Application of Discrete Event System to Insect Population Dynamic

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Abstract – This work describes an application of queueing network to model the insect population. The interarrival time and service time are both exponentially distributed. Preliminary results have been obtained to show the development of the insect population. Future work for the model's potential development and uses are also discussed.

Index Terms – Discrete event system; Queueing system; Olive fly; Population dynamic; Insect modeling.

I. INTRODUCTION

A .Pest control and insect life cycle

Pest management and control, as it is readily understood, are vital to a sustained agricultural production since, without it, long-term reliable income cannot be ensured. Nowadays chemical protection is the most widely used method for pest control. However, control methods relying on the use of chemical products pose a health risk for man and animals, unnecessary treatments increase production costs, cause more environmental pollution and can lead to the development of resistance to pesticide. Therefore, it becomes more and more important and necessary to know or estimate the state of pest population, because if the control action applied at the correct moment, a reduced number of pesticide treatments can achieve the same level of pest control.

Simulation models have been introduced as a way to assess its current state of pest population and to determine the optimal pest control strategy, especially in some cases, the ideal timing for treating a crop is a certain stage of the infestation's life cycle that is not easily detectable in the field. The quality of a decision support tool concerning the timing and kind of crop-protection actions are highly dependent on the effectiveness of the simulation model used to assess and forecast the development of crop pests.

This work aims to model the population of olive fly -- the most damaging insect of olive tree in Portugal. Olive growing is an important activity for the economic, social and ecological well being of the Mediterranean region. It represents a relatively cheap source of high quality vegetable fat and its importance spans the areas of agriculture and food industry. In Portugal this crop represents a significant proportion of the total agricultural production. The olive fly, *Bactrocera oleae*, its attacks may potentially account for 50-60% of the total insect pest damage, causing a reduction in the number and/or size of the fruits with a subsequent reduction in yield and quality of the fruit and oil.

The olive fly's life cycle is composed of four distinct phases: egg, larva, pupa and adult (Figure 1). The first three phases are called pre-imaginary phases. Adult insects must be considered separately, depending on their sex.

Female adults pass through three stages: pre oviposition, oviposition and post oviposition. Male adults pass through a pre-mature stage before reaching sexual maturity.

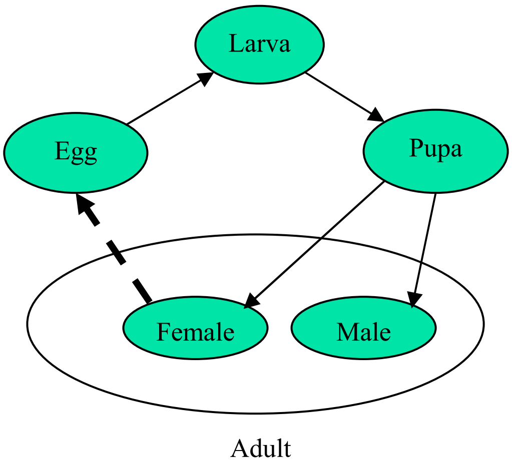

Fig. 1 Olive fly's life cycle

B. The relationship between a queueing system and a life stage of insect

Queuing systems have three major features: demand, resource and performance. In a queueing system, transactions arrive at a resource and demand service; the resource accepts the transaction and has a distribution of service time. The combination of arrivals and service produce a system performance.

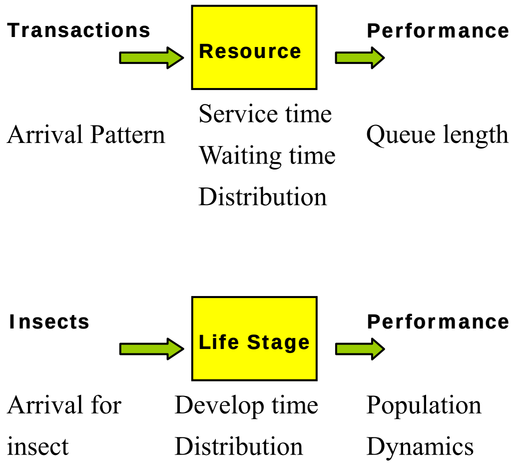

Fig. 2 The relationship between a queueing system and a life stage of insect.

In an insect life stage, insects arrive at a life stage with a time distribution, the system time, which is the sum of waiting time and service time, is the time insect spent in the life stage. The performance is the number of insects in a life stage at any time.

