

CARNEGIE MELLON UNIVERSITY
APPLIED STOCHASTIC PROCESSES
(COURSE 18-751)
HOMEWORK 9

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Q.1

(a)

① The R.V. total number of cricket balls is a sum of random number of R.V.s.

$$Z = x_1 + x_2 + x_3 + \dots + x_N$$

$$N \sim \text{Poisson}(5), \quad X \sim \text{Poisson}(2)$$

$$P_X(x) = \begin{cases} \frac{u^x e^{-u}}{x!} & x=0,1,2,\dots \end{cases}$$

$$\begin{aligned} \theta_X(u) &= \sum_{x=0}^{\infty} \frac{e^{jx} u^x e^{-u}}{x!} = \sum_{x=0}^{\infty} \frac{(eu)^x}{x!} e^{-u} \\ &= e^{eu} e^{-u} \\ &= e^{u(e-1)} \end{aligned}$$

$$\therefore \theta_N(s) = e^{5(e-1)} \quad \theta_X(u) = e^{2(e-1)}$$

$$\begin{aligned} \theta_Z(s) &= \theta_N(\ln \theta_X(u)) \\ &= e^{5(e^{\ln \theta_X(u)} - 1)} \\ &= e^{5(e^{2(e-1)} - 1)} = e^{5(\theta_X - 1)} \end{aligned}$$

(b)

(b)

$$\begin{aligned}\Theta_X(s) &= \sum_{x=-\infty}^{\infty} e^{sx} P_X[X=x] \\ &= \sum_{x=0}^{\infty} e^{sx} P_X[X=x] \quad , \text{ non-negative} \\ &= e^{s \cdot 0} P_X[X=0] + \sum_{x=1}^{\infty} e^{sx} P_X[X=x] \\ &= P_X[X=0] + \sum_{x=1}^{\infty} e^{sx} P_X[X=x] \\ \lim_{s \rightarrow -\infty} \Theta_X(s) &= \lim_{s \rightarrow -\infty} \left(P_X[X=0] + \sum_{x=1}^{\infty} e^{sx} P_X[X=x] \right) \\ &= P_X[X=0] + \lim_{s \rightarrow -\infty} \sum_{x=1}^{\infty} e^{sx} P_X[X=x] \\ &= P_X[X=0] + \sum_{x=1}^{\infty} \lim_{s \rightarrow -\infty} e^{sx} P_X[X=x] \\ &= P_X[X=0] + \sum_{x=1}^{\infty} P_X[X=x] \lim_{s \rightarrow -\infty} e^{sx} \\ \lim_{s \rightarrow -\infty} e^{sx} &= 0 \Rightarrow = P_X[X=0] + \sum_{x=1}^{\infty} P_X[X=x] \cdot 0 \\ &= P_X[X=0] \\ \therefore \text{ For Discrete non-negative R.V. } \lim_{s \rightarrow -\infty} \Theta_X(s) &= P_X[X=0] \\ \Theta_Z(s) &= e^{5(e^{2(e^s-1)}-1)} \quad , \quad Z \text{ is a discrete non-negative R.V.} \\ \therefore \lim_{s \rightarrow -\infty} e^{5(e^{2(e^s-1)}-1)} &= P_Z[Z=0] \\ P_Z[Z=0] &= \lim_{s \rightarrow -\infty} e^{5(e^{2(e^s-1)}-1)} = e^{5(e^{-2}-1)} \quad \lim_{s \rightarrow -\infty} e^s = 0 \\ &= 0.0133 \\ \therefore \underline{P_Z[Z=0] = 0.0133} \end{aligned}$$

(c,d)

