Maharashtra, India
Pump for nutrient/buffer solution	Operating voltage: 12V DC, Flow rate: 3.6 l/min, Maximum Pressure: 6.9 kg/cm^2	Allied Spares & Auto Parts Manufacturing Corporation Private Limited, Gujarat, India
Arduino Nano 33 IoT	SAMD21 Controller with 32 bit, Maximum input voltage: 21 V DC, 14 Digital pins, 8 Analog pins, 2.4GHz range, Wifi and Bluetooth supported	Arduino, Monza, Lombardia, Italy
SSR	Input voltage:3-32 V DC, Load voltage: 24-380 V AC, Load Current: 25A	Generic, Maharashtra, India

(a)

(b)



(c)

Figure 2. (a) External and (b) Internal structure of hydroponic set up (c) Embedded system used in experiment for preparation of training dataset

Dataset preparation and analysis

The data collected from sensors was filtered (outliers omitted) and divided into two parts: 696 samples for training and 174 samples for testing LSTM model. The controller recorded two year data with a sampling interval of 4 hr in each day. The training dataset comprises of two inputs (EC and pH) and one output (T_{on}_EC or T_{on}_pH). The distribution of EC, pH and T_{on} of pump of proposed hydroponic system with respect to time represents in Figure 3. The plot indicates that T_{on} rises as pH increases whereas T_{on} reduces as EC increases, since EC and pH fluctuate linearly with respect to T_{on} and opposite to each other. The median, mode and standard deviation of EC and pH was 6.37, 5.8, 0.52 and 670.34, 486.81 and 183.82 µs/cm, respectively, while T_{on} has 2.41s mean, 2.49 s mode and 0.21s standard deviation.

Design of Fuzzy Logic Controller (FLC)

FLC has been widely applied in agriculture sector to designed controlled greenhouse (Jomaa et al., 2019), hydroponic farm (Puno et al., 2020), irrigation intelligent system (Krishnan et al., 2020), autonomous robotic system for transplanting (Jin et al., 2020). In this study two FLC was applied to control EC and pH of solution individually and results of FLC was compared with newly designed MPC. The FL system involved three steps: fuzzification, rule evaluation and defuzzification. Fuzzification is a method to define and transform input/output variables in the form of MF. Once MFs are defined, fuzzy rules are declared in inference engine which decide the controlling actions on the basis of inputs. The last step of FL system is defuzzification which generates single optimized crisp value (0 or 1) from multiple fuzzy outputs based on fuzzy set. The fuzzy inference system and defuzzification logic used to develop FLC was mamdani and centroid. In proposed pH controller, input and output MF each has three variables pH_Low, pH_Optimal, pH_High, Ton_Low, Ton_Optimal and Ton_High, respectively which are defined in Equations 1, 2 and 3. The MF represented in triangular form and surface view shows that T_{on} of buffer solution pump increases stepwise from 0 to 4s as pH increases from 0 to 14 (Figure 4).

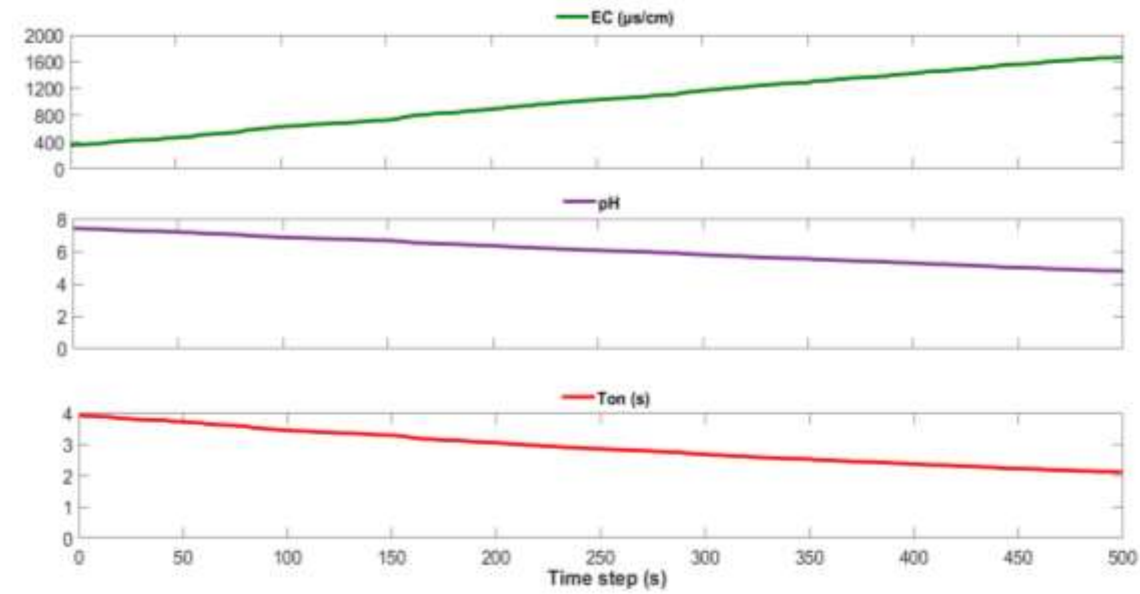
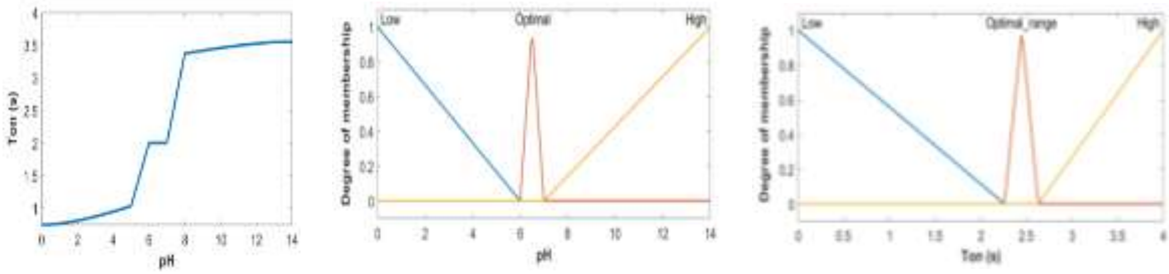


Figure 3. Variation of EC, pH and T_{on} of hydroponic system with respect to time

The FL system of above parameters was used as FLC block in simulation design of pH controller (Figure 5). The input supplied to FLC block through a threshold switch which initially one time passes the pH value stored in testing dataset and after that plant (pH system) supplied the updated pH. FLC controller generates T_{on} on the basis of current pH value. The pH system block used mathematical modelling of hydroponic system to produce pH on the basis of T_{on} of buffer solution pump. The mathematical relationship between pH and T_{on} obtained for hydroponic system to develop pH system block (Figure 6) was expressed in Equation 7. The pH produced from system was stored in memory cell B and further used as input to FLC for updating pH.