C. *The relationship between a queueing network and the life cycle of insect.*

As discussed in *B*, insect pass though discrete life stage can be modelled as a queueing system.. Therefore, a network of queueing system can then represent the entire life cycle.

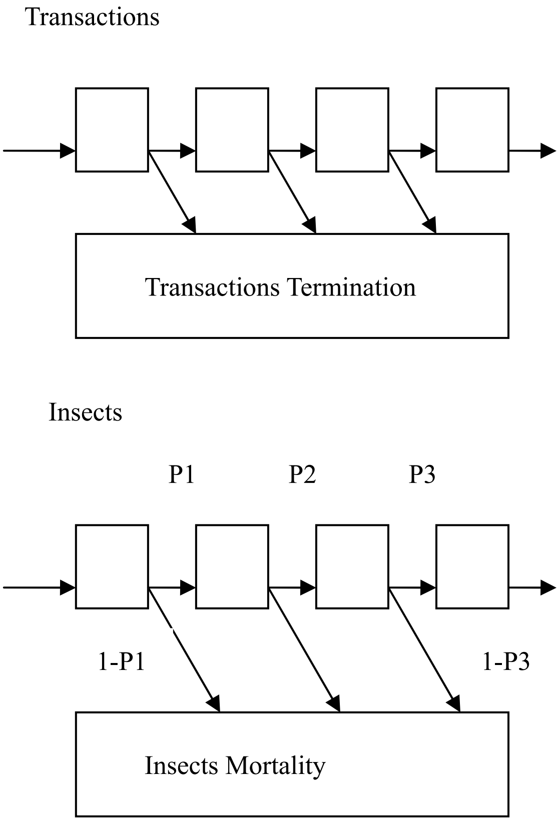

Fig. 3 The relationship between a queueing network and the life cycle of insect.

The transition from one recourse to another may be probabilistic. In insect life cycle, the transition probability represents the probability of survival from one life stage to another. For example, in figure 3, the probability of hatching from egg to larva is p1, the mortality rate for egg is equal to 1-p1. There is another probability p2 of maturing from larva to pupa, and then p3 from pupa to adult

II. MODEL DEFINITION

A. Performance of queueing system.

A simple queueing system for one insect phase is represented in Figure 4. It is a single-server system with infinite storage capacity. For the first stage of the insect – egg, the arrival process follows a Poisson distribution with a parameter λ and service time is exponentially distributed with $\mu 1$ and $\mu 2$ for two different "classes" of insects, respectively correspond to the insects which are going to die and those complete its development and move to next insect phase.

For the later insect stage after egg, the arrival rate is a distribution depending on this "move-to-next" event time in the previous life stage.

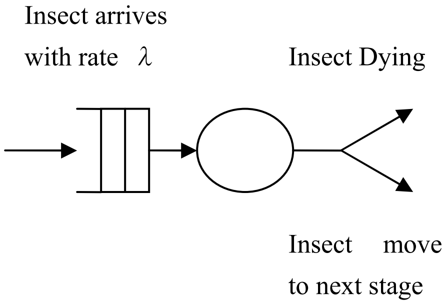

Fig. 4 A simple queueing system for one insect phase.

In order to formulate the model, we define:

Y_K is the kth *interarrival time* time, which is the time elapsed between the (k-1)th and kth insect arrival;
Z_K is the kth service time required for kth insect to be served;
A_K is the arrival time of kth insect;
D_K is the departure time of kth insect;
W_K is the waiting time of kth insect;
S_K is the system time of kth insect.
Note that
$D_K = A_K + S_K$
$S_K = W_K + Z_K$

The stochastic event sequence generated through

$$E' = \arg\min \{Y_i\}$$

B. The stochastic Petri net model

Petri can be used to represent the dynamic behavior of a queueing system.

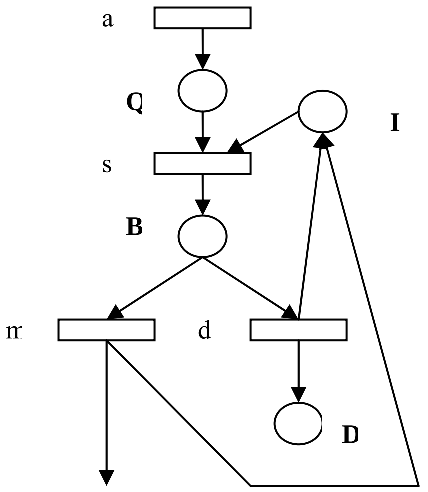

Fig. 5 Petri net model of one insect phase queueing system in initial state [0, 1, 0, 0]
*A token should be placed in I.

