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Plant stress propagation detection and monitoring with disruption propagation network modelling and Bayesian network inference

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ABSTRACT

Plant stresses and diseases cause major losses to agricultural productivity and quality. Left unchecked, stresses and diseases can spread and propagate to nearby plants, causing even more damage, necessitating early detection. To address this challenge, the Agricultural Robotic System for Plant Stress Propagation Detection (ARS/PSPD) is developed. In this cyber-physical system, the robot agents are assigned scanning tasks to detect stresses in greenhouse plants. The problem of plant stress propagation detection is formulated with disruption propagation network modelling, which captures the plant stress occurrence and propagation mechanisms. The network modelling enables better situation awareness and augments the development of advanced collaborative scanning protocols. Five collaborative scanning protocols are designed and implemented in this research, with one protocol serving as a baseline, three protocols utilising disruption propagation network analysis, and one protocol utilising Bayesian network inference. The scanning protocols minimise errors and conflicts in scanning task allocation and enable better plant stress detection. The five ARS/PSPD collaborative scanning protocols are validated with numerical experiments, using agricultural greenhouses as experiment settings. The experiments show that the scanning protocol using Bayesian network inference outperforms all other protocols in all scenarios, with 16.92% fewer undetected plant stresses and 12.28% fewer redundant scans.

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KEYWORDS
Bayesian network; cyber-physical systems; disruption propagation; plant stress; Bayesian methods

1. Introduction

Agricultural plants are susceptible to abnormal stress situations, even in a controlled greenhouse environment (Guo, Dusadeerungsikul, and Nof 2018). Such stress situations include sudden changes in water levels, temperature, humidity, diseases, and pests. Irreversible damage can occur if effective and reliable stress/disease detection is not provided. Agricultural production losses from stresses and diseases can be as high as approximately 40% of food production in the world (Oerke and Dehne 2004). Early detection and monitoring of plant stress are essential to ensure agricultural productivity. On one hand, exhaustive scanning of all plants is economically infeasible, due to the time-consuming nature of the scanning activities (Dusadeerungsikul and Nof 2019). Currently, plant stress detection activities performed by human operators are highly labour-intensive (Khan, Martin, and Hardiman 2004). These activities involve human operators walking into the plot and scan plant locations. On average, in order to cover 8 hectares of plotting areas, an operator often walks approximately 20 km per day to perform the scanning tasks, inspecting the plant parts such as leaves and stems for a sign of stresses or diseases (Wang et al. 2018). The limited number of operators and the amount of working time available often result in reduced accuracy of scanning and delayed detection of stresses and diseases.

Undetected stresses/diseases can spread and propagate to nearby plants, causing significant losses of agricultural productivity. Early detection of plant stresses and diseases is necessary to ensure agricultural productivity and quality. This is possible due to recent advances in agricultural robotics, agricultural cyber-physical systems, and plant stress/disease detection technologies. Agricultural robotics enables the automation of repetitive scanning tasks in an agricultural environment (Bechar and Vigneault 2016; Dusadeerungsikul and Nof 2019). Agricultural cyber-physical systems enable complex sharing of information and knowledge, as well as sophisticated telerobotic and telecollaboration capabilities (Guo, Dusadeerungsikul, and Nof 2018). Furthermore, these systems are augmented by the advancements in plant stress/disease detection technologies such as hyperspectral imaging (Alsuwaidi, Grieve, and Yin 2018;

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Wang et al. 2018), sensor-based monitoring of crops yield and environmental conditions (Ferentinos et al. 2017), and machine visualisation, mapping, and guidance for autonomous robotics (Dar, Edan, and Bechar 2011).

All of the aforementioned capabilities, however, must be guided by an agricultural robotic system supported with collaborative intelligence, scanning protocols, heuristics, algorithms, and knowledge-based information. In this work, the Agricultural Robotic System for Plant Stress Propagation Detection (ARS/PSPD), one main contribution of this research, is developed. The ARS/PSPD model expands upon the agricultural robotic system (ARS) frameworks (Guo, Dusadeerungsikul, and Nof 2018; Dusadeerungsikul and Nof 2019) and the collaborative response to disruption propagation (CRDP) methodology (Nguyen and Nof 2019). Specifically, ARS/PSPD focuses on the plant stress detection function of the ARS, which assigns robot agents scanning tasks to find and detect stresses in greenhouse plants. Adapting CRDP to the plant stress detection problem results in the formulation of the plant stress propagation detection problem with disruption propagation network modelling, which is another contribution of this research. This PSPD formulation captures the plant stress occurrence and propagation mechanisms, enabling better situation awareness and augments the development of advanced collaborative scanning protocols. A total of five collaborative scanning protocols are designed and implemented in ARS/ PSPD. The scanning protocols minimise errors and conflict in scanning task allocation and enable better detection of plant stress. The first scanning protocol is the random scanning protocol, which is the baseline protocol for comparison. The second, third, and fourth scanning protocols are adaptive scanning protocols that utilise existing plant stress information and stress propagation network topology to assign scanning tasks. The fifth scanning protocol, Bayesian network-driven scanning protocol, constructs a Bayesian network based on existing plant stress information, and infer the probability of plant stress of unscanned locations. The application of Bayesian network inference to the ARS/PSPD model is the third contribution of this work. To validate the PSPD formulation and the five collaborative scanning protocols, numerical experiments are conducted. The experiment results show that the Bayesian network-driven scanning protocol outperforms the three adaptive scanning protocols, which in turn outperform the baseline random scanning protocol.

The remainder of the article is organised as follows. Section 2 summarises previous research related to this work. Section 3 specifies the ARS/PSPD model, the accompanying PSPD problem formulation, and the five collaborative scanning protocols. Section 4 describes the numerical experiments of the plant stress detection simulation. Section 5 discusses the conclusions and future work directions. The list of abbreviations and mathematical notations is given in Table 1.

Table 1. List of abbreviations and notations.

General abbreviations and notations	Plant stress propagation detection formulation
ARS Agricultural robotic system	e A directed edge, representing a stress propagation direction
$\mathrm{ARS}_{\mathrm{Single}}(t)$ ARS' single agent at time t	E Set of directed edges
$\mathrm{ARS}_{\mathrm{Group}}(t)$ ARS' group of collaborating agents at time t	$E^{in}(n)$ Set of incoming edges of plant n
A_x Agent x	$E^{out}(n)$ Set of outgoing edges of plant n
C Conflict	L Grid length of the greenhouse
CRDP Collaborative response to disruption propagation	M_1 First performance metric of ARS, the total number of undetected stresses
CRM Collaborative requirement matrix	M_2 Second performance metric of ARS, the total number of redundant scans
CRP Collaboration requirement planning	n A plant (represented as a node in the network)
C_{xy} Cost of agent x performing task y	n_{next} Next plant to be scanned
E Error	N The set of nodes/plants
EPCR Error prevention n and conflict resolution	$N^{in}(n)$ Set of incoming nodes of plant n
$N_r(t)$ Set of constraints r at time t	$N^{out}(n)$ Set of outgoing nodes of plant n
PSPD Plant stress propagation detection	$O(n)$ Scanning/observation status of plant n
t Time t	O_b Scanning budget
T_y Task y	O_p General notation for the collaborative scanning protocols
	O_{Random} Random scanning protocol
	O_{Adaptive} Adaptive basic scanning protocol
	O_{InDegree} Adaptive in-degree scanning protocol
	$O_{\mathrm{DualDegree}}$ Adaptive dual-degree scanning protocol
	O_{BayesNet} Bayesian network-driven scanning protocol
	p_0 Probability of origin stress
	$S_0(n)$ Final stress status of plant n
	$S_0(n)$ Origin stress status of plant n
	W Grid width of the greenhouse

2. Background

2.1. Agricultural robotics for plant stress detection and monitoring

Plant stresses and diseases are serious problems in agriculture production (Vurro, Bonciani, and Vannacci 2010), with agricultural production losses up to 40% per year (Strange and Scott 2005). Particularly dangerous are the plant stresses and diseases capable of propagating from plants to plants, which are common occurrences due to the large-scale and high-density nature of agricultural production (Strange and Scott 2005). Propagation of plant stress/disease primarily occurs due to the close proximity between plants, and the spread is typically from one plant to the ones around that plant. Agricultural robotics has been utilised for helping engineers, researchers, and farmers perform routine tasks such as irrigating, harvesting, and fertilising for more than two decades (Keicher and Seufert 2000; Reid et al. 2000; Dusadeerungsikul 2020; Sreeram 2020). Due to the importance of plant stress and disease management, agricultural robotics has also been applied to assist farmers in plant stress monitoring tasks, i.e. detecting plant stresses and monitoring plant conditions (Åstrand and Baerveldt 2002). Autonomous mobile robots with remote sensing have also been developed (Iida et al. 2013) to collect plant status data (Diker and Bausch 2003) and environmental condition data (Nagasaka et al. 2004). The main advantages of using the robots with sensors include performance consistency as well as contact avoidance, which help preventing diseases from propagating/spreading to other plants (due to the physical contact). Agricultural robots are also designed to minimise maneuvering non-value-added time and space (Spekken and de Bruin 2013). Robot manipulators are usually mounted with additional equipment such as navigation subsystems (Xue, Zhang, and Grift 2012), sensors (Xue, Zhang, and Grift 2012), sprayers (Ko et al. 2014), and Wi-Fi (Ishibashi et al. 2013). Such equipment not only gathers information at the location but also enables the mobile robot in the fields to connect with the host and other agents (Sai et al. 2016). Because the agricultural robotic system requires multiple different agent types such as robots, sensors, and humans, the system needs to be capable of planning and prioritising agent sequence as well as resolving conflicts (Ishibashi et al. 2013; Dusadeerungsikul and Nof 2019). Agricultural robotics systems show superior performance in terms of cost-effectiveness and detection ability compared to the traditional methods (Bochtis et al. 2011).

2.2. Collaborative control theory, conflict and error detection, and disruption propagation response

Collaborative control theory (CCT) is a principle for the design of a collaborative multi-agent system (Nof 2007). The relevant CCT principles to this research are collaboration requirement planning, error prevention and conflict resolution, collaborative fault tolerance (Nof et al. 2015). The well-designed systems with collaboration and multiple agents are shown to be more reliable, require lower cost, and complete tasks faster (Moghaddam and Nof 2017). CCT has been extensively applied to various settings, for example, telerobotics for collaborative life-cycle management in nuclear handling tasks (Zhong, Wachs, and Nof 2013), capacity and demand sharing (Yoon and Nof 2010; Moghaddam and Nof 2014), and cyber-physical system (Nayak et al. 2016).