(a) (b) (c)

Figure 4. (a) Surface view (b) Input membership function (c) Output membership function of fuzzy logic system to control pH

$$\text{pH\_Low}\ (x) = \begin{cases} 1, & x \le 0 \\ \frac{6-x}{6-0}, & 0 \le x \le 6 \\ 0, & x \ge 6 \end{cases} \tag{1}$$

$$\text{pH\_Optimal}\ (x) = \begin{cases} 0, & x \le 6 \text{ or } x \ge 7 \\ \frac{x-6}{6.5-6}, & 6 \le x \le 6.5 \\ \frac{7-x}{7-6.5}, & 6.5 \le x \le 7 \end{cases} \tag{2}$$

$$\text{pH\_High}(x) = \begin{cases} 0, & x \le 7 \\ \frac{x-7}{14-7}, & 7 \le x \le 14 \\ 1, & \mathrm{x} \ge 14 \end{cases} \tag{3}$$

$$\text{Ton\_Low}\ (x) = \begin{cases} 1, & x \le 0 \\ \frac{2.26-x}{2.26-0}, & 0 \le x \le 2.26 \\ 0, & x \ge 2.26 \end{cases} \tag{4}$$

$$\text{Ton\_Optimal}\ (x) = \begin{cases} 0, & x \le 2.26 \text{ or } x \ge 2.63 \\ \frac{x-2.26}{2.45-2.26}, & 2.26 \le x \le 2.45 \\ \frac{2.63-x}{2.63-2.45}, & 2.45 \le x \le 2.63 \end{cases} \tag{5}$$

$$\text{Ton\_High}(x) = \begin{cases} 0, & x \le 2.63 \\ \frac{x-2.63}{4-2.63}, & 2.63 \le x \le 4 \\ 1, & \mathrm{x} \ge 4 \end{cases} \tag{6}$$

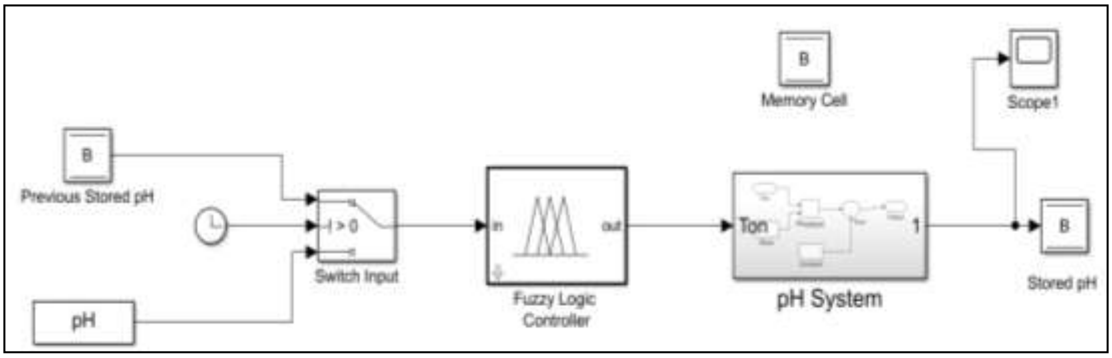


Figure 5. Simulation design of FLC to maintain pH in hydroponic system

The rules to design FLC for pH controller are: If pH is high then T_{on} is high; If pH is optimal then T_{on} is optimal; If pH is low then T_{on} is low. Similarly for designing FL system for EC controlling in hydroponic farm, the input MF was defined by four variables EC_Low, EC_Medium, EC_Optimal and EC_High and output MF by Ton_Low, Ton_Medium, Ton_Optimal and Ton_High (Figure 7 b and c).

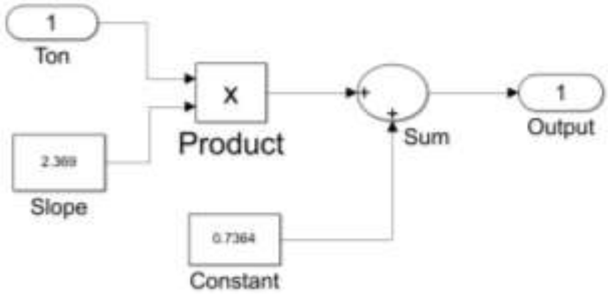


Figure.6 Simulation design of pH system block

$$\text{Output (pH)} = 2.369 \times \mathrm{T_{on}} + 0.7364 \tag{7}$$

These MFs are represented by Equations 8-15. The surface view indicates that T_{on} vary from 4 to 1.13 as EC vary from 0 to 3000 (Figure 7a). The developed FLC takes input from switch, which initially supplied testing data following with prior output of the EC system. The output of FLC provides T_{on} for the nutrient pump, and this T_{on} was sent to the hydroponic EC system, which used mathematical modelling (Equation 16) to generate EC and store it in memory cell (Figure 8). The memory cell data was further sent as input from switch to FLC and again EC was updated. The simulation design of EC system was indicates in Figure 9.

$$\text{EC\_Low (x)} = \begin{cases} 1, & x \leq 0 \\ \frac{300-x}{300-0}, & 0 \leq x \leq 300 \\ 0, & x \geq 300 \end{cases} \tag{8}$$

$$\text{EC\_Medium (x)} = \begin{cases} 0, & x \leq 300 \text{ or } x \geq 900 \\ \frac{x-300}{600-300}, & 300 \leq x \leq 600 \\ \frac{900-x}{900-600}, & 600 \leq x \leq 900 \end{cases} \tag{9}$$

$$\text{EC\_Optimal(x)} = \begin{cases} 0, & x \leq 900 \text{ or } x \geq 1800 \\ \frac{x-900}{1200-900}, & 900 \leq x \leq 1200 \\ \frac{1800-x}{1800-1200}, & 1200 \leq x \leq 1800 \end{cases} \tag{10}$$

$$\text{EC\_High (x)} = \begin{cases} 0, & x \leq 1800 \\ \frac{x-1800}{3000-1800}, & 1800 \leq x \leq 3000 \\ 1, & \mathrm{x} \geq 3000 \end{cases} \tag{11}$$

$$\text{Ton\_Low}(x) = \begin{cases} 1, & x \le 1.13 \\ \dfrac{1.13 - x}{1.13 - 0}, & 0 \le x \le 1.13 \\ 0, & x \ge 1.13 \end{cases} \tag{12}$$

