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Pests Phototactic Rhythm Driven Solar Insecticidal Lamp Device Evolution: Mathematical Model Preliminary Result and Future Directions

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ABSTRACT The solar insecticidal lamp (SIL) is an electronic device designed for physical pest control, widely utilized in orchards and farmland. Currently, the characteristic of the phototactic rhythm of pest is commonly ignored in the design of SILs, hindering pest control. This phenomenon is particularly evident in the prolonged turning ON/OFFlamp, which leads to inefficient energy utilization due to the lack of adjustment for peak pest activity. To address this issue, four models based on the phototactic rhythm of pests are developed to adjust the insecticidal timing of SIL for precise pest control. These mathematical models are established considering the phototactic rhythm of four pests that exert the most significant impact on crops, namely *Mythimna seperata*, *Helicoverpa armigera*, *Proxenus lepigone*, and *Cnaphalocrocis medinalis*. The results indicate that mathematical modeling of the phototactic rhythm of the pest is valuable in capturing their nocturnal activity patterns. The proposed mathematical model can help to optimize the ON/OFFtime of SIL for pest control. The integration of electronic devices, such as SIL in pest management represents a noteworthy advancement in agricultural electronics, contributing to the progress of smart and sustainable agriculture.

INDEX TERMS Mathematical model, pest control, pests phototactic rhythm curve, regression method, solar insecticidal lamp.

I. INTRODUCTION

With the widespread adoption of Internet of Things (IoT) technologies, electronic devices in agriculture continue to evolve, driving the agricultural industry toward intelligent and environmentally sustainable practices [1], [2]. Notably, technologies such as smart irrigation systems [3], farmland monitoring systems [4], and pest monitoring systems [5], [6] have seamlessly incorporated advanced features and electronic components. This integration has resulted in heightened efficiency in agricultural production and optimized management practices [7].

The solar insecticidal lamp (SIL), a type of electronic equipment designed for physical pest control, exploits the inherent biological characteristics of pests. These characteristics include phototaxis, sensitivity to specific wavelengths, and color preference, which are pivotal in achieving effective pest management [8], [9], as depicted in Fig. 1.

Fig. 2 presents a partial schematic diagram of the SIL circuit. During daylight hours, solar energy is harnessed by the SIL through its solar panel, and the energy is stored in a rechargeable battery. During night hours, pests are attracted

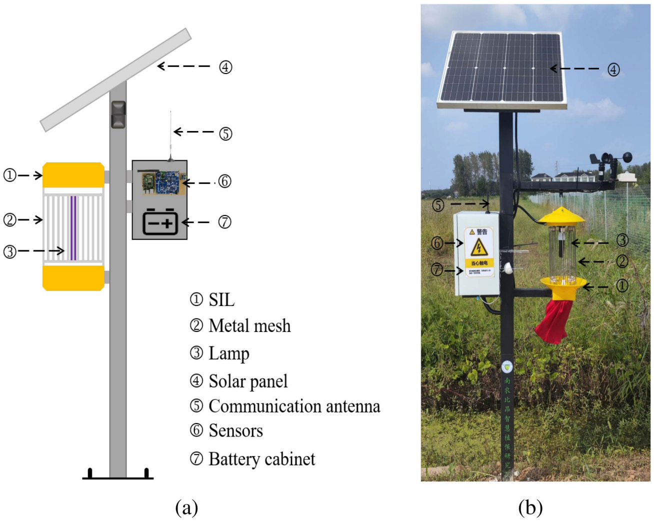

FIGURE 1. Solar insecticidal lamp (SIL) node. (a) SIL schematic. (b) Actual SIL product.

by the light source, which leads them to collide with the metal mesh. After impact, the high-voltage metal mesh will release high-voltage pulse currents, effectively eliminating pests [10]. To comprehensively monitor the operational status of the SIL, various sensors are integrated into the SIL node. As depicted in Fig. 3, these include solar panel voltage and current sensors, a humidity sensor (DHT11), a temperature sensor (DS18B20), a sound sensor, as well as voltage and current sensors [11]. Controlled by an Arduino microcontroller, these sensors collect data, which is then transmitted to a Raspberry Pi for further processing.

By the year 2023, the SIL has gained widespread adoption in the commercial market, with numerous regions extensively deploying SIL electronic products, as illustrated in Table 1. Serving as an environmentally friendly pest control electronic product, SIL exhibits substantial potential for applications in the agricultural field. The national government actively supports and promotes the use of SIL electronic products to popularize green and ecofriendly agricultural pest control technologies [9]. Consequently, there is a need to optimize and upgrade SIL electronic products to further enhance their performance and application value, thereby making a more significant contribution to green pest control in the agricultural sector.

Due to the unique phototactic rhythm displayed by pests during nighttime, they are drawn toward the light emitted by the SIL when activated [23]. Furthermore, the behavioral traits of different pests dictate variations in their outbreak times (sudden increase in pest numbers) [24], [25]. Nocturnal pest phototactic rhythm curve patterns can generally be classified into three types: 1) single-peaked, 2) double-peaked, and 3) multipeaked [26]. Illustrated in Fig. 4, the curve for *Mythimna seperata* represents the single-peak type of pest phototactic rhythm [27], the curve for *Helicoverpa armigera* represents the double-peak type [26], and the curve for *Nilaparvata lugens Stal* represents the multipeak type [28]. The pest phototactic rhythm shifts backward with the delay of sunset due to the pest's high sensitivity to daylight timing. Despite fluctuations in environmental conditions, the rhythm of the same pest across different generations maintains a degree of regularity [24], [26]. Considering that the pest phototactic rhythm curve pattern cannot be directly applied to SIL devices, we have established the mathematical model for the pest phototactic rhythm based on these phototactic rhythm curves, hereinafter referred to as the pest phototactic rhythm mathematical model.

Currently, the SIL predominantly determines insecticidal timing through traditional timed switch control, neglecting the phototactic rhythm characteristics of pests. As a consequence, SIL lacks adaptive adjustment of insecticidal timing based on pest population density and fails to intelligently manage energy consumption. To address this limitation, it is imperative to integrate the phototactic rhythm characteristics of pests into SIL electronic devices, enabling precise pest control.

By exploiting and analyzing the phototactic rhythm of pests, the SIL can adjust its insecticidal working time according to the active cycles of the pests. This not only improves the efficiency of attracting and killing pests but also achieves optimal pest control. The results of this article provide important guidance for achieving more effective and environmentally friendly pest management in agriculture.

The contributions of this article are outlined as follows.

1) This study innovatively integrated regression algorithms with the phototactic rhythm curve pattern of pests, pioneering the development of mathematical models for the phototactic rhythms of pests.
2) Specifically, the model accuracy for *Mythimna seperata* reached 90%, significantly aiding in the identification of critical periods of pest outbreaks.
3) Moreover, this article introduces a novel concept of mathematically modeling the hourly phototactic rhythm curves of pests.

The rest of this article is organized as follows. Section II delves into the related works. The proposed mathematical modeling of the pest phototactic rhythm is detailed in Section III, encompassing the dataset description, and model introduction. Following that, Section IV presents the results and analysis. Finally, Section V concludes this article.