In agricultural tasks, CCT principles are applied for several processes to improve processes and communication between agents (Dusadeerungsikul, Nof, and Bechar 2018). The CCT principles have been implemented to improve the selection of robotic end-effectors for harvesting vegetables and fruits (Zhong, Nof, and Berman 2015). In addition, CCT has been applied to develop cyber-physical systems for stress monitoring in the greenhouse, called MDR-CPS (Guo, Dusadeerungsikul, and Nof 2018). The MDR-CPS has shown that with collaboration, the system will (1) minimise operation cost, (2) have higher error and conflict tolerance, and (3) respond faster to the new request. Moreover, CCT has also been utilised for managing local agents in the monitoring system by managing detailed operations such as robot routing and adaptive search algorithms to avoid conflicts and errors and minimise mismatch cost (Dusadeerungsikul and Nof 2019). CCT principles have also been applied to the collaborative response of propagating disruptions (Zhong and Nof 2015; Nguyen and Nof 2019), which include plant stress propagation as a sub-problem. Disruption propagation can be modelled as a complex network to enable better collaboration, task allocation, and situation awareness (Nguyen 2020). Using the CRDP framework, a complex network is created with the subjects of disruptions modelled as nodes, and the potential disruption propagation directions modelled as edges. The CRDP framework also recommends the use of network structure analysis (Nguyen and Nof 2020) and network centrality analysis (Nguyen and Nof 2018) to provide insights into the propagation pattern. Knowledge of the disruption propagation pattern can further increase the disruption response effectiveness.

2.3. Stress monitoring systems and protocols

Engineers and researchers have been developed and applied many techniques for improving the monitoring systems and protocols to detect biotic and abiotic plant stress (Jackson 1986). Biotic stresses include weeds and plant pathogens, whereas abiotic stresses include heat, chill, and nutrient deficiencies (Behmann et al. 2015). Modern stress monitoring systems are usually composed of humans, robots, and sensors. The three agents are responsible for different tasks in the system, and researchers have tried to improve such tasks by minimising unnecessary operations or reducing system failure. Examples of techniques that researchers used for improving stress monitoring systems are image processing and analyzing (Behmann, Steinrücken, and Plümer 2014; Dusadeerungsikul et al. 2019), machine learning

(Behmann et al. 2015; Gómez et al. 2019), deep learning (Singh et al. 2018; Saleem, Potgieter, and Arif 2019), neural network (Bhattacharya et al. 2020), support vector machines (Guerrero et al. 2012), and unfold principal component analysis (Villez, Steppe, and De Pauw 2009). Statistical inference techniques such as Bayesian network inference can also be applied in this problem context (Yet et al. 2016). The aforementioned works mainly concern the process of identifying plant stresses and diseases (including propagation), and there remains a dearth of research regarding the detection of propagation of stresses and diseases.

Apart from the techniques to improve the monitoring procedure, it is necessary to have a system structure that optimises the interaction between agents due to the complexity of collaborative interactions. Also, in the modern system, the agents are distributed and decentralised for more efficient work and better system performance. Task Administration Protocol (TAP), which is an optimisation workflow, is usually used for coordinating tasks to resources (e.g. agents) in the system at a suitable time (Nof et al. 2015). With the well-designed protocol, errors, conflicts, and operational costs are minimised while the quality of the outcome is optimal. The TAP has been applied for plant monitoring process and shows superior improvement compared to the current practice (Dusadeerungsikul et al. 2020).

3. Agricultural robotic system for plant stress propagation detection (ARS/PSPD)

In this section, the Agricultural Robotic System for Plant Stress Propagation Detection (ARS/PSPD) model is introduced and explained. This section specifies the agents, tasks, information exchange, and knowledge sharing involved in the ARS that are concerned with detecting propagating plant stress. Then, the mathematical formulation of the plant stress propagation detection problem is presented. The collaborative scanning protocols are then presented. An illustration of the ARS/PSPD model is presented in Figure 1.

3.1. *Specification of the ARS/PSPD model*

The ARS/PSPD model is the expansion of the ARS model (Guo, Dusadeerungsikul, and Nof 2018; Dusadeerungsikul and Nof 2019), with the specific focus on the plant stress propagation detection problem. To tackle the plant stress propagation problem, the Collaborative Response to Disruption Propagation (CRDP) framework is applied in this research (Nguyen and Nof 2019). Per the ARS model, the ARS/PSPD model consists of multiple intelligent agents: human agents, robot agents, software agents, and sensors. The environment of concern is a greenhouse, consisting of multiple plants and plant locations. The plants in this environment are subjected to stresses, which are conditions that can reduce plant productivity. These stresses are often not confined to a single plant, and the underlying conditions can propagate to nearby plants. Such propagations are referred to as plant stress propagation in this work. The goal of ARS/PSPD is to assign scanning tasks to its robot agents to detect plant stresses in the greenhouse concerned, with a limited scanning budget.

Each single robot agent in the ARS/PSPD is a robot mounted on a telerobotic/remote-controlled or autonomous mobile platform. Each robot agent is equipped with an end-effector carrying multiple sensors and/or spectral image cameras to scan the plants for possible stresses. This technology is enabled by the recent advances in agricultural robotics (Bechar, Meyer, and Edan 2009; Wang et al. 2018). The sensor results and/or images captured are then transferred to the ARS/PSPD system for analysis, through a combination of expert knowledge and machine learning techniques. The analysis, within the scope of this work, either returns a positive or negative stress condition. Expert knowledge can also provide the probability of plant stress occurrence given the current situation of the greenhouse, as well as the potential plant stress propagation directions. This plant stress detection approach addresses the limitations of the highly labour-intensive approach of using human agents to inspect every single plant manually.

Stressful conditions for plants are often not limited to a single plant location, and can often propagate to nearby plants if the stresses are not detected and responded to promptly (Dusadeerungsikul and Nof 2019). In this work, this mechanism is called plant stress propagation. Examples of stress propagation include spreading plant diseases and pests and/or extreme environmental conditions that affect a larger section of the greenhouse. The Collaborative Response to Disruption Propagation (CRDP) framework has established that utilising the knowledge of disruption propagation can improve response performance (Nguyen and Nof 2019). In the case of ARS/PSPD, the relevant disruptions are the plant stresses, and the response activities are the scanning activities of the robot agents. The application of the CRDP framework in ARS results in the PSPD portion of this research. Specifically, the CRDP framework recommends the detailed formulation of the PSPD problem using network theory, as specified in detail in subsection 3.2. Advanced analytics and protocols can then be developed to improve plant stress detection performance, as discussed in subsection 3.3. Advanced analytics are meaningful measures and indices that summarise and

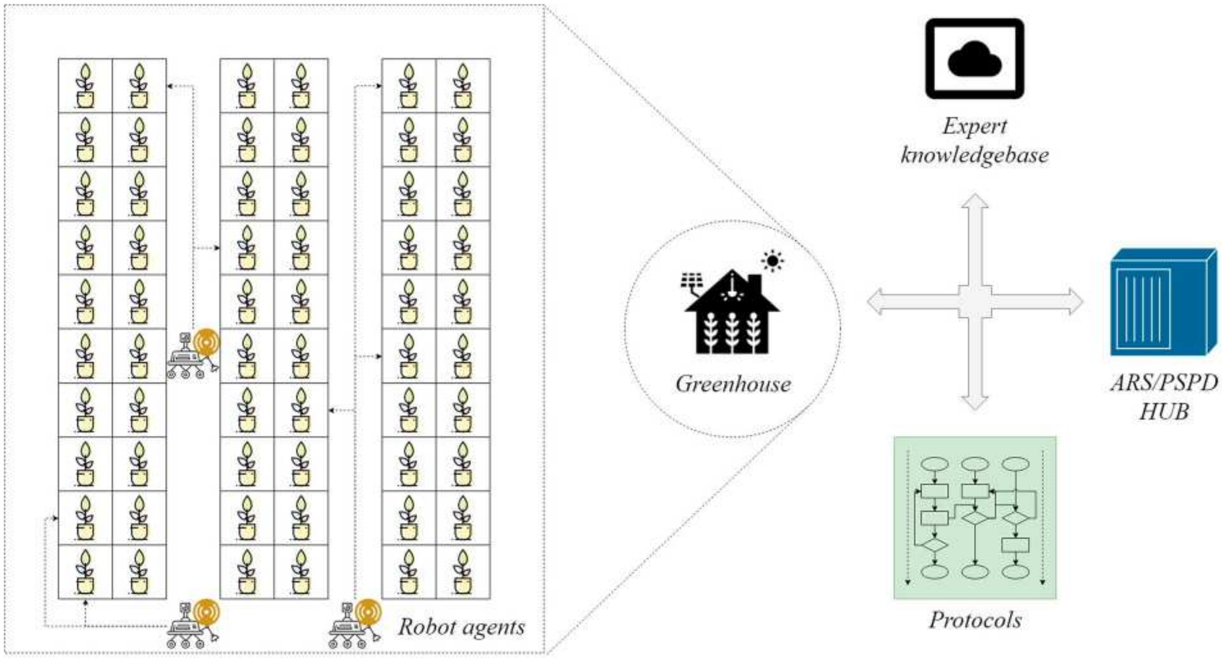

Figure 1. ARS/PSPD illustration.

condense the different status measures of the greenhouse. Based on the advanced analytics, collaborative scanning protocols can be developed and implemented to minimise errors and conflicts, as well as to ensure the desirable detection of plant stress.

The design of the ARS/PSPD model is supported by the Collaborative Control Theory, particularly the principles Collaboration Requirement Planning (CRP) and Error Prevention and Conflict Resolution (EPCR). This support is inherited from the previous work on ARS (Guo, Dusadeerungsikul, and Nof 2018; Dusadeerungsikul and Nof 2019). The CRP concept can be applied to the assignment of agents to tasks. The planning phase of CRP aims to develop the collaborative requirement matrix (CRM), which can be represented as below.

$$A_x \times T_y \rightarrow \text{CRM} \tag{1}$$

A_x represents the available agent x and T_y denotes task y. The CRM is the matrix that contains $CRM(A_x, T_y)$ elements representing the cost of agent x to perform task y as follows.

$$\text{CRM}(A_x, T_y) = \begin{cases} C_{xy}; & \text{if agent } x \text{ can perform tasks } x \\ M; & \text{otherwise} \end{cases} \tag{2}$$

C_{xy} is the cost of agent x performs task y and M is a large number representing the situation that agent x cannot perform task y ($M > \max(C_{xy})$).

The ARS/PSPD system involves multiple agents, as well as complex interactions and collaboration, inevitably leading to conflicts and errors. The EPCR principle enables and augments the prevention, detection, and resolution of errors and conflicts in order to minimise performance loss. Errors occur when the input, output, and/or intermediate results of ARS/PSPD do not meet specifications or expectations. An error is defined as follows.

$$\exists E[\text{ARS}_{\text{Single}}(t)]], \textit{if}\, (\text{State}_{\text{ARS}_{\text{Single}}}(t)) \overset{\text{Dissatisfy}}{\rightarrow} N_r(t) \tag{3}$$

Where $\boldsymbol{E}$ is an error, $\text{ARS}_{\text{Single}}(t)$ is the ARS' single agent at time t, $\text{State}_{\text{ARS}_{\text{Single}}}(t)$ is the state of the agent at time t, and $N_r(t)$ is the set of constraints, r, at time t.

A conflict refers to the difference between the information, goals, plans, operations, or activities of a group of collaborating agents. A conflict is defined as follows.

$$\exists C[\text{ARS}_{\text{Group}}(t)]], \textit{if}\, (\text{State}_{\text{ARS}_{\text{Group}}}(t)) \overset{\text{Dissatisfy}}{\rightarrow} N_r(t) \tag{4}$$

Where $\boldsymbol{C}$ is a conflict, $\text{ARS}_{\text{Group}}(t)$ is the ARS' group of collaborating agents at time t, $\text{State}_{\text{ARS}_{\text{Group}}}(t)$ is the state of the group of collaborating agents at time t, and $N_r(t)$ is the set of constraints, r, at time t. The errors and conflicts relevant to ARS/PSPD have been discussed in the previous work on ARS (Dusadeerungsikul and Nof 2019).