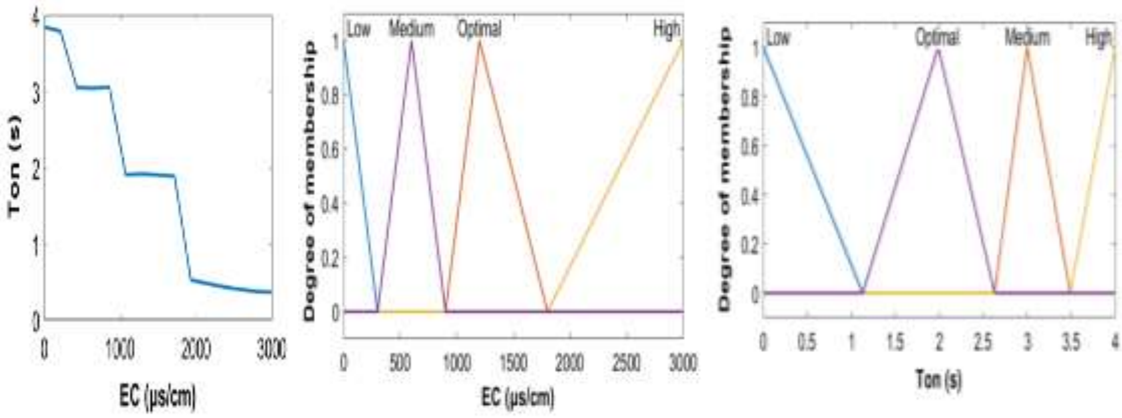
$$\text{Ton\_Optimal}(x) = \begin{cases} 0, & x \le 1.13 \text{ or } x \ge 2.63 \\ \dfrac{x - 1.13}{1.99 - 1.13}, & 1.13 \le x \le 1.99 \\ \dfrac{2.63 - x}{2.63 - 1.99}, & 1.99 \le x \le 2.63 \end{cases} \tag{13}$$

$$\text{Ton\_Medium}(x) = \begin{cases} 0, & x \le 2.63 \text{ or } x \ge 3.49 \\ \dfrac{x - 2.63}{3 - 2.63}, & 2.63 \le x \le 3 \\ \dfrac{3.49 - x}{3.49 - 2.63}, & 3 \le x \le 3.49 \end{cases} \tag{14}$$

$$\text{Ton\_High}(x) = \begin{cases} 0, & x \le 3.49 \\ \dfrac{x - 3.49}{4 - 3.49}, & 3.49 \le x \le 4 \\ 1, & x \ge 4 \end{cases} \tag{15}$$

The rules of FLC inference system to design EC controller are: If EC high then Ton low; If EC low then T_{on} high; If EC medium then T_{on} medium; If EC optimal then T_{on} optimal.

$$EC = 2780 - T_{on} \times 883.4 \tag{16}$$



(a) (b) (c)

Figure 7. (a) Surface view (b) Input membership function (c) Output membership function of fuzzy logic system to control EC

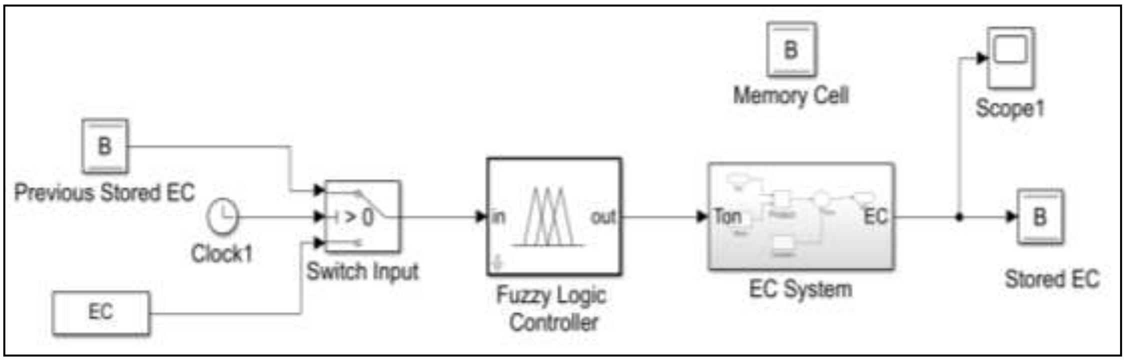


Figure 8. Simulation design of FLC to maintain EC in hydroponic system

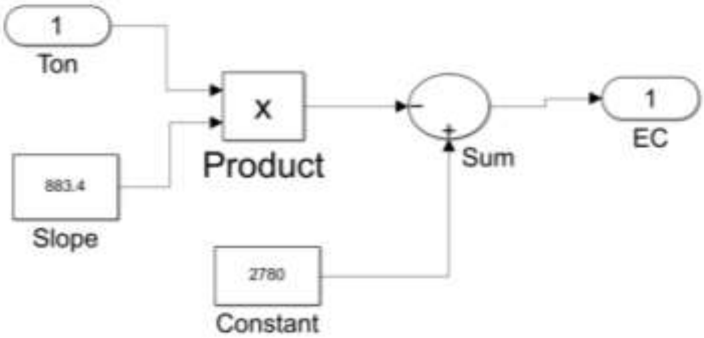


Figure 9. Simulation design of EC system block

Long Short Term Memory (LSTM)

In the proposed system DL based model LSTM was applied to design model predictive controller for controlling nutrients in hydroponic farm. Previous researches illustrates that DL model is more effective than ML models in interpreting meaningful outcomes and enabling high level abstraction from raw complex non-linear data (Chandel et al., 2022; Dubey et al., 2022; Ebrahimi et al., 2019; Sezer et al., 2020). The primary reasons for shifting from DL to ML model in current scenario are improvements in computational power, extracting input features automatically, greater performance, capacity to learn implicit features and a user-friendly model building platform (Sezer et al., 2020). LSTM is one of the most prominent DL model for the analyses of time series datasets in various fields (speech recognition, load forecasting, financial time series analysis, predicting environmental parameters, etc.). LSTM is an advanced version of RNN which solve vanishing /exploding gradient issue and uses internal memory cells to store and retrieve both short-term and long-term data. Hence weight updates, hyper-parameters and optimization algorithm of LSTM is similar to RNN (Hochreiter & Schmidhuber, 1997).

