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Review

Wireless sensor networks for greenhouses: An end-to-end review

Aarti Kochhar[a,b,*], Naresh Kumar[a,*]

[a] University Institute of Engineering and Technology, Panjab University, Chandigarh, India
[b] Lovely Professional University, Phagwara, India

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ABSTRACT

Integration of Wireless Sensor Networks (WSN) in the field of agriculture has provided a new direction for the production of crops. The same can be applied particularly to greenhouses. Greenhouses provide a protected environment for plants and crops. This paper reviews the role of WSN in monitoring of greenhouses. The paper presents an end-to-end survey; starting from the layout of crops in greenhouses, wireless technology used for communication of sensors, techniques to choose transmission interval or rate. Layouts and sampling techniques are also classified and compared. Other than these, the paper also studies various prediction models and decision supporting techniques adopted in greenhouses for efficient integration and management of WSN. These prediction models are also comprehensively analyzed in this work.

1. Introduction

Modern day scenario of agriculture has changed. Over the years, population has increased. According to UN's world population prospect 2017 report, population is estimated to reach 9.8 billion by 2050 (United Nations, 2017). Along with population, demand for food is also multiplying. According to Food and Agriculture Organization of the United Nations (FAO), although there are 30,000 types of edible plants available, humans cultivate only 4% of it (FAO, 1999). The agricultural land has considerably reduced due to various factors like urbanization and industrialization. To cope up with these situations, modern-day technological solutions are required. Other than this, water scarcity, increase in fertilization and dynamic climate changes have also strained to integrate technology to achieve required production in agriculture with minimum wastage of resources. WSN is one prominent technology that has developed over past few years and has found its path in many applications like military, defense, healthcare, agriculture, etc. In agriculture, WSN is particularly used to achieve a state called Precision Agriculture (PA). PA works on the phenomenon of observing (using sensors) and responding (using actuators) and tries to achieve parametric values and conditions required for optimum health and yield of crop. PA also focuses on optimizing resources used for production. Fig. 1 shows the complete process of monitoring and control in a field. Sensors are placed at required stations in suitable and optimal deployment. Sensed information is sent to central repository through available wireless channel. After analyzing the information, either that information is utilized for futuristic improvements or appropriate control action is commanded.

Greenhouse or Polyhouse is an agricultural innovation to provide a regulated and controlled environment to crops. Greenhouse forms a closed loop in itself and crops are shielded from outside environment. It forms a protected environment for cultivation and has great importance in the era of changing climatic conditions. So greenhouse is an example of precision agriculture. Greenhouses work on the concept of the greenhouse effect. Sunlight comes inside greenhouse through transparent roof and walls. Due to closed structure, heat is not able to escape and trapped inside greenhouse. Modern-day greenhouses are equipped with artificial systems to provide ventilation, light, heat, etc. A modern greenhouse may have exhaust fans, sprinklers or cellulose cooling pads. It may have provision for artificial lighting. Majority of energy in greenhouse is consumed by heating and ventilation systems (Khoshnevisan et al., 2013). WSN can help in controlling these equipment and provide an optimized environment to crops.

1.1. Motivation

When keyword 'WSN' was searched on Google scholar, about 345,000 results were found. Till 2010, 57,200 results were found and after 2010, 78,600 results were found. After 2015, only 33,200 related works were found. On searching keyword 'greenhouse', a total of 2,330,000 results appeared. Before 2010, it was 1320000, after 2010 it was 110000, after 2015 it was 246000. If we combine both keywords, total results appeared were only 7120. Till 2010, only 1190 results appeared and after 2010, 6190 results were found. After 2015, only

* Correspoding authors.
E-mail addresses: aarti.21661@lpu.co.in (A. Kochhar), naresh_uiet@pu.ac.in (N. Kumar).

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Fig. 1. Complete process of monitoring and control.

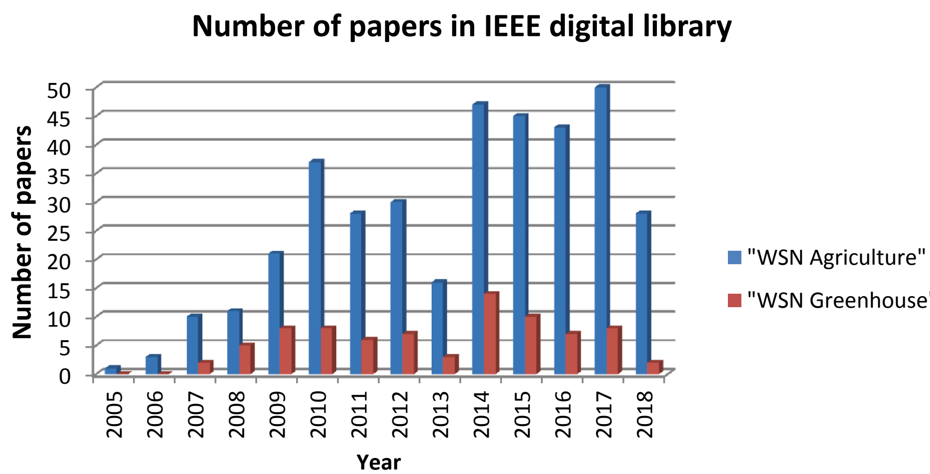

Fig. 2. Number of papers published in IEEE.

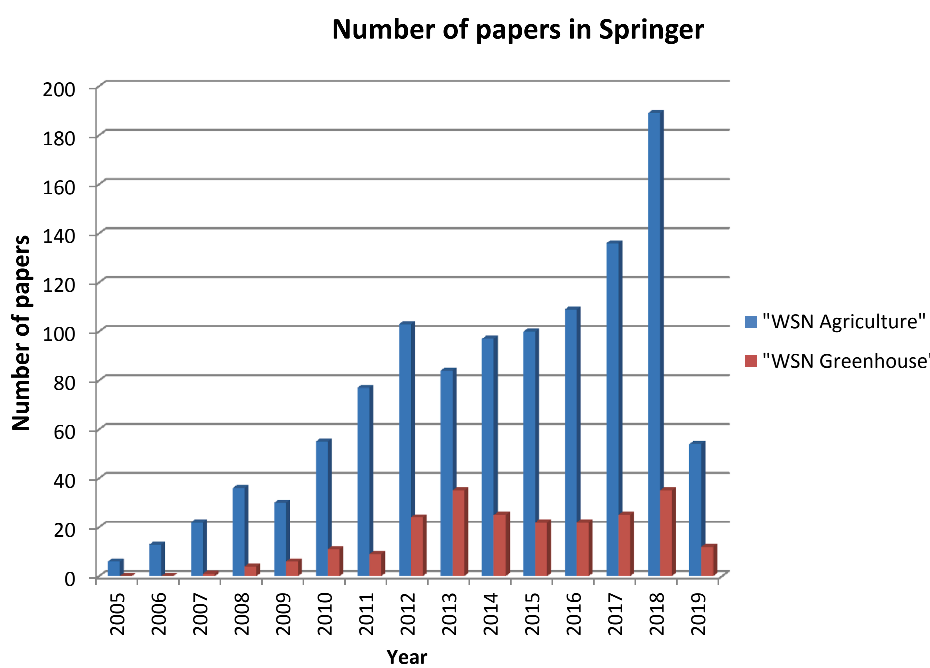

Fig. 3. Number of papers published in Springer.

2390 results were found. Searching individually on the IEEE digital library, keyword 'WSN' gave about 17,700 results; keyword 'greenhouse' gave about 3800 results. Shockingly, on searching both keywords together, only 80 results appeared. Out of these 80, 79 were conference papers. Authors feel that WSN has the potential to bring a green revolution like scenario in greenhouse culture. However, the research in the area is very limited. As shown in Figs. 2–4, as compared to WSN driven agricultural research, papers on greenhouse facilitated by WSN technology are very limited. The research for application of WSN in a greenhouse has picked up momentum in past 10 years but still has a wide scope. Data presented for 2018 is not complete. Only available papers at the time of writing this paper are considered. Papers for 2019 are early access papers.