3.2. The formulation of the plant stress propagation detection problem

In this subsection, the formulation of the plant stress propagation detection problem is presented. In ARS/

PSPD, the set of plants consists of the plants in the agricultural greenhouse environment. Each plant can be subjected to stresses that can propagate once to a set of predetermined directions. Applying the Collaborative Response to Disruption Propagation (CRDP) framework (Nguyen 2020), each plant is modelled as a node $n \in N$, and each possible propagation from one plant to another is modelled as a directed edge $e = (n_i, n_j) \in E$. The CRDP framework specifies client system, the disruption propagation, and the response mechanisms. Applying the framework to this problem, the client system corresponds to the plants, the disruption propagation corresponds to the plant stress/disease, and the response mechanisms correspond to the scanning activities. The CRDP framework recommends the network modelling of the disruption-client interaction, namely, the stress propagation directions. This modelling enables and augments the scanning decisions by the improved situation awareness.

An example of the network modelling is given (Figure 2). In this example, a 5×3 plant grid with 2 stress propagation directions (orthogonal directions) is converted to a 15-node and 22-edge network.

The network modelling can represent sophisticated combinations of stress propagation directions and patterns by drawing the corresponding directed edges between the plants. For example, diagonal stress propagation directions can be included with diagonal directed edges (in the case presented in Figure 2). Any combination of propagation directions can also be represented this way. Furthermore, 'jumping' propagation from one node to another node further away (distance more than 1) can also be represented by drawing the corresponding directed edges. To properly apply the ARS/PSPD model, it is necessary that the network representation of the stress propagation be constructed according to previous knowledge or expert knowledge, which is enabled by the inclusion of expert knowledge.

Based on the set of nodes N and the set of edges E, the set of incoming edges $E^{in}(n)$ for each plant n is defined as

$$E^{in}(n) = \{(n_i, n_j) \in E : n_j \equiv n\} \tag{5}$$

The set of incoming nodes of each plant n is defined as

$$N^{\text{in}}(n) = \{n_j \in N : \exists (n_i, n_j) \in E : n_j \equiv n\} \tag{6}$$

Similarly, the set of outgoing edges $E^{\text{out}}(n)$ for each plant n is defined as

$$E^{\text{out}}(n) = \{(n_i, n_j) \in E : n_i \equiv n\} \tag{7}$$

The set of outgoing nodes of each plant n is defined as

$$N^{\text{out}}(n) = \{n_i \in N : \exists (n_i, n_j) \in E : n_i \equiv n\} \tag{8}$$

In ARS, stresses affecting a plant can propagate to nearby plants, due to location and environmental factors. To model this behaviour, the stress origin probability $p_0 \in [0, 1]$ is defined, which is the probability that each plant has a source of stress that stresses the plant itself and potentially nearby plants. This origin stress status $S_0(n)$ of a plant n is defined as

$$S_0(n) = \begin{cases} 1, & \text{with probability } p_0 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

These origin stresses can propagate stresses along the outgoing edges. Formally, the final stress status of each plant $S(n)$ is defined as

$$S(n) = \begin{cases} 1, & \begin{array}{l} \text{if } S_0(n) = 1 \text{ or} \\ \exists n_i \in N^{in}(n) : S_0(n_i) = 1 \end{array} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

An example of origin stress status and final stress status is given (Figure 3). A total of 3 plants are affected by $S_0(n) = 1$, leading to 8 plants being affected by $S(n) = 1$.

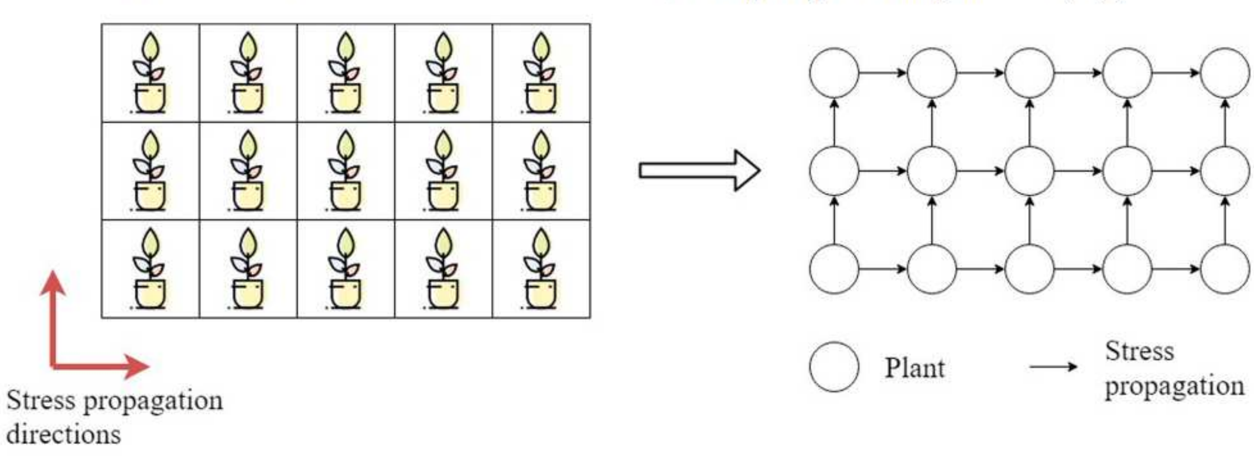

Figure 2. Network modelling of stress propagation example.

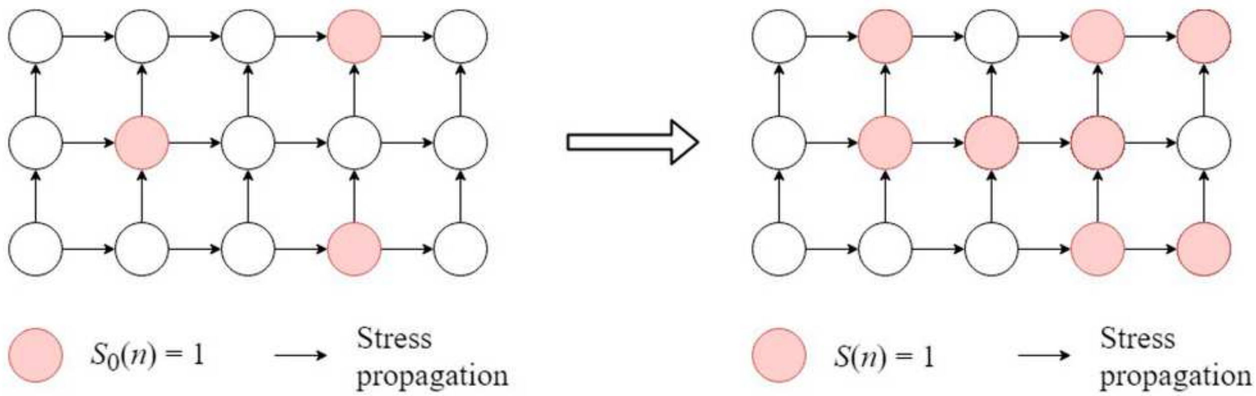

Figure 3. Stress propagation example.

The information about $S_0(n)$ and $S(n)$ is not known to ARS until a plant n is scanned/observed. The scanning/observation status $O(n)$ of a plant n, which is a decision variable, is defined as

$$O(n) = \begin{cases} 1, & \text{plant } n \text{ is observed} \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

Setting $O(n) \leftarrow 1$ allows ARS to see the status of $S(n)$. For most applications, the number of scans is limited due to the time-consuming nature of the stress scanning process (Dusadeerungsikul and Nof 2019). In the scope of this work, the maximum number of scans allowed is defined as $O_b \in \mathbb{N} \cap [0, |N|]$, which denotes the maximum number of scans allowed for a particular simulation run.

$$O_b \geq \sum_{n \in N} O(n) \tag{12}$$

To guide the scanning/observation decisions, different collaborative scanning protocols, generally denoted as $O_{(\text{protocolname})}$, are developed and employed. The selected scanning protocol for a simulation run is denoted as O_p. These protocols are discussed in the following subsection.

Two performance metrics with minimisation goals are defined to measure the effectiveness of the scanning decisions. The first performance metric $M_1 \in [0, 1]$, the undetected stress ratio, is defined as

$$M_1 = \frac{|\{n \in N : S(n) = 1 \text{ and } O(n) = 0\}|}{|N|} \tag{13}$$

The performance metric M_1 is the total number of stressed plants that were not scanned divided by the total number of plants. An alternative formula for M_1 is

$$M_1 = \frac{\sum_{n \in N} \max(0, S(n) - O(n))}{|N|} \tag{14}$$

The second performance metric $M_2 \in [0, 1]$, the redundant scanning ratio, is defined as

$$M_2 = \frac{|\{n \in N : O(n) = 1 \text{ and } S(n) = 0\}|}{O_b} \tag{15}$$

The performance metric M_2 is the total number of scanned plants that were not stressed divided by the maximum number of scans allowed. An alternative formula for M_2 is

$$M_2 = \frac{\sum_{n \in N} \max(0, O(n) - S(n))}{O_b} \tag{16}$$

The ARS simulation logic is as follows.

ARS step 1: Initialise N, E, p_0, O_b, O_p

ARS step 2: $\forall n \in N$: Compute $E^{\text{in}}(n), E^{\text{out}}(n), N^{\text{in}}(n), N^{\text{out}}(n)$

ARS step 3: Initialise origin stress : $\forall n \in N$:
  if $\text{unif}(0, 1) < p_0 : S_0(n) \leftarrow 1$, else $S_0(n) \leftarrow 0$

ARS step 4: Propagate stress : $\forall n \in N$:
  if $S_0(n) = 1$ or $(\exists n_i \in N^{in}(n) : S_0(n_i) = 1)$:
    $S(n) \leftarrow 1$
  else : $S(n) \leftarrow 0$

ARS step 5: Allocate scanning :
  For $i := 0$ to O_b :
  Decide $O(n)$ according to O_p, resulting in n_{next}
  $O(n_{next}) \leftarrow 1$

ARS step 6: Compute M_1, M_2

In the ARS simulation logic, ARS step 1 initialises the parameters needed for the simulation. Step 2 computes the derived sets of incoming/outgoing nodes and edges for each node. These sets are defined for the convenience of future simulation steps and scanning protocols. Step 3 initialises the origin stress $S_0(n)$, and step 4 propagate such stresses along the outgoing edges to $S(n)$. Step 5 allocates the scanning decisions according to the selected plant stress scanning protocol O_p and the maximum number of scans O_b allowed. The different scanning protocols are discussed in subsection 3.3.

Step 6 computes the system performance metrics M_1, the undetected stress ratio, and M_2, the redundant scanning ratio.

3.3. The collaborative scanning protocols for the detection of plant stress

Within the scope of this research, five different collaborative scanning protocols, generally referred to as O_p, are specified and validated. Following the EPCR principle, the ARS/PSPD system uses the scanning protocols to ensure that the scanning results $O(n)$ are shared across the system, and those plant locations are not scanned twice in a short period of time. The selected scanning protocol specifies the respective analysis that the ARS/PSPD uses and the next scanning location.

