Frost monitoring cyber-physical system: a survey on prediction and active protection methods

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***Abstract*—Frost damage in broadacre cropping and horticulture (including viticulture) results in substantial economic losses to producers and may also disrupt associated product value chains. Frost risk windows are changing in timing, frequency, and duration. Faced with the increasing cost of mitigation infrastructure and competition for resources (e.g. water and energy), multi-peril insurance, and the need for supply chain certainty, producers are under pressure to innovate in order to manage and mitigate risk. Frost protection systems are cyber-physical systems comprising of sensors (event detection), intelligence (prediction), and actuators (active protection methods). The Internet of Things communication protocols joining the cyber-physical system components are also evaluated. In this context, this paper introduces and reviews existing methods of frost management. This paper focuses on active protection methods because of their potential for real-time deployment during frost events. For integrated frost prediction and active protection systems, prediction method, sensor types, and integration architecture are assessed, research gaps are identified and future research directions proposed.**

***Index Terms*—Frost Prediction, Frost Protection, Machine Learning, Cyber-Physical Systems**

I. Introduction

As the growth of the global population continues, the yield of food production should follow this growth to avoid future food shortages [1]. Although many environmental factors are affecting the yield of food, this paper focuses on frost, which can be a cause of food shortages in countries relying on frost intolerant crops [2]. The direct economic loss of lost production through frost damage can be substantial. For example, in 1998, the Wimmera region of Australia lost an estimated 60% of its wheat crop due to frost, costing 200 million AUD [3]. More recent research from 2016 shows that frost events incur a loss of 120 million to 700 million AUD annually from the Australian broadacre agriculture sector [4]. The frost event also adversely impacted on jobs along the supply chain [5].

The global trend of climate change has not only increased the average temperature of the Earth's climate system, but also induced greater instability in weather patterns, which lead towards a higher risk of frost damage [6], [7]. Recent changes in the spatial and temporal characteristics of frost events have been attributed to climate change [4]. Frost prediction models that depend on historical weather data could be challenged. Therefore, real-time active responses provided by Cyber-Physical Systems (CPSs) are required to predict and mitigate the risk of frost damage accurately in the face of these challenges.

This paper discusses the frost prediction methods in terms of the capability of real-time prediction as well as the requirements of relevant spatial and temporal resolution. In practical terms, and in addition to the obvious requirement of reliability and accuracy, desirable attributes of frost prediction methods must also include a reduction in the cost of frost protection and being able to provide crop managers appropriate warning time in order to implement effective response strategies [8], [9]. The process of prediction and protection could be automated by leveraging CPSs with controllers controlling actuators based on sensor outputs, assuming the outputs have been preconditioned via some form of analytical processes in order to trigger a correct and timely response [10]. Therefore, and given CPSs by their nature conduct real-time operations [10], this paper focuses on the short-term active frost protection methods, rather than the long-term passive frost protection methods.

The primary aim of this paper is to identify current challenges and research gaps in automating real-time frost protection systems with minimal operational cost. The major contributions of this paper are listed as follows:

1) Analysis of existing frost prediction algorithms and methods.
2) Summary of the existing work on active frost protection applications and methods.
3) Overview of protection systems leveraging frost prediction models.
4) Identification of current research gaps and future directions.

The rest of this paper is organized as follows: Section II presents the methodology of the survey. Section III provides an overview of relevant technologies and concepts. This overview includes background on frost, machine learning, and CPS. Section IV demonstrates an analysis of current work on frost prediction models. Then, Section V presents the existing frost protection methods categorized in passive and active methods. Section VII provides insights on the deployment of IoT protocols in terms of power consumption, communication range and cost factors in a frost protection CPS. Section VI, the limitations of current automated frost protection systems are discussed. With the research gaps on frost prediction models and limitations of automated frost protection systems concluded, Section VIII proposes future research directions. Finally, Section IX offers concluding remarks.

II. Methodology

The literature analysis process consists of four stages. The first stage aims to collect, filter, and categorize relevant literature related to frost prediction methods, active frost protection methods, and frost protection systems in the agricultural sector. This stage involves three steps, which are literature searching, literature filtering, and literature categorization. In the first step, journal papers and conference articles are searched in scientific databases. These scientific databases are *Google Scholar*, *IEEE Xplore* and *ScienceDirect*. The following queries are used for the literature search:

- *["frost"] AND ["prediction" OR "forecast" OR "detection"]*
- *"frost protection"*

After preliminary filtering with document titles and abstracts, 53 documents have been chosen. Then, the second round of filtering ensures that the whole collection is only related to the prediction of frost occurrence, protection with active methods and protection systems in the agriculture sector. Papers that as been analyzed in referenced survey papers are also removed. At the end of this step, the number of papers reduced to 30. The final step of the first stage aims to classify the literature collection into fields of frost prediction, frost protection, and protection systems. The classification process is conducted in the sequence of the three fields. A paper can belong to more than one field because some aspects of these fields can be overlapping. For example, a work on protection systems could also involve novelty in prediction methods.

During the second stage, the papers from the first stage are analyzed in their corresponding fields. In the field of frost prediction, the prediction method, data source, data type, and model performance are surveyed. Also, the instantaneity, spatial resolution, and temporal resolution of prediction methods are evaluated. Then, some work on common frost protection methods is concluded in terms of the protection method and research aim. Finally, the protection methods and alarm systems of frost protection systems are analyzed.

In the third stage, existing works on IoT communication protocols are searched to compare the transmission range, power consumption, and cost for a frost protection CPS. The following keywords are used to search in the *Google Scholar*, *IEEE Xplore* and *ScienceDirect* databases:

- *"IoT communication protocols"*
- *"IoT communication protocols agriculture"*

The result of these queries contains 7 survey papers including the transmission range, and power consumption of IoT communication protocols, this research stage aims to select a few suitable protocols using existing transmission range, and power consumption results. The selected protocols are further analyzed in the next stage with cost factors.

III. Technologies and Concepts

This section provides a background of the technologies and concepts relevant to frost prediction and protection systems. The concepts of frost, CPS, and machine learning are discussed.