1.2. Contribution

In this paper, we surveyed the application of WSN in greenhouses. This survey provides an end-to-end review. So this review can assist novice researchers in the field. The paper can be referred at every stage of deployment and implementation of a wireless sensor network in a greenhouse. The paper provides help at very first stage i.e. nodes placement or layout. Section 2 discusses layout techniques of sensors in a greenhouse. This review can also help in reducing data effectively by choosing appropriate sampling techniques. Since the paper focuses on sampling techniques implemented in greenhouses, so certain advantage of experience can be taken. After choosing transmission interval on the basis of sampling technique at second stage, data needs to be

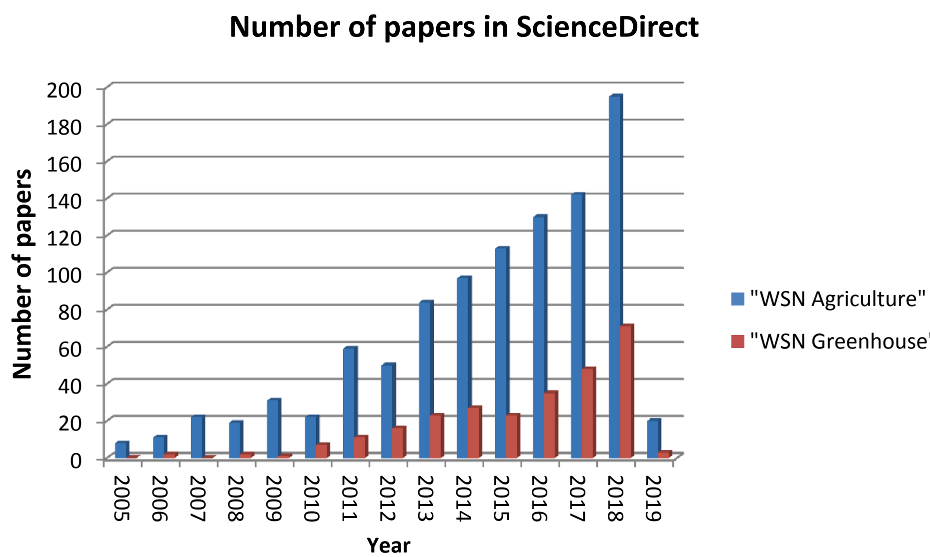

Fig. 4. Number of papers published in ScienceDirect.

transmitted at third stage using communication technologies. Section 3 discusses data sampling techniques and Section 4 discusses various communication technologies adopted for sensor communication particularly in greenhouses. The review also lends a helping hand at the last stage of analysis and decision making. Section 5 discusses the significance of prediction models and popular prediction models for a greenhouse environment. Section 6 presents various techniques implemented for support of decision making. This paper also classifies layouts and sampling techniques implemented in greenhouses.

2. Layouts

Layout means the way in which something is arranged. Layout should not be confused with topology. Topology refers to placement of nodes to represent direction of flow of information while layout is physical placement of nodes. Layout is also referred to as physical topology sometimes. Sensor layout is an important fact which must be paid appropriate attention. Greenhouse is a very dynamic environment where parameters change spatially as well as temporally. Crops will grow over time and will eventually affect performance of sensors. A large greenhouse will have particularly many microclimatic zones within itself. It may have heterogeneous zones where parameters and overall environment differ from the surrounding zones within a single greenhouse. These microclimates exist both horizontally as well as vertically in a greenhouse. Monitoring of these parameters requires non-uniform deployment of sensors. Irrigation and fertilization patterns can also help in deciding location of sensors. In this paper, layout of sensors in a greenhouse has been categorized broadly as horizontal layout and vertical layout. Many authors working in the field of monitoring and control of greenhouse have proposed few other layout concepts also which have been covered in third subsection of this section.

2.1. Horizontal layout

Conventional systems have either random or grid layout of sensors in greenhouse. Mancuso and Bustaffa (2006) proposed to place the 6 nodes in rows and columns crossing each other to form a grid. The grid covered an area of 20 by 50 m of tomato greenhouse. Bridge node was placed along the longer edge of greenhouse in the middle. Similar setup can be sited to cover a larger greenhouse like 30 by 30 length units using 900 sensors placed on all the junctions (Ferentinos and Tsiligiridis, 2007). Shah et al. (2009) used the same layout to monitor a small okra greenhouse of 6 by 9 m. In another scenario, rather than placing sensor nodes in grid layout, authors propose to divide the geographic area of field in grids and site 2–3 nodes in each grid. Nodes on the edge of grid are shared with neighboring grid. Base station is positioned on one edge of greenhouse (Quynh et al., 2015). Nodes within grid provide more flexibility and better free space coverage than layout with nodes on junctions of grid. Another variant of grid are tessellations (Caicedo-Ortiz et al., 2018). Grids are normally visualized as repeated patterns of squares or rectangles. Tessellations are tiles formed by regular polygons. These polygons can be triangles, squares, hexagons, etc. Tessellations inherit the simplicity of grids and have an additional advantage of covering free spaces. It avoids overlapping and maintains uniformity in communication. For example, nodes placed on edges of such tessellations are equidistant (Poe and Schmitt, 2009). Authors further enhance the concept by introducing layers of tessellations. Fig. 5 shows examples of tessellations and Fig. 6 represents layers of tessellations. Nodes in different layers are represented with different notations. Layers surround the central point of tessellation.

Relation between number of nodes (N) and number of layers (C) is given in Eq. (1).

$$N = (2\,C + 1)^2 \tag{1}$$

Song et al. (2011) modify the grid layout to increase the network lifetime. Within grid, hierarchal cluster topology is presented. Parent nodes are proposed to have redundant nodes to improve the network lifetime over uniform positioning. The algorithm is called as Redundant Node Deployment Algorithm (RNDA). RNDA utilizes the concept of load balancing to increase network lifetime. With few numbers of redundant nodes, network lifetime can be prolonged for thousands of rounds. Other than grid, random layout is also simple. While grid is the most commonly used layout, Raheemah et al. (2016) preferred to deploy directional antennas to construct a row-only layout. Transmitter was placed in front of each row to develop a path loss model in mango greenhouse.

Although greenhouse is a closed loop control system in itself, it can't be assumed to be completely independent of outside climatic conditions. Sometimes there is a requirement of monitoring outside environment of greenhouse along with the inside environment. So during layout stage, appropriate sensors should be placed outside the greenhouse to measure outside environmental parameters like temperature, humidity, rain, etc. Outside sensors can form their own topology isolated from inside sensor nodes or if sensors need to communicate, it should be in range. Dan et al. (2015) divided the 200 nodes in type 'A'

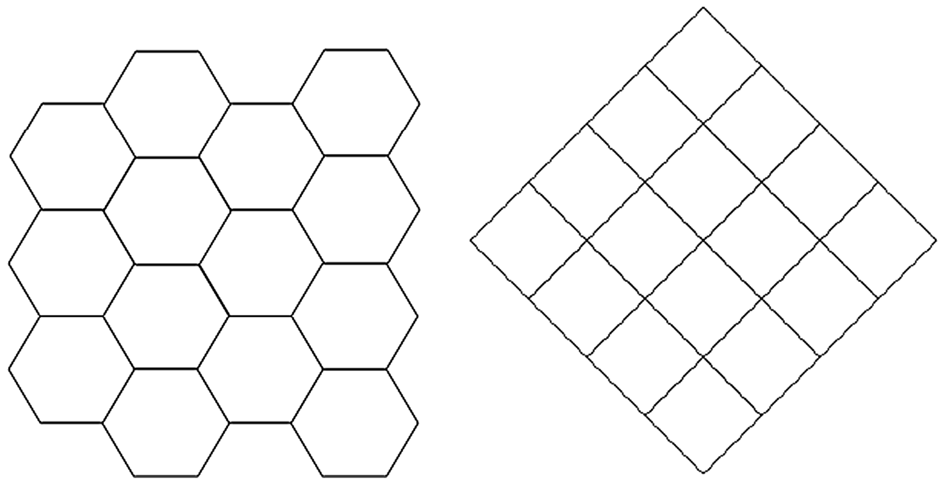

Fig. 5. Tessellations.

and type 'B'. Type 'A' are sensor nodes for outside climate monitoring and type 'B' are sensors for inside climate monitoring. Many other authors also preferred a weather station outside the greenhouse for the accuracy of measurements (Azaza et al., 2016; Pahuja et al., 2013; López-Martínez et al., 2018). Layout can also be decided on the basis of microclimatic properties. 24 sensors, 2 gateways and 48 wireless cameras were positioned in four regions in a *Phalaenopsis* orchid greenhouse to find dependence of growth of leaves on various parameters. These four regions were: well-ventilated region, hot and less humid region, a sultry region and a humid region (Liao et al., 2017). Although in this work authors placed the sensors and wireless cameras uniformly but heterogeneity and dynamics of the region can be considered as a factor while deciding number of nodes in each region. Along with static sensors, mobile sensors can also be deployed to have a reliable greenhouse monitoring system. 120 nodes and 4 gateways were placed in an orchid greenhouse for monitoring purpose. Out of these 120, 52 nodes were fixed and remaining 68 were moving at the pace of 0.15 m/s. Topology was formed every 30 min using Dynamic Convergecast Tree Algorithm (DCTA). Longest measured distance between nodes was 75.6 m (Jiang et al., 2016). Potential of mobile nodes for monitoring of greenhouses is still an almost unexplored area.