O_{Random}: Random scanning protocol, which randomly selects unobserved plants $n \in N : O(n) = 0$ to scan (Dusadeerungsikul and Nof 2019). This protocol is the baseline protocol, with which the other four more advanced scanning protocols are compared to. The random scanning protocol ensures scanning coverage but does not consider stress propagation. All unobserved plants received the same probability of being selected. Formally,

$$n_{\text{next}} \leftarrow \text{randomly select from } \{n \in N : O(n) = 0\} \tag{17}$$

ARS does not see $S_0(n)$, thus, computing the probability $P(S_0(n) = 1)$ and $P(S(n) = 1)$ is necessary. From the definition of $S_0(n)$, the probability of origin stress is

$$P(S_0(n) = 1) = p_0, \forall n \in N \tag{18}$$

Combined with the definition of final stress, and given no other information, formally Ø, the probability of final stress is

$$\begin{aligned} P(S(n) = 1|\emptyset) &\\ = 1 - \prod_{n_i \in N^{in}(n)} &(1 - P(S_0(n) = 1), \quad \forall n \in N \\ \Leftrightarrow P(S(n) = 1|\emptyset) &\\ = 1 - \prod_{n_i \in N^{in}(n)} &(1 - p_0) \\ = 1 - (1 - p_0)^{|N^{in}(n)|}&, \quad \forall n \in N \end{aligned} \tag{19}$$

Because the selections of $O(n)$ are completely random, and independent from the values of $S(n)$ (whether observed or not), the expected values of M_1 and M_2 can be estimated. This means the expected value for M_1 is as follows:

$$\begin{aligned} E(M_1) &= \frac{O_b \times \sum_{n \in N} P(S(n) = 1|\emptyset)}{|N|} \\ &= \frac{O_b \times \sum_{n \in N}(1 - (1 - p_0)^{|N^{in}(n)|})}{|N|} \end{aligned} \tag{20}$$

And the expected value for M_2 is

$$\begin{aligned} E(M_2) &= \frac{O_b \times \sum_{n \in N} P(S(n) = 0|\emptyset)}{|N|} \\ &= \frac{O_b \times \sum_{n \in N} (1 - p_0)^{|N^{in}(n)|}}{|N|} \end{aligned} \tag{21}$$

O_{Adaptive}: Adaptive basic scanning protocol, which prioritises plants with higher numbers of incoming nodes/plants that have been detected to be stressed, tie-breaking randomly (Dusadeerungsikul and Nof 2019). The main idea behind this scanning protocol is that the nodes next to the found-to-be-stressed nodes are more likely to be stressed than others. Using the nodes and edges defined, this protocol has been reformulated as

$$\begin{aligned} n_{\text{next}} \leftarrow \operatorname*{argmax}_{n \in N : O(n) = 0} \{|\{n_i \in N^{in}(n) : O(n_i) = 1 \\ \text{and } S(n_i) = 1\}|\} \end{aligned} \tag{22}$$

The alternative formulation is

$$n_{\text{next}} \leftarrow \operatorname*{argmax}_{n \in N : O(n) = 0} \left\{ \sum_{n_i \in N^{in}(n)} O(n_i) * S(n_i) \right\} \tag{23}$$

An example of O_{Adaptive} is provided (Figure 4). In this brief example, the nodes 3, 6, 7, 9, 13, and 15 have been scanned, thus $O(n) = 1$ for those nodes. Nodes 3, 6, and 15 are found to be not stressed with $S(n) = 0$, and nodes 7, 9, and 13 are found to be stressed with $S(n) = 1$. Using O_{Adaptive}, n_{next} is determined to be node 8, with a selection value of 2 (due to nodes 7 and 13 found to be stressed). Other nodes with selection values of 1 include nodes 2, 4, 10, and 14.

O_{InDegree}: Adaptive in-degree scanning protocol, which prioritises plants based on the numbers of incoming nodes/plants that have been detected to be stressed and not stressed, tie-breaking randomly. Two coefficients $\alpha, \beta \in \mathbb{R}$ are used to adjust the weights between stressed and not stressed nodes. This protocol expands upon O_{Adaptive} by considering nodes that have been found to be stressed and not stressed. Formally:

$$n_{\text{next}} \leftarrow \operatorname*{argmax}_{n \in N : O(n) = 0} \left\{ \begin{aligned} &\alpha \times |\{n_i \in N^{in}(n) : O(n_i) = 1 \\ &\text{and } S(n_i) = 1\}| - \\ &\beta \times |\{n_i \in N^{in}(n) : O(n_i) = 1 \\ &\text{and } S(n_i) = 0\}| \end{aligned} \right\} \tag{24}$$

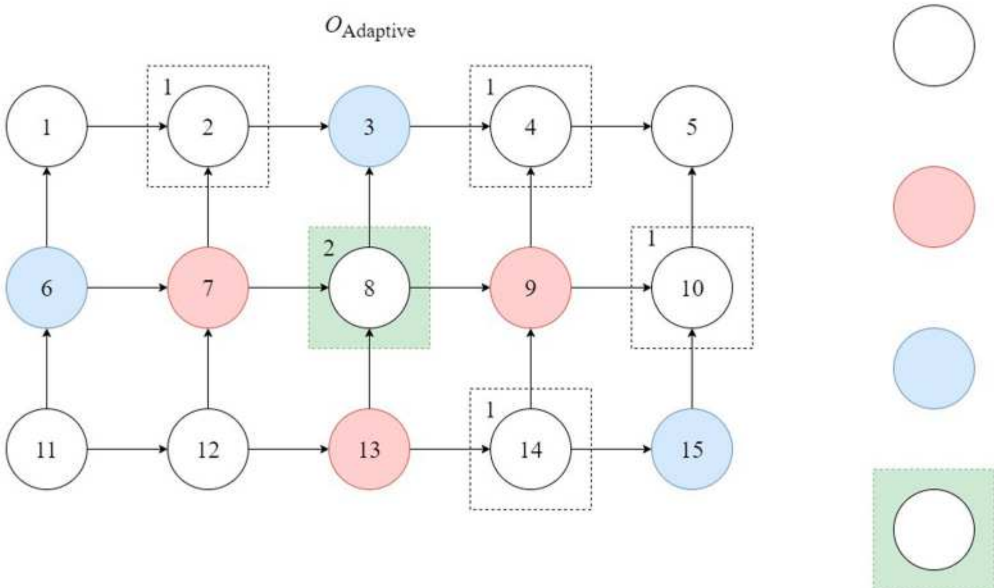

Figure 4. Illustration of adaptive search scanning protocol.

The alternative formulation is

$$n_{\text{next}} \leftarrow \underset{n \in N : O(n)=0}{\operatorname{argmax}} \times \left\{ \sum_{n_i \in N^{in}(n)} O(n_i) \times ((\alpha + \beta) \times S(n_i) - \beta) \right\} \quad (25)$$

An example of O_{InDegree} is provided (Figure 5). In this example, the nodes 1, 3, 6, 7, 8, 9, 13, and 15 have been scanned, thus $O(n) = 1$ for those nodes. Nodes 1, 3, 6, and 15 are found to be not stressed with $S(n) = 0$, and nodes 7, 8, 9, and 13 are found to be stressed with $S(n) = 1$. Using O_{InDegree}, with $\alpha = 1$ and $\beta = 0.5$, n_{next} is determined to be node 14, with the selection value of 1 (due to node 13 found to be stressed). Other nodes with selection values of 0.5 include nodes 2, 4, and 10. If O_{Adaptive} is used, nodes 2, 4, 10, and 14 would all receive the selection values of 1 instead.

$O_{\text{DualDegree}}$: Adaptive dual-degree scanning protocol, which prioritises plants based on the numbers of both incoming and outgoing nodes/plants that have been detected to be stressed and not stressed, tie-breaking randomly. The coefficients $\alpha, \beta, \gamma, \delta \in \mathbb{R}$ can be adjusted. This protocol expands upon O_{InDegree} by considering both incoming nodes and outgoing nodes. Formally:

$$n_{\text{next}} \leftarrow \underset{n \in N : O(n)=0}{\operatorname{argmax}} \times \left\{ \begin{array}{l} \alpha \times |\{n_i \in N^{in}(n) : O(n_i) = 1 \\ \text{and } S(n_i) = 1\}| - \\ \beta \times |\{n_i \in N^{in}(n) : O(n_i) = 1 \\ \text{and } S(n_i) = 0\}| + \\ \gamma \times |\{n_j \in N^{out}(n) : O(n_j) = 1 \\ \text{and } S(n_j) = 1\}| - \\ \delta \times |\{n_j \in N^{out}(n) : O(n_j) = 1 \\ \text{and } S(n_j) = 0\}| \end{array} \right\} \quad (26)$$

The alternative formulation is

$$n_{\text{next}} \leftarrow \underset{n \in N : O(n)=0}{\operatorname{argmax}} \times \left\{ \begin{array}{l} \displaystyle\sum_{n_i \in N^{\text{in}}(n)} O(n_i) \times ((\alpha + \beta) \times S(n_i) - \beta) + \\ \displaystyle\sum_{n_j \in N^{\text{out}}(n)} O(n_j) \times ((\gamma + \delta) \times S(n_j) - \delta) \end{array} \right\} \quad (27)$$

An example of $O_{\text{DualDegree}}$ is provided (Figure 6), which is similar to the example provided in Figure 5. Using $O_{\text{DualDegree}}$, with $\alpha = 1$, $\beta = 0.5$, $\gamma = 0.5$, and $\delta = 0.25$, n_{next} is determined to be node 14, with selection value of 1.25 (due to node 13 found to be stressed). Nodes 4 and 10 receive selection values of 0.5, and node 2 receives the selection value of 0.25.

O_{BayesNet}: Bayesian network-driven scanning protocol. This protocol utilises Bayesian network inference (Pearl 1985; Pearl and Paz 1987) to determine the probability of each plant being stressed, based on all

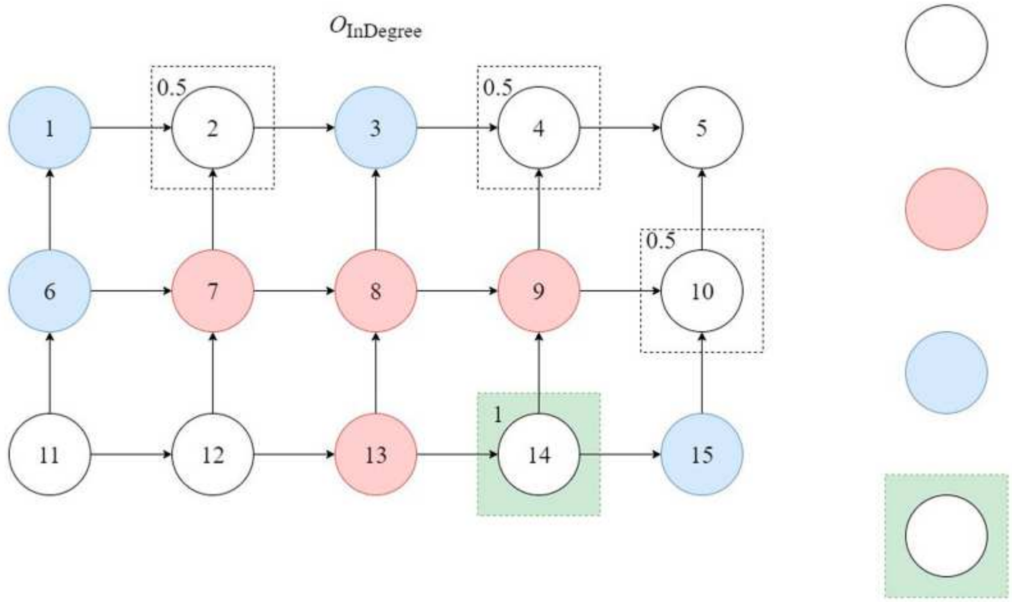

Figure 5. Illustration of in-degree scanning protocol.