A. Concepts of Frost

The definition of frost typically follows either the physical process itself, or the effect of its occurrence can vary in different literature. Through the former, frost refers to the phenomenon of ice crystal generation from dew or vapor [11], as "...the occurrence of an air temperature of 0 ^{o}C or lower, measured at the height between 1.25 and 2.0 m above soil level, inside an appropriate weather shelter." The second definition focuses on the damage of crops. The term "frost protection" is also ambiguous. Freeze damage or injury is caused by plants in an environment under a critical temperature, where water freezes within and damages the cells of crops [12]. As the words "frost" and "freeze" are often used as substitutes of each other and the term "frost protection" is used more frequently, "frost protection" generally means "freeze protection" [11]. Therefore, in this paper, frost protection is defined as protecting crops from freeze damage or injury.

The authors of [9] categorized frost into radiation frost and advection frost (freeze) (Table I). Radiation frosts occur in nights with calm wind and clear skies. During the event of a radiation frost, the temperature drops due to the natural radiation of heat [12]. Hence, temperature inversions occur, whereas advection frosts are formed without temperature inversions and in the presence of through wind. In addition, advection frosts are formed by a body of cold air moving to the site through wind [12].

TABLE I
Environmental Characteristics of Radiation and Advection Frosts. [9]

Property \ Frost Type	**Radiation Frost**	**Advection Frost**
Wind Speed	<5 mph	>5 mph
Cloud Coverage	Clear sky	Could be with cloud
Cold Air Thickness	30–200 ft	500–5000 ft
Inversion	Inversion develops	No inversion

B. Cyber-Physical Systems

The fourth industrial revolution or Industry 4.0 leverages CPS as a core element to improve the efficiency and effectiveness of industrial systems [10], [13]. CPSs are hybrid systems of physical and logical elements joined by communication capabilities to provide safe and reliable control on physical entities [14]. Figure 1 demonstrates a basic CPS architecture. This architecture consists of sensors for data collection from the environment, actuators to perform an action affecting the environment, intelligence to control the actuators based on sensor data and network to communicate between the prior three elements [15]. In addition to these elements, CPSs also incorporate different technologies such as Wireless Sensor Networks (WSNs), the Internet of Things (IoT) and machine learning to achieve the goal of operational efficiency and effectiveness in industrial operations. The rest of this subsection describes the relationship between CPS and these different technologies in the agricultural context.

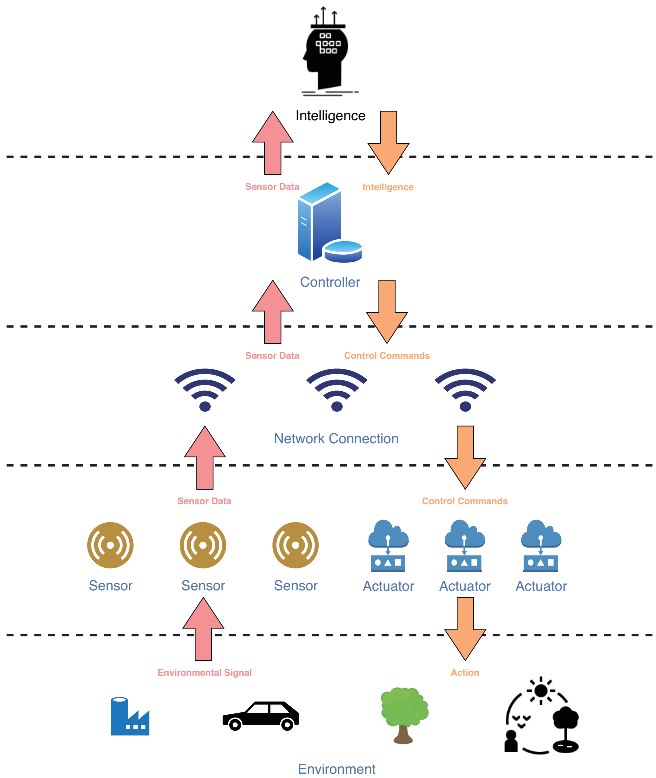

Fig. 1. Basic CPS Architecture. [15]

WSN is a vast network that utilizes many low power and low-cost sensor nodes. With the aid of different communication protocols and network topologies, WSNs can provide manageability to the sensors and actuators within the network [16]. This manageability would aid CPSs to control and operate a high number of sensors and actuators to interact with the environment [17]. In an agricultural context, a terrestrial WSN with reliable and dense communications could be deployed to monitor the environment [18]. The advantages of deploying such a network in agricultural applications are low cost, a low impact on the environment, real-time information feedback, and high efficiency (Table II) [19]. Therefore, WSN is highly compatible with agricultural applications to act as a data gatherer for CPSs.

TABLE II
ADVANTAGES OF WSN IN AGRICULTURE. [19]

Advantage	**Description**
Low cost	Allows dense deployment to accurately monitor the environment.
Low impact on the environment	Reduces possible cause of stress on crops and animals by the system itself.
Real-time information feedback	Farmers can actively response to environmental changes and adjust their strategy.
High efficiency	Incorporation of sensors and actuators to replace previous manual work.

IoT and CPS are similar concepts. From [14], previous works often separate IoT and CPS from the perspectives of control, platform, internet, and human, but the authors of [14] pointed out that these distinctions are unclear and insufficient. However, CPS is developed from a systems engineering and control perspective, and IoT focuses on networking and information technology [14]. Therefore, in this paper, the controlling and monitoring ability of CPS is recognized, and the networking and communication ability of IoT highlighted. Thus, IoT is viewed as an autonomous network of wirelessly connected entities through sensors [20]. As CPSs require interaction with different subsystems, IoT can be viewed as an enabler for CPSs to connect with devices for controlling and monitoring [21], [22]. Furthermore, IoT within CPSs is described as Industrial IoT (IIoT) [22]. As IIoT provides a massive amount of information, big data analytics are essential to process this information from the sensors [21]. Within the field of big data analytics, machine learning is often incorporated to extract patterns, draw novel insights, and provide intelligence from existing data in IoT networks [23]. Machine learning is also applied to frost prediction with various sensor data.