II. RELATED WORK

A. DEVELOPMENT PROCESS OF SIL

Since 1950, the development of insecticidal lamp (IL) has gone through a total of five stages from IL 1.0 to IL 5.0, as shown in Fig. 5. Initially, in the 1950s, simple trap lamps, such as black lamps and high-pressure pump lamps, became popular due to their effectiveness in trapping pests, marking the advent of the IL 1.0 era [29]. In the 1990s, with the continuous advancement of electronic components, IL 2.0 built on the significant improvements of IL 1.0 for black lamps. The frequency-vibration and wind-suction ILs quickly gained widespread application due to their superior

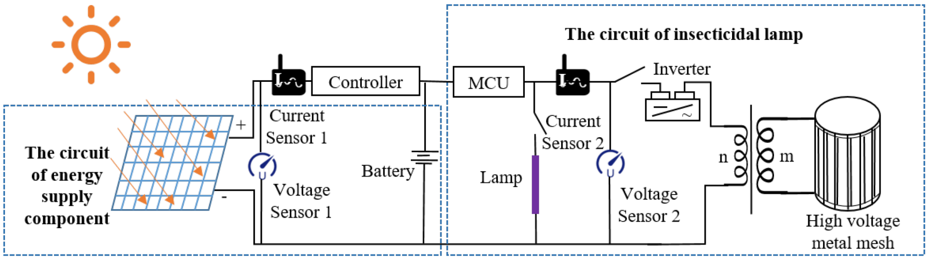

FIGURE 2. Part of an SIL circuit block diagram. The SIL circuit can be divided into three main components as follows. i) The energy supply component circuit (e.g., solar panel and battery). ii) The IL circuit (e.g., lamp, high-voltage metal mesh and microcontroller unit). iii) The controller circuit (e.g., charge and discharge control, time control (manual timed lamp ON/OFFcontrol), and rain control (turn OFFthe SIL control during the rain).

TABLE 1. News Items of SIL Applications Across China

Paper	News headline	Region	Plant	SIL's number	Type of SIL	Whether added the pest mathematical model	Company
2011 [12]	Xinyu installed 20, 000 SILs.	Jiangxi Xinyu	Rice	20 000	SIL	No	N/A
2014 [13]	1, 300 insecticidal lamps in Chongren "stand guard" rice fields.	Jiangxi Fuzohu	Rice	1300	SIL	No	N/A
2014 [14]	The Ren County horticultural farm thousand acres of standardized vegetable base using Cloudflare SIL to improve the value of agricultural products.	Jiangxi Fuzohu	Tea plant	400	SIL	No	Yunfei Technology Development Company
2016 [15]	In Dean County nearly a thousand SILs "on the job."	Jiangxi Dean	Orchard	900	SIL	No	N/A
2016 [16]	Xinyang city Yunfei brand solar paddy insecticidal lamp is highly efficient and harmless.	Henan Xinyang	Rice	36	SIL	No	Yunfei Technology Development Company
2018 [17]	Fugong Forestry Bureau introduces Henan Yunfei technology insecticidal lamp to guard walnut growth.	Yunnan Fugong	Walnut	200	SIL	No	Yunfei Technology Development Company
2018 [18]	Dongying will install 300 SILs this year to build three new trapping demonstration areas.	Shandong Dongying	Forestry	300	SIL	No	N/A
2019 [19]	Xingtang county Agricultural Bureau purchases Yunfei solar insecticidal lamps.	Hebei Xingtang	Vegetables	12	SIL	No	Yunfei Technology Development Company
2020 [20]	Suichuan tea plant SIL picture case.	Jiangxi Jian	Tea plant	2000	SIL	No	Suzhou Shangke New Energy Company
2022 [21]	Insecticidal lamp in high standard farmland "lamps up" the road of rural revitalization in Hunan.	Hunan Zhangjiajie	Rice	560	Wind-suction SIL	No	Chengdu Beang Technology Company
2023 [22]	Draw the river water to cook new tea–Suichuan "tea county" a new chapter.	Jiangxi Jian	Tea plant	1000	Wind-suction SIL	No	N/A

1 N/A represents no relevant expressions mentioned in the news.

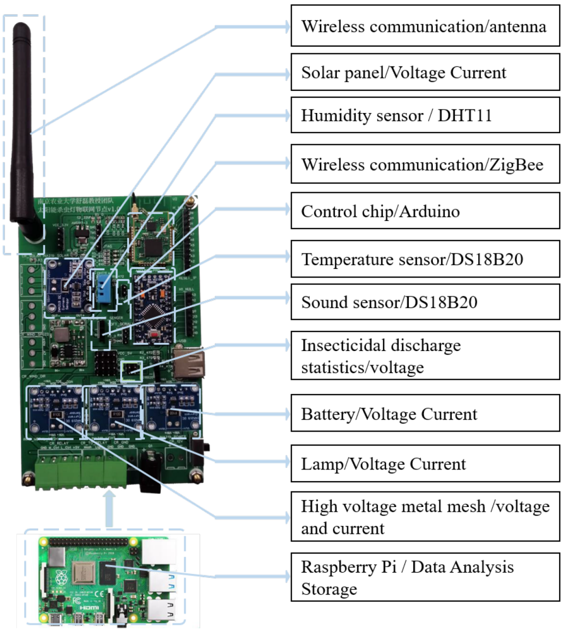

FIGURE 3. Different sensors integrated on an SIL board. (The boxes on the right side are the names of the sensors corresponding to the left side, respectively).

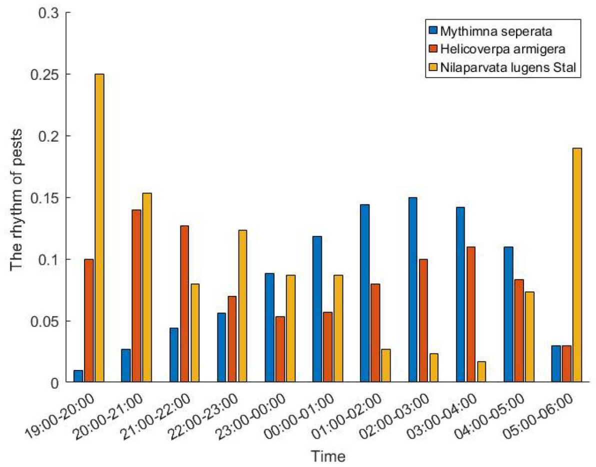

FIGURE 4. Three main pest phototactic rhythm patterns.

insecticidal efficiency compared to traditional black lamps [10], [30]. However, during this period, IL 1.0 and IL 2.0 still relied on lead-acid batteries as energy sources. Therefore, in the early 21st century, solar panels were introduced into ILs, and LED light sources also began to develop initially [31]. This innovation marked the beginning of the IL 3.0 era. The addition of solar panels not only solves the problem of energy supply but also brings a new direction for more environmentally friendly and efficient IL technology. In the 2013s, with the development of the network, the emergence of networked SILs ushered in the era of IL 4.0, which greatly enhanced the ability of data transmission between the SILs and the backend system [9], [32]. However, there are challenges in the communication between nodes within the networked SIL, and it is imperative to enhance the mutual communication and security functions between nodes. The continuous evolution of intelligent technologies has begun to emerge. SIL-IoTs have made a significant contribution to pest monitoring and control, with SIL nodes being able to diagnose malfunctions and reduce manual maintenance through Zigbee network communication [9]. In the future, the integration of mathematical or AI models of pest phototactic rhythm into SILs will help effectively control pests during peak pest periods and further enhance their application in pest management.