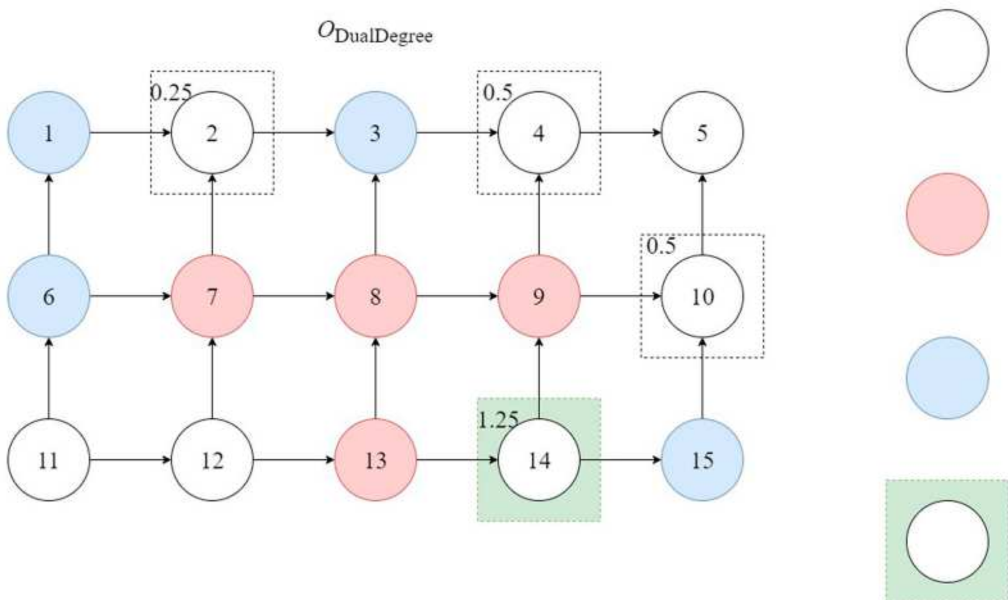

Figure 6. Illustration of dual-degree scanning protocol.

observations/scanning already done. Given a causal diagram, a Bayesian network can be used to answer conditional probability queries about an event happening. In this work, a Bayesian network is constructed using the network model from ARS/PSPD to establish the conditional dependencies between the stress occurrences of the different nodes. Utilising the scanning results, the Bayesian network can then infer the probabilities $P(S_0(n)|$ scanning results) and $P(S(n)|$ scanning results). This information is then used to select the next scanning decision.

To construct the Bayesian network representing the plant stress propagation problem, the following BayesNet logic is used:

BayesNet step 1: Initialise BayesNet

BayesNet step 2: $\forall n \in N,$ within BayesNet :

Create a BayesNet node for $S_0(n)$

Set 2x1 probability table for $S_0(n)$ of BayesNet with

$P(S_0(n) = 0) = 1 - p_0$

$P(S_0(n) = 1) = p_0$

Create a BayesNet node for $S(n)$

Create a BayesNet edge $(S_0(n), S(n))$

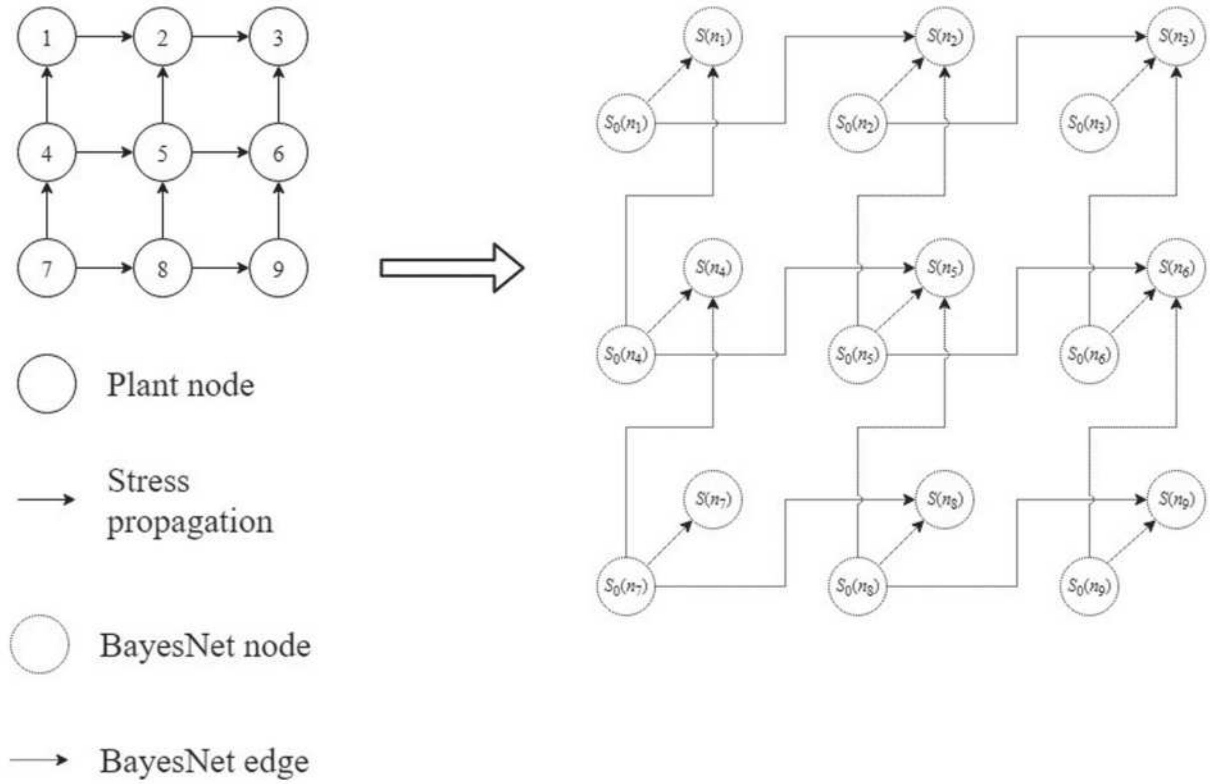

Figure 7. BayesNet formulation example.

BayesNet step 3: $\forall e = (n_i, n_j) \in E$, within BayesNet :
Create a BayesNet edge $(S_0(n_i), S(n_j))$
BayesNet step 4: $\forall n \in N$, within BayesNet :
Set conditional probability table for $S(n)$ given all incoming edges :
Number of rows $= 2^{|\{\text{incoming BayesNet edges to } S(n)\}|}$
Number of columns $= |\{$incoming BayesNet edges to $S(n)\}| + 2$
For each row of this conditional probability table :
If $S(n) = 0$, set $P(S(n) = 0) = 0$ if any incoming BayesNet edge is 1, and 0 otherwise
If $S(n) = 0$, set $P(S(n) = 1) = 1$if any incoming BayesNet edge is 1, and 0 otherwise

BayesNet step 1 initialises the BayesNet representing the plant stress propagation problem. Step 2 creates a BayesNet node representing $S_0(n)$ for each node $n \in N$, and a corresponding probability table for the nodes. The probability of $1 - p_0$ and p_0 are determined from the ARS simulation logic. For each node $n \in N$, Step 2 also creates a BayesNet node representing $S(n)$ and a BayesNet edge from $S_0(n)$ to $S(n)$. Step 3 refers to E, and for each $e = (n_i, n_j) \in E$, create a BayesNet edge from $S_0(n_i)$ to $S(n_j)$. An example of a BayesNet formulation from a 9-node and 12-edge network is given (Figure 7).

Step 4 creates all conditional probability tables for all $S(n)$ of all $n \in N$. For each $n \in N$, the dimension of conditional probability table for $S(n)$ depends on the number of incoming BayesNet edges of $S(n)$, which is 1 or greater. The case of 1 is when $N^{in}(n) = \emptyset$, and the only incoming BayesNet edge of $S(n)$ is $S_0(n)$. In the network provided in Figures 4–6, there are nodes with 0 in-degree (such as node 11), 1 in-degree (such as node 1), and 2 in-degree (such as node 5), and their BayesNet conditional probability tables are given (Table 2). The conditional probability values are determined from the ARS simulation logic step 4.

The scanning protocol O_{BayesNet} initialises the BayesNet, and updates the set of observations after each scanning decision allocation. Each observed node $n \in N$ with $O(n) = 1$ would have its corresponding $S(n)$ status updated in the BayesNet. Then, the probability of each unobserved node being stressed (with $O(n) = 0$) can be computed. Exact Bayesian network inference requires exponential time, but the belief propagation algorithm, which requires polynomial time, can also be used (Pearl 1982). The scanning protocol O_{BayesNet} then proceeds to select an unobserved node with the highest probability of being stressed, given all observations already made. Formally,

$$n_{\text{next}} \leftarrow \underset{n \in N: O(n)=0}{\text{argmax}} \{P(S(n) | \{S(n^*) : O(n^*) = 1, \forall n^* \in N\})\} \tag{28}$$

Table 2. Example of BayesNet conditional probability table, using the example given in Figure 4.

		$S_0(n_{11})$	$P(S(n_{11}) = 0 \mid S_0(n_{11}))$	$P(S(n_{11}) = 1 \mid S_0(n_{11}))$
		0	1	0
		1	0	1
	$S_0(n_1)$	$S_0(n_6)$	$P(S(n_1) = 0 \mid S_0(n_1), S_0(n_6))$	$P(S(n_1) = 1 \mid S_0(n_1), S_0(n_6))$
	0	0	1	0
	0	1	0	1
	1	0	0	1
	1	1	0	1
$S_0(n_4)$	$S_0(n_5)$	$S_0(n_{10})$	$P(S(n_5) = 0 \mid S_0(n_4), S_0(n_5), S_0(n_{10})$	$P(S(n_5) = 1 \mid S_0(n_4), S_0(n_5), S_0(n_{10})$
0	0	0	1	0
0	0	1	0	1
0	1	0	0	1
0	1	1	0	1
1	0	0	0	1
1	0	1	0	1
1	1	0	0	1
1	1	1	0	1

The information $S(n^*)$ is already available to the system because $O(n^*) = 1$ for all $n^* \in N$, and $P(S(n) \mid \{S(n^*) : O(n^*) = 1, \forall n^* \in N\})$ is provided by the BayesNet.