All the above-discussed literature considered a single network but few authors tried to investigate the concept of multiple networks or multiple topologies for the monitoring of single greenhouse. These networks can be totally isolated, have little interdependence or total interdependence. In a tomato greenhouse, sensors were deployed uniformly in cluster tree topology while routing nodes formed a triangular lattice grid. Sensor network and routing nodes' network had total interdependence (Yang et al., 2015). Different network can also be formed for separate type of sensors. Riquelme et al. (2009) proposed to deploy separate network of soil sensor nodes and environmental sensor nodes. To monitor quality of water used for irrigation, another isolated network was deployed. Although the deployed field was not a greenhouse, idea of individual isolated networks for soil sensors and environmental sensors can provide new paradigm to greenhouse monitoring.

The horizontal layouts are summarized in Table 1. For deployment of sensor in a layout, along with number of sensors, crop and measured parameter is an important factor. Although grid topology seems to be simple to be deployed, it may be over the edge deployment and wastage of nodes sometimes in greenhouse environment. Overlap is a serious issue in square grid layout. Secondly, few environmental parameters do not change within few meters in a greenhouse. So for measurement of parameters like temperature, humidity and illumination, grid layout does not work optimally. For parameters where range of variability of parameter is within few meters like soil temperature, soil moisture, soil

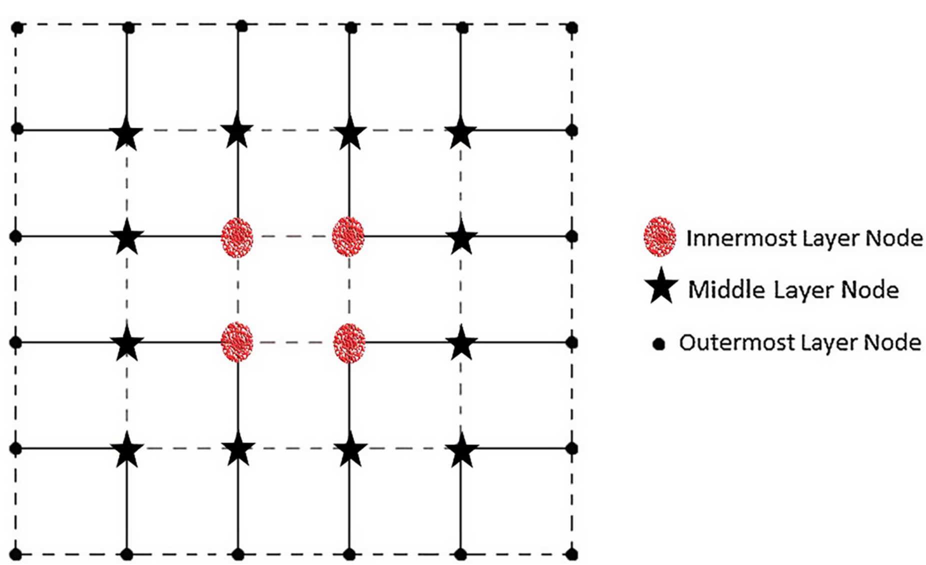

Fig. 6. Layers of tessellations.

Table 1
Horizontal layout.

Layout	Reference	Crop	Number of Nodes	Area	Measured Parameters
Grid	Mancuso and Bustaffa (2006)	Tomato	7 (including one gateway)	20 m × 50 m	Air Temperature, Humidity and Soil temperature
Inside and outside	Dan et al. (2015)		200	35 m × 200 m	Temperature, Humidity, CO_2 concentration and Illumination
	Azaza et al. (2016)	Basil		374 m × 211 m × 195 m	Temperature, Humidity, CO_2 concentration and Illumination
	Pahuja et al. (2013)	Chilli	7	30 m × 48 m	Temperature, Humidity, VPD
Tessellations	Caicedo-Ortiz et al. (2018)	Cassava	Depending on number of layers	10026 m^2	Temperature and Soil Moisture
Divided in regions	Liao et al. (2017)	Orchid	24 nodes and 2 gateways	130 cm × 140 cm × 150 cm	Temperature, Humidity and Illumination
Rows only	Raheemah et al. (2016)	Mango	273 (7 on each tree, 3 lanes of 13 trees in each row)	50 m × 10 m x5m	
Fixed and moving nodes	Jiang et al. (2016)	Orchid	120 (52 fixed, 68 moving)	72 m × 36 m × 10 m	Temperature, Humidity, Illumination and Soil Moisture, Chlorophyll content
Separate topology for sensors and routers	Yang et al. (2015)	Tomato	30 (20 sensors, 9 routers, 1 gateway)	50 m × 50 m	Temperature, Humidity, Sap flow, Stem diameter, leaf thickness, leaf wetness

pH, etc., grid layout is suitable but requires more number of sensors and hence costs more. For example if in a certain field, range of variability of soil moisture is 15 m then distance among nodes should be less than 15 m for efficient monitoring. Tessellations are still an unexplored area. By optimizing number of layers, node's density can be optimized. Including the idea of outside sensors can help in considering the ignored factors of outside environment also. Analysis of outside parameters like illumination and wind speed can add an additional perspective to the monitoring of greenhouses. For crops grown inside greenhouse, VPD (Vapor Pressure Deficit) is more enlightening parameter than relative humidity. VPD represents the difference between actual moisture level in air and moisture level at full saturation. As the difference between two increases, VPD increases. So, crops try to draw more water from roots and rate of transpiration increases. If VPD is less, water condenses out of air on crop leaves. Thus VPD provides assistance for disease forecast. For analysis purpose like in an application where a control group needs to be compared with experiment group, field divided in region fits best. The concept of moving nodes seem very attractive but it comes with the constraints of movement path without hindrance of crop environment. Greenhouses spread over hectares, moving nodes can provide an additional aid in monitoring. For parameters having short range of variability, moving node can be put into practice to avoid the cost of dense network. For touch based sensors like chlorophyll content meter, a robotic moving node can ease the monitoring process. Isolation of topology of sensors and routers prolongs the network lifetime and manages the risk. Triangular lattice topology used for routing nodes helped in reducing overlapping. Isolation of network for sensitive sensors like CO_2 concentration sensor with compatibility issues can also help in prolonging the lifetime. In case of supplemental light sources, sensors should be rightly positioned to capture the true value of illumination or irradiance reaching crop.

2.2. Vertical layout

As the name suggests, sensors are not deployed at ground level in vertical layout system. Since all the crops grow in vertical direction either upwards or downwards, vertical layout has a special significance for greenhouse climate control. Growth and foliage of crop greatly affect the communication range of sensor (Yang et al., 2015), so vertical layout seems to be one of the prominent solutions. This survey classifies all the variants of vertical layouts in a typical greenhouse. In the starting years of sensor era, when sensors were quite expensive, greenhouses used to have a single sensor node on the roof in the centre. As predicted by Moore's law, level of integration increased and helped in cut down on prices. This enabled the deployment of multiple sensors to increase the accuracy and reliability of monitoring system. Few proposed to have all sensor nodes at single height (Akkaş and Sokullu, 2017; Lixuan et al., 2014) while other authors suggested placing sensors at separate height levels (Ahonen et al., 2008; Raheemah et al., 2016; Pahuja et al., 2013) (Harris et al., 2016; Srbinovska et al., 2015; Zou et al., 2017). Pahuja et al. (2013) used the model to monitor parameters at canopy level and above canopy level of crop while Harris et al. (2016) utilized it for calibration purpose. In another variant of vertical layout, sensors were positioned on ground and only coordinators were placed at raised level or in center in case of single coordinator (Mancuso and Bustaffa, 2006; Sabri et al., 2011).

To monitor soil parameters, sensors may need to be placed vertically downwards i.e. underground (Rishi and Kumar, 2013). Yu et al. (2011) proposed to place only antennas at separate heights to increase communication range whereas sensors are on ground level. Communication distance increases with an increase in antenna height but only till 1 m because after that height, tomato tree does not interfere. So the height levels of sensors depend upon height of crop. Vertical layout can support in acquiring growth related parameters of crop like NDVI (Normalized Difference Vegetation Index). NDVI depends upon spectral data of crop canopy reflectance. Mathematically, NDVI can be represented as

Table 2
Vertical Layout.

Layout	Reference	Crop	Number of height zones	Height levels	Number of nodes	Measured Parameter	Focused Area
Sensors at separate heights	Ahonen et al. (2008)	Tomato	4	120 cm, 176 cm, 295 cm, 310 cm	4	Temperature, Humidity, CO_2 concentration and irradiance	Microclimate Monitoring
	Raheemah et al. (2016)	Mango	7	0.5 m, 1 m, 1.5 m, 2 m, 2.5 m, 3 m, 3.5 m	7 on each tree		Estimating path loss model
	Pahuja et al. (2013)	Chilli	2	Above canopy (1.5 m) and below canopy		Temperature, Humidity, VPD	Microclimate Monitoring
	Harris et al. (2016)		7		2 set of sensors (14 sensors)	Soil Chloride concentration	Calibration of sensor
	Zou et al. (2017)	Tomato	2	0.5 m and 3 m	2	Temperature, Humidity, Luminosity and Wind speed	Predictive Modeling of parameters
	Srbinovska et al. (2015)	Pepper vegetable	Height was changed with growth of plant	Final height was 2.5 m	3 nodes and 5 nodes in two different scenarios tested	Temperature, humidity and Soil pH	Monitoring
Sensors at one height level	Akkaş and Sokullu (2017)		1		7	Temperature, Humidity, Luminosity and Pressure	Monitoring
	Lixuan et al. (2014)	Strawberry	1	1 m	3	NDVI	Prediction crop growth
Sensor and coordinator at separate level	Mancuso and Bustaffa (2006)	Tomato	1	Coordinator at height of 65 cm	7	Air Temperature, Humidity and Soil temperature	Monitoring
	Sabri et al. (2011)		1	Coordinator at height of 3.5 m in middle	4	Temperature and Humidity	Fuzzy inference system

in Eq. (2).

$$\mathrm{NDVI} = \frac{R_{ni} - R_v}{R_{ni} + R_v} \tag{2}$$

where R_{ni} is near infrared spectral reflectance from crops and R_v is visible light spectral reflectance from crops.