C. Machine Learning

As the significance of machine learning is indicated above, this section explains some of the machine learning techniques leveraged by the frost prediction applications reviewed in the sections below. Machine learning is a technique incorporating statistical methods to build models from historical datasets [24]. Machine learning methods can be classified into supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [24]. The evaluated recent frost prediction literature uses both supervised learning and unsupervised learning methods (Table III & IV). Supervised learning methods are trained by a dataset of input data with labeled desired outputs [24]. On the contrary, unsupervised learning methods are trained with a dataset that only contains input data [24]. Clustering methods are used to create a model for unsupervised learning methods [25]. After that, the result clusters are interpreted by experts to provide certain meanings [25]. The rest of this subsection presents some machine learning methods found in frost prediction related literature. In these methods, linear regression, logistic regression, decision tree, random forest, and Artificial Neural Network (ANN) are discussed as supervised learning methods. Also, unsupervised learning methods such as Principle Component Analysis (PCA) and Self-Organizing Map (SOM) are reviewed.

1) Linear Regression: Linear regression is a statistical modeling method aimed to approximate the relationship between independent variables and dependent variables [26]. Usually, linear regression solves regression problems by approximating continuous numeral outputs [26].

$$f(X) = W \cdot X + b \tag{1}$$

Equation 1 is the general form of the linear regression model [26]. $f(X)$ represents the estimated output by the model. W indicates a vector of coefficients to be calculated. X is the input vector. Finally, b denotes a scalar of the bias. W and b are the variables to be learned during the training process [26]. This learning is achieved through optimization techniques such as gradient descent and aimed to minimize the difference between the estimated $f(X)$ and the real output [26]. This difference can be measured in different ways. A common method is the Mean Squared Error (MSE) [26].

2) Logistic Regression: Logistic regression is usually used to solve classification problems, which require the output as multiple discrete classes [27]. Logistic regression solves the classification problems by providing the confidence value of a class [27]. The basic logistic regression model is based on the Sigmoid function (Equation 2) [27]. Similar to the model of linear regression, W, X and b represent the vector of coefficients, the input vector, and the bias scalar, respectively. Since the output of the Sigmoid function is a value between 0 and 1 [27], the confidence of prediction can be determined.

$$f(x) = \frac{1}{1 + e^{-W \cdot X + b}} \tag{2}$$

The loss function to be optimized is the log-likelihood (Equation 3) [27]. Y is the actual class of the relevant X. This loss can also be minimized with gradient descent [27].

$$log(g) = \sum_{i=1}^{n} Y_i log(f(X_i)) + (1 - Y_i) log(1 - f(X_i)) \tag{3}$$

3) Decision Tree: Similar to logistic regression, decision trees are also used to solve classification problems [28]. Decision trees are built by separating a set of labeled dataset into two subsets, recursively [28]. There are many methods of separation. An example is the ID3 method. For each split in ID3, the aim is to choose the split based on a value of an input attribute [29]. A value-attribute pair is chosen with the split to minimize the entropy of the subsets [29]. The entropy is a statistical term given by Equation 4 [29]. In this equation, X, y_1 and y_2 represents the input dataset, the first class of the actual output and the second class of the actual output, respectively.

$$H = \sum_{X} [-P(y_1|X) log_2 P(y_1|X) - P(y_2|X) log_2 P(y_2|X)] \tag{4}$$

4) Random Forest: Random forest is an ensemble learning method based on decision trees [30]. It provides a low correlation between different trees in the forest, avoiding the domination of a few strong attributes in decision tree features [30]. This is achieved by training multiple decision trees with randomly picked data from the training set and considering only some randomly chosen attributes of the data for each tree [30].

5) Artificial Neural Network: There are many different names of ANNs, including deep feedforward networks, feedforward neural networks, and multilayer perceptrons. In this paper, only the term "ANN" is used. The basic ANN model consists of three layers. The input layer, the hidden layer, and the output layer [31]. Equation 5 presents the general function of an ANN with an input layer, two hidden layers, and an output layer [31].

$$f(X) = f^{output}(f^{hidden2}(f^{hidden1}(X))) \tag{5}$$

ANNs can be used to solve both classification and regression problems, depending on the nature of the output layer [31]. Thus, the loss function could be similar to linear regression and logistic regression. However, the optimization method is slightly different. The learning algorithm applies gradient descent through backpropagation [31].

6) Principal Component Analysis: A common usage of PCA is dimensionality reduction, which decreases the amount of data by removing entire attributes from the dataset [32]. The original dataset is converted to a new dataset containing the most information content or variance [32]. The orthogonal factor scores are another result of PCA. These scores can be further analyzed for the relationship between different attributes [32].

7) Self-Organizing Map: SOM is a type of ANN that can be used for clustering with the neurons are organized in a two-dimensional grid [33]. Through multiple iterations, the neurons would move towards locations with a high density of data points [33]. The learning of such an algorithm is through a random selection of a data point [34]. The neuron closest to the selected data point moves towards the data point by a preset distance, which is the learning rate [34]. Other neurons within a certain radius of the closest neuron are considered as the neighbors. These neighbors also move towards the data point. This process repeats with the update of the learning rate and the radius after each iteration [34].

IV. Frost Prediction Methods

Frost prediction methods aim to detect an incoming frost event. In this paper, frost events are categorized as classification methods and regression methods. Classification methods classify an input case into frost or no frost events for a future period of time, whereas regression methods predict the minimum temperature of a future period of time. As weather conditions could vary due to small spatial variations [8], [35], spatial resolution is essential for frost prediction. Also, real-time prediction and high temporal resolution prediction are both important to save the protection cost. The operational cost of active protection methods can be reduced as prediction resolution increases. This also gives the farmers more time to decide their tactics [8]. The rest of this section presents and discusses some relevant work on frost prediction with the three identified factors: instantaneity, high spatial resolution, and high temporal resolution.

A. Classification Methods

Current classification methods focus on prediction of a possible frost event over a following period of time [8], [36], [37], [38], [39], [40], [41]. Table III summarizes works on classification methods. A primitive method is described by [36]. The major contribution of the work is to measure the value created by frost forecasting. However, it also records farmers using temperature from the weather forecast with their empirical experiences to decide whether to switch on their protection heaters or not. This method is neither real-time nor high in temporal resolution as the prediction covers the whole night. As many farms scattering across a large county are using the same data source, this method fails to achieve high spatial resolution.

TABLE III
FROST CLASSIFICATION PREDICTION METHODS.