4. Experiment results

In this section, numerical experiments are conducted to illustrate and validate the plant stress detection simulation and the plant stress scanning protocols. A square grid is used as the layout of the greenhouse, as is typical in the agricultural greenhouse setting (Liu, Yuan, and Wang 2006; Brien et al. 2013; Kochhar and Kumar 2019). The size of the grid is 10-by-10, resulting in a total of 100 nodes. The potential stress propagation directions are the four cardinal directions (up/north/N, down/south/S, left/west/W, and right/east/E), which are commonly studied in greenhouse experiment designs (Brien et al. 2013). Due to symmetry within the 10-by-10 grid, only five combinations of stress propagation directions are necessary: 1-direction, 2-direction-opposite, 2-direction-orthogonal, 3-direction, and 4-direction. 1-direction is either N/S/W/E, and due to geometrical symmetry within the 10-by-10 grid, only one case is necessary. 2-direction is either NS/NW/NE/SW/SE/WE, but can be further reduced to 2-direction-opposite (NS, WE) or 2-direction-orthogonal (NW, NE, SW, SE). 3-direction is either NSW/NSE/NEW/SWE, and due to symmetry, only one case is necessary. 4-direction is one case of NSWE. Therefore, only five combinations of propagation directions are investigated.

Six cases of p_0 are investigated: 0.05, 0.10, 0.15, 0.20, 0.25, and 0.30. The scanning budget O_b is 50. The five scanning protocols described in 3.2 are applied: O_{Random}, O_{Adaptive}, O_{InDegree}, $O_{\text{DualDegree}}$, and O_{BayesNet}. The numerical experiments are conducted on Python 3, and the calculations supporting O_{BayesNet} are provided by the library Pomegranate (Schreiber 2014, 2017). The performance metrics M_1, total number of undetected stresses, and M_2, total number of redundant scans, are reported. Both M_1 and M_2 are minimisation objectives. A total of 100 replications (randomising origin stress statuses $S_0(n)$ for all nodes $n \in N$) are simulated for each factorial combination. Given five cases of stress propagation direction, six cases of p_0, and five cases of scanning protocols O_p, this set of experiments involve a total of 150 factorial combinations, and a total of 15,000 simulation runs.

The performance comparison between scanning protocols O_p (with 95% confidence interval bars) are provided in Table 3 and Figure 8.

The results in Table 3 and Figure 8 are averaged across all cases of stress propagation directions and stress origin probability. The scanning protocol O_{Adaptive} outperforms O_{Random} by 20.6% with respect to number of undetected stresses M_1 and by 15.9% with respect to number of redundant scans M_2, with statistical significance. The scanning protocol O_{BayesNet} outperforms O_{Random} by 35.4% in M_1 and by 27.3% in M_2, with statistical significance. The three scanning protocols O_{Adaptive}, O_{InDegree}, and $O_{\text{DualDegree}}$ do not provide statistically significant differences in performance. Also, the scanning protocol O_{BayesNet} outperforms the next best scanning protocol by

Table 3. Summary of comparison between scanning protocols.

Scanning protocol O_p	Number of undetected stresses M_1	Number of redundant scans M_2
O_{Random}	0.22027	0.57088
O_{Adaptive}	0.17473	0.47981
O_{InDegree}	0.17126	0.47287
$O_{\text{DualDegree}}$	0.17840	0.48715
O_{BayesNet}	**0.14227**	**0.41479**
	−16.92%	−12.28%

Values different from other values of the same category with statistical significance at $\alpha = 0.05$ are underlined.
The best value of a performance metric is **bolded**, and compared with the next best value.

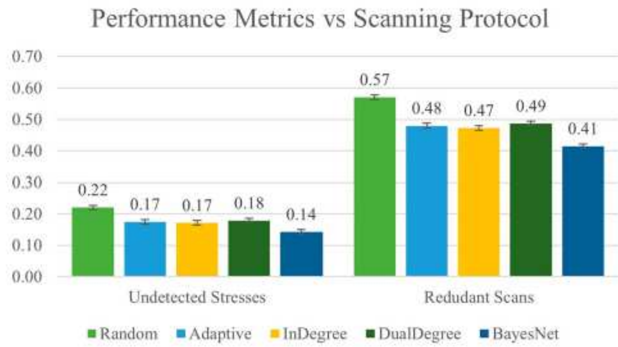

Figure 8. Comparison between scanning protocols.

16.92% in M_1 and by 12.28% in M_2, with statistical significance. These results indicate that the scanning protocol O_{BayesNet} provides superior stress detection performance (due to the lower number of undetected stresses M_1), as well as superior scanning efficiency (due to the lower number of redundant scans M_2).

The performance comparison between scanning protocols O_p (with 95% confidence interval bars), grouped by stress propagation directions, are provided in Table 4 and Figure 9.

The results in Table 4 and Figure 9 are averaged across all cases of stress origin probabilities, and grouped by the stress propagation directions. In all five cases of stress propagation directions, the scanning protocol O_{BayesNet} provides the highest performance in both M_1 and M_2, whereas the baseline scanning protocol O_{Random} provides the lowest performance. In the case of 1-direction, the next best scanning protocol is $O_{\text{DualDegree}}$. In the case of 2-direction-opposite, the next best scanning protocol is O_{InDegree}. In the case of 2-direction-orthogonal, the three scanning protocols O_{Adaptive}, O_{InDegree}, and $O_{\text{DualDegree}}$ provide similar performance. The performance gap in the two cases of 3-direction and 4-direction, both O_{Adaptive} and O_{InDegree} are next best in terms of performance in both M_1 and M_2. With respect to M_1, the performance gaps between O_{BayesNet} and the next best scanning protocol is lowest with the 2-direction-opposite case, and highest with the 1-direction case. With respect to M_2, the performance gaps between O_{BayesNet} and the next best scanning protocol is lowest with the 2-direction-opposite case, and highest with the 4-direction case. The first observation is that the scanning protocol O_{BayesNet} provides superior stress detection performance and superior scanning efficiency in all stress propagation direction cases. The second observation is that the next best scanning protocol is not necessarily the more advanced scanning protocol $O_{\text{DualDegree}}$.

The performance comparison between scanning protocols O_p(with 95% confidence interval bars), grouped by stress origin probability p_0, are provided in Table 5 and Figure 10.

The results in Table 5 and Figure 10 are averaged across all cases of stress propagation directions, and grouped by the stress propagation probabilities. In all six cases of p_0, the scanning protocol O_{BayesNet} provides the highest performance in both M_1 and M_2, whereas the baseline scanning protocol O_{Random} provides the lowest performance, all with statistical significance. The M_1 performance gap between O_{BayesNet} and the next best O_p decreases as p_0 increases, from 60.8% with 0.05 to 12.67% with 0.30. Also, M_1 steadily increases with higher p_0, which is due to the higher number of stresses. The M_2 performance gap between O_{BayesNet} are the next best O_p increases from 5.35% at $p_0 = 0.05$ to 15.31% at $p_0 = 0.10$, and then stabilises around 12% to 15%. Also, M_2 steadily decreases with higher p_0, because of the higher number of stresses. Based on the results in Table 5, it is observed that O_{BayesNet} outperforms all other scanning protocols across all p_0 scenarios. It is also observed that the three scanning protocols O_{Adaptive}, O_{InDegree}, and $O_{\text{DualDegree}}$ perform relatively similar to each other, across all stress probability p_0.

To summarise the experiment results:

(1) The scanning protocol O_{BayesNet} provides the best detection performance in both M_1 and M_2 across all experiment scenarios, with statistical significance.

Table 4. Summary of comparison between scanning protocols, grouped by stress propagation directions.

Scanning protocol O_p	1-dir		2-dir-opp		2-dir-ort		3-dir		4-dir	
	M_1	M_2	M_1	M_2	M_1	M_2	M_1	M_2	M_1	M_2
O_{Random}	<u>0.158</u>	<u>0.703</u>	<u>0.206</u>	<u>0.595</u>	<u>0.209</u>	<u>0.6</u>	<u>0.248</u>	<u>0.512</u>	<u>0.281</u>	<u>0.443</u>
O_{Adaptive}	0.129	0.646	0.141	0.466	0.176	0.529	0.198	0.411	0.233	0.347
O_{InDegree}	0.126	0.640	<u>0.125</u>	<u>0.434</u>	0.176	0.534	0.196	0.408	0.233	0.347
$O_{\text{DualDegree}}$	<u>0.111</u>	<u>0.610</u>	0.140	0.464	0.179	0.542	<u>0.213</u>	<u>0.443</u>	0.247	0.376
O_{BayesNet}	<u>**0.93**</u>	<u>**0.574**</u>	<u>**0.118**</u>	<u>**0.419**</u>	<u>**0.135**</u>	<u>**0.452**</u>	<u>**0.168**</u>	<u>**0.359**</u>	<u>**0.198**</u>	<u>**0.276**</u>
	minus;16%	−6%	−6%	−3%	−22%	−14%	−14%	−14%	<u>**0.198**</u>	<u>**0.276**</u>

Values different from other values of the same category with statistical significance at $\alpha = 0.05$ are <u>underlined</u>.
The best value of a performance metric is **bolded**, and compared with the next best value.

Figure 9. Comparison between scanning protocols, grouped by stress propagation directions.

Table 5. Summary of comparison between scanning protocols, grouped by stress origin probability

	Number of undetected stresses M_1					
Scanning protocol O_p	$p_0 = 0.05$	$p_0 = 0.10$	$p_0 = 0.15$	$p_0 = 0.20$	$p_0 = 0.25$	$p_0 = 0.30$
O_{Random}	0.0714	0.15044	0.2081	0.25544	0.30026	0.33624
O_{Adaptive}	0.0377	0.09774	0.15362	0.20554	0.25444	0.29938
O_{InDegree}	0.035	0.09364	0.15014	0.2028	0.2511	0.29492
$O_{\text{DualDegree}}$	0.0365	0.09958	0.15616	0.21082	0.2616	0.30576
O_{BayesNet}	**0.0137**	**0.04794**	**0.01123**	**0.01717**	**0.02293**	**0.02786**
	−60.8%	−48.8%	−25.2%	−15.3%	−8.67%	−5.53%
	Number of redundant scans M_2					
Scanning protocol O_p	$p_0 = 0.05$	$p_0 = 0.10$	$p_0 = 0.15$	$p_0 = 0.20$	$p_0 = 0.25$	$p_0 = 0.30$
O_{Random}	0.86828	0.71452	0.5946	0.49692	0.41104	0.33992
O_{Adaptive}	0.8014	0.60912	0.48564	0.39712	0.3194	0.2662
O_{InDegree}	0.796	0.60092	0.47868	0.39164	0.31272	0.25728
$O_{\text{DualDegree}}$	0.799	0.6128	0.49072	0.40768	0.33372	0.27896
O_{BayesNet}	**0.7534**	**0.50892**	**0.40308**	**0.32952**	**0.26916**	**0.22468**
	−5.35%	−15.31%	−15.79%	−15.86%	−13.93%	−12.67%

Values different from other values of the same category with statistical significance at $\alpha = 0.05$ are underlined. The best value of a performance metric is **bolded**, and compared with the next best value.

(2) The three scanning protocols O_{Adaptive}, O_{InDegree}, and $O_{\text{DualDegree}}$ outperform the baseline scanning protocols O_{Random} in both M_1 and M_2 across all experiment scenarios, with statistical significance.

(3) The three scanning protocols O_{Adaptive}, O_{InDegree}, and $O_{\text{DualDegree}}$ only show statistically significant difference in terms of M_1 and M_2 performance when comparing different stress propagation scenarios.