The current input and preceding output are simultaneously received by LSTM cell and information is processed through several gates present in cell. The sequenced data can be examined based on cell state because previous information is preserved as the cell state. The gate has three components: input, output and forget. The data selection process is controlled by the input gate and amount of data to be forgotten is determined by forget gate. The appropriate remaining previous data was store in cell state and passed by forget gate through a hyperbolic tangent function. The output gate combines current input data and cell state before sending it to next cell (Dubey et al., 2022). As soon as predefined time step is achieved, the final output of LSTM model is generated. In this study, LSTM model was trained with 80% of dataset, validated on 10% and tested with remaining 10% of dataset. The model was tuned with different hyper-parameters to obtained optimized result, which is shown in Table 2. The model was trained with 3 inputs, 1 output, Adam optimizer, hyperbolic tangent (tanh) as state activation function, sigmoid as gate activation function, 100 number of hidden units, 0.2 dropout factor, 100 epochs, 30 batch size, initial learning rate 0.02, bias learning rate factor 1 and mean square error (MSE) as loss function. LSTM model in proposed system comprises of six layers: input layer, lstm layer, dropout layer, regression layer and two fully connected layers. Equations 17 to 21 represents functions of input, output and forget gates of LSTM model (Hochreiter & Schmidhuber, 1997).

$$F_t=\sigma_s\left(A_F x_t+B_F y_{t-1}+U_F\right) \tag{17}$$

$$I_t=\sigma_s\left(A_I x_t+B_I y_{t-1}+U_I\right) \tag{18}$$

$$O_t=\sigma_s\left(A_O x_t+B_O y_{t-1}+U_O\right) \tag{19}$$

$$c_t=F_t*c_{t-1}+I_t*\sigma_k\left(A_c x_t+B_c y_{t-1}+U_c\right) \tag{20}$$

$$y_t=O_t*\sigma_y(c_t) \tag{21}$$

where F_t, I_t and O_t represents gate functions and U, c_t, y_t and x_t indicates bias, cell state, output and input vectors. A and B are weight matrix, σ_s is sigmoid function, * is element-wise product and σ_k and σ_y are hyperbolic tangent functions. LSTM was trained on MATLAB R2021a (MathWorks, Natick, USA) supported with Deep Learning Toolbox on a desktop computer (64 bits) running on Windows 10 operating system with an Intel Core I7 processor clocked at 2.60 GHz, RAM 16 GB, and GPU 6 GB of NVIDIA GeForce GTX 1660.

Design of Model Predictive Controller (MPC)

LSTM model was used to predict EC or pH of hydroponic system 1 hr ahead on the basis of current EC and pH level of nutrient solution. To achieve this objective LSTM was not only used to predict EC/pH, but also used to control EC/pH by adjusting T_{on} of pumps. The physical model of LSTM based MPC for hydroponic system was designed and tested in Simulink environment in MATLAB R2021a (Simulink©, Ver 2.0, The Mathworks Inc., Natick MA 01760-1500). The Stateful predict block was used in simulink design to applied trained LSTM network for predicting T_{on} of pH buffer solution pump (Figure 10 a). Initially testing dataset provides two inputs to LSTM: EC and error_pH (difference of measured pH and reference pH)

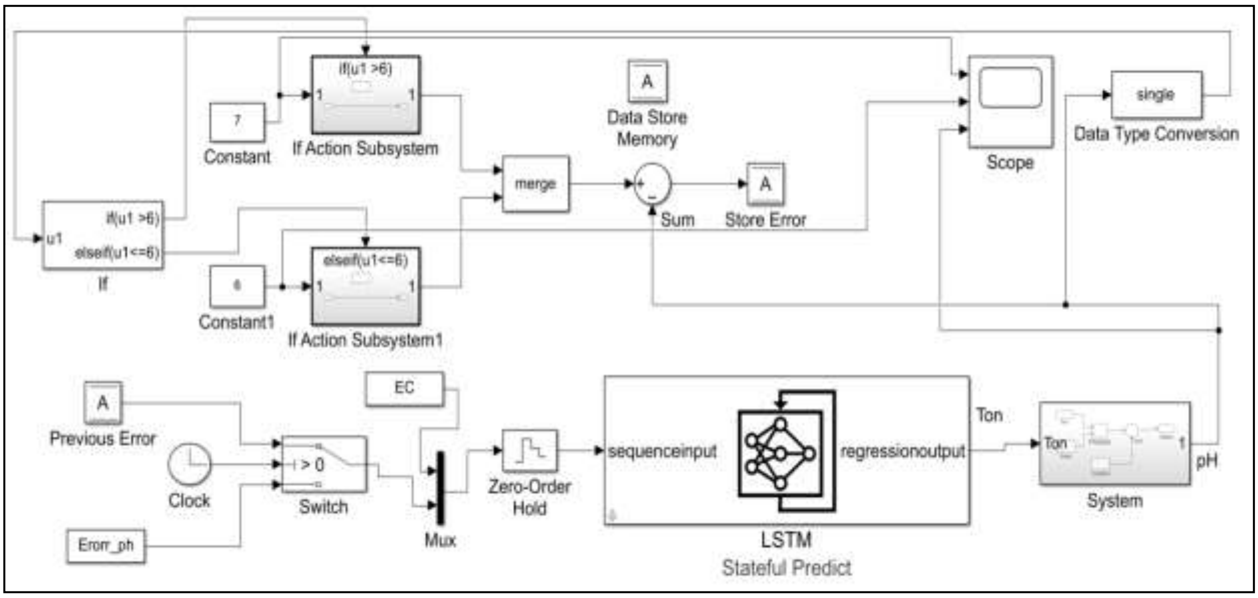
Table 2. Tuning parameters to train LSTM model for forecasting operating time of pumps to control EC and pH

Parameter	**Value**	**Parameter**	**Value**
Epoch	50, 100*	No. of hidden units	50, 100*

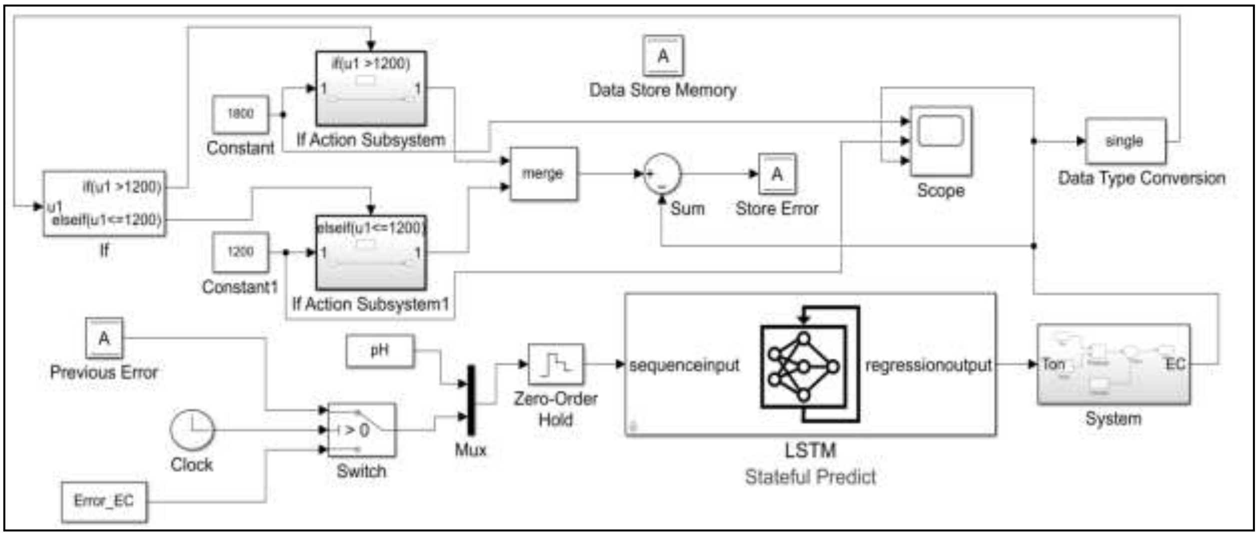
Batch size	10, 20, 30*	Optimizer	Adam*, Sgdm
Learning rate	0.01, 0.02*, 0.05	Dropout factor	0.1, 0.2*, 0.5