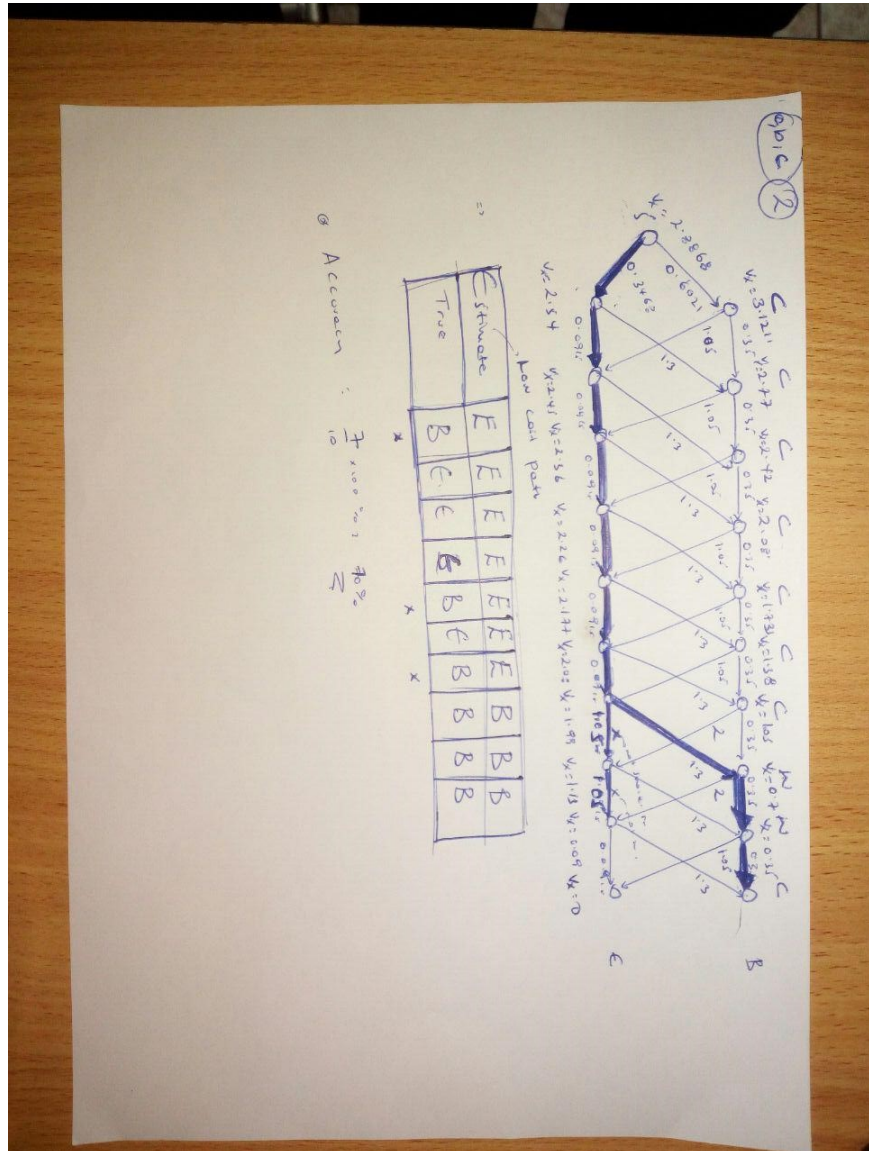
① $\mu_z = \mu_x + \mu_y = 2 \times 5 = 10$ $\sigma_z^2 = \sigma_x^2 + \sigma_y^2 = \sigma_x^2$
 $\sigma_z^2 = \sigma_x^2 + \sigma_y^2 = 5 \times 2^2 + 2 \times 5 = 30$
 $\Rightarrow \sigma_z = \sqrt{30} \approx 5.477$

② We want to find N such that $P[z < N] > 0.99$
 $\Rightarrow 1 - P[z > N] > 0.99$
 $\Rightarrow P[z > N] < 0.01$
Using normal bounds
 $P[z > N] < \frac{\sigma_z}{N} < 0.01$
 $\Rightarrow P[z > N] < 0.01 = \frac{\sigma_z}{N}$
 $\Rightarrow N = \frac{\sigma_z}{0.01} = \frac{10}{0.01} = 1000$

For tighter bounds we use Chebyshev bounds.
 $P[|z - \mu_z| > N] < \frac{\sigma_z^2}{N^2} < 0.01$
 $\Rightarrow N = \sqrt{\frac{\sigma_z^2}{0.01}} = \sqrt{\frac{30}{0.01}} = \sqrt{3000} \approx 54.77 \approx 55$
 $\Rightarrow P[|z - 10| > 55] < 0.01$
 $P[z > 65] + P[z < -45] < 0.01$
 $P[z > 65] < 0.01$
 $\Rightarrow P[z > 65] > 0.99$
we take $N = 65$

Q.2

(a,b,c)