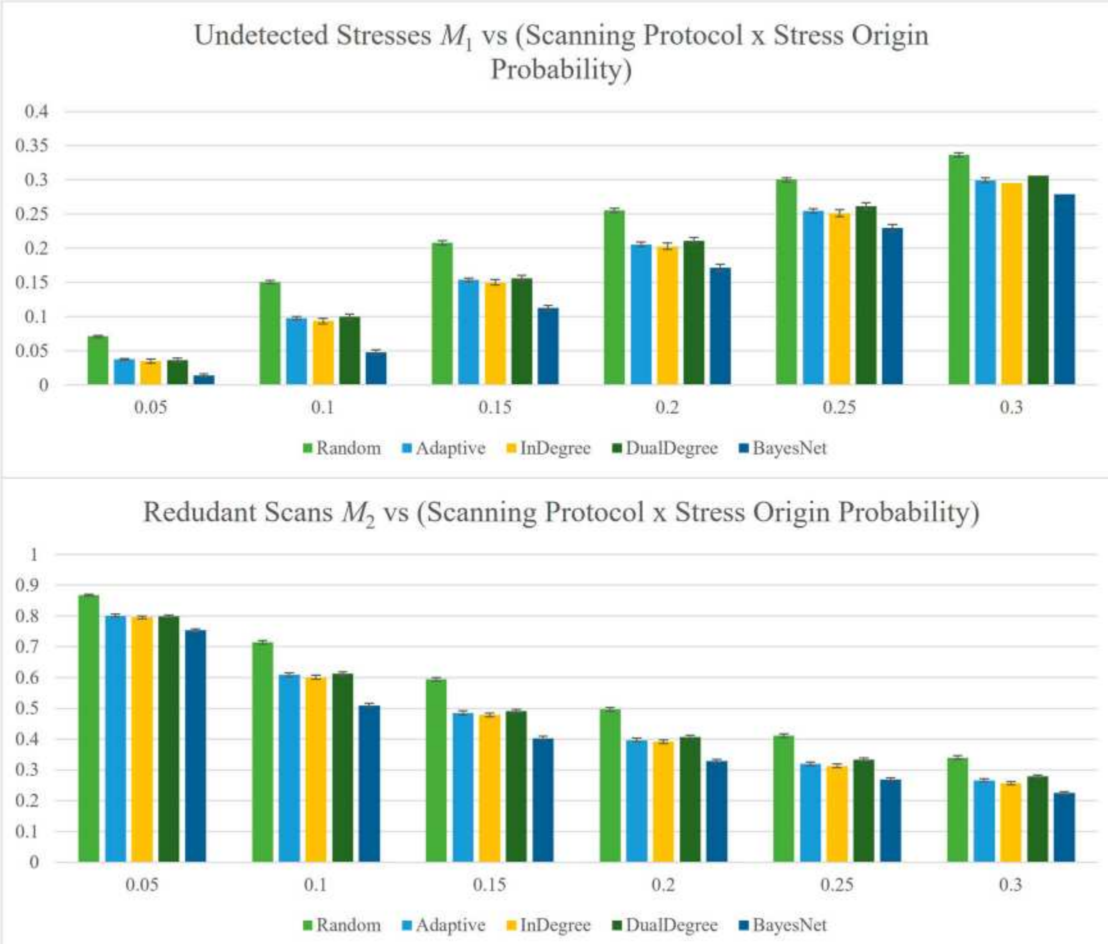

Figure 10. Comparison between scanning protocols, grouped by stress origin probability.

5. Conclusion and discussion of applications

This paper presents the Agricultural Robotic System for Plant Stress Propagation Detection (ARS/PSPD), which focuses on the plant stress detection function of the ARS. Leveraging the cyber-physical nature of ARS and the network modelling capability of CRDP results in the formulation of the plant stress detection problem. This PSPD formulation captures the plant stress occurrence and propagation mechanisms, enabling better situation awareness and augments the development of advanced collaborative scanning protocols. A total of five collaborative scanning protocols are designed and implemented in ARS/ PSPD. The scanning protocols minimise errors and conflict in scanning task allocation and enable better detection of plant stress. The first scanning protocol is the random sampling scanning protocol, which is the baseline protocol for comparison. The second, third, and fourth scanning protocols are adaptive scanning protocols that utilise existing plant stress information and stress propagation network topology to assign scanning tasks. The fifth scanning protocol, Bayesian network-driven scanning protocol, constructs a Bayesian network based on existing plant stress information, and infers the state of plant stress of unscanned locations. To validate the PSPD formulation and the five collaborative scanning protocols, numerical experiments are conducted. The experiment results show that the Bayesian network-driven scanning protocol outperforms the three adaptive scanning protocols, which in turn outperform the baseline random sampling scanning protocol.

From this research, the following recommendations are made to greenhouse managers, supervisors, and researchers involved in plant stress detection and monitoring:

(1) The plant locations in the greenhouse should be specified, modelled, and monitored to allow better awareness and identification of plant stresses.
(2) The occurrence mechanisms and propagation mechanisms of plant stresses should be investigated, understood, and incorporated into the plant stress detection and monitoring activities.

(3) The information obtained from both stress-positive scans and stress-negative scans should be utilised to infer the stress statuses of unscanned plant locations.

Future research is recommended to further expand the ARS/PSPD model and/or to enrich the research in plant stress propagation detection and monitoring:

(1) Different types of plant stresses with different occurrence and propagation behaviours could be explored. Each plant type could have different propagation probabilities as well. Better scanning decision analytics need to be developed to address this complexity. Then, field experiments could be conducted to validate the improved model and decision analytics.
(2) More complex workflow problems and issues should be considered: Multiple agent travelling; Scanning and travelling interruptions and preemption due to new information; Complex time constraints (travelling and scanning) coupled with physical robot limitations (battery recharging or equipment calibrating).
(3) Expanding the ARS/PSPD model to the case of limited or unavailable propagation pattern knowledge. This case could require the use of statistical and machine learning techniques to infer the propagation directions.
(4) Include human-in-the-loop design, which allows humans to intervene in the system's task allocation and decision-making.
(5) Investigating and applying the property of high stress/non-stress certainty into the scanning decisions. The high certainty of stress/non-stress could allow the skipping of scanning, due to certain nodes having very high probability of having stress/non-stress, further improving scanning performance.

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Data availability statement

There is no data set associated with this work. The quantitative details of the model used and the numerical experiments have been provided in the article.

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References

Alsuwaidi, Ali, Bruce Grieve, and Hujun Yin. 2018. "Combining Spectral and Texture Features in Hyperspectral Image Analysis for Plant Monitoring." *Measurement Science and Technology* 29 (10): 104001. doi:10.1088/1361-6501/aad642.

Åstrand, Björn, and Albert Jan Baerveldt. 2002. "An Agricultural Mobile Robot with Vision-Based Perception for Mechanical Weed Control." *Autonomous Robots* 13 (1): 21–35. doi:10.1023/A:1015674004201.

Bechar, Avital, Joachim Meyer, and Yael Edan. 2009. "An Objective Function to Evaluate Performance of Human-Robot Collaboration in Target Recognition Tasks." *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews* 39 (6): 611–620. doi:10.1109/TSMCC.2009.2020174.

Bechar, Avital, and Clément Vigneault. 2016. "Agricultural Robots for Field Operations: Concepts and Components." *Biosystems Engineering* 149: 94–111. doi:10.1016/j.biosystemseng.2016.06.014.

Behmann, Jan, Anne-Katrin Mahlein, Till Rumpf, Christoph Römer, and Lutz Plümer. 2015. "A Review of Advanced Machine Learning Methods for the Detection of Biotic Stress in Precision Crop Protection." *Precision Agriculture* 16 (3): 239–260.

Behmann, Jan, Jörg Steinrücken, and Lutz Plümer. 2014. "Detection of Early Plant Stress Responses in Hyperspectral Images." *ISPRS Journal of Photogrammetry and Remote Sensing* 93: 98–111.

Bhattacharya, Debangshu, Subhashis Banerjee, Shubham Bhattacharya, B. Uma Shankar, and Sushmita Mitra.2020. "GAN-Based Novel Approach for Data Augmentation with Improved Disease Classification." In *Advancement of Machine Intelligence in Interactive Medical Image Analysis*, edited by Om Prakash Verma, Sudipta Roy, Subhash Chandra Pandey, and Mamta Mittal, 229–239. Singapore: Springer. https://doi.org/10.1007/978-981-15-1100-4_11.

Bochtis, D. D., C. G. Sørensen, R. N. Jørgensen, M. Nørremark, I. A. Hameed, and K. C. Swain. 2011. "Robotic Weed Monitoring." *Acta Agriculturae Scandinavica Section B: Soil and Plant Science* 61 (3): 202–208. doi:10.1080/09064711003796428.

Brien, Chris J., Bettina Berger, Huwaida Rabie, and Mark Tester. 2013. "Accounting for Variation in Designing Greenhouse Experiments with Special Reference to Greenhouses Containing Plants on Conveyor Systems." *Plant Methods* 9 (1): 5. doi:10.1186/1746-4811-9-5.

Dar, Itamar, Yael Edan, and Avital Bechar. 2011. "An Adaptive Path Classification Algorithm for a Pepper Greenhouse Sprayer." In *American Society of Agricultural and Biological Engineers Annual International Meeting 2011, ASABE 2011*, 1:288–302. doi:10.13031/2013.38107.

Diker, Kenan, and Walter C. Bausch. 2003. "Radiometric Field Measurements of Maize for Estimating Soil and Plant Nitrogen." *Biosystems Engineering* 86 (4): 411–420. doi:10.1016/j.biosystemseng.2003.08.016.

Dusadeerungsikul, Puwadol Oak. 2020. "Operations Analytics and Optimization for Unstructured Systems: Cyber Collaborative Algorithms and Protocols for Agricultural Systems." doi:10.25394/PGS.12218531.v1.

Dusadeerungsikul, Puwadol Oak, Vasileios Liakos, Francesco Morari, Shimon Y. Nof, and Avital Bechar. 2020. "Smart Action." In *Agricultural Internet of Things and Decision Support for Precision Smart Farming*, 225–277. Elsevier. doi:10.1016/B978-0-12-818373-1.00005-6.

Dusadeerungsikul, Puwadol Oak, and Shimon Y. Nof. 2019. "A Collaborative Control Protocol for Agricultural Robot Routing with Online Adaptation." *Computers and Industrial Engineering* 135: 456–466. doi:10.1016/j.cie.2019.06.037.

Dusadeerungsikul, Puwadol Oak, Shimon Y. Nof, and Avital Bechar. 2018. "Detecting Stresses in Crops Early by Collaborative Robot-Sensors-Human System Automation." In *IISE Annual Conference and Expo 2018*, 1084–1089. Orlando, FL, United states: Institute of Industrial and Systems Engineers, IISE.

Dusadeerungsikul, Puwadol Oak, Shimon Y. Nof, Avital Bechar, and Yang Tao. 2019. "Collaborative Control Protocol for Agricultural Cyber-Physical System." *Procedia Manufacturing* 39: 235–242. doi:10.1016/j.promfg.2020.01.330.