Table 2 summarizes the papers deploying vertical layout. Similar as horizontal layout, vertical layout also depends on measured parameter. For soil chloride concentration or soil pH, sensors need to be sited vertically down. For wind speed, sensor needs to be placed outside and at a certain minimum height. Since CO_2 is heavier than air, so CO_2 sensors are more affective at below canopy level of crop. Similarly, while monitoring illumination or irradiance reaching leaves of crop, light sensors should be located above leaf level to avoid shading zones. Another important parameter to be observed is height levels. While placing sensors at different height zones, canopy level of the crop should be considered to avoid interference. For example, if monitored crop is tomato then placement of antenna of node should be above 1 m to maintain connectivity. If crop changes the height to sizeable level during growth cycle, for example pepper, then height of the node should be incremented as the crop grows or other solutions like long distance routing node should be implemented (Yang et al., 2015).

2.3. Others

Other than horizontal and vertical layout of sensors in greenhouse, few other layouts are also proposed. Hybrid of both layouts can also prove to be quiet promising in monitoring of greenhouse. Aiello et al. (2018) proposed to have 20 sensor nodes at 5 different points and 4 different heights from 0.7 m to 3.8 m. This hybrid layout was deployed for disease forecasting. In another work, lettuce was grown in a greenhouse on shelves with 9 sensor nodes on each shelf. To check and compare the reliability of proposed system, few shelves were deployed with fans and other without fans. Number of shelves changed in various experiments (Jiang et al., 2018). As shown in Fig. 7, Nodes can also be placed in 3D row-column-height based grid structure (López-Martínez et al., 2018).

Table 3 summarizes papers deploying hybrid vertical and horizontal layout.

Model greenhouse is one of the common layouts used for verification and testing (Park and Park, 2011; Thakur et al., 2018; Pascual et al., 2015). Model greenhouse is smaller than the normal greenhouse and replicates the interior environment of actual greenhouse. Home greenhouses are also an example of model greenhouses. So only single sensor node is sufficient to monitor it and information is directly communicated to server without any bridge or gateway. Park and Park (2011) tested the performance of a dew condensation control system in a model greenhouse. Model greenhouse examples are shown in Fig. 8.

Change in one parameter in a greenhouse may affect the other parameter. Illumination or radiation intensity can affect the measurement of temperature and humidity. Ferentinos et al. (2017) analyzed the effect of various radiation intensity levels on error in temperature and relative humidity readings. So it was proposed to keep nodes

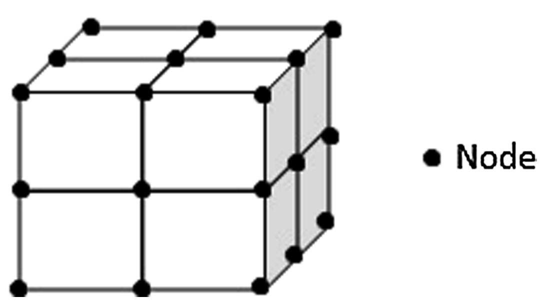

Fig. 7. 3D grid layout.

Table 3
Hybrid vertical and horizontal layout.

Reference	Crop	Number of nodes	Number of height zones	Height levels	Area	Focused area
Aiello et al. (2018)	Horticulture	100 (20 motes at 5 points)	4	0.7 m, 1.5 m, 2.2 m, 3.8 m	24 m × 30 m	Disease forecasting
Jiang et al. (2018)	Lettuce	37 (9 on each of the four shelves, one gateway)	4	Between ground to 200 cm	255 cm × 560 cm, each shelf of 120 cm × 60 cm	Monitoring and disease forecasting
López-Martínez et al. (2018)	Tomato	38 (12 sensors at 3 heights, 1 gateway, one outdoor weather station)	3	0.23 m, 0.93 m, 1.56 m	32 m × 32 m	Monitoring

shaded or boxed, whereas shaded sensor nodes performed better than completely boxed sensor nodes. Kuroda et al. (2015) also proposed to place the nodes inside a box. Nodes can also be deployed in tiers or master-slave like architecture. In tier-based layout, few sensor nodes only sense the data while other few having additional capability can also aggregate and process the data. Lowest level tier nodes send the measured data to upper level tier. Upper level sensor nodes may process the data if required or may directly send to its upper level tier. Nodes in the highest level are connected to gateways or central repositories (Bai et al., 2018; Wang et al., 2013).

3. Sampling techniques

Sampling in the terms of statistical analysis means taking few samples from a larger population. Sampling of data in terms of WSN is a separate term but yet closely related. Sampling is the process of sending data samples through a transceiver to next sensor node, gateway or directly to central server. Sampling has a deep impact on network lifetime. Most of the energy consumption in the setup of a WSN is consumed by transceiver or radio (Didioui, 2014). As shown in Fig. 9, radio consumes most of the energy in a wireless sensor network. So optimizing the data transmission or sampling can help in reducing overall energy consumption and hence prolonging the network lifetime.

Sampling technique decides how much out of the measured data is transmitted via transceiver and at what frequency. Since in a typical greenhouse environment value of parameters may not change for even hours, so it is not required to transmit data frequently. Greenhouse monitoring requires application-specific sampling techniques. This section surveys various sampling techniques being used by various researchers in literature for greenhouse environment control.

Simplest of all is periodic sampling i.e. sending data at periodic intervals. Periodic sampling is the most commonly used sampling technique, although sampling interval may be different ranging from few seconds to hours (Ahonen et al., 2008; Park and Park, 2011; Mancuso and Bustaffa, 2006; Liao et al., 2017; Pascual et al., 2015; Rishi and Kumar, 2013; Aiello et al., 2018; Lamprinos et al., 2015; Zhang et al., 2017; Kassim et al., 2017; Sampaio and Motoyama, 2017a; Gupta and Quan, 2018; Harris et al., 2016; Srbinovska et al., 2017; Mat et al., 2015; Ferentinos et al., 2014; Srbinovska et al., 2015; Chuang et al., 2014; Zou et al., 2017). Small sampling interval reduces error in measurement but increases energy consumption and vice-versa. So there is a tradeoff between energy consumption and sampling error. Finding appropriate sampling period is one of the challenges in design of monitoring systems (Cullen et al., 2000). Real-time sampling is a technique for real-time monitoring (Azaza et al., 2016; Thakur et al., 2018; Akkaş and Sokullu, 2017; Park et al., 2011). Crops grown in critical weather conditions or highly dynamic environment may require real-time monitoring. It requires the transceiver to be always in on state to sample data; hence it is not energy efficient. In threshold or level cross sampling, data is communicated only if it crosses an alarming or preset level. Mekki et al. (2015) proposed to send measured value of temperature, humidity, moisture, CO_2 concentration and light intensity only if it crosses a preset value. Pawlowski et al. (2009) suggested another variant of level cross sampling i.e. data is transmitted only when there is a significant difference in current and last sampled value. This difference (δ) is preset as a threshold. If $x(t_k)$ is present sampled value and $x(t_s)$ is previous sampled value, then Eq. (3) represents the relation.

$$|x(t_k) - -x(t_s)| > \delta \tag{3}$$

It is also called send-on-delta sampling. Instead of considering actual value of signal, present and previous value of error can also be taken into account. Authors proposed an additional control presented in Eq. (4) to increase the stability.

$$t_k - t_s \geqslant t_{max} \tag{4}$$

where t_{max} is maximum sampling interval. The control rule says that if

Fig. 8. Examples of model greenhouse (Park and Park, 2011; Thakur et al., 2018).