Year	Prediction Method	Input Data	Output	Performance	Real-time	High Spatial Resolution	High Temporal Resolution
1976 [36]	Weather Forecast	Temperature, Empirical experience	Indication of frost or no frost	N/A	**X**	**X**	**X**
1984 [8]	Weather Forecast, Manual Monitoring	Temperature, Dew point	Indication of frost or no frost	N/A	✓	✓	✓
1996 [37]	ANN	Daily max temperature, Daily min temperature, Humidity at 1900, Cloud cover, Wind speed at 1900, Wind direction at 1900	Min temperature $\leq$ 1.0 OR Min temperature $>$ 1.0	Rate of correct predictions: 88% - 94%	**X**	**X**	**X**
2009 [38]	SOM, ANN	Temperature, relative humidity, wind direction, wind speed and dew point	Indication of frost or no frost	N/A	**X**	**X**	**X**
2016 [39]	Logistic Regression, Decision Tree	Min temperature, grass min temperature, dew point, Difference of max & min temperature, mean relative humidity, min relative humidity	Indication of frost or no frost	Probability of detection (Logistic Regression): 0.747 - 0.816. Probability of detection (Decision Tree): 0.731 - 0.866	**X**	✓	**X**
2017 [40]	Random Forest	Temperature, relative humidity, solar radiation, dew point, wind speed and direction	Indication of frost or no frost	Overall success rate: 79% - 98%	**X**	✓	**X**
2018 [41]	Logistic regression	Temperature, relative humidity, weather station data	Indication of frost or no frost	True positive rate: 0.82 - 0.88	✓	✓	**X**
2019 [42]	ARIMA	Dry bulb temperature at 60 cm above ground sunrise, Dry bulb temperature at 60 cm above ground sunset, Dew point at sunset, Wet bulb temperature at 60 cm above ground at sunset, Relative Humidity at sunset	Indication of frost or no frost	True positive rate: 0.60 - 1.00	**X**	✓	**X**

In [8], the farmers achieved real-time prediction with high spatial resolution and temporal resolution. However, their method uses a substantial amount of human labor. As the temperature reaches a preset point, farmers are informed by an alarm [8]. Then, the farmers would continuously monitor the temperature and dew point for the whole night to decide if a protection mechanism needs to be triggered [8]. This method matches all the preset criteria. However, it requires much manual intervention, and hence, it cannot be automated. On the other hand, the authors of [8] proves that protection mechanisms do not require to be switched on all night during a frost event. This gives motivation for developing a high temporal resolution prediction method to save operational costs on protection.

The authors of [37] leveraged a classification ANN to predict the occurrence of frost events for the coming night. The input of the model is temperature, humidity, cloud coverage, wind speed, and direction [37]. With these inputs, the model detects frost by labeling the input as "Temperature $\leq$ 1.0" and "Temperature $>$ 1.0." The label "Temperature $\leq$ 1.0" indicates frost. The temporal resolution of this method is low because it is predicting frost occurrence for the whole night. Also, the spatial resolution of this method is questionable, since the data source is from Catania, Italy and it is unclear that these data are from multiple sources or not. Similarly, the ability for real-time prediction is also questionable since there is no experiment on the real-time inference of the model.

The authors of [38] aimed to create a frost prediction model with two stages of processing of the raw weather data. The first stage categorizes weather data into clusters using SOM. With the result of these clusters, a classification algorithm would classify new inputs as frost or non-frost events. However, this research only demonstrated results for the first stage of the study. Further evidence is required for the performance of the prediction algorithm.

Logistic regression and decision trees are also leveraged for frost event prediction. These machine learning techniques are applied to compute the next day occurrence of a frost event using weather data collected from weather stations in Korea [39]. Prediction with a high temporal resolution still remains an issue as the prediction period is one-day long.

The authors of [40] improved the temporal resolution for classification methods to the next 12 hours. However, it is still not sufficient for creating a real-time protection system. Data are collected from weather stations of the Maule region of Chile. Each model is trained using the dataset from only one region. Therefore, this method demonstrates a high spatial resolution.

The problem of temporal resolution still persists in [42]. However, it is still significant that the authors viewed the problem as a time series prediction problem using the Autoregressive Integrated Moving Average (ARIMA) model. This method allows the detection of all frost events in the test data. Unfortunately, the trade-off is high false alarms, which would increase the operational cost for the farmers to protect their crops.

B. Regression Methods

Earlier frost prediction regression methods are based on descriptive models of thermal radiation and heat convection [50], [51], [52], [53]. In more recent work, neural networks demonstrated improvements in the results using the descriptive methods as a baseline [46]. Since the more recent methods have better results and the descriptive methods have already been analyzed in-depth, this paper focuses on later models based on statistical methods and machine learning. However, descriptive methods can provide rapid and economically feasible predictions [54]. Therefore, the potential of these descriptive methods should be explored further in the future.

Table IV summarizes works on regression methods. Most of the regression methods focus on predicting the minimum temperature of a future period of time with given historical or current inputs [41], [44], [45], [46], [47], [48], [49]. However, the method demonstrated in [43] is an exception. It is still considered as a regression method because the predictands are numerical values. This method uses Southern Oscillation Index (SOI) data, temperature and historical data of the date of last frost and the number of frosts to re-predict the date of last frost and the number of frosts of the coming year. Correlation analysis and linear discriminant analysis are conducted to find the relationship between SOI and the predictands. Furthermore, PCA and iterative clustering are used to study SOI phases. Unfortunately, this work cannot be applied in real-time as the results require years of historical data. Also, the temporal resolution of prediction is one year as this work predicts the date of last frost and the number of frost events of the coming year.

In [45], multiple models of temperature are produced considering the effect of the wind machine to predict temperature for different times of the day. This model predicts real-time with high spatial and temporal resolution as the data collected are from a 0.5 km^2 vineyard. However, this model fails to consider wind as a possible input factor as the study region is usually windless. Therefore, this method would be accurate for the study region of other windless regions. The model could fail in regions with winds as a significant factor affecting temperature.

The authors of [44] extended their work [37] from a binary classification model to a multi-class classification model with eight ranges of minimum temperatures. Since this is not merely predicting an occurrence of a frost event and even the model is a classification model, this method is considered as a frost regression prediction method. However, the limitations still persist. Spatial resolution and real-time prediction capability of this method remain questionable as the source of data are vague and there is no test conducted for real-time inference. Temporal resolution is still low because the predictand is accounted for the next 24-hours. Also, prediction with two output classes demonstrates the highest accuracy. Therefore, extending towards multiple classes does not contribute to the improvement of frost prediction.