As showed in figure 5, we begin by considering 4 events (transitions) driving the system:
Event set T = {a, s, m, d }; Place set P = {Q, I, B, D}
a: insect arrives
s: service starts
m: service completes and insect moves to next stage

d: service completes and insect dies

Q – Queue, the token number (queue length) here represents the number of insect for this stage

I – Idle

B – Busy Server

D – Died insects queue

Note that after event *s*, two events *m* and *d* will be happened based on probability, which indicated the survival rate and mortality rate.

Since $p(i,x) = \lambda i \, / \, \Lambda(x)$, and these two events *m* and *d* are exponentially distributed with $\mu 1$ and $\mu 2$, the survival rate and mortality rate are respectively $\mu 1 / (\mu 1 + \mu 2)$ and $\mu 2 / (\mu 1 + \mu 2)$.

C. The queueing network for entire insect life cycle

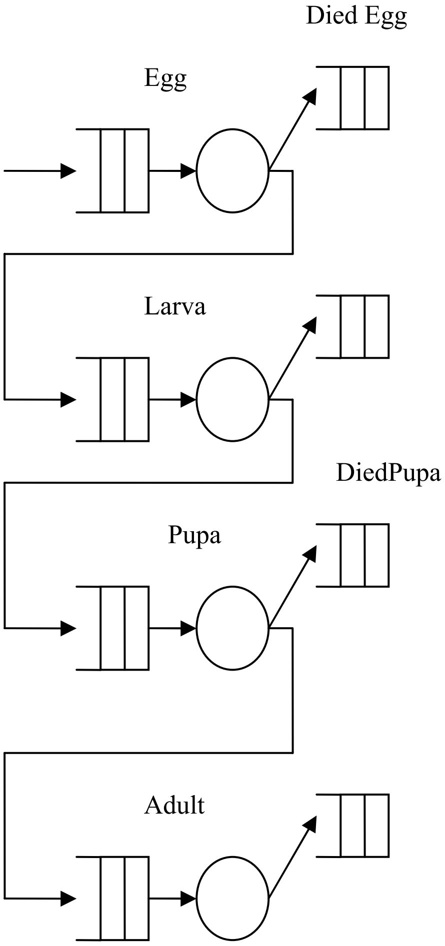

Fig. 6 The queueing network for one generation of the insect.

The queueing network for entire life cycle can be built by connecting all queueing system of 4 insects phase, showed in figure 6. The sum of all queue length in those 4 queueing system represents the population size of insect. Each stage has different parameter for $\mu 1$ and $\mu 2$. After egg, the arrival rate depends on the event *m* in previous life stage.

III. RESULTS AND CONCLUSIONS

Simulation results agreed closely with the real field data as it showed in figure 7. Blue curve shows the simulation of insects population, and the read curve is the capture data from the field.

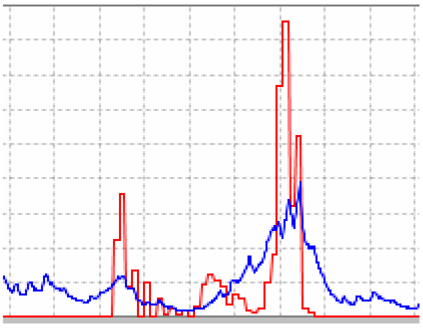

Fig 7. The simulation results (blue) and real field data (red).

The value of discrete event system model describing the dynamics of the insect population has been demonstrated in the simulation of Olive Fly. The advantage are:

- Insect life stage can be represented by queueing syetem with a distribution function
- Lower population levels can be accurately modeled
- The mode is designed as close as the real population
- The model is relatively inexpensive

FUTURE WORK

The model has shown its potential for future research on insect population dynamics. Future work should compare with more data obtained in lab and field experiments, such as the trapped insect's number, the data of field sampling investigation, etc. Forth more, in this approach, the parameters were tuned manually, in order to improve its accuracy and confirm the validity of the model, the proposed solution is to use evolutionary algorithms, possibly genetic algorithms, to search for good combinations of parameters, and then optimize the model.

To find the optimal control strategy for the insect population, the model can also be used for simulate the effect of pesticide by adding a fixed kill in different insect stage.

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