(d)

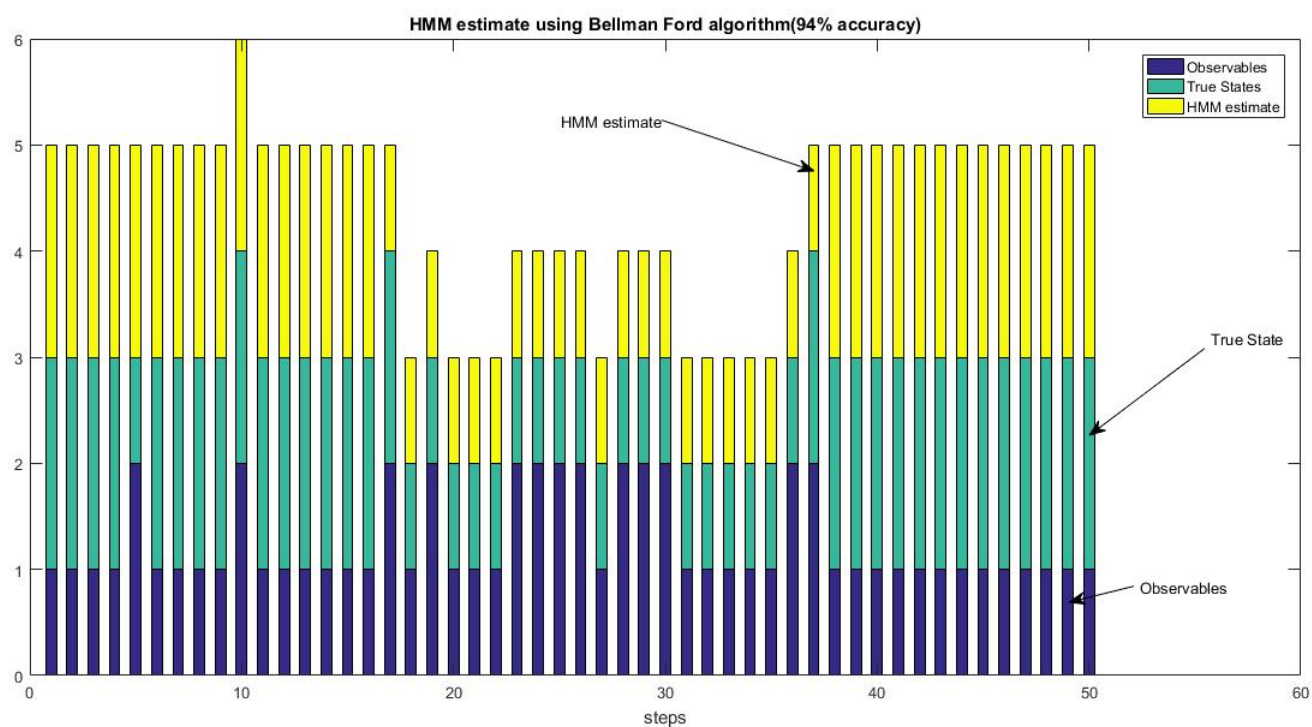


Figure 1: HMM with Bellman Ford (94% accuracy)

Accuracy = 94%

Errors typically occur at transitions

Interpretation of the graph

Observables (length of the bar)

1: Correct

2: Wrong

True states and Estimate(length of the bar)

1: Bored

2: Engaged

To check the accuracy of the estimate, compare the lengths of the estimate and the true value.

Q.3 Kalman Filter

(a)