B. MATHEMATICAL MODELING OF THE PEST PHOTOTACTIC RHYTHM

The nocturnal phototaxis behavior of pests exhibits distinctive patterns influenced by their phototactic rhythm. Modeling and predicting these behavioral patterns can serve as a valuable method for anticipating pest outbreaks in advance. Numerous studies have already concentrated on predicting and modeling the phototactic behavior of pests, as indicated in Table 2.

In [33], the application of a multivariate fuzzy regression method in predicting the population dynamics of the second generation of *Ostrinia furnacalis* was explored. The multi-level discriminant analysis method was used to conduct a prediction study of the second generation of *Helicoverpa armigera* [34]. To study the effects of precipitation and temperature on their population dynamics, the prediction model for the occurrence of the second generation of *Ostrinia furnacalis* was established [36]. It used multiple linear regression and polynomial regression methods. The meteorological data from China Shandong Province and the development of a dynamic climate prediction model for *Ostrinia furnacalis* were analyzed in [37]. To predict the population of Australian *Helicoverpa armigera*, the regression methods were compared with bioclimatic methods [35]. The linear relationship method between the occurrence of *Helicoverpa armigera* in cornfields and meteorological factors was constructed using support vector regression [40]. The influence of meteorological factors on the prediction of *Helicoverpa armigera* was discussed in [38]. It was found that there was little correlation between tropical maize pest population and temperature, humidity, and rainfall. Therefore, the pest modeling method based on regression mathematical models has achieved significant results in predicting pest occurrence. Integrating these advanced technologies with agricultural practices has the potential to promote the development of sustainable and intelligent agriculture, achieving resource conservation, reducing labor costs, and enhancing overall productivity.

Polynomial regression, Gaussian regression, and Fourier regression have been widely employed for forecasting fruit composition and content [41], [42]. These methods play a pivotal role in evaluating the quality of agricultural products, leveraging their efficient data processing capabilities and precise predictive outcomes. Despite their notable success in predicting the quality of agricultural products, their application to pest control remains largely unexplored. Therefore,

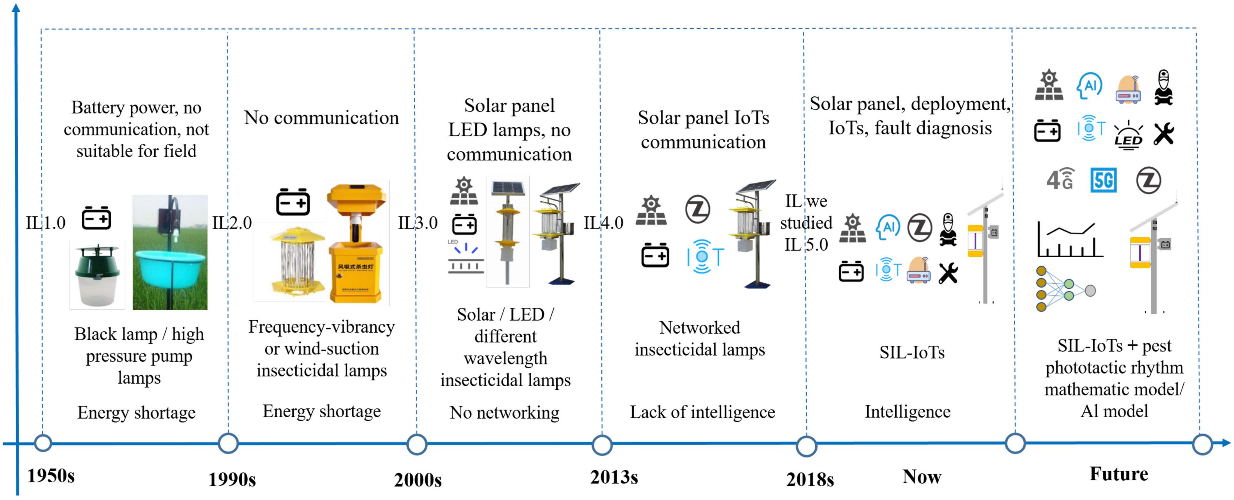

FIGURE 5. History of ILs and development trend.

TABLE 2. Summary of Related Work on Mathematical Model of Pest Behaviors

Paper	Pests	Region	Research time	Device	Predictive time unit	Goal of the research	Meteorological factor	Modeling mothod	Model type	Can be applied to SIL
2000 [33]	Ostrinia furnacalis	China Shandong	1985–1994	N/A	Yearly	Prediction of *Ostrinia furnacalis* eggs for early warning of infestations	Rainfall	Multiple fuzzy regression	M model	No
2000 [34]	Helicoverpa armigera	China Shandong	1982–1993	N/A	Yearly	Prediction of pests occurrence period for early warning of infestations	Temperature, rainfall	Multiple linear regression	M model	No
2005 [35]	Helicoverpa armigera	Australia	7–11	N/A	Monthly	Prediction of pests peak time for early warning of infestations	Temperature, rainfall	Linear regression	M model	No
2007 [36]	Ostrinia furnacalis	China Shandong	1989–2003	N/A	Yearly	Prediction of pests occurrence period for early warning of infestations	Temperature, rainfall	Combinatorial forecasting model	M model	No
2014 [37]	Ostrinia furnacalis	China Shandong	2003–2013	N/A	Yearly	Prediction of pests occurrence period for early warning of infestations	Temperature, humidity, wind speed, air pressure, illumination, rainfall	Linear regression	M model	No
2018 [38]	Ostrinia furnacalis	Indonesia	2006–2016	N/A	Monthly	Predicting the extent of pest occurrence	Temperature, humidity, rainfall	Linear regression	M model	No
2023 Our studied datasets	Helicoverpa armigera [26] Cnaphalocrocis medinalis [26]	China-Nantong	1999–2003	20W dual-wave pest lure lamp	Hourly	Although literature [27] [26, 39] provides a detailed analysis of pest data, it does not address mathematical modeling of pest behavior. This paper aims to adjust the SIL on/off time for effectively eliminate pests during the peak activity periods.	Temperature, humidity, wind speed	Polynomial, gaussian, fourier regression	M model	Yes
	Proxenus lepigone [39]	China Beijing	2012	Searchlight						
	Mythimna seperata [27]	China Shandong	2014–2015	Time-divided autonomous trapping device						

1. N/A represents no relevant expressions mentioned in the papers.
2. Paper [35] is not labeled with the year of the study and 7–11 indicates that the study was conducted from July to September.
3. M model represents the mathematical model.

FIGURE 6. Four main pests. (The pictures come from [24]).

exploring the potential application of the regression methods in pest control holds significant practical importance and offers extensive research prospects.

While commendable results have been achieved, these findings are primarily rooted in extensive years and months of modeling for long-term pest control in agriculture. The field of pest prediction and early warning in agriculture heavily relies on long-term prediction methods. Despite the effectiveness of these methods in foreseeing long-term trends in pest outbreaks, they fall short in enabling SILs to achieve intelligence ON/OFFinsecticidal time. Consequently, there is an urgent need for the development of a mathematical model for pest control and management. This study aims to establish the pest phototactic rhythm mathematical model based on an hourly time scale, enhancing the accuracy of pest prediction in time series. To ensure the reliability and stability of the mathematical model, this article, for the first time, employs the regression method to develop hourly predictive methods for four major pests as follows. *Mythimna seperata*, *Helicoverpa armigera*, *Proxenus lepigone*, and *Cnaphalocrocis medinalis*.