*Optimized hyper-parameters applied during training of LSTM

A timer switch was employed in the design which first time pass error_pH from testing dataset and on next duration from memory cell A. The output of switch forwarded to multiplexer block which add error_pH and EC. Further the multiplexer output send to zero order hold block to store the input for few seconds and passed it to LSTM block. The regression output predicted by LSTM was T_{on} of next time steps which was transmitted to hydroponic system which convert T_{on} to pH using mathematical model shown in Figure 6. The pH generated by hydroponic system was compared with reference pH after passing through data type conversion block and error stored in memory cell A, which further transmitted as next input to multiplexer through switch. Since optimal pH has range 6 to 7 for proper growth of lettuce and Chinese cabbage. Hence, if and else block was incorporated in design, when measured pH of hydroponic system was less than 7 then reference signal was set to 6 otherwise 7. The scope block was applied to visualize the behaviour of input and output signals of designed systems to control pH. Similar algorithm was applied to design EC controller, the difference between the two designs was that in EC controller error_EC and pH was considered as input and T_{on}_EC was the output and optimal range was 1200-1800μs/cm (Figure 10 b). Also, the hydroponic system uses mathematical model (Figure 9) which convert T_{on}_EC to EC. The performance of LSTM model to predict T_{on}_EC and T_{on}_pH



(a)



(b)

Figure10. Simulation design of Model Predictive Controller to maintain (a) pH (b) EC in hydroponic system

was evaluated by root mean square error (RMSE), mean average error (MAE) and sum of squared error (SSE) using Equations 22-24.

$$\text{MAE}=\frac{1}{N}\sum_{i=1}^{N}\left|y_i-\hat{y}\right| \quad (22)$$

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\hat{y}\right)^2} \quad (23)$$

$$\text{SSE}=\sum_{i=1}^{N}\left(y_i-\hat{y}\right)^2 \quad (24)$$

Result

The accuracy of trained DL model LSTM to predict on-off time of buffer or nutrient solution pump was estimated in terms of RMSE on validation dataset. The experiment was conducted for batch sizes of 10, 20, 30, and 40 at epochs 50 and 100. Table 3 lists the training and validation results obtained for various epoch and batch size combinations. The outcomes of experiment shows that as epochs increases RMSE decreases and performance of model improved. However the training and validation performance of model become stable under 100 epochs, hence there is no need to increase more epochs after 100. Also, up to 50 epochs model does not converged successfully, hence epochs increased up to 100. Similarly if increase the batch size up to 30 accuracy of model increases for both T_{on}_pH and T_{on}_EC prediction and beyond 30 batch size the error of model increases. The model achieved minimum training and validation RMSE at 100 epoch and 30 batch size of 0.19 and 0.23 s for T_{on}_pH and 0.22 and 0.25 s for T_{on}_EC, respectively. The training and validation plots of LSTM (Figure 11 and 12) indicates that initially there was a steep descend change occurred and RMSE was continuously up to 80 epoch, after that it become stable and model goes to converged successfully at 100 epoch. The training and validation RMSE are almost similar at 100 epoch and 30 batch size and no over-fitting or under-fitting take place. The performance of LSTM was similar for both T_{on}_pH and T_{on}_EC prediction. The minimum training and validation loss achieved by LSTM for T_{on}_pH forecasting was 0.03 s and for T_{on}_EC was 0.04 s.

Table 3. Training and validation performance of LSTM model at different epochs and batch sizes

Epochs	**Batch Size**	**T_{on}_pH (s)**		**T_{on}_EC (s)**	
		Training RMSE	**Validation RMSE**	**Training RMSE**	**Validation RMSE**
50	10	0.51	0.53	0.42	0.48
50	20	0.43	0.45	0.40	0.45
50	30	0.41	0.42	0.38	0.41
50	40	0.45	0.48	0.41	0.44
100	10	0.38	0.32	0.35	0.41
100	20	0.25	0.30	0.30	0.36
100	30	0.19	0.23	0.22	0.25
100	40	0.28	0.32	0.25	0.34

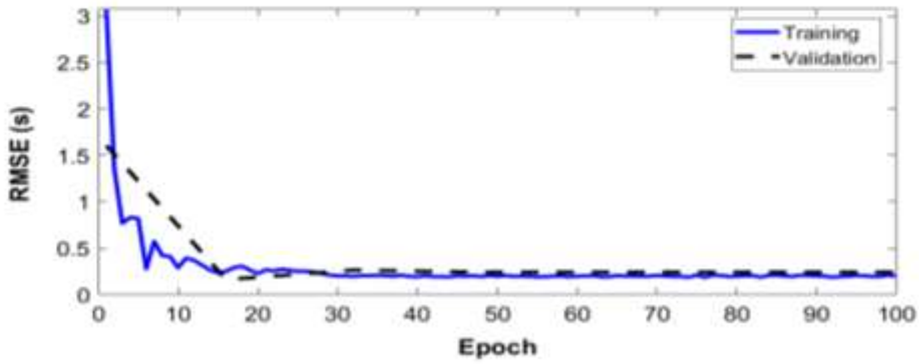


Figure 11. Training and validation performance of LSTM to predict T_{on}_pH of buffer solution pump

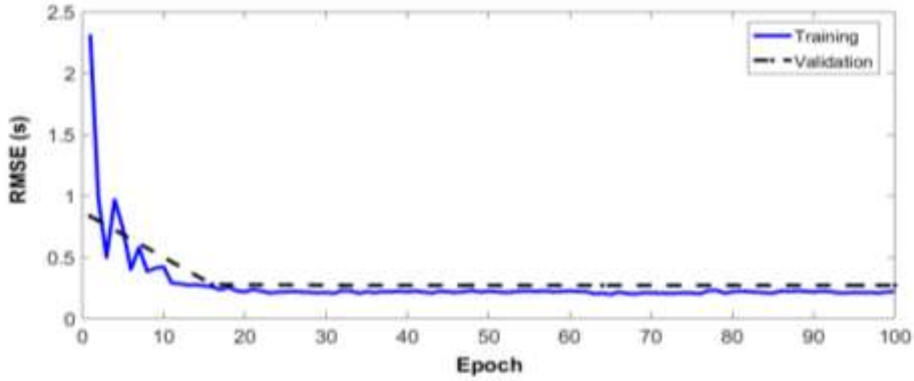


Figure 12. Training and validation performance of LSTM to predict T_{on}_EC of nutrient solution pump