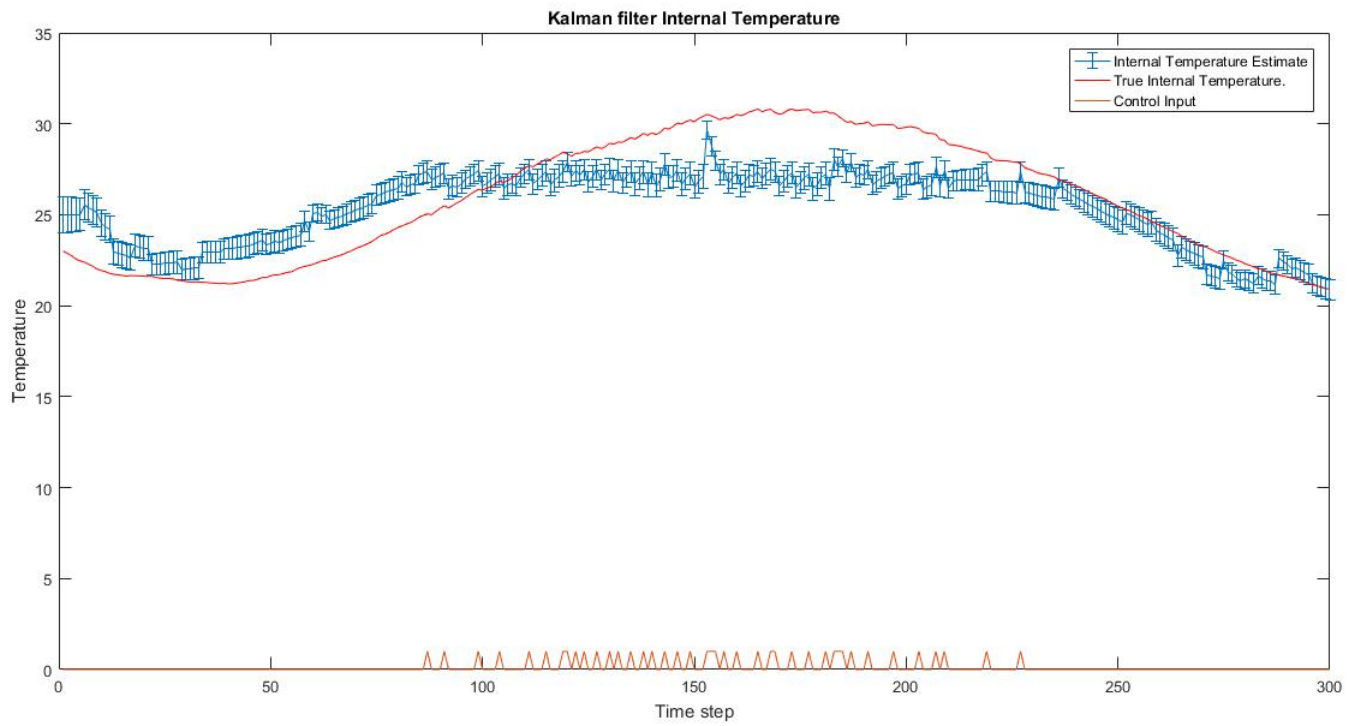


Figure 2: Kalman Filter for Temperature control

(b)