III. MODELING BASED ON PEST PHOTOTACTIC RHYTHM CURVES

A. DATASET DESCRIPTION

Rice, wheat, corn, and soybeans are the primary crops in China, driving the development of the country's agricultural economy. However, pest infestations severely limit their yield, necessitating effective pest control measures. Currently, *Mythimna seperata*, *Helicoverpa armigera*, *Proxenus lepigone*, and *Cnaphalocrocis medinalis* are the main pests of these crops, as shown in Fig. 6.

Building upon our previous review [24], the dataset from historical literature has been organized and summarized, followed by further research to expand upon them. The pest behavior is influenced not only by time factor but also by meteorological factors, including temperature, humidity, and precipitation. Establishing and analyzing their phototactic rhythm mathematical models in specific environments can help reduce the complexity of these models. The pest's active outbreak period is from June to September, and it is of interest to study the mathematical model of pest phototactic rhythm for this period.

The objective of this study is to establish the phototactic rhythm mathematical models for four types of pests. To accurately demonstrate the phototropic behavior of the pest, this article normalizes the pest populations to gain a clearer understanding of their activity patterns and distribution at night, as shown in Table 3. During the research [24], pest data from historical literature during the period from June to September were selected. Specifically, data on *Mythimna seperata*1 and *Mythimna seperata*2 were continuously collected using a time-divided autonomous trapping device in Ningjin County, Shandong Province, China, from 2014 to 2015 [27]. Concurrently, in Nantong City, Jiangsu Province, China, from 1999 to 2003, data on *Helicoverpa armigera*1, *Helicoverpa armigera*2, *Cnaphalocrocis medinalis*1, and *Cnaphalocrocis medinalis*2 were gathered using 20W dual-wave pest lure lamp [26]. In addition, data on *Proxenus lepigone*1 and *Proxenus lepigone*2 were obtained through continuous collection using searchlights in Beijing city (China) in 2012 [39]. During the data collection period, the temperature was maintained between 25° C and 30° C, with no precipitation occurring at night. We selected four representative sets of pest phototactic rhythm data, focusing particularly on the nighttime period from 18:00 PM to 05:00 AM the following day. This period was divided into hourly intervals, denoted as t. Based on the pest data within these time segments, we developed the phototactic rhythm mathematical models for pests, aiming to more accurately predict their activity patterns.

B. REGRESSION METHOD

In this study, two mathematical models are explored, such as static and dynamic models. Static models, used to describe a system or process at a specific point in time, focus on those system properties that do not change over time. In contrast, dynamic models take into account the evolution of a system over time, where its current state is not only determined by current inputs but is also influenced by historical states and historical inputs. Artificial intelligence (AI) models are representative of dynamic models. In this article, the static model is mainly used to explore the relationship between pest numbers over time, which is established through regression methods. Specifically, we used polynomials, Gaussian equations, and Fourier equations to construct mathematical models for the four pests. As shown in Fig. 7, the input variables are the set of time points and the number of pests at the time points as a percentage of the total pests. The output is a mathematical model of the phototropic rhythms of the pests.

This article aims to mathematically model the pest phototactic rhythm using three distinct types of methods: Polynomial, Gaussian, and Fourier. These methods exhibit versatility and are well-suited for accurately describing various nonlinear

TABLE 3. Nornaized Pest Data From Historical Literature

Pest \ Time	19:00–20:00	20:00–21:00	21:00–22:00	22:00–23:00	23:00–00:00	00:00–01:00	01:00–02:00	02:00–03:00	03:00–04:00	04:00–05:00	5:00–06:00
Mythimna seperata1	0.01	0.02	0.05	0.06	0.08	0.07	0.18	0.20	0.19	0.11	0.03
Mythimna seperata2	0.02	0.02	0.01	0.03	0.05	0.08	0.15	0.16	0.17	0.16	0.11
Helicoverpa armigera1	0.00	0.33	0.30	0.11	0.07	0.03	0.02	0.01	0.04	0.01	0.03
Helicoverpa armigera2	0.27	0.10	0.08	0.09	0.07	0.04	0.06	0.05	0.10	0.11	0.09
Cnaphalocrocis medinalis1	0.10	0.21	0.11	0.06	0.04	0.06	0.07	0.11	0.12	0.10	0.03
Cnaphalocrocis medinalis2	0.03	0.08	0.15	0.07	0.02	0.09	0.07	0.07	0.18	0.13	0.10
Proxenus lepigone1	0.30	0.23	0.07	0.10	0.11	0.14	0.02	0.01	0.01	0.00	0.00
Proxenus lepigone2	0.43	0.27	0.12	0.10	0.03	0.02	0.03	0.01	0.00	0.00	0.00

1. The values in the table represent the proportion of the pest number to the total pest number.

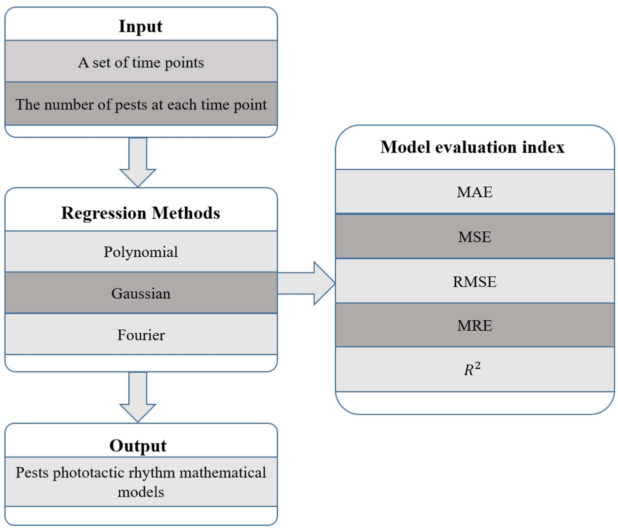

FIGURE 7. Regression methods based on phototactic rhythm mathematical models.

relationships that may exist among different variables. Notations used in this article are listed in Table 4.

Polynomial model is adept at capturing data trends through the utilization of different degrees of polynomial. Gaussian model proves valuable in portraying the distribution of local extreme points in the data, while Fourier model excel at modeling periodic changes in data.

The polynomial modeling is a common method of approximating real data using the polynomial formula. This model proves useful in describing the observed trend or pattern in the data, with the degree of the polynomial determining the complexity of the curve. The polynomial model can be expressed as shown in the following:

$$p(t) = a_u t^u + a_{u-1} t^{u-1} + \cdots + a_1 t + a_0 \tag{1}$$

where the coefficients $a_u, a_{u-1}, \cdots, a_1, a_0$ represent the parameters of the model, while u denotes the degree of the polynomial.

Multivariate Gaussian models are constructed by overlaying multiple Gaussian models and prove effective in fitting intricate data distributions. The formula can be expressed as follows:

$$g(t) = \sum_{i=1}^{m} d_i \exp\left(-\frac{(t-b_i)^2}{2c_i^2}\right) \tag{2}$$

where m represents the number of Gaussian models, d_i, b_i, and c_i, respectively, represent the amplitude, center position, and standard deviation of the ith Gaussian model.

The Fourier model is a fundamental periodic function, which can be expressed as a linear combination of a series of sine and cosine functions. The equation can be expressed as follows:

$$f(t) = e_0 + \sum_{k=1}^{\infty} (e_k \cos(kt) + h_k \sin(kt)) \tag{3}$$

where e_0, e_k, and h_k are constant coefficients and k denotes a positive integer. The frequencies of these sine and cosine functions are integer multiples of the fundamental frequency.