It was inferred from Figure 13 and Figure 14 that DL model generalizes very well on the testing dataset and a minimum difference was observed between actual and predicted values. The average error was estimated by comparing actual and predicted T_{on}_pH or T_{on}_EC was 0.23 or 0.24 s. The overall performance of LSTM model was evaluated on testing dataset of NFT hydroponic system in real-time and found that model efficiently predicted T_{on}_pH or T_{on}_EC with low RMSE (0.24 s for T_{on}_pH and 0.27 s for T_{on}_EC) (Table 4). The output of LSTM model was used in MPC controller to adjust EC or pH of hydroponic system and the performance of MPC was compared with FLC. The MPC and FLC design was simulated in MATLAB simulink environment was analysed for 125 time steps on testing dataset.

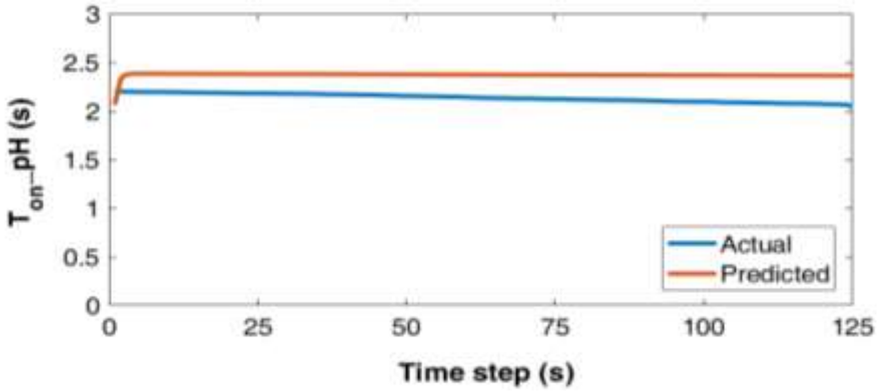


Figure 13. Actual and predicted operating time of buffer solution pump (T_{on}_pH) on testing dataset estimated by LSTM

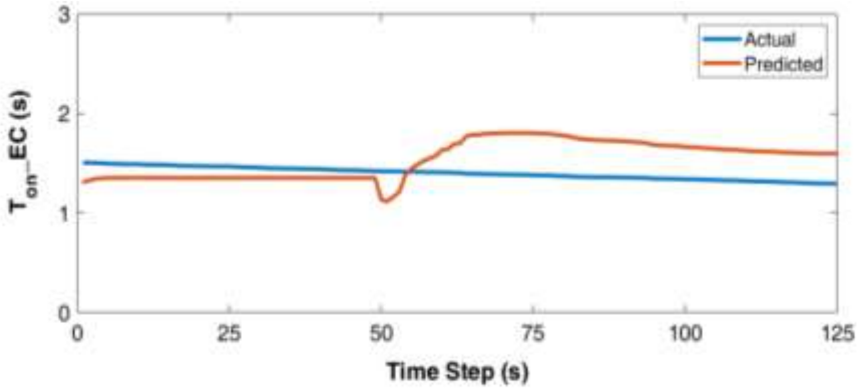


Figure 14. Actual and predicted operating time of nutrient solution pump (T_{on}_EC) on testing dataset estimated by LSTM

Table 4. Performance parameters of LSTM model to predict T_{on}_pH and T_{on}_EC on testing dataset

Parameter	**LSTM**	
	T_{on}_pH (s)	**T_{on}_EC (s)**
MAE	0.23	0.24
SSE	7.24	9.06
RMSE	0.24	0.27

It was inferred from experimental results that initially pH was 5.5 when selected from testing dataset, after that MPC adjust it and maintain pH between 6 and 7 throughout simulation period (Figure 15). However, FLC decrease pH from initial value to 3 and remain constant throughout the testing period. Similarly in EC controller design, initial EC was 1140 µs/cm and MPC adjust EC between 1200 and 1800 µs/cm, whereas FLC set EC below 1200 µs/cm (Figure 16). Thus FLC failed to maintain EC and pH in desired range, while MPC efficiently and robustly maintain them in optimal range. In FLC under-fitting occurred for pH and EC, however MPC converged successfully without any under-fitting or over-fitting.

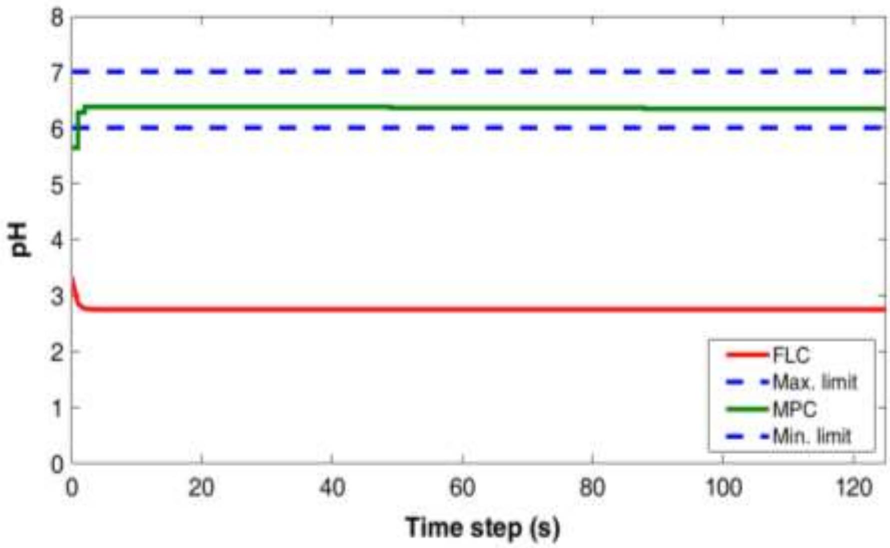


Figure 15. Simulation results of FLC and MPC controller to regulate pH in hydroponic system