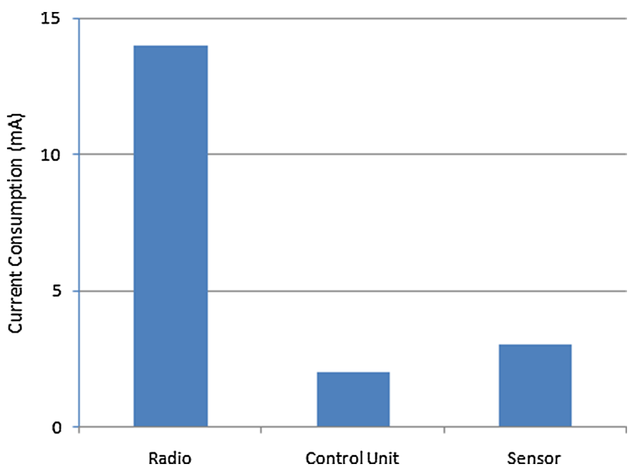

Fig. 9. Current consumption in a WSN node (Didioui, 2014).

certain time (t_{max}) has passed since last sample taken then data will be sampled irrespective of δ. If δ is large, sampled data is less but error in measurement is more. To reduce number of sample-events of highly variable parameter like wind speed, it was proposed to use filtering. Threshold can be set manually by farmers with the help of an expert or strategic artificial intelligence techniques can be used.

Sampling techniques can be made adaptive as per parameter value i.e. sample frequently in critical ranges of temperature, humidity, etc. So the tradeoff between sampling error and energy consumption can be balanced. Bai et al. (2018) proposed adaptive multirate sampling. In adaptive multirate sampling, sensors adjust their sampling rate according to rate of change of parameter. Measurement rate (λ) was calculated as shown in Eq. (5):

$$\lambda(t_{i,k}) = \begin{cases} 3h, & y_i(t_{i,k}) - y_i(t_{i,k-1}) < \alpha_1 \\ 2h, & \alpha_1 < y_i(t_{i,k}) - y_i(t_{i,k-1}) < \alpha_2 \\ h, & y_i(t_{i,k}) - y_i(t_{i,k-1}) > \alpha_2 \end{cases} \quad (5)$$

where i refers to sensor node state vector, $y_i(t_{i,k})$ refers to data transmitted by sensor i at present instant and $y_i(t_{i,k-1})$ refers to data transmitted by same sensor at previous instant. h is preset sampling interval and hence decides the sampling rate. Parameters α_1 and α_2 affect the number of transmission. For example, if α_2 is a small value then sampling interval is selected as h, so number of transmissions will be relatively high. In dynamic multirate sampling, rate of sampling is changed according to time of the day. For example, since temperature change is relatively slow in 00:00–08:00 than 08:00–14:00, so sampling rate is slower in former than latter. Dynamic multirate sampling has less number of transmissions than non-multirate sampling. Adaptive multirate sampling has number of transmissions even less than dynamic multi-rate sampling. Also adaptive multi-rate sampling is more flexible and fluctuations are relatively less when temperature changes slowly.

Sampling technique can also be made adaptive of type of parameter i.e. temperature, humidity, soil pH, soil moisture, etc. Soil data needs to be sampled more frequently than environmental parameters. Light intensity's information needs to be sampled less frequently than environmental parameters. Although varying with parameter, sampling is still periodic (Quynh et al., 2015). Periodic Sampling with averaged Delayed Transmission (PSDT) is another technique to deal with tradeoff issue. Data is sampled frequently but not transmitted frequently. Data sampled over a longer duration is averaged and sent with a delay. Pahuja et al. (2013) proposed to sample the temperature and humidity data at every 2 min interval but send the average value at 15 min interval. Lixuan et al. (2014) considered number of measurements for averaging rather than interval. Data was periodically sampled and averaged over 10 readings. Another sampling technique suggested in literature takes advantages of both PSDT and threshold sampling. Data is averaged over the interval but sent only if it has significant difference from previous value (Sabri et al., 2011).

Rather than working on an algorithm, sampling can also be done on receiving instruction. This instruction can be from a control center (Song et al., 2011; López-Martínez et al., 2018) or from an observer (Guo et al., 2018). Sampling on instruction helps in synchronization of data signal from all the nodes. It has a good capability in risk handling but it is not suitable for monitoring of all type of crops. It is an application-specific technique. Rate of data transmission may depend on type of crop also.

Table 4 summarizes the sampling techniques and its key features in the last column. Number of transmissions for periodic sampling is calculated on the basis of sampling interval. For sampling interval of 5 min, data is transmitted 12 times in an hour and 288 times in a day. Similarly, if sampling interval is 5 s, data is transmitted 17,280 times per day. Long interval between samples incurs lesser number of transmissions. So, longer interval between samples saves energy at the cost of reliability of data. Number of transmissions for threshold level cross sampling depends upon the dynamics of environment in greenhouse. If environment is frequently changing, number of transmissions will be high. Number of transmissions shown in table for send-on-delta sampling is for 8 days as acquired by Pawlowski et al. (2009). Similarly data represented for adaptive multirate sampling and dynamic multirate sampling is acquired by Bai et al. (2018) and Quynh et al. (2015) opted different sampling rate for different parameters. Light data was sampled once every 30 s, Temperature was sampled once every 10 s, Air humidity was sampled once every 5 s and soil parameters were sampled once every 2 s. Using sampling interval, number of transmissions are calculated for per day. For PSDT averaged over time sampling, data is sampled every 2 min but average value is transmitted every 15 min (4 times in an hour). So, number of transmissions is 96/day. For PSDT, averaged over readings, data is sampled every 2 min but transmitted after acquiring 10 readings i.e. after 20 min (3 times in an hour). So, number of transmissions is 72/day. Number of transmissions will change if number of readings to be acquired before transmission is changed.

Table 4
Sampling techniques.

Sampling Technique	Number of Transmissions	Remarks
Periodic (Ahonen et al., 2008; Park and Park, 2011; Liao et al., 2017; Pascual et al., 2015; Rishi and Kumar, 2013; Aiello et al., 2018; Lamprinos et al., 2015; Zhang et al., 2017 and others)	17,280/day for $h = 5$ s 288/day for $h = 5$ min 5/day for $h = 5$ h	• Reliable but less energy efficient. • Reliability decrease with increase in h. • Suits for highly dynamic and critical environment.
Threshold level cross (Mekki et al., 2015)	Depends on changing environmental parameters	• Prone to sampling error. • May fail in case of faulty sensor and then human intervention is required. • Energy efficient. • Suits for less dynamic environment like greenhouse.
Send-on-delta (Pawlowski et al., 2009)	Parameter / $\delta = 3\%$ / $\delta = 5\%$ Inside temp. 469 279 Outside temp. 762 353 Humidity 674 358 Solar Radiation 826 553 Wind Speed 5720 3715 Wind Direction 5003 3255	• Data is for eight days. • Higher the δ, lesser the number of transmissions. • In case of faulty sensors, sampling may have stability issues. • Further, more control rules can be added to increase stability.
Adaptive multirate sampling (Bai et al., 2018)	18 for $h = 5$ 22 for $h = 10$ 18 for $h = 14$	• Units of time interval not clearly mentioned but can be assumed to be minutes. • Data is for $\alpha_1 = 0.5$ and $\alpha_2 = 1.0$ • Data is average number of transmissions. • Tradeoff between power consumption and accuracy can be balanced by optimizing α_1 and α_2.
Dynamic Multirate Sampling (Bai et al., 2018)	20 for $h = 5$ 40 for $h = 10$, 14	• Data is averaged number of transmissions. • Not suitable for slowly changing environment.
Adaptive with parameter (Quynh et al., 2015)	Parameter / Transmissions Temp. 8640/day Air Humidity 17,280/day Soil Humidity 43,200/day Soil pH 43,200/day Light 2880/day	• Energy consumption is less than techniques having same transmission interval for all parameters. • Sending data of different parameters in separate packets incurs additional energy wastage.
PSDT averaged over time (Pahuja et al., 2013)	96/day (sample over 2 min, send average over 15 min)	• Data is sampled at shorter interval for accuracy but it is sent with a delay after averaging over a specific period to save power. • Power efficient yet accurate and reliable. • Data transmission has latency that is independent of sampling rate.
PSDT averaged over readings (Lixuan et al., 2014)	72/day (sample over 2 min, send average over 10 readings)	• Data is sampled at shorter interval for accuracy but it is sent after averaging over a specific number of readings to save power. • More power efficient and accurate than PSDT averaged over time. • Data transmission has latency but it depends on sampling rate.

4. Communication technology

Sensors need to communicate to send the sensed data to control centre. Connectivity in typical greenhouse is required among sensors and sensors to gateway or a base station. The connectivity can be entirely wireless or hybrid wired-wireless. In this section, technologies used for connectivity of sensors in greenhouse application are surveyed.