To assess the performance of the mathematical model in terms of reliability and stability, standardized performance metrics are used in this study. These include correlation coefficient (R-squared, R^2), root-mean-square error (RMSE), mean absolute error (MAE), and mean relative error (MRE). When the R^2 value is close to 1 and the error indicator decreases, it indicates that the stability and accuracy of the mathematical model is high. These quantitative metrics provide an objective evaluation of the model's performance, thus ensuring the accuracy and reliability of the mathematical model in pest management.

TABLE 4. Notation

Notation	Description
t	A set of time points
$p(t)$	The polynomial model
$g(t)$	The Gaussian model
$f(t)$	The Fourier model
$a_u, a_{u-1}, \cdots, a_1, a_0$	The parameters of the model, while u denotes the degree of the Polynomial
m	The number of Gaussian model
d_i	The amplitude of the ith Gaussian model
b_i	The center position of the ith Gaussian model
c_i	The standard deviation of the ith Gaussian model
e_0	The average or dc component of the signal is a constant term
e_k	The Fourier series coefficients, indicating the amplitude of each sine wave
h_k	The Fourier series coefficients, indicating the amplitude of each cosine wave
k	The multiple of the frequency is a positive integer
y_i	The actual value of the sample
$\widehat{y}_i$	The predicted value of the sample
$\overline{y}_i$	The mean of the actual values
n	The number of predicted samples
R^2	The correlation coefficient
MAE	The mean absolute error
MRE	The mean relative error
RMSE	The root mean squared error

R^2 is a statistical measure used to evaluate the accuracy and reliability of the regression method. It ranges between 0 and 1, and the closer it is to 1, the better the model fit. The calculation of R^2 is represented by

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y}_i)^2} \tag{4}$$

where y_i is the actual value of the sample, $\widehat{y}_i$ is the predicted value of the sample, $\overline{y}_i$ is the mean of actual values of the sample, and n is the number of predicted samples.

MAE represents the average of the absolute difference between the predicted and true values. As shown in

$$\text{MAE} = \frac{1}{2} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{5}$$

where y_i is the actual value of the sample, $\widehat{y}_i$ is the predicted value of the sample, and n is the number of predicted samples.

MRE is a commonly used metric to evaluate the performance of the model. As represented in (6), MRE is a method of comparing the relative error between the predicted and true values

$$\text{MRE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \tag{6}$$

where y_i is the actual value of the sample, $\widehat{y}_i$ is the predicted value of the sample, and n is the number of predicted samples.

RMSE is a commonly used measure of the accuracy of a regression method, calculated as the square root of the average of the squares of the differences between the predicted and true values. Compared to MAE, RMSE is more sensitive and penalizes larger errors more heavily. However, it is also more susceptible to extreme values. A smaller RMSE indicates a better fit of the model, indicating a smaller prediction error

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{7}$$

where y_i is the actual value of the sample, $\widehat{y}_i$ is the predicted value of the sample, and n is the number of predicted samples.

IV. MODEL RESULTS AND DISCUSSIONS

All the modelings are conducted on a system running Windows 11 with the following hardware configuration: Python executes the simulations on a laptop equipped with a 64-bit Windows 11 operating system, 16.0 GB RAM, and a 2.6-GHz-Core i7-10750 CPU.

The main objective of this section is to model four different types of pests through their historical data and to detail the results of modeling the phototactic rhythm of these pests. To assess the accuracy of the polynomial, Gaussian distribution, and Fourier methods employed, the key performance metrics, such as R^2, RMSE, MAE, and MRE are analyzed. According to [27], *Mythimna seperata* takeoff within half an hour after sunset and are relatively active during the late night. As a pest that is active in the morning, they tend to form a single peak in the early morning. The results of the *Mythimna seperata* modeling are shown in Fig. 8. The four models can describe the behavior of *Mythimna seperata* well, but there are differences in their accuracy performance. Specifically, the Gaussian second-order modeling has a better accuracy among these four models, as shown in Table 5.

Through this comprehensive analysis, we found that the Gaussian second-order mathematical model exhibited the smallest error on these evaluation metrics, followed by the polynomial mathematical model. Therefore, for *Mythimna seperata*, Gaussian second-order modeling is the most effective one, its formula can be derived from (2), as shown in the following:

$$g(t) = 0.049 \exp\left(-\frac{(t - 6.725)^2}{2 * 3.754^2}\right)$$

TABLE 5. Comparison of Evaluation Indexes of Mathematical Models for Four Pests

Pest	Regression method	MAE	MSE	RMSE	MRE	R^2
Mythimna seperata	ploy5	0.02	0.00	0.02	0.35	0.88
	g1	0.02	0.00	0.02	0.42	0.86
	g2	0.02	0.00	0.02	0.35	0.90
	f1	0.02	0.00	0.03	0.46	0.83
Helicoverpa armigera	ploy5	0.05	0.00	0.07	0.00	0.44
	g1	0.05	0.01	0.08	0.00	0.28
	g2	0.09	0.02	0.13	0.00	0.28
	f1	0.05	0.01	0.07	0.00	0.35
Cnaphalocrocis medinalis	ploy5	0.03	0.00	0.03	0.37	0.54
	g2	0.03	0.00	0.03	0.37	0.53
	f1	0.03	0.00	0.03	0.43	0.45
Proxenus lepigone	ploy4	0.03	0.00	0.04	0.00	0.90
	g1	0.03	0.00	0.04	0.00	0.88

1. ploy5 represents the polynomial fifth-order model.
2. g1 represents the Gaussian first-order model.
3. g2 represents the Gaussian second-order model.
4. f1 represents the Fourier first-order model.
5. ploy4 represents the Polynomial fourth-order model.

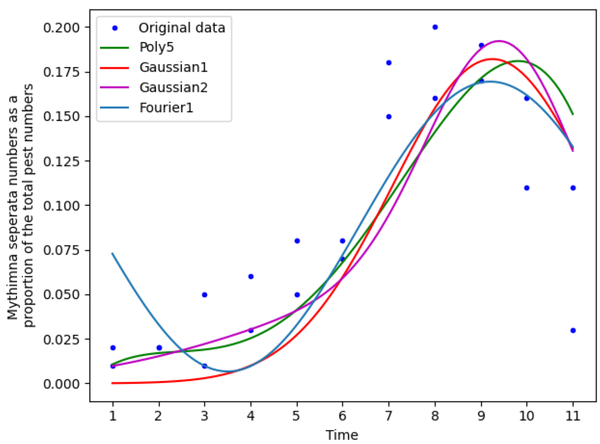

FIGURE 8. Comparison of four mathematical models (polynomial, Gaussian distribution, and Fourier methods) of *Mythimna seperata*'s phototactic rhythm.