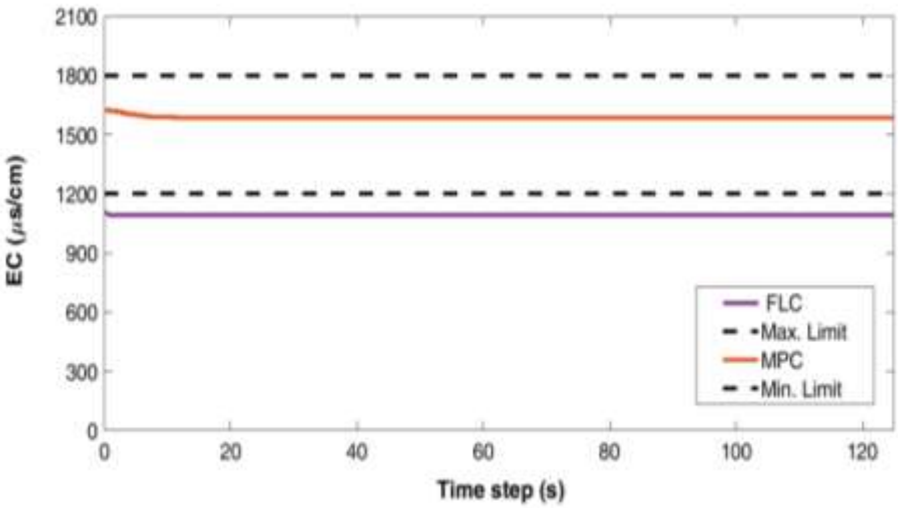


Figure 16. Simulation results of FLC and MPC controller to regulate EC in hydroponic system

Furthermore, MPC outperformed FLC (136.55 s and 61.04 s) in predicting T_{on}_pH and T_{on}_EC, with SSE of 7.24 and 9.06 s, respectively (Table 5). As compared to FLC, the overall performance enhanced by MPC was 61% for EC regulation and 77% for pH regulation.

Table 5. Performance of MPC and FLC to estimate operating time of pumps

Parameter	T_{on}_pH (s)		T_{on}_EC (s)	
	MPC	**FLC**	**MPC**	**FLC**
MAE	0.23	1.04	0.24	0.67
SSE	7.24	136.55	9.06	61.04
RMSE	0.24	1.04	0.27	0.69

Discussion

AI based DL models provides an opportunity to gathered, analyze, process and extract significant information robustly and competently in any field/stream. This significant data can be used to control or automate the physical system. In the proposed work, the same approach was applied, and it was concluded that the DL model can be effectively employed for nutrient management in NFT-based hydroponic system. Currently, FL, linear regression and NN were applied in hydroponic system for predicting nutrient concentration or T_{on} of actuators to control nutrient requirement. The linear regression can forecast the nutritional requirement of hydroponic crop with an RMSE of 51.47 ml on the basis of three inputs pH, level of solution and dissolved nutrient concentration in solution (Harsapranata et al., 2022). FL predicted T_{on} of the pumps for adjusting the pH and TDS level in the solution used in the hydroponic farm with an RMSE of 2.57 or 1.87 s for pH up or down and 2.1 or 37.2 s for TDS up or down, respectively. However, ANFIS outperforms the conventional technique FL and increases pH and TDS overall prediction accuracy by 67% (Vincentdo & Surantha, 2023). The automatic AI based controlling system helps farmers in managing nutrients for hydroponic crop easily and appropriately. An IoT-based NFT hydroponic system was designed and implemented using a predictive controller based on a bayesian network that engender output decisions (on-off) for actuators (pumps or solenoid valves) depending on sensor's input. In comparison to manual control, the bayesian network increased crop yield by 66.67% and had a prediction accuracy of 84.53% and RMSE of 0.32 on the testing dataset (Alipio et al., 2019).

However, all these ML based approaches required proper technical knowledge for selection of input features in NN, deciding threshold values for on-off controller in bayesian network, selecting MF in FL. Also, these algorithms depend only on current inputs and produce outputs accordingly. While DL model LSTM automatically detects attributes from input training dataset and generates result on the basis of current data and previous history. It store both short-term and long-term memory and applied them with present inputs to make future predictions at different time steps. Due to these peculiarities, LSTM has recently been applied in smart farming. Since crop growth stages and environmental conditions continuously vary the nutrients level in a solution, it is very challenging to estimate EC and pH with high degree of accuracy. DL based model LSTM has been successfully applied in soilless culture to estimate the ion concentration of nutrient solution 1 h ahead with an RMSE of 1.48 meq L^{-1} (Moon et al., 2019). LSTM was also employed in a hydroponic system to forecast the EC of root-zone nutrient solutions in soilless cultures, and the testing prediction accuracy achieved was 72% (Moon et al., 2018).

In this study LSTM was not only used to make prediction but also helps in controlling the EC and pH of hydroponic solution. The proposed LSTM based MPC design achieved better accuracy (RMSE=0.24s for T_{on}_pH and 0.27s for T_{on}_EC) than conventional FLC to maintain nutrients of solution at appropriate level for hydroponic crop lettuce and Chinese cabbage. The performance of MPC was significantly better than FLC because LSTM efficiently extract large amount of information/features from time-series data and utilize them to make proper decisions. A FL would become overloaded and render computation inefficient and complex if it attempts to use the same amount of input data as an LSTM. Additionally, LSTM can forecast outcomes several hours ahead and giving pumps sufficient time to adjust the solution's EC and pH levels, while FL lacks this property. The proposed design can also be applied to other crops using relatively training dataset of that crop with the help of transfer learning approach. It can enable systematic management of nutrient solutions in hydroponic farms, while minimizing resource waste and manpower.

Conclusion

Agriculture is currently advancing more in the direction of hydroponics and aeroponics, which enable plants to grow anywhere indoor or outdoor in less space, without the need of soil. In soilless cultivation, it is difficult to manually monitor the EC and pH level in nutrient solution and maintain it at the optimum value according to crop requirements. This study proposes a deep learning based MPC design to predict pumps T_{on} and control EC and pH of solution used in hydroponic system. The time-series data used to train DL model LSTM was accumulated by sensors and Arduino 33 IoT controller in real-time from NFT based hydroponic system. The experiment was designed and simulated to control EC and pH for hydroponic crop lettuce and Chinese cabbage. In previous researches FLC was commonly used to control nutrients of hydroponic farm; however the effectiveness of these controllers depends on the selection of input and output MFs. This study also presents a comparative analysis of MPC and FLC in regulating the nutrients level. Both controllers were designed and tested in simulink environment in MATLAB software and results illustrate that MPC perform better than FLC to maintain EC and pH between desired range. Additionally, MPC achieved minimum MAE (0.23s for T_{on}_pH and 0.24s for T_{on}_EC) for prediction as compared to FLC. The proposed design can also be used for regulating nutrients of other hydroponic crops. Thus, DL based MPC was found to be a powerful, effective and flexible approach to estimate and control nutrients for optimal growth of hydroponic crops.