Similarly, ANN is also used to predict the minimum temperature of the night with daytime variables and previous day minimum temperature [46], but in a regression model. The model is built with high spatial resolution as data from individual weather stations is leveraged. However, the model is not tested for real-time inference. Also, the temporal resolution is limited, as it only predicts the minimum temperature of the night. On the other hand, an important result of this work is that the deep learning models have the potential to outperform the traditional descriptive models.

ANN is further leveraged to predict frost for the next 24 hours using rough sets [47]. The data is collected from a weather station located in Hunan, China. Therefore, the spatial resolution of the prediction is high. However, the method is predicting for the next 24 hours, which indicates low temporal resolution.

Similar work is done in [48]. ANN is applied on datasets from multiple weather stations of Central Chile to predict the next day minimum temperature with fewer parameters. Since the method is also predicting for the next day, low temporal resolution is still an issue.

The authors of [49] introduced the concept of WSN into frost prediction regression applications. They used WSN to increase the reliability of the data collection process. This ensures a high spatial resolution of prediction. Also, this system allows real-time inference, as the decision process is based on real-time data. However, the temporal resolution remains low as they are only predicting the minimum temperature of the coming night.

The authors of [41] also used WSN to predict frost occurrence. It performs both regression and classification methods using the random forest and logistic regression, respectively. Also, an external weather station is introduced to the temperature readings from WSN sensors. As WSN is used for data collection, the prediction method can conduct real-time prediction with high spatial resolution. Again, the temporal resolution remains low as prediction is for next day minimum temperature and next day frost occurrence. However, the significance of this work is using the Synthetic Minority Oversampling Technique (SMOTE), which significantly improves the performance of random forest and logistic regression models.

In conclusion, both classification and regression methods all predict with high spatial resolution as the data are collected from a sole weather station or using WSN. On the other hand, most systems are not tested for the capability of real-time prediction. Since most of the methods predict for the next day or the next 24-hour, the methods could potentially be extended for a higher temporal resolution. However, classifica-

TABLE IV
FROST REGRESSION PREDICTION METHODS.

Year	Prediction Method	Input Data	Output	Performance	Real-time	High Spatial Resolution	High Temporal Resolution
1996 [43]	Correlation analysis, Linear Discriminant analysis, PCA, Clustering	SOI phases data, Temperature, Historical dates of last frost and number of frosts each year	Date of last frost, number of frosts	N/A	X	X	X
1997 [44]	ANN	Previous day min temperature, Previous day max temperature, Cloud cover, humidity at 1900, Wind speed and direction at 1900	A range of next 24-h min Temperature	Rate of correct predictions: 94%	X	X	X
2003 [45]	Linear Regression	Elevation, Time of local sunset, Radiation received during the previous day, Distance to wind machines.	Temperature	Standard error: 0.24 - 0.60	✓	✓	✓
2006 [46]	ANN	Air Temperature, Soil Temperature, Relative Humidity, Wind velocity, Average Wind velocity, Max temperature of day, Min temperature of previous day, Daytime length	Min temperature of the night	Percent correct: 87.8% - 95.6%	✓	✓	X
2012 [47]	ANN	Max temperature, Min temperature, Average temperature, Max wind speed, Precipitation, Cloud cover, Moisture, Pressure, Humidity at 1900, Wind direction at 1900, Wind speed at 1900, 2 previous days min temperature, 5 previous days min temperature	Min temperature for the next 24 hours	True rate: 88%	X	✓	X
2018 [48]	ANN	Air temperature, Relative humidity, radiation, Precipitation, and Wind direction and speed	Next day min temperature	Accuracy: 0.97 - 0.99	X	✓	X
2018 [49]	Linear Regression	Temperature, Dew point, Humidity	Min temperature of the night	N/A	X	✓	X
2018 [41]	Random forest	Temperature, Relative humidity, Weather station data	Next day min temperature	True positive rate: 0.75 - 0.9	✓	✓	X

tion methods are hard to extend because, in the case of hourly or higher resolution prediction, the indication of frost events is complex compared to next day predictions. For example, as frost already occurs in the first hour of the event, in the second hour it is hard to indicate if the existing frost appears due to the environmental factor of the second hour or the first hour. On the contrary, an extension on regression methods is more straightforward as the hourly minimum temperature can be measured with a temperature sensor.

V. FROST PROTECTION METHODS

Frost protection methods consist of passive protection methods and active protection methods [55], [56]. Passive protection methods are applied before the event of frost and are usually cheaper. However, passive methods might not provide sufficient heat to resist frost injury [56], whereas active protection methods are applied during the event of frost to preserve heat on the crops for protection. Active protection methods are usually expensive due to manual operation and maintenance costs [56]. Therefore, this paper focuses on the exploration of automated systems to mitigate the operational cost of active protection methods. The rest of this section introduces both passive and active protection methods, but emphasizing on the works of active protection methods.

A. Passive Frost Protection Methods

Table V lists the advantages and disadvantages of some common passive frost protection methods. A common aspect of passive frost protection methods is that these methods need to be applied before the frost events [55], [56]. Hence, passive frost protection methods are not explored in this paper, as this paper focuses on real-time automated protection systems. On the other hand, passive methods are usually less expensive and effective against advection frosts [9]. Thus, passive methods could be a complement to the active protection methods.

B. Active Frost Protection Methods

Table VI lists the advantages and disadvantages of some common active frost protection methods. Active frost protection methods are applied during an event of frost [56]. Therefore, active frost protection methods can be implemented on a real-time frost protection CPS. However, active protection methods are usually ineffective against advection frosts because of the high cost of large scale deployment and the lack of natural heat source in the environment [59]. The rest of this subsection demonstrates some works on active frost protection methods to summarize the current research trend.