4.1. Zigbee

Idea of Zigbee floated in 1990s but Zigbee was standardized by Zigbee alliance in early years of 2000s. Zigbee operates in 2.4 GHz ISM (Industrial, Scientific and Medical) band. Zigbee is based on IEEE 802.15.4 standard. IEEE 802.15.4 is a standard for layer 1 and layer 2 (Fenzel, 2013). Zigbee is defined for layer 3 and above. Other than providing communication, Zigbee provides routing, authentication and mesh networking facilities. Due to mesh networking, Zigbee can support 65,000 devices in network. In Zigbee, three types of devices are defined: Zigbee end devices, Zigbee routers and Zigbee coordinators. Sensors are Zigbee end devices that don't have any routing capability but can communicate the data to parent node. Zigbee routers have the capability to route the data and Zigbee uses AODV (Ad-hoc On-demand Distance Vector) as routing protocol. Zigbee coordinator is the core and single control station of the network. Zigbee can communicate in range of 10–20 m, has low-duty cycle and low power consumption. Hence it is suitable for management of greenhouse environment (Zigbee Specification, 2004). Zigbee is most widely used for intra-sensor communication in a greenhouse (Park and Park, 2011; Mancuso and Bustaffa, 2006; Mirabella and Brischetto, 2011; Azaza et al., 2016; Rodriguez et al., 2017; Pascual et al., 2015; Aiello et al., 2018; Jiang et al., 2016; Yang et al., 2015; Lamprinos et al., 2015; Pahuja et al., 2013; Guo et al., 2018; Sabri et al., 2011; Thakur et al., 2018; Kassim et al., 2017; Sampaio and Motoyama, 2017a; Gupta and Quan, 2018, Mat et al., 2015; Singh et al., 2015; Wang et al., 2013; Lixuan et al., 2014; López-Martínez et al., 2018).

4.2. GPRS

GPRS stands for General Packet Radio Service. GPRS was standardized by European Telecommunications Standard Institute (ETSI) and was launched in year 2000. It is a packet based service for GSM (Global System for Mobile) devices. GPRS doesn't have a range limitation. Also, its advanced versions provide increased data rate (Schiller, 2012). Since in GPRS, users share the resources, so delay is dependent on it. GPRS was used in greenhouse environment to send regular alerts on farmer's phone (Dan et al., 2015; Mekki et al., 2015). These alerts were periodic and required the farmer's GSM phone to be in coverage area. GPRS can also be used for data logging of greenhouse environment (Azaza et al., 2016; Mat et al., 2015). Rishi and Kumar (2013) proposed an intelligent irrigation system based on GSM. Lixuan et al. (2014) proposed to send spectral data of crop canopy reflectance to remote server using GPRS. It is suitable for remote monitoring of greenhouse also (Yang et al., 2015; Kassim et al., 2017; Wang et al., 2013). Mostly GPRS was used for sensor to base station or gateway to base station communication. GPRS's main advantage is its wide availability over the world but soon it may phase out for acquisition of higher data rate services like 4G and 5G. GPRS is cost effective for low data rate applications like greenhouse monitoring but 4G and 5G may not be.

4.3. Wi-Fi

Wi-Fi stands for Wireless Fidelity. Wi-Fi is based on IEEE 802.11 standard and utilizes radio frequency band. Wi-Fi is trademarked by Wi-Fi Alliance that constitutes a group of companies. Wi-Fi was launched in late years of 1990s. It has a communication range of 20–100 m. Wi-Fi network has an access point, through which all the devices communicate (Schiller, 2012). Wi-Fi was used in greenhouse for the connection of sensors or gateway to central server. It provides speed of 2–54 Mbps, so data can be sent with tolerable latency. Thakur et al. (2018) proposed the use of ESP8266 Wi-Fi module to send data to base station, from where farmer can monitor it. Wi-Fi was mostly used for gateway to central server or cloud communication (Guo et al., 2018; Jiang et al., 2018). Using Wi-Fi for sensor to sensor communication can be energy consuming and affect lifetime of network. Wi-Fi can be used to connect multiple greenhouses spread over a wide region with heterogeneous systems deployed (López-Martínez et al., 2018).

4.4. LoRa (Long Range)

LoRa is another communication enabling technology for agriculture (dos Santos et al., 2019). It was developed by a group of companies called as LoRa Alliance (Alliance, 2017). It is owned by Semtech Corporation, California. LoRa has long range i.e. in kilometers and low power consumption, so it helps in deploying LPWAN (Low Power Wide Area Networks). LoRaWAN (LoRa Wide Area Network) is a network based on LoRa technology. LoRa gateways receive the data from LoRa end devices and direct it to LoRa servers. LoRa trade-offs data rate to attain long range of communication. It executes on the unlicensed band like 169 MHz, 868 MHz, 433 MHz. Implementation using unlicensed bands does not need any permission but are vulnerable to interference. Due to its long range, LoRa can support remote monitoring applications like greenhouse monitoring. Reka et al. (2019) suggested implementing LoRa for greenhouse. LoRa can handle thousands of nodes and can communicate over wide range. It can communicate over distances ranging from 5 km to 10 km. Still, it manages to have low power consumption and hence lifetime of 10–20 years. Authors argue that Zigbee can handle only few hundred of nodes; hence LoRa can be deployed for greenhouses spread over hectares. LoRa is mainly used for gateway to central server communication.

4.5. Bluetooth

Bluetooth was initially standardized by IEEE 802.15.1. Now, Bluetooth Special Interest Group (SIG) regulates standardization and licensing of Bluetooth technologies. Bluetooth consumes less power and was developed for WPAN (Wireless Personal Area Network). Bluetooth deploys spread spectrum hopping. It can support a data rate of 1–3 Mbps depending upon the version. Class 3 Bluetooth devices have range of 1 m, class 2 has range of 10 m and class 1 has range of 100 m. The technology needs the devices to form a connection before transmitting data. In a communication, one of the device acts as a master while other acts as a slave. Slave node in one network can be a master in the adjoining network. Ad-hoc network formed by bluetooth enabled devices are called as piconets. Many piconets combine to form a scatternet (Bluetooth Specification, 2017). Hong and Hsieh (2016) used RN41 bluetooth module to build an automatic irrigation system in a lettuce greenhouse. Bluetooth can be used for sensor to sensor communication and if the range limitations permit, it can also be used for sensor to gateway or gateway to base station communication.

4.6. Others

Other than these commonly used technologies, there were few wireless technologies that are not widely used but still got a place in greenhouse WSN environment in few projects. To increase the speed and reliability, LAN can also be used to send data to base station, whereas sensors still communicate wirelessly. It is a kind of hybrid system (Mancuso and Bustaffa, 2006). A Controlled Area Network (CAN) based wired bus is also another option for greenhouse (Mirabella and Brischetto, 2011). A suitable bridge is provided between wired and wireless system. Serial port can also be used for sensor or gateway to base station communication in a greenhouse (Song et al., 2011; Sampaio and Motoyama, 2017a; Srbinovska et al., 2015). Pahuja et al. (2013) proposed connecting actuators to PC through industrial serial networking standard RS-485. Zhang et al. (2017) used USB (Universal Serial Bus) for sending data from gateway to base station in a cotton greenhouse. Other than USB, RS-232 regulated ports can also be used for serial transmission. Serial transmissions are faster than parallel transmissions. Although serial port promises burst data transformation in less time, it can put a bound on the expansion of network. Gupta and Quan (2018) proposed using XStream proprietary RF (Radio Frequency) modem for communication between coordinator/gateway and control station.

XStream is a long range radio communication module, which can transmit in range of 5–16 km. As shown in Fig. 10, central control station was an application on PC which was connected to XStream modem using USB.[1]

Kuroda et al. (2015) proposed a long haul sensor network and used 400 MHz band for communication. Results show that 400 MHz band under ARIBT67 radio standard performs better than 2.4 GHz band communication. It has better packet reachability and less packet loss even in the case of obstructed path. It can transfer to a range of 100 m without a relay node. Since the 400 MHz band communication is less affected by obstruction; hence it is more suitable for greenhouse environment. Sensor to coordinator communication was proposed via I^2C interface.

4.7. Performance comparison of communication technologies

Table 5 compares the above-mentioned communication technologies for parameters like range, operating frequency band, network size, cost, data rate, power consumption and communication mode. Range is one of the limitation factors in greenhouse monitoring environment. In each case, there is a trade-off among range, data rate and power consumption. Communication technology with high data rate has high power consumption.

Wi-Fi and Bluetooth devices provide more data rates and consume more power than Zigbee. Hence, it has less average lifetime than Zigbee network. Since greenhouse environment does not need high rate of

[1] http://ftp1.digi.com/support/documentation/ds_xstream_modem.pdf.

Fig. 10. Central control station connected to Xstream modem (Gupta and Quan, 2018).