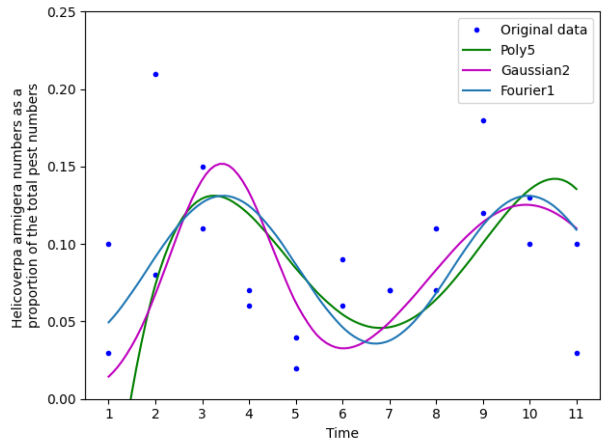

FIGURE 9. Comparison of three mathematical models (polynomial, Gaussian distribution, and Fourier method) of *Helicoverpa armigera*'s phototactic rhythm.

$$+ 0.148 \exp\left(-\frac{(t-8.496)^2}{2 * 1.639^2}\right). \quad (8)$$

The next best model is the polynomial method, whose equation can be derived from (1), which is shown in the following:

$$\begin{aligned} \mathrm{p}(t) = 4.247 \times 10^{-5} t^5 - 0.00143 \times t^4 + 0.01636 \\ \times t^3 - 0.0759 \times t^2 + 0.1506t - 0.07773 \end{aligned} \quad (9)$$

where t represents the time segment when the *Mythimna seperata* appears at night, $0 < t \leq 11$, e.g., t=1 represents *Mythimna seperata* at the time segment of 18:00–19:00.

In general, *Helicoverpa armigera* tends to migrate at sunset and be more active at sunrise [26]. The phototactic rhythm of *Helicoverpa armigera* belongs to a multimodal pattern, which cannot be adequately represented by a Gaussian first-order model. Therefore, in this article, only polynomial, Gaussian second-order, and Fourier models are used to model the phototactic rhythm curve of *Helicoverpa armigera*.

Fig. 9 shows that three models can describe the bimodal distribution of *Helicoverpa armigera* well. Due to the uncertainty of the outbreak time of *Helicoverpa armigera*, the accuracy of modeling with these three models varies. Specifically, we found that the polynomial fifth-order model has a better accuracy among these three models, as shown in Table 5.

Notably, for *Helicoverpa armigera*, the Polynomial fifth-order model exhibited the smallest loss and highest correlation coefficient among the three models. Therefore,

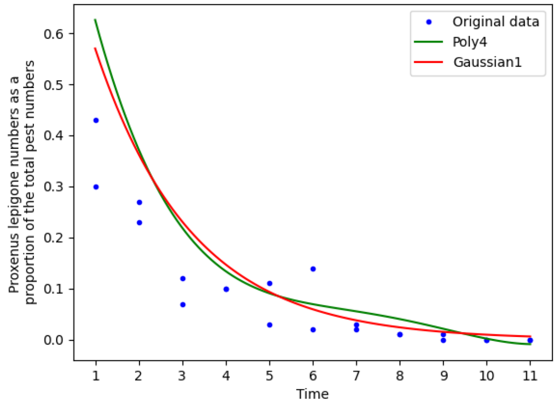

FIGURE 10. Comparison of two mathematical models (polynomial and Gaussian method) of *Proxenus lepigone*'s phototactic rhythm.

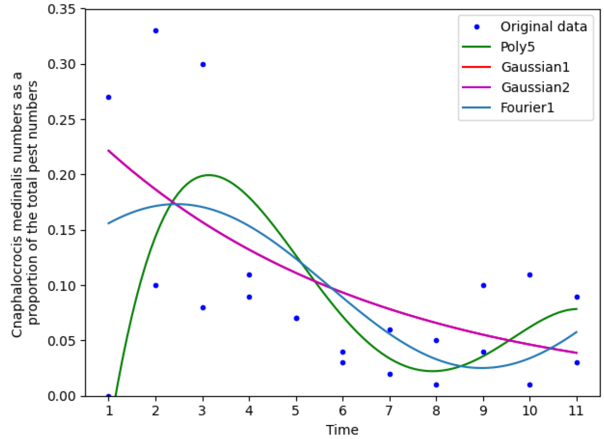

FIGURE 11. Comparison of four mathematical models (polynomial, Gaussian distribution, and Fourier model) of *Cnaphalocrocis medinalis*'s phototactic rhythm. (Due to the small error in the modeling effect of Gaussian first-order and Gaussian second-order, the curves tend to be the same).

for the *Helicoverpa armigera*, the most efficient modeling is achieved with the polynomial fifth-order method, as shown in the following:

$$\mathrm{p}(t) = 6.731 \times 10^{-5} t^5 - 0.002534 \times t^4 + 0.03417 \times t^3 - 0.1996 \times t^2 + 0.4756t - 0.2421 \quad (10)$$

where t represents the time segment when the *Helicoverpa armigera* appears at night, $0 < t \leq 11$, e.g., t=1 represents *Helicoverpa armigera* at the time segment of 18:00–19:00.

Fig. 10 displays the polynomial and Gaussian first-order model of *Proxenus lepigone* phototactic rhythm. It can be observed that both models are effective in depicting the activity level of pests at various times of the night. In particular, on cloudy and rainless nights, *Proxenus lepigone* exhibits relatively high activity during the first half of the night [39]. Since *Proxenus lepigone* shows only one peak in the first half of the night, the suitable modeling models among the four considered are limited to polynomial and Gaussian first-order methods. Table 5 shows the key performance metrics, such as R^2, RMSE, MAE, MRE, and we observe that the R^2 value of the fourth-order polynomial is higher than the Gaussian first-order. Therefore, the higher prediction accuracy of *Proxenus lepigone* can be achieved by using fourth-order polynomials.

As shown in Table 5, we compared the errors and correlation coefficients of the models and found that while both the fourth-order polynomial and the Gaussian first-order models showed good accuracy, the polynomial fourth-order mathematical model had a smaller error. Therefore, the polynomial fourth-order method is the most effective model for *Proxenus lepigone*, and its formula is shown in the following:

$$\mathrm{p}(t) = 0.0003187 \times t^4 - 0.00827 \times t^3 + 0.07854 \times t^2 - 0.3402t + 0.6448 \quad (11)$$

where t represents the time segment when the *Proxenus lepigone* appears at night. By comparing the evaluation metrics, the polynomial fifth-order method is the best among the four models.

As the migratory pest, *Cnaphalocrocis medinalis* exhibits distinct nocturnal activity, characterized as an all-night active type [26], [43]. Due to its migratory nature, the outbreak timing of *Cnaphalocrocis medinalis* is highly unpredictable. This uncertainty poses a particular challenge to pest control and management, making effective control measures difficult.

As shown in Fig. 11, using polynomial, Gaussian first-order, Gaussian second-order, and Fourier function models cannot fit the pests phototactic rhythm curve well due to the scattered data, with the Gaussian first and second-order models showing similar results. Table 5 shows the comparison of MAE, MSE, RMSE, MAR, and R^2 of the four models. Although the modeling results are unsatisfactory, the polynomial fifth-order model is the best among the four models

$$\mathrm{p}(t) = 6.808 \times 10^{-5} t^5 - 0.002485 \times t^4 + 0.03363 \times t^3 - \times t^2 + 0.4852t - 0.1788 \quad (12)$$

where t represents the time when the *Cnaphalocrocis medinalis* appears at night, $0 < t \leq 11$, e.g., t=1 represents *Cnaphalocrocis medinalis* at the time segment of 18:00–19:00.

V. APPLICATION AND DISCUSSIONS

A. APPLYING STATIC MATHEMATICAL MODEL

The modeling analysis yielded several noteworthy findings. First, the phototactic rhythm mathematical model of all four pest species showed significant diurnal variations, with peaks and troughs shifting at different time intervals. Second, the hourly modeling approach provided a more refined analysis of pest phototactic rhythm, allowing for a more accurate assessment of pest behavior and activity patterns.