The majority of works on active frost protection methods are related to sprinklers [60], [61], [62], [63], [65] and driven

TABLE V
COMMON PASSIVE FROST PROTECTION METHODS. [9], [55], [56], [57]

Protection Method	Protection Mechanism	Advantages	Disadvantages
Site Selection	Avoidance of frost prone area. Choosing a site with soil in favor of heat transfer and storage. Choose higher spots to avoid dense cold air.	Could completely avoid frost.	Heat in soil might not be sufficient after a cloudy day.
Cold Air Drainage	Placement or removal of vegetation and other obstacles to control cold air drainage.	Can provide high degree of protection when the drainage pattern is known.	Could lead to erosion with the removal of plants and vegetation.
Plant Selection	Select frost resistant plants.	Significantly reduces the risk of frost damage.	Limited to certain crop types.
Canopy Trees	Enhance downward radiation	Efficient protection method.	N/A
Plant Covers	Reduce heat loss to the air from the crops.	Good for small plants	Deficient ventilation could cause diseases. Might not be effective without an external heat source. High labor cost for implementation and removal.
Soil Cultivation Planning	Cultivation releases heat from soil.	N/A	N/A
Irrigation	Wet soil allows better heat transfer and storage.	Can be used for other farming applications.	High installation cost.
Cover crops Removal	Increases direct radiation to the soil.	N/A	Might cause erosion.
Soil Covers	Warming the soil.	N/A	Covering with vegetive mulches might reduce head transfer into the soil.
Chemical Treatment	Activate cold resistance or delay bloom.	Effective method.	Not suitable to all crop types.

TABLE VI
COMMON ACTIVE FROST PROTECTION METHODS. [9], [55], [56], [57], [58]

Protection Method	Protection Mechanism	Advantages	Disadvantages
Heaters	Converting fuel to heat to replace crop heat loss.	Lower installation cost.	Expensive fuel cost. Not efficient as heat loss to the sky.
Wind Machines	Mix warm air above with the cooler air at the surface	Efficient usage of fuel.	High installation cost. Induce noises. Fan could be damaged during heavy wind or supercooled fog.
Helicopters	Moving warm air above towards the surface.	High area coverage.	High operational cost.
Sprinklers	Heat releases when water changes its state.	Low operational cost and labor requirement.	High installation cost. Require large volume of water. Some could be affected by the wind drift effect.
Artificial Fog	Smoke or fog traps radiating heat.	Effective for radiation frost	Only effective for a relative short time. Cause pollution.

TABLE VII
WORKS ON ACTIVE FROST PROTECTION METHODS.

Year	Protection Method	Research Aim
1981 [60]	Sprinkler	Prediction of the application rate required to keep a leaf at 0^{o}C.
1986 [61]	Sprinkler	Investigation on the water requirement for frost protection.
1992 [62]	Sprinkler & Enclosure	Comparison of effect of protection between various settings of the enclosure and application rates of the sprinklers.
2002 [63]	Sprinkler	Comparison between efficiencies of microsprinklers and microsprayers.
2009 [64]	Electrically heated cables	Testing the effectiveness of the electrically heated cables.
2016 [65]	Sprinkler	Investigation on the effect of application rate towards the surface temperature of tea leaves.
2018 [58]	Wind machines, Selective Inverted Sink (SIS), Helicopters	Review on the control, effectiveness and working environment of air disturbance technology on frost protection.
2019 [66]	Wind machines	Investigation on the effectiveness of portable wind machines comparing to the stationary wind machines.

by air disturbance technologies [58], [66]. The ultimate goal of most works on sprinklers is to improve the efficiency of water usage. To achieve this, heat convection mechanisms are studied to estimate efficient water application rates for frost protection [60], [61]. Furthermore, choosing the suitable rate of application is important as over-irrigation would cause water logging issues and under-irrigation would cause potential frost injuries [65].

Some other works on sprinklers emphasize the comparison between different equipment setups. For example, in [62], settings of different sprinkler application rates with or without plant enclosure are compared to detect the setting with a higher temperature under the same environment. As a result, the setting with the enclosure and a high rate water application of 1.22 cm h^{-1} is proven to maintain the highest temperature. Another work [63] compares the efficiency between microsprinklers and microsprayers. Microsprinklers generally have better performance than microsprayers due to a higher rate of water flow. However, the difference is not significant with a temperature above 3^{o}C.

Other than sprinkler irrigation methods, air disturbance technologies are also widely studied. The authors of [58] provided a review of protection methods depending on air disturbance technologies. These methods include wind machines, selective inverted sinks (SIS), and frost protection helicopters. The review of these methods is conducted in terms of working principle, control factors, and selection criteria. As a result, the advantages of air disturbance technologies are a long-lasting period of protection and high effectiveness against radiation frosts. However, the common limitations are high initial cost, the presence of disturbing noise, dependency on the limited access of power supply, reliance on strong thermal inversion, and suitable wind direction.

To reduce the initial installation cost of wind machines, portable wind machines are proposed. A study [66] compares portable wind machines with stationary wind machines. As mentioned, portable wind machines do not require expensive initial installation costs and permanent installation. Also, some other advantages are less fuel consumption, less noise, and compatibility with different wind conditions. However, the portable wind machines are less effective than the stationary wind machines due to their lower engine power, narrower coverage angle, and lower height.

Finally, a novel method of frost protection is proposed in [64]. To mitigate the environmental requirements and water resource requirements on conventional heaters, wind machines and sprinklers, electrical heated cables are implemented to protect vines against frost damages. This method is effective as it significantly reduced loss from 46% to 13%. However, the use of electrical cables around vineyards would require extra care for the farmers during daily operations. Thus, potentially increasing manual labor cost. Moreover, large scale deployment would also incur a high manual labor cost.

VI. Integrated Frost Prediction and Active Protection Systems

This section explores some implementations of frost protection CPSs (Table VIII). In 1984, a primitive implementation of an automated frost protection system placed temperature sensors near the crops [8]. When the temperature reaches a preset point, a bedroom alarm as the actuator will be triggered to alert the farmers to switch on protection equipment. In more recent works, the triggering of protection equipment is automated with different frost prediction methods [64], [67], [68], [69]. However, most of these works still rely solely on temperature sensors to trigger the operation of protection equipment. A more sophisticated prediction algorithm could be implemented to provide a larger reaction window during periods with rapid changes in the environment.

TABLE VIII
Works on Automated Frost Protection Systems.