5. Prediction models

Prediction models are optimization models which are used to predict parameter values for which sensors are not available like photosynthesis. This prediction is made on the basis of available parameters. Other control systems take action when problem has already occurred i.e. when parameters are out of the bound of thresholds. This may lead to partial loss of crop. Predictive modeling can help in building a proactive model. These models can predict values of common parameters like temperature, humidity, etc. on the basis of previous data to execute proactively and reduce sampling load. Prediction models learn from certain training data sets to make predictions. Third type of prediction models is regression type models; that are normally used to find relationship among various parameters. Artificial neural networks can be used as one of the tools to implement predictive modeling. As shown in Fig. 11, a typical neural network has three-layer architecture: Input layer, hidden layer and output layer. Nodes in a layer are called as neurons. Data is fed at input layer to get predicted parameters at output. Links between input layer and hidden layer, hidden layer and output layer have weights. Before forwarding the calculated weighted output to next layer, hidden layer and output layer apply an activation function. Activation function is transfer function of the layer, which defines linearity or non-linearity of the network. Depending upon characteristics, a neural network may have multiple hidden layers also. Certain previous datasets are provided to the neural network first for training purpose. After being trained, network provides the output of the required dataset (Kriesel, 2007). This section presents various prediction models adopted for the prediction of parameters in a greenhouse.

Table 5
Performance comparison of communication technologies.

	Range	Frequency Band	Network Size (Jawad et al., 2017)	Cost	Data Rate	Power Consumption	Communication Mode
Zigbee	10–20 m	2.4 GHz	65,000 nodes per network	Low	20–250 Kbps	Low	Peer to Peer
GPRS	In range of mobile network area	900–1800 MHz	1000 nodes per network	High	56–114 Kbps	High	Base station to device
Wi-Fi	20–100 m	2.4 GHz	32 nodes per network	High	2–54 Gbps	High	Access point to device
LoRa	10 km +	169 MHz 868 MHz 433 MHz	10,000 nodes per gateway	Moderate	0.3–50 Kbps	Low	Peer to Peer
Bluetooth	1–100 m depending upon class	2.4–2.485 GHz	8 nodes per piconet	Low	1–3 Mbps	Moderate	Master Slave and Peer to Peer
XStream	5–16 km	2.4 GHz	7 channels, each with 65,000 addresses	Low	10–20 Kbps	Low	Peer to Peer

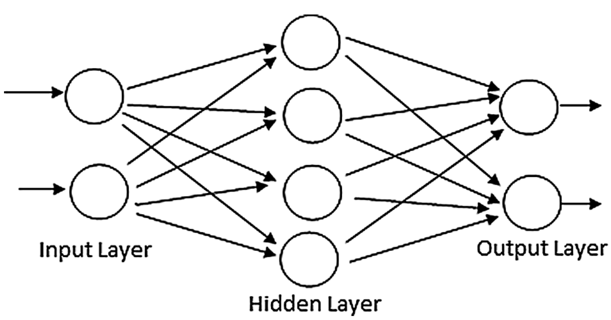

Fig. 11. Simple neural network.

transmission, so Zigbee provides appropriate solution. Zigbee can support 65,000 devices in a network, so network can also be extended over large area. LoRa provides wide communication range with low data rate. So, LoRa is also valuable for widely spread greenhouses but for larger number of devices in network, it has high latency. So Zigbee should be preferred over LoRa if data communication is required only over few meters. XStream also provides long range communication with low data rate. Difference between LoRa and XStream is of operating frequency and network size. Also, XStream supports cloud based services. Zigbee, LoRa and XStream operate in peer to peer communication mode. Wi-Fi network has an access point which acts as a router for all communication among devices. Similarly GPRS has a gateway or base station for device communication. Bluetooth is a short range device with small network size. It suits for small home based greenhouses. GPRS has high communication range but also has high cost and power consumption. GPRS suits for messaging based alert services for greenhouse monitoring.

5.1. Prediction on the basis of available parameters

Jiang et al. (2015) proposed to predict photosynthesis rate on the basis of available parameters like air temperature, air humidity, light intensity and CO_2 concentration. BPNN (Back Propagation Neural Network) model was used for training and testing. BPNN propagates the error computed at output of simple neural network back in the network to recalculate weights. It is a type of supervised learning. There were total 7 hidden layers in BPNN model. *Logsig* was used as input transfer function of hidden layer and *purelin* was output transfer function. Total 144 samples were taken. Out of that 132 were used for training and rest 12 was used for testing. The model was used to optimize CO_2 concentration to find maximum photosynthesis rate for tomato crop in seedling stage. Ting et al. (2015) also worked to find the optimum CO_2 concentration but for tomato crop in flowering stage. To enhance the performance of BPNN, PCA (Principal Component Analysis) processing was used. PCA removed redundancy from input data before feeding it to BPNN model. K-fold cross validation was used to check error. Yuhan et al. (2015) proposed to use K-means clustering instead of PCA for

Table 6
BPNN comparison with 10-fold cross validation and its own variants.

Prediction model	R (Correlation Coefficient)	MAE (Mean Average Error)	ARE (Absolute Relative Error)	RMSE (Root Mean Square Error)
10-fold cross validation	0.9523	1.0319	0.5941	1.94
BPNN	0.9899	1.23	0.9682	1.46
BPNN + complete attribute set (9 attributes)	0.9964	0.6958	0.728	0.7428
BPNN + reduced attribute set (6 attributes)	0.9965	0.4026	0.453	0.3245

processing of data i.e. it discretizes the data. Authors also further proposed to use reduction theory to reduce number of input attributes from 9 to 6. Table 6 compares BPNN with 10-fold cross validation and its own variants. BPNN has better accuracy and correlation coefficient than 10-fold cross validation. Also, BPNN with reduced number of attributes performs best. It has highest accuracy and trains two times faster than model with complete attribute set.

Other than photosynthesis, number of sensor nodes required for a greenhouse can also be predicted. Sampaio and Motoyama (2017b) estimated number of sensor nodes required on two bases: number of addresses available for sensor nodes and traffic distribution and modeling. Srbinovska et al. (2017) proposed to predict lifetime of network of nodes in a greenhouse using energy consumption estimation.

Lixuan et al. (2014) deployed four optical channels to collect crop canopy reflectance data. This spectral data was collected by intelligent photoelectric sensors, which convert it to electric signal and send it to gateway. Collected data is processed to calculate crop growth parameter NDVI as shown in Eq. (2).

Above all prediction models aided in predicting parameters for which no sensors are available but prediction models can also help in predicting parameters for which sensors are available.

5.2. Prediction on the basis of previous data

Rather than collecting data for complete duration, predictive modeling helps in predicting next few samples on the basis of last few samples. This sets a new paradigm in energy consumption optimization of WSN. If few samples are predicted rather than collecting, it decreases the load on transceiver and hence saves energy. Rodriguez et al. (2017) proposed to predict greenhouse environmental parameters. Last few hours data was used to predict next 30 min of data. Linear regression, Neuronal network and SVM (Support Vector Machine) were used as prediction models. 70% of the sampled data was used for training; rest of the 30% was used for testing purpose. Comparison proved SVM to be a better prediction model than linear regression in terms of error. SVM was first introduced for classification. It is a supervised learning model. Fig. 12 describes the main idea behind SVM.

SVM maps the input to a higher dimensional space and a hyper plane marks the margin between two classes. Based on training set, SVM first marks the margins of classes and then categorizes the given input into mapped classes. These margins can further be optimized for efficient solution. SVM has a benefit of lesser number of parameters over BPNN (Chorowski et al., 2014). ELM (Extreme Learning Machine) model can also be used to predict temperature and humidity in a greenhouse (Liu et al., 2016). To predict next sample, last three samples were used. Model's hidden layer had 26 nodes and *sin* as activation function. ELM was proposed as a single hidden layer feed-forward network. Input weights of the feed forward network are inherited from past or randomly selected and kept constant. Only output weights are adjusted to minimize error. Due to random selection of input weights, ELM is faster than SVM and back propagation. ELM also has the capability of universal approximation (Chorowski et al., 2014).

Mathematically, ELM prediction model can be represented as in Eq. (6).

$$s_j = \sum_{i=1}^{H} \gamma_i f(\alpha_i x_j + \beta_i) \quad j = 1, 2, \cdots\cdots..Q \tag{6}$$

where, α_i is input weight of ith neuron, β_i is bias of ith neuron, γ_i is output weight of ith neuron. x is input vector and s is corresponding output vector. Q is number of training samples. f is activation function. H is number of hidden layer neurons. Input vector is multiplied with input weights and bias is added to it. After applying activation function, output weights are multiplied. In ELM prediction model, specifically α and β are chosen randomly, hence it has poor stability.

KELM (Kernel based ELM) prediction model was also proposed as an advancement. KELM introduced the implementation of stable kernel functions on ELM to improve the performance. As compared to BPNN, Elman and SVM, ELM is better in terms of training speed, generalization, error and correlation coefficient (Huang et al., 2006). ELM has an advantage of global optimal solution. KELM is 2.9 times faster than ELM, has better generalization ability and stability.