Based on the above-mentioned analysis, several discussion points can be raised, including the following:

(a) (b)

FIGURE 12. Pest monitoring lamp. (a) Remote information-based pest monitoring and reporting system.[1] (b) Intelligent pest monitoring lamp.[2]

1) Why study the pest phototactic rhythm mathematical model?
   This article mainly focuses on modeling the phototactic rhythm curves of four pest species. Unlike previous studies, in this article, the modeling time segments are refined to hourly time scales by making them precise. In addition, considering the significant influence of environmental meteorological factors on the phototactic rhythms of pests, this study conducted an in-depth analysis of the phototactic rhythms of pests under specific environmental conditions and successfully constructed corresponding mathematical models. These models not only provide theoretical support for pest behavior prediction and forecasting but their application to the SIL is expected to significantly enhance the pest control effect.
2) What equipment can be used to collect these datasets?
   Most research on modeling pest phototactic rhythm has utilized SILs to collect the dataset due to their relatively low cost. Due to traditional SILs lack of intelligence, manual annotation remains the only method for data collection. With the development of AI technology, pest forecast lamps have been widely adopted for pest monitoring and early warning. Fig. 12 shows pest monitoring lamps from two different manufacturers, which mainly attract different pests by specific wavelengths. They can determine the species, and density based on the number and distribution of pests around the lamp, thus providing scientific recommendations for pest control. However, the high cost of pest forecast lamps (ranging from \$6963.8 to \$25 069.6 [24]) limits their usage in the data collection of pest phototactic rhythm models. Therefore, an intelligent electronic device is required for efficient dataset collection.
3) How can the accuracy of the mathematical model be improved?
   This study is primarily based on data from the historical paper [24], which is characterized primarily by a temporal dimension. However, pest activity patterns are influenced not only by temporal factors but also by substantial weather and environmental variables. Therefore, to augment the precision of mathematical models in predicting pest phototactic rhythms, it is crucial to incorporate a comprehensive range of weather and environmental data along with observational records of pest activities. Vital data encompass metrics such as precipitation levels, air temperature, and humidity. The assimilation of this multidimensional data array is key in extracting pivotal features, thereby markedly enhancing the predictive accuracy of the mathematical model in question.
4) What kind of researchers are needed to promote research development in this field?
   In this research field, there is a need for scientists with interdisciplinary knowledge in agricultural entomology and computer science. These researchers should have a deep understanding of pest classification, morphology, life cycles, and habits, enabling them to accurately identify different pest characteristics for effective observation and analysis of their behavior. In addition, they must possess strong capabilities in mathematical modeling and data analysis, which are crucial for developing and optimizing algorithms and software for precision and sustainable agriculture. Furthermore, these researchers should have a comprehensive understanding of modern technologies and electronic devices, and be capable of applying these technologies in agricultural production to enhance efficiency and reduce resource wastage, thus supporting the achievement of more effective and sustainable agricultural production.
5) How mathematical models of pest phototactic rhythms will be applied?
   As shown in Fig. 13, this study first derives the appropriate mathematical model based on the phototropic pattern of pests. The mathematical model of pest phototactic rhythm can be placed at the frontend or backend of the SIL device. Considering that different crops may face different kinds of pest problems, this study selects the appropriate mathematical model according to the needs of a particular crop. Subsequently, the selected mathematical model is integrated with the optimization algorithm and successfully embedded into a Raspberry Pi device for practical application. It is possible to optimize the optimal operating time of the SIL, which not only improved the efficiency of pest control but also optimized the efficiency of energy use.

B. APPLYING AI MODEL

In recent years, the extensive application of AI and machine learning technologies have significantly advanced early pest prediction [49], [50], contributing to the development of smart agriculture [51], as demonstrated in Table 6. To

[1] [Online]. Available: https://www.cdbeyond.com/a/37.html
[2] [Online]. Available: https://www.hoire.cn/Product/znzb

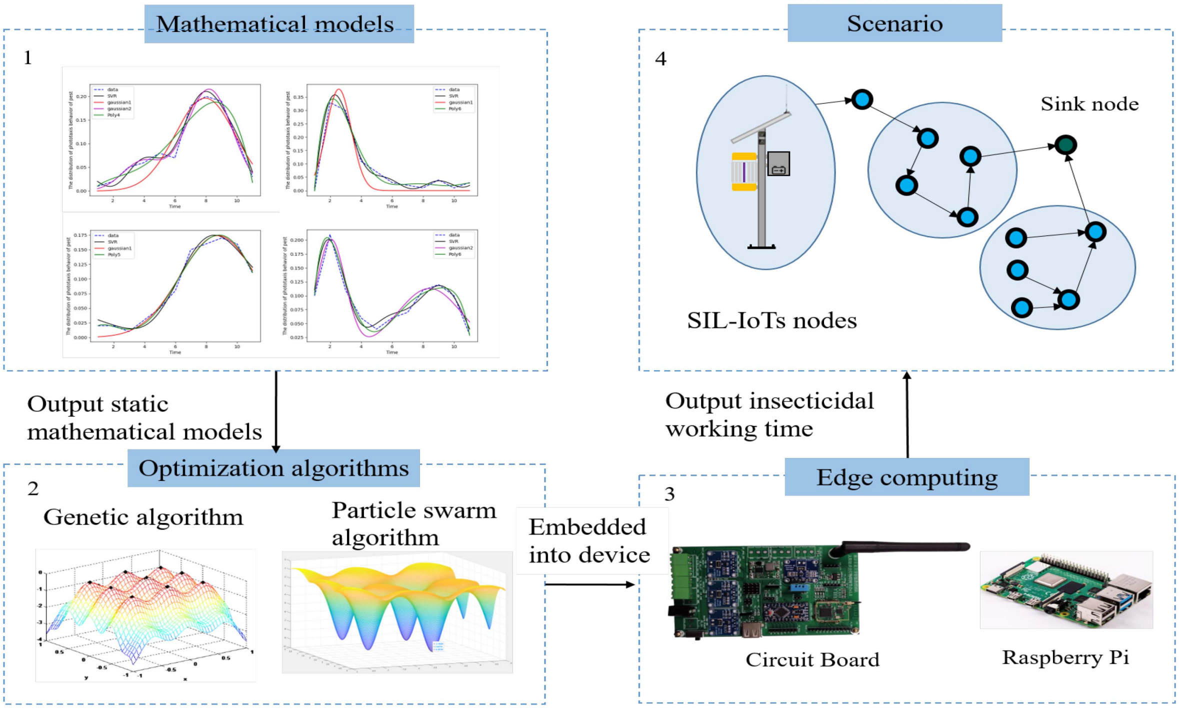

FIGURE 13. Flowchart of the mathematical model for pest phototactic rhythm. At first, the mathematical models are derived based on the pattern of the phototactic rhythm of pests. Then, these mathematical models are combined with an optimization algorithm and successfully embedded into a Raspberry Pi for practical application. Eventually, the method can determine the optimal insecticidal working time of the SIL, which not only improved the pest control efficiency but also optimized the energy efficiency.