Year	Protection Method	Alarm System
1984 [8]	Manual trigger of wind machine, Sprinklers, Heaters	Temperature sensors, Bedroom alarm
2008 [67]	Artificial Smoke	Temperature sensors, Fuzzy controller
2009 [68]	Sprinklers	Thermistors
2009 [64]	Electrical heating cable	Air temperature sensors, Timer switch
2012 [69]	Artificial cloud burner	WSN temperature sensors, Fuzzy controller
2017 [57]	N/A	WSN Temperature sensors, Public weather forecast service
2019 [70]	N/A	WSN sensors, Weather station service, Multivariate index
2019 [71]	N/A	WSN sensors, Weather station data

More recent works introduced external weather services, which calibrate with the deployed WSN sensors to provide better prediction [57], [70], [71]. Unfortunately, most of these works are still in an earlier stage. Therefore, there are limited results on prediction or integration with a protection method. As demonstrated by Table VIII, these systems require integration with some actuators to become complete CPSs.

Another common issue of the current automated frost protection systems is low fault tolerance. As current systems are all unsupervised and depend on a small number of sensors and actuators, unavailability due to hardware defects or accidents on any of them could disable the whole system. As a consequence, the crops would suffer from frost damage. A more sophisticated system with high fault tolerance should be designed to eliminate this consequence.

VII. IoT Communication Protocols for Frost Protection Applications

In this section, different IoT communication protocols are compared and evaluated in two stages. The set of criteria in the first stage is formed by evaluating IIoT requirements with the background of frost protection applications to choose the relevant factors. Then, the IoT communication protocols are compared and filtered using the result factors. Finally, protocols are further considered in a perspective of cost.

From [72], the requirement factors for IIoT networks are listed in Table IX. These factors are evaluated considering

TABLE IX
IIoT REQUIREMENTS [72].

Requirement Factor	Description
Latency	Can be improved by smaller packets and simpler protocols.
Reliability	Related to the amount of transmission errors.
Throughput	The amount of transmitted data in a fixed amount of time. High throughput is important for applications such as high resolution images or videos transmission.
Interference-robust capability	The ability against interference generated by other electrical equipment and communication systems.
Fading-robust capability	The ability against signal degradation due to wave reflection and scattering.
Energy efficiency	Energy efficiency is important for environment with limited number of stable terminals.
Communication range	The one-hop transmission distance.

the operational environment of frost protection systems to be included as a prioritized factor. The evaluated frost protection systems are all utilizing single or a small number of sensors for a relatively large field with limited amount of data transmitted [57], [64], [67], [68], [69], [70], [71]. Therefore, the system does not require a high throughput. Also, under the critical temperature, the freezing process is a (relatively) slow procedure up to 30 minutes with 10% of crop allowed to be eliminated for the purpose of thinning [8]. Thus, ultra low latency transmission is not required. Some latency and errors can be tolerated. With real-time inference of frost prediction methods, the system should still provide timely predictions. Overall, latency, reliability, and throughput are not critical factors for frost protection systems.

As agricultural IoT applications are mostly deployed in rural communities [73], the environmental characteristics of rural areas are influential for frost protection systems. The authors of [74] demonstrated that there are significantly less path loss and more extended transmission range in rural areas than suburban areas. Therefore, as frost protection systems are deployed in rural regions, interference-robust capability and fading-robust capability are not considered as priorities.

Since rural farmlands have a limited number of power terminals, and the wiring costs are high [73], the IoT nodes for agricultural applications have limited energy sources. Therefore, these IoT nodes need to be energy efficient to maintain the availability of the network [75]. Hence, energy efficiency is chosen as a factor of the criteria. On the other hand, the average European farm size is 16.6 ha [76], and the average Australian farm size is 4,331 ha [77]. Wireless communication covering such vast land requires a longer one-hop distance or an increase in the number of forwarding relays [78]. Since this affects the coverage of the network and the number of forwarding relays as a cost factor, communication range of IoT protocols is also evaluated. In the next paragraph, the energy consumption and communication range of some common IoT protocols are compared.

From Table X, medium to high energy consumption protocols include Bluetooth, Wi-Fi, WiMAX, Cellular. Operation with these networks result with a lower life span of the application [75]. Hence, these protocols are not suitable. On the other hand, protocols with low energy consumption often operate with a limited communication range around 100 - 200 m [79], [80], [81]. Therefore, more relays are required to forward the signals to the sink [78]. The Low Power Wide Area Network (LPWAN) protocols (LoRaWAN, SigFox and NB-IoT) are the only low energy consumption and long communication range protocols that are evaluated. Therefore, LoRaWAN, SigFox and NB-IoT are further analyzed with cost factors in the next stage.

TABLE X
COMPARISON OF IOT COMMUNICATION PROTOCOL ENERGY CONSUMPTION AND COMMUNICATION RANGE. [79], [80], [81], [82]

Criteria / Protocol	Energy Consumption	Communication Range
6LoWPAN	Low	Short (10 - 100 m)
Bluetooth	Medium	Short (10 - 100 m)
ZigBee	Low	Short (10 - 100 m)
RFID	Low	Short (up to 200 m)
NFC	Low	Short (<1 m)
Z-Wave	Low	Short (30 - 100 m)
Li-Fi	Low	Short (around 10 m)
Wi-Fi	High	Short (1 - 100 m)
WiMAX	Medium	Long (<50 km)
Cellular	High	Long (several km)
LoRaWAN	Low	Long (5 - 30 km)
SigFox	Low	Long (10 - 40 km)
NB-IoT	Low	Long (1 - 10 km)

The authors of [82] split the cost of LPWAN protocols into spectrum cost, deployment cost, and end-device cost. From Table XI, NB-IoT is the most cost-ineffective in all three types of cost. Also, as LTE cellular coverage is not available for some farms [82], NB-IoT is not suitable for frost protection applications. If NB-IoT is not considered, the deployment cost would be the most significant for other LPWAN protocols. Private local networks can be deployed with cheaper LoRaWAN gateways instead of expensive base stations [82]. This significantly reduces deployment costs. From a cost perspective, among the assessed LPWAN protocols, LoRaWAN should be the most suitable for frost protection applications.