Few of the work in literature also tried using both type of prediction models discussed in Sections 5.1 and 5.2 together. Zou et al. (2017) proposed to predict inside temperature and humidity of greenhouse by taking previous inside temperature, previous inside humidity, outside humidity, outside temperature, solar radiation and wind speed as input to prediction model. B-ELM (Bidirectional ELM) has reduced number of hidden nodes and better learning capabilities than ELM. It reduces the number of hidden nodes without compromising performance. B-ELM does not take input weights randomly but calculate it for one iteration. This further improves the speed as compared to network with completely random input weights (Yang et al., 2012). It was proposed to optimize B-ELM prediction model using convex optimization. Convex optimization proposes to find unique global minima in a set of local minima forming convex function (Boyd and Vandenberghe, 2004). CB-ELM (Convex Bidirectional ELM) suggests recalculating output weights of hidden layer whenever a new node enters. Recalculation helps in faster convergence of CB-ELM network. Convex optimization helps in better generalization performance of CB-ELM than any network with *sin* activation function. It performs better than SVM, BPNN, B-ELM and RBF (Radial Basis Function). RBF implements radial basis functions as activation functions. It can be implemented as a kernel with other models.

Table 7 summarizes the comparison of various prediction models in terms of various parameters. Comparing these prediction models with

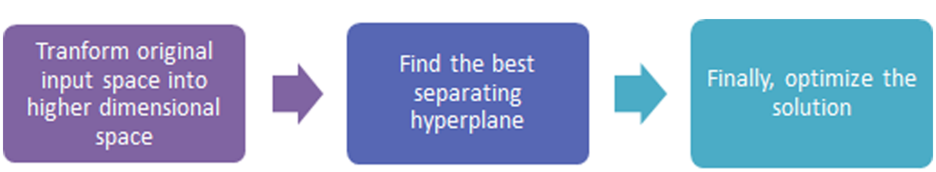

Fig. 12. Steps of SVM classification.

Table 7
Comparison of prediction models.

	Training Speed	Generalization capability	Error	Stability	Universal approximation capability
BPNN	Very low	Low	Moderate	Low (Increase with number of nodes)	Not good
SVM	Low	Moderate	High	Moderate	Not good
ELM	Moderate	Moderate	Moderate	Moderate	Good
KELM	Moderate	High	Low	High	Good
B-ELM	High	Same as ELM at reduced number of hidden nodes	Low	High	Good
CB-ELM	High	High	Low	High	Good

objective values is not possible due to difference in parametric basis, so models are compared in the table descriptively. Summarizing in terms of error, it is observed that CB-ELM has the best accuracy and RBF has the least. Back-Propagation algorithms have better accuracy than SVM. In terms of training speed, ELM and its variant models perform the best. Back-Propagation algorithms are 33 times slower than ELM but still 25 times faster than SVM. Since ELM and its variants are feed-forward networks, so these are good universal approximators. BPNN has low generalization capability.

5.3. Regression based prediction model

Regression is statistical prediction technique which is used to form a relationship among different variables. Since greenhouse is a closed loop environment in itself, change in one variable can affect other climatic or soil variables. Depicting dependence of dependent variable on independent variables can lend a hand in optimization of resources. Mancuso and Bustaffa (2006) suggested finding impact of correlation of temperature and humidity on yield, disease formation and overall cultivation. Regression was used to form a relationship between soil moisture and Working Duration of Pump. Thus water usage for irrigation was optimized on the basis of this prediction (Hong and Hsieh, 2016). Shah et al. (2009) proposed to optimize water and pesticide usage both using prediction model. Data was collected for 3 months to calculate evapotranspiration (ET) and leaf wetness duration. It was deduced that rate of evapotranspiration decreased with decrease in soil moisture. So relation between ET and soil moisture was formed to take irrigation decisions. Similarly, leaf wetness duration was used to forecast infection index of grape berries. Based on this infection index, pesticide was sprayed when required. Along with timings, amount of pesticide was also optimized. Liao et al. (2017) proposed to predict relationship between growth of leaves and environmental factors. Wireless cameras were deployed to check leaf growth parameters. Cultivation area was divided into 4 regions and test was conducted for each region to check relation between leaf growth and temperature, relative humidity and illumination. One-way ANOVA, two-way ANOVA and Games-Howell test was conducted to analyze relation in four regions. Region with temperature less than 30°C and relative humidity less than 75% showed maximum daily average growth. Temperature had no impact on leaf growth while humidity had great impact. Environmental parameters can also affect sensor's performance. Ferentinos et al. (2014) tried to analyze the effect of various environmental parameters on RSSI (Received Signal Strength Indicator) value, voltage and energy consumption of sensor nodes. A strong correlation between voltage of sensor nodes and temperature-humidity (T-H) was found. A correlation between energy consumption and T-H was also there. Relation of T-H with RSSI value was relatively weak. RSSI value mostly depended upon distance from the base station. Patil et al. (2008) presented various prediction models to predict tropical greenhouse temperature in six different seasons: Rainy, winter, summer, mid-rainy, mid-summer and mid-winter. ARX (Auto Regressive model with an external input), ARMAX (Auto Regressive Moving Average model with an external input) and NNARX (Neural Network Auto Regressive model with an external input) was used to estimate inside temperature with outside air temperature, outside air humidity, outside solar radiation and cloud cover as input to prediction model. Auto regression models depend on previous values of data while moving average models produce a series of rolling averages to give the idea of followed trend.

6. Decision support systems

In a greenhouse control system, various decision supporting techniques were also adopted. Most commonly used techniques were fuzzy logic and fusion. Fuzzy logic can be thought of as a mechanization of human thought process. Fuzzy logic tries to copy the way a human thinks (Zadeh, 2008). Instead of precisely mentioning the value of parameters in a greenhouse, fuzzy logic can offer a better way out. A fuzzy logic based control system was used in a Basil greenhouse to optimize water consumption (Azaza et al., 2016). With temperature, humidity, CO_2 concentration, illumination as input to fuzzy logic system, ventilation rate, heating rate, CO_2 flow rate, artificial shading, illumination and humidification/dehumidification was taken as output. Deviation of internal and external T-H (Temperature-Humidity) from a setpoint was taken as input to control ventilation and heating. Fuzzy logic controller saved 22% energy and 33% water. Pahuja et al. (2013) proposed to use fuzzy logic to control VPD in a Chilli greenhouse. Genetic algorithm was proposed as an add-on to fuzzy logic system to make membership function adaptive (Gottschalk et al., 2003).

Fusion is another technique frequently used in literature for the optimization of decision support system. Multisensor fusion can help in better decision making. It increases the reliability of system by reducing probability of false alarms. Each sensor sends its data to control center. Control center fuses the data from all the sensors to make a reliable and global decision. Aiello et al. (2018) proposed "k out of n" fusion technique. It suggests summing individual decisions of only those sensors that have value above a set threshold. Bai et al. (2018) proposed a hierarchal fusion technique. Since regions in a greenhouse are locally consistent, sensors collect the data and send to cluster head for cluster-level fusion. Cluster heads send the data to sink for sink-level fusion. This is also called as two-stage data fusion.

To make the best of both worlds, Zhang et al. (2017) proposed fuzzification as technique to fuse data. Two parameters i.e. leaf angle and chlorophyll concentration were fused to judge the vigor of cotton. Weighted average fuzzy arithmetic operators were used to make final decisions. Thus fusion and fuzzy logic techniques can help in the better contribution of WSN in greenhouses. These techniques enhance the decision making capability of the overall WSN system.

7. Conclusion and future work

A state-of-art review for the inclusion of WSN in greenhouse application is presented in this paper. Various layouts for placing sensors in greenhouses are reviewed, classified and analyzed. These layouts can be horizontal or vertical across the greenhouse. Other than horizontal and vertical, many other placements are also explored. After layouts, various sampling techniques for choosing transmission interval are also studied in this paper. Focusing a greenhouse set-up, the trade-off between energy consumption and accuracy is also discussed for these sampling techniques. Technologies deployed for communication of sensor networks among themselves and with gateway or server are also discussed. Other than common communication technologies like Zigbee, Bluetooth, Wi-Fi; many other technologies and hybrid systems are also explored. Zigbee and LoRa suits best for transmission of data in a greenhouse environment, where LoRa can also be used for inter-greenhouse sensor communication over large area. Prediction models built on the basis of previous data in the time series and on the basis of other parameters are also presented. Regression based prediction models are also reviewed in this paper. At last, few techniques strengthening decision making of the WSN systems in a greenhouse are also discussed.

Although being worked upon from past few years, the implementation of WSN in greenhouses still has so many open challenges. Major challenge is lifetime of the network. Optimizing transmission interval on the basis of a sampling technique can reduce energy consumption and hence increase the network lifetime but it compromises the fidelity of data. So balancing this trade-off is a big challenge. Various signal processing techniques can be explored in further optimization to solve the issue. Even though Zigbee suits best in terms of energy and cost for greenhouse environment but it routes packets on the basis of shortest path. Due to eventual growth of crops in a greenhouse, shortest path may not always be the best path. So, communication technologies require special routing and link quality parameters for greenhouse scenario. Reduction of number of nodes in a per unit coverage area is also a considerable challenge to balance cost vs. coverage area trade-off. Further, cloud technologies can also be integrated with WSN to handle layout and communication limitations.

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