TABLE 6. Comparison of Different AI Models for Pest Prediction

Paper	Pests	Region	Research time	Device	Predictive time unit	Aim	Meteorological factor	Modeling mothod	Model type
2018 [44]	Fruit tree pests	China Shanxi	2008–2018	N/A	Monthly	Prediction the extent of the pest attacks	Humidity, illumination, temperature	Bp neural network	AI model
2019 [45]	Cotton pests	India	N/A	N/A	N/A	Prediction of the pest occurrence degree	Temperature, humidity, wind speed, illumination	Lstm	AI model
2021 [46]	Whitefly	Pakistan	2018–2019	N/A	Monthly	Prediction the pest occurrence degree	Temperature, humidity, wind speed, rainfall	Neural network	AI model
2022 [47]	Fruit fly	Kenya	2017–2020	N/A	Weekly	Prediction the extent of the pest attacks	Temperature, humidity, rainfall	Bp neural network	AI model
2023 [48]	Whitefly	Pakistan	2018–2022	N/A	Weekly	Prediction the pest occurrence degree	Temperature, humidity, rainfall, wind speed, illumination	Neural network	AI model

1. N/A represents no relevant expressions mentioned in the papers.
2. AI model represents the artificial intelligence model.

enhance the accuracy of pest population prediction, an improved backpropagation neural network method has been proposed [44]. In addition, long short-term memory (LSTM) is employed to analyze the relationship between weather factors and pest occurrence, exploring potential patterns in pest occurrence and weather changes [45]. In [46], a pest prediction system was developed to forecast white fly invasions through preventive measures. To improve the efficiency of pest management in plantations, an expert system for midterm pest prediction has been established through neural networks, achieving weekly pest predictions [47]. Furthermore, Saleem et al. [48] predicted the degree of pest occurrence through multidimensional data. While these studies have shown positive results, these methods

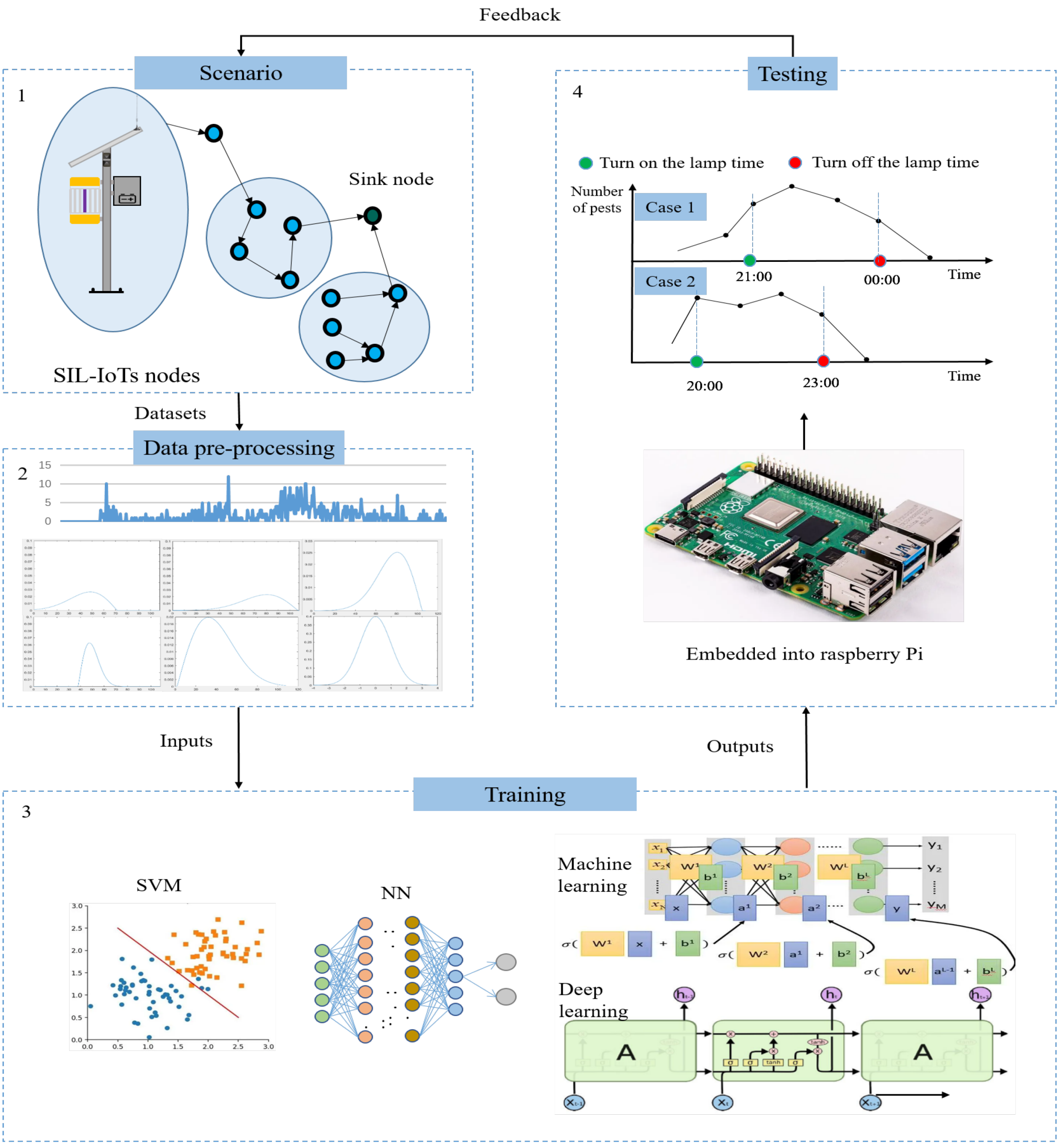

FIGURE 14. Flowchart of the AI model for pest phototactic rhythm. Initially, the data collected by SIL are uploaded to the edge node allowing users to download it via end devices. Next, the collected data on pests' phototactic rhythm are preprocessed as necessary and important features are selected for AI model training. Once the training is completed, the model weights are embedded into the Raspberry Pi device for testing and validation. The AI model is analyzed for periods of high pest activity to output the optimal insecticidal working time. Finally, this optimal insecticidal working time information is fed back to the SIL.

also have limitations, such as slow convergence speed and susceptibility to falling into local optima. To mitigate the risk of overfitting, AI models often employ simpler structures and data augmentation techniques [52]. By optimizing network weights and thresholds, these methods can rapidly and accurately predict the extent of pest occurrences [44].

As shown in Fig. 14, in the future, after collecting the hourly data, the data are first preprocessed as necessary. The key features are selected for further AI model training, including but not limited to support vector machines, deep neural networks, and transformer architectures. This step not only focuses on model selection and training but also includes a careful comparison of the performance of each model to ensure that the most appropriate algorithm is selected. The carefully trained and tuned models are then deployed into Raspberry Pi devices. To achieve optimal insecticide working times, the models will be fed back to SIL through a series of field tests. This will involve not only an efficiency analysis of energy use but also the optimization of insecticidal times. Through these explorations, the aim is to continually refine the model to suit a wider range of scenarios and needs, with the ultimate goal of improving pest control efficiency.

VI. CONCLUSION

This study aims to develop the mathematical models for the phototactic rhythm of pests, which is the static mathematical model. Utilizing regression methods, we explored mathematical models of pest phototactic rhythm on an hourly basis. Particularly *Mythimna seperata*, achieving a model accuracy of 90%. Future research should focus on validating these models with more extensive data, considering diverse environmental and climatic factors. It will further explore the application of AI models to multidimensional feature data. The application of SIL in diverse crop environments promises to meet the pest management needs of farmers and consumers, paving the way for more sustainable and efficient agricultural pest control practices.

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