Ferentinos, Konstantinos P., Nikolaos Katsoulas, Antonis Tzounis, Thomas Bartzanas, and Constantinos Kittas. 2017. "Wireless Sensor Networks for Greenhouse Climate and Plant Condition Assessment." *Biosystems Engineering* 153: 70–81. doi:10.1016/j.biosystemseng.2016.11.005.

Gómez, Diego, Pablo Salvador, Julia Sanz, and Jose Luis Casanova. 2019. "Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data." *Remote Sensing* 11 (15): 1745.

Guerrero, J. M., G. Pajares, M. Montalvo, J. Romeo, and M. Guijarro. 2012. "Support Vector Machines for Crop/Weeds Identification in Maize Fields." *Expert Systems with Applications* 39 (12): 11149–11155. doi:10.1016/j.eswa.2012.03.040.

Guo, Ping, Puwadol Oak Dusadeerungsikul, and Shimon Y. Nof. 2018. "Agricultural Cyber Physical System Collaboration for Greenhouse Stress Management." *Computers and Electronics in Agriculture* 150: 439–454. doi:10.1016/j.compag.2018.05.022.

Iida, Michihisa, Ryo Uchida, Huaping Zhu, Masahiko Suguri, Hiroki Kurita, and Ryohei Masuda. 2013. "Path-Following Control of a Head-Feeding Combine Robot." *Engineering in Agriculture, Environment and Food* 6 (2): 61–67. doi:10.1016/S1881-8366(13)80028-6.

Ishibashi, Maya, Michihisa Iida, Masahiko Suguri, and Ryohei Masuda. 2013. "Remote Monitoring of Agricultural Robot Using Web Application." *IFAC Proceedings Volumes (IFAC-PapersOnline)* 4 (PART 1): 138–142. doi:10.3182/20130828-2-SF-3019.00047.

Jackson, Ray D. 1986. "Remote Sensing of Biotic and Abiotic Plant Stress." *Annual Review of Phytopathology* 24 (1): 265–287.

Keicher, R., and H. Seufert. 2000. "Automatic Guidance for Agricultural Vehicles in Europe." *Computers and Electronics in Agriculture* 25 (1–2): 169–194. doi:10.1016/S0168-1699(99)00062-9.

Khan, Akhtar, Philip Martin, and Phil Hardiman. 2004. "Expanded Production of Labor-Intensive Crops Increases Agricultural Employment." *California Agriculture* 58 (1): 35–39. doi:10.3733/ca.v058n01p35.

Ko, Min Hyuc, Beom-Sahng Ryuh, Kyoung Chul Kim, Abhijit Suprem, and Nitaigour P Mahalik. 2014. "Autonomous Greenhouse Mobile Robot Driving Strategies from System Integration Perspective: Review and Application." *IEEE/ASME Transactions On Mechatronics* 20 (4): 1705–1716.

Kochhar, Aarti, and Naresh Kumar. 2019. "Wireless Sensor Networks for Greenhouses: An End-to-End Review." *Computers and Electronics in Agriculture* 163: 104877. doi:10.1016/j.compag.2019.104877.

Liu, Xuemei, Jin Yuan, and Kesheng Wang. 2006. "A Problem-Specific Genetic Algorithm for Path Planning of Mobile Robot in Greenhouse." *IFIP International Federation for Information Processing* 207: 211–216. doi:10.1007/0-387-34403-9_28.

Moghaddam, Mohsen, and Shimon Y. Nof. 2014. "Combined Demand and Capacity Sharing with Best Matching Decisions in Enterprise Collaboration." *International Journal of Production Economics* 148: 93–109. doi:10.1016/j.ijpe.2013.11.015.

Moghaddam, Mohsen, and Shimon Y. Nof. 2017. "The Collaborative Factory of the Future." *International Journal of Computer Integrated Manufacturing* 30 (1): 23–43. doi:10.1080/0951192X.2015.1066034.

Nagasaka, Yoshisada, Qin Zhang, Tony E Grift, Yutaka Kanetani, Naonobu Umeda, and Takuo Kokuryu. 2004. "An Autonomous Field Watching-Dog Robot for Information Collection in Agricultural Fields." In *2004 ASAE Annual Meeting*, 1.

Nayak, Ashutosh, Rodrigo Reyes Levalle, Seokcheon Lee, and Shimon Y. Nof. 2016. "Resource Sharing in Cyber-Physical Systems: Modelling Framework and Case Studies." *International Journal of Production Research* 54 (23): 6969–6983. doi:10.1080/00207543.2016.1146419.

Nguyen, Win P V. 2020. "Collaborative Response to Disruption Propagation (CRDP)." Purdue University Graduate School. doi:10.25394/PGS.12218513.v1.

Nguyen, Win P V, and Shimon Y. Nof. 2018. "Resilience Informatics for Cyber-Augmented Manufacturing Networks (CMN): Centrality, Flow and Disruption." *Studies in Informatics and Control* 27 (4): 377–384. doi:10.24846/v27i4y201801.

Nguyen, Win P V, and Shimon Y. Nof. 2019. "Collaborative Response to Disruption Propagation (CRDP) in Cyber-Physical Systems and Complex Networks." *Decision Support Systems* 117: 1–13. doi:10.1016/j.dss.2018.11.005.

Nguyen, Win P V, and Shimon Y Nof. 2020. "Strategic Lines of Collaboration in Response to Disruption Propagation (CRDP) Through Cyber-Physical Systems." *International Journal of Production Economics* 230: 107865.

Nof, Shimon Y. 2007. "Collaborative Control Theory for E-Work, e-Production, and e-Service." *Annual Reviews in Control* 31 (2): 281–292. doi:10.1016/j.arcontrol.2007.08.002.

Nof, Shimon Y., José A. Ceroni, Wootae Jeong, and Mohsen Moghaddam. 2015. *Revolutionizing Collaboration Through E-Work, e-Business, and e-Service*. Edited by José A. Ceroni, Wootae Jeong, and Mohsen Moghaddam. Berlin, Heidelberg: Springer Berlin Heidelberg: Imprint: Springer.

Oerke, E.-C., and H.-W. Dehne. 2004. "Safeguarding Production—Losses in Major Crops and the Role of Crop Protection." *Crop Protection* 23 (4): 275–285. doi:10.1016/J.CROPRO.2003.10.001.

Pearl, Judea. 1982. *Reverend Bayes on Inference Engines: A Distributed Hierarchical Approach*. Pittsburgh, PA: Cognitive Systems Laboratory, School of Engineering and Applied Science .

Pearl, Judea. 1985. "Bayesian Networks a Model of Self-Activated Memory for Evidential Reasoning." In *Proceedings of the 7th Conference of the Cognitive Science Society*, 329–334.

Pearl, J., and A. Paz. 1987. "Graphoids: A Graph-Based Logic for Reasoning about Relevance Relations." In *Advances in Artificial Intelligence. Vol. II*, edited by B. Du Boulayet al., 357–363. Seattle, WA: University of California (Los Angeles). Computer Science Department.

Reid, John F, Qin Zhang, Noboru Noguchi, and Monte Dickson. 2000. "Agricultural Automatic Guidance Research in North America." *Computers and Electronics in Agriculture* 25 (1–2): 155–167.

Sai, Zou, Yang Fan, Tang Yuliang, Xiao Lei, and Zhao Yifong. 2016. "Optimized Algorithm of Sensor Node Deployment for Intelligent Agricultural Monitoring." *Computers and Electronics in Agriculture* 127: 76–86.

Saleem, Muhammad Hammad, Johan Potgieter, and Khalid Mahmood Arif. 2019. "Plant Disease Detection and Classification by Deep Learning." *Plants* 8 (11): 468.

Schreiber, Jacob. 2014. "Pomegranate." *GitHub Repository*.

Schreiber, Jacob. 2017. "Pomegranate: Fast and Flexible Probabilistic Modeling in Python." *The Journal of Machine Learning Research* 18 (1): 5992–5997.

Singh, Asheesh Kumar, Baskar Ganapathysubramanian, Soumik Sarkar, and Arti Singh. 2018. "Deep Learning for Plant Stress Phenotyping: Trends and Future Perspectives." *Trends in Plant Science* 23 (10): 883–898.

Spekken, Mark, and Sytze de Bruin. 2013. "Optimized Routing on Agricultural Fields by Minimizing Maneuvering and Servicing Time." *Precision Agriculture* 14 (2): 224–244.

Sreeram, Maitreya. 2020. "Human-in-the-Loop of Cyber Physical Agricultural Robotic Systems." doi:10.25394/PGS.13303490.v1.

Strange, Richard N, and Peter R Scott. 2005. "Plant Disease: A Threat to Global Food Security." *Annual Review of Phytopathology* 43 (1): 83–116. doi:10.1146/annurev.phyto.43.113004.133839.

Villez, Kris, Kathy Steppe, and Dirk J W De Pauw. 2009. "Use of Unfold PCA for On-Line Plant Stress Monitoring and Sensor Failure Detection." *Biosystems Engineering* 103 (1): 23–34.

Vurro, Maurizio, Barbara Bonciani, and Giovanni Vannacci. 2010. "Emerging Infectious Diseases of Crop Plants in Developing Countries: Impact on Agriculture and Socio-Economic Consequences." *Food Security* 2 (2): 113–132. doi:10.1007/s12571-010-0062-7.

Wang, Dongyi, Robert Vinson, Maxwell Holmes, Gary Seibel, Avital Bechar, Shimon Y. Nof, Yaguang Luo, and Yang Tao. 2018. "Early Tomato Spotted Wilt Virus Detection Using Hyperspectral Imaging Technique and Outlier Removal

Auxiliary Classifier Generative Adversarial Nets (OR-AC-GAN)." *2018 ASABE Annual International Meeting*. St. Joseph, MI: ASABE. doi:10.13031/aim.201800660.

Xue, Jinlin, Lei Zhang, and Tony E Grift. 2012. "Variable Field-of-View Machine Vision Based Row Guidance of an Agricultural Robot." *Computers and Electronics in Agriculture* 84: 85–91.

Yet, Barbaros, Anthony Constantinou, Norman Fenton, Martin Neil, Eike Luedeling, and Keith Shepherd. 2016. "A Bayesian Network Framework for Project Cost, Benefit and Risk Analysis with an Agricultural Development Case Study." *Expert Systems with Applications* 60: 141–155. doi:10.1016/j.eswa.2016.05.005.

Yoon, S. W., and Shimon Y. Nof. 2010. "Demand and Capacity Sharing Decisions and Protocols in a Collaborative Network of Enterprises." *Decision Support Systems* 49 (4): 442–450. doi:10.1016/j.dss.2010.05.005.

Zhong, Hao, and Shimon Y. Nof. 2015. "The Dynamic Lines of Collaboration Model: Collaborative Disruption Response in Cyber–Physical Systems." *Computers & Industrial Engineering* 87: 370–382. doi:10.1016/j.cie.2015.05.019.

Zhong, Hao, Shimon Y. Nof, and Sigal Berman. 2015. "Asynchronous Cooperation Requirement Planning with Reconfigurable End-Effectors." *Robotics and Computer-Integrated Manufacturing* 34: 95–104.

Zhong, Hao, Juan P. Wachs, and Shimon Y. Nof. 2013. "A Collaborative Telerobotics Network Framework with Hand Gesture Interface and Conflict Prevention." *International Journal of Production Research* 51 (15): 4443–4463. doi:10.1080/00207543.2012.756591.