Declarations

Conflict of Interest - There is no conflict of interest among authors associated with this study.

Funding - No fund has been received for this study; it is self-funded by the authors.

Availability of data and code - The data and code can be shared on request.

References

Alipio, M. I., Cruz, A. E. M. D., Doria, J. D. A., & Fruto, R. M. S. (2019). On the design of Nutrient Film Technique hydroponics farm for smart agriculture. *Engineering in Agriculture, Environment and Food*, *12*(3), 315–324.

Bacalla, A. C., & Vinluan, A. A. (2019). Hydroponics farm monitoring using data fusion and fuzzy logic algorithm. *Journal of Advanced Agricultural Technologies Vol*, *6*(2).

Chandel, N. S., Chakraborty, S. K., Rajwade, Y. A., Dubey, K., Tiwari, M. K., & Jat, D. (2021). Identifying crop water stress using deep learning models. *Neural Computing and Applications*, *33*, 5353–5367.

Chandel, N. S., Rajwade, Y. A., Dubey, K., Chandel, A. K., Subeesh, A., & Tiwari, M. K. (2022). Water Stress Identification of Winter Wheat Crop with State-of-the-Art AI Techniques and High-Resolution Thermal-RGB Imagery. *Plants*, *11*(23), 3344.

Chang, C.-L., Hong, G.-F., & Fu, W.-L. (2018). Design and implementation of a knowledge-based nutrient solution irrigation system for hydroponic applications. *Transactions of the ASABE*, *61*(2), 369–379.

Chen, C.-H., Jeng, S.-Y., & Lin, C.-J. (2022). Fuzzy logic controller for automating electrical conductivity and pH in hydroponic cultivation. *Applied Sciences*, *12*(1), 405.

Dubey, K., Jain, Y. K., & Sharma, V. (2022). A Comparative Study of Deep Learning based MODWT-LSTM and Machine Learning Model to Predict Environmental Parameters of Polyhouse. *In Proceedings of the 2022 IEEE International Conference on Current Development in Engineering and Technology (CCET)*, 1–8.

Ebrahimi, M., Mohammadi-Dehcheshmeh, M., Ebrahimie, E., & Petrovski, K. R. (2019). Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: Deep Learning and Gradient-Boosted Trees outperform other models. *Computers in Biology and Medicine*, *114*, 103456.

Escorcia-Gutierrez, J., Gamarra, M., Soto-Diaz, R., Pérez, M., Madera, N., & Mansour, R. F. (2022). Intelligent agricultural modelling of soil nutrients and ph classification using ensemble deep learning techniques. *Agriculture*, *12*(7), 977.

Fakhrurroja, H., Mardhotillah, S. A., Mahendra, O., Munandar, A., Rizqyawan, M. I., & Pratama, R. P. (2019). Automatic ph and humidity control system for hydroponics using fuzzy logic. *In Proceedings of the 2019 International Conference on Computer, Control, Informatics and Its Applications (IC3INA)*, 156–161.

Filho, A. F. M., de Azevedo, C. A. V., de Queiroz Almeida Azevedo, M. R., Fernandes, J. D., da Silva, C. R., & Fernandes, P. D. (2018). Monitoring, calibration and maintenance of optimized nutrient solutions in curly lettuce (Lactuca sativa, L.) hydroponic cultivation. *Australian Journal of Crop Science*, *12*(4), 572–582.

Fuangthong, M., & Pramokchon, P. (2018). Automatic control of electrical conductivity and PH using fuzzy logic for hydroponics system. *In Proceedings of the 2018 International Conference on Digital Arts, Media and Technology (ICDAMT)*, 65–70.

Harsapranata, A. I., Manongga, D., & Wijono, S. (2022). Liner Regression Analysis In Forecasting Hydroponic Plant Nutrient Needs. *INFOKUM*, *10*(5), 222–226.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780.

Jin, X., Chen, K., Zhao, Y., Ji, J., & Jing, P. (2020). Simulation of hydraulic transplanting robot control system based on fuzzy PID controller. *Measurement*, *164*, 108023.

Jomaa, M., Abbes, M., Tadeo, F., & Mami, A. (2019). Greenhouse modeling, validation and climate control based on fuzzy logic. *Engineering, Technology & Applied Science Research*, *9*(4), 4405–4410.

Kinkar, C. R., & Jain, Y. K. (2021). Low Latency Based Convolutional Recurrent Neural Network Model for Speech Command Recognition. *Information Technology and Control*, *50*(4), 656–673.

Krishnan, R. S., Julie, E. G., Robinson, Y. H., Raja, S., Kumar, R., & Thong, P. H. (2020). Fuzzy logic based smart irrigation system using internet of things. *Journal of Cleaner Production*, *252*, 119902.

Mohanraj, G., Luhach, A. K., & Kumar, S. (2023). Epidemic prediction using machine learning and deep learning models on COVID-19 data. *Journal of Experimental & Theoretical Artificial Intelligence*, *35*(3), 377–393.

Moon, T., Ahn, T. I., & Son, J. E. (2018). Forecasting root-zone electrical conductivity of nutrient solutions in closed-loop soilless cultures via a recurrent neural network using environmental and cultivation information. *Frontiers in Plant Science*, *9*, 859.

Moon, T., Ahn, T. I., & Son, J. E. (2019). Long short-term memory for a model-free estimation of macronutrient ion concentrations of root-zone in closed-loop soilless cultures. *Plant Methods*, *15*(1), 1–12.

Puno, J. C. V., Haban, J. J. I., Alejandrino, J. D., Bandala, A. A., & Dadios, E. P. (2020). Design of a nutrient film technique hydroponics system with fuzzy logic control. *In Proceedings of the 2020 IEEE Region 10 Conference (TENCON)*, 403–408.

Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing*, *90*, 106181.

Singh, H., & Dunn, B. (2016). *Electrical conductivity and pH guide for hydroponics* [Technical Report]. Oklahoma Cooperative Extension Service.

Ubah, J., Orakwe, L., Ogbu, K., Awu, J., Ahaneku, I., & Chukwuma, E. (2021). Forecasting water quality parameters using artificial neural network for irrigation purposes. *Scientific Reports*, *11*(1), 24438.

Verma, M. S., & Gawade, S. D. (2021). A machine learning approach for prediction system and analysis of nutrients uptake for better crop growth in the Hydroponics system. *In Proceedings of the 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, 150–156.

Vincentdo, V., & Surantha, N. (2023). Nutrient Film Technique-Based Hydroponic Monitoring and Controlling System Using ANFIS. *Electronics*, *12*(6), 1446.

Zheng, K., Zhang, Q., Hu, Y., & Wu, B. (2021). Design of fuzzy system-fuzzy neural network-backstepping control for complex robot system. *Information Sciences*, *546*, 1230–1255.