TABLE XI
COSTS OF LPWAN IMPLEMENTATION. [82]

Cost / Protocol	Spectrum Cost	Deployment Cost	End-device Cost
SigFox	Free	>4000€ per base station.	<2€
LoRaWAN	Free	>100€ per gateway. >1000€ per base station.	3 - 5€
NB-IoT	>500 M€ per MHz	>15000€ per base station.	>20€

VIII. Discussion on Current Limitations and Future Directions

This section provides an overall discussion on frost prediction methods, frost protection methods, and integrated frost protection systems. After outlining the common aspects of the current state, limitations are concluded to lead to possible future implementations. Several limitations are avoiding the construction of effective, real-time, and automated frost protection CPS.

a) Model accuracy is limited by the quality of local historical data: From Tables III and IV, most prediction methods leverage machine learning techniques to build the prediction models. Although machine learning methods demonstrate results with high accuracy, their dependency on historical sensor data could be a limitation towards higher accuracy. The demand for higher accuracy is valid because any false-negative results of frost prediction could induce a substantial loss to the agricultural sector.

This limitation on model accuracy is consistent with the constraints of machine learning models. As machine learning models are highly dependant on data, data quality is often influential to the performance of the model [83]. In most systems, data is collected by sensors. Therefore, data quality is highly bounded by the characteristics of the sensors. In an IoT context, sensor data could arrive with noises, errors, and discontinuities [23]. These data could corrupt the dataset and result in an inaccurate machine learning model. A possible solution would be applying various data cleaning techniques on the training dataset to remove the noises, eliminate the errors, and patch the discontinuities [84].

Another limitation of machine learning models is generality. Machine learning can provide models of the patterns from the training dataset with high generality. However, it cannot provide an accurate output beyond the patterns of the training dataset [85]. This phenomenon also applies to deep learning models [86]. The issue of generality could appear in both spatial and temporal dimensions. In the spatial dimension, as most machine learning models are built with local data, it could only provide accurate results within a local scope. Moreover, most model building and testing processes are also conducted with local data. Therefore, the generality of models is not confirmed at other locations. In the temporal dimension, since the patterns of future climate change are unpredictable [87], models based on climate data from earlier years might decrease in accuracy. Possible mitigation techniques include rebuilding the models with a recent dataset and application of a self-adaptive learning model such as reinforcement learning.

b) Prediction models have low temporal resolutions: According to Table III and IV, the current frost prediction methods often predict the occurrence of any frost for the next 12 and 24 hours. Therefore, the protection equipment needs to be switched on for 12 to 24 hours to minimize the risk of frost damage. However, by the results from manual observations [8], the duration of a frost event could be shorter. Thus, the operational time of frost protection equipment could be reduced to save the operational cost. A solution provided by [8] is manual monitoring, which would incur extra human labor costs. To eliminate this human labor cost, a potential improvement would be increasing the temporal resolution of prediction to hourly or even minute by minute prediction. As a result, this improvement could achieve the automatic operation of protection equipment with fewer operational hours.

c) Prediction models are often not tested in real-time scenarios: Frost prediction in the agricultural sector allows farmers to plan their tactics to protect the crops and retain psychological comfort [8]. However, current frost prediction models demonstrate limited evidence of operation in a real-time scenario. To construct an operational cost-efficient protection system, real-time prediction results with the high temporal resolution are required. As a result, an efficient operation scheme can be generated by the system. In conclusion, tests for real-time prediction models leverage live WSN data acquisition should be conducted to confirm the capability of real-time predictions.

d) Active frost protection methods are vulnerable against advection frosts [59]: Currently, large scale deployment of an active frost protection method is not economically feasible [59]. However, from Table VII, most research of active protection methods lay in the field of sprinklers and wind machines. These methods are vulnerable to advection frosts. An economically feasible active protection method could be a future research field to eliminate the vulnerability. This method could benefit from passive protection methods to reduce the cost and increase effectiveness against advection frosts [9]. Also, the potential of some chemical solutions has not been fully revealed. Ice nucleation inhibitors protect crops from frost damage by limiting the ice nucleation process. This is achieved through the inhibition of bacterial ice nucleating agents [88], [89]. The chemical solutions could be applied using the existing irrigation systems or sprayers to reduce the manual labor required.

e) Current frost protection systems have low fault tolerance: Most frost protection systems from the works of Table VIII rely on only one or a small number of sensors and actuators. These systems would have a low tolerance for any system fault. Consequently, this would induce inaccurate decisions and even unavailability of the whole system. The faults can be classified into device faults and network faults [90]. Device faults are generated by malfunctioning nodes and sinks, whereas, network faults are originated from the outage of network connections between devices [91]. The cause of these faults spans across the hardware layer, the software layer, the network layer, and the application layer [91]. The authors of [91] separated fault tolerance mechanisms into three categories, including redundancy-based, clustering-based, and deployment-based mechanisms [91]. Redundancy-based techniques are redundancy of data, path, reports, and nodes. As current frost protection systems operate with a few sensors and actuators, redundancy-based methods can increase the reliability of the system [92]. However, a trade-off between cost and reliability needs to be further evaluated [92]. The second type of fault tolerance technique is related to clustering. Clustering is a technique that increases the overall network lifespan by utilizing local cluster heads [93]. Clustering-based fault tolerance mechanisms could be applied to minimize the fault during cluster head selection [92]. This mechanism might not be active on current frost protection systems with a few nodes, but it can be applied to future systems implementing node redundancy. The final type of fault tolerance mechanism is the deployment-based mechanism [91]. Deployment-based mechanisms focus on topology control to adapt the network to the changes of node condition, noise, and interference [91]. These mechanisms can be applied to increase the reliability of the system [91], thereby reducing the possible economic loss of frost damage induced by system errors.

A final future direction would link back to the aim of the paper. According to Table VIII, some of the automated protection systems are lacking integration with a sophisticated prediction method, while other methods require actuators for frost protection. Therefore, the final future direction is the integration of a sophisticated prediction method leveraging sensor data with a protection actuator to form a real-time accurate frost protection CPS.

IX. Conclusion

Automated frost protection CPS would increase efficiency, effectiveness, and reduce the cost of frost protection. However, to achieve this goal, a prediction method is required to provide real-time predictions to a controller to decide whether or not to start the protection actuator. Once these are achieved, frost protection processes can be conducted with high effectiveness, high reliability, and low operational cost with minimal human intervention. This paper provides reviews focusing on frost prediction methods, frost protection methods, and automated frost protection systems. The limitations of these elements are also discussed. Finally, these limitations are summarized and lead to a list of possible future developments to extend these limitations.

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