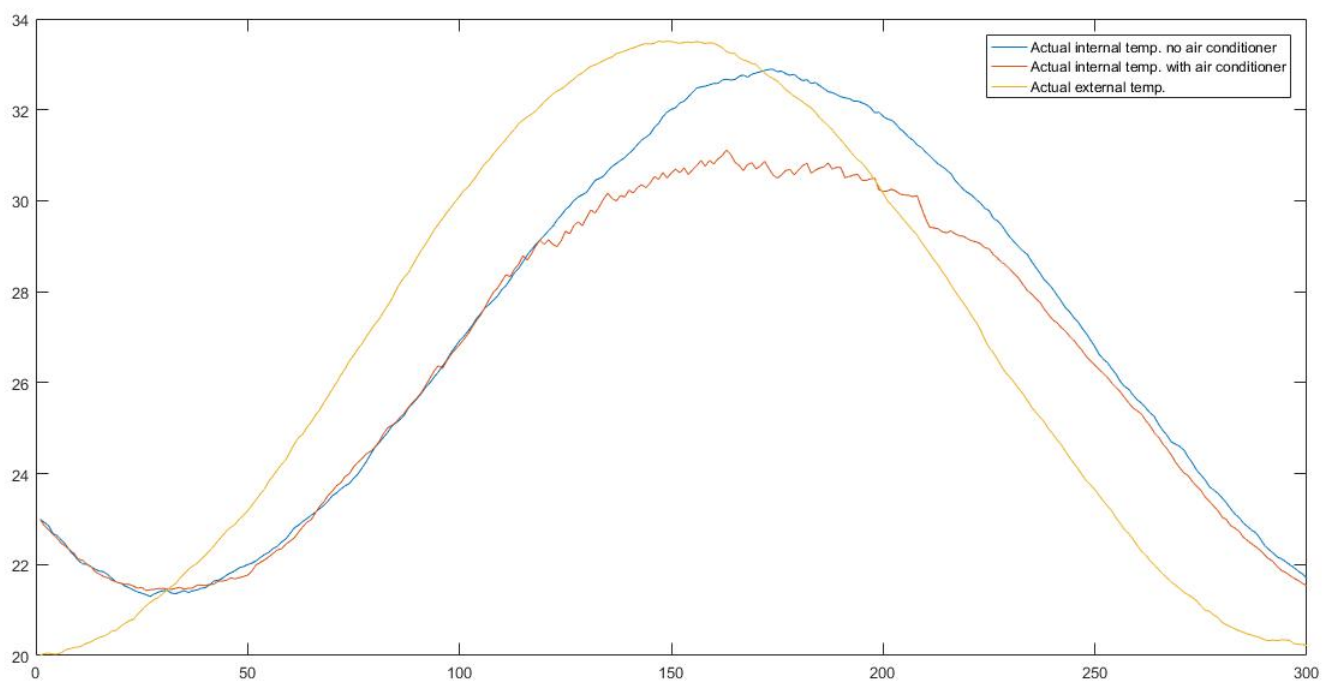


Figure 3: Kalman Filter for Temperature control

The internal temperature swings within an acceptable range (doesn't go beyond 29-30 degrees) whereas internal temperature without the air conditioner could go up to 33 degrees.

Code Appendix

```
1 function [tempGraph,VX,stateS,HMMestimate] = create_graph(P,O,Y,  
    N,PI_0)  
2 tempGraph = zeros(4,N-1);  
3 VX = zeros(2,N);  
4 VX(:,N) = zeros(2,1);  
5 selectedEdges = zeros(2,N);  
6 for i=1:N-1  
7     currentO = O(:,Y(i+1));  
8     currentO = [currentO(:),currentO(:)];  
9     tempGraph(:,i) = -log10(P(:).*currentO(:));  
10 end  
11  
12 for i=N-1:-1:1  
13     [VX(1,i),selectedEdges(1,i+1)] = min(tempGraph(1:2,i) + VX(:,  
        i+1));  
14     [VX(2,i),selectedEdges(2,i+1)] = min(tempGraph(3:4,i) + VX(:,  
        i+1));  
15 end  
16  
17 currentO = O(:,Y(1));  
18 stateSedges = -log10(PI_0.*currentO(:));  
19 [stateS,stateSbestedge] = min(stateSedges + VX(1));  
20 stateSbestedge  
21 selectedEdges  
22 HMMestimate = zeros(1,N);  
23 HMMestimate(1) = stateSbestedge;  
24 for i=2:N  
25     HMMestimate(i) = selectedEdges(HMMestimate(i-1),i);  
26 end  
27 end  
  
-  
  
1 clear;  
2 clc;  
3 P = [0.9,0.1;0.1,0.9];  
4 O = [0.5,0.5;0.9,0.1];  
5  
6 %Bored = 1;  
7 %Engaged = 2  
8 %Correct = 1  
9 %Wrong = 2  
10  
11  
12 [states,observables] = simMC(50,P,O);  
13  
14  
15 display_states(states);  
16 display_observables(observables);  
17  
18 [edgeWeights,VX,stateS,HMMestimate] = create_graph(P,O,  
    observables,50,[0.5;0.5]);
```

```

19 display_states(HMMestimate);
20 accuracy = 100*(sum(HMMestimate==states)/50);
21 fprintf('Accuracy of HMM estimate:%2.2f percent\n',accuracy);
22 figure
23 bar([observables' states' HMMestimate'], 0.5, 'stack');
24 xlabel('steps')
25 legend('Observables', 'True States', 'HMM estimate');

1 clear;
2 clc;
3 A=[0.95 0.05;0 1];%state transtion matrix
4 H=[1 0;0 1];%measurment transition
5 X= zeros(2,300);% blind prediction
6 Var = zeros(2,300);
7 Xh=X;%estimate
8 P = zeros(2,2,300);%estimate covariance
9 K=P;%gain
10 Xh(:,1)= [25,25];%initial state estimate
11 numberOfTimeSteps = 299;
12 Q = [0.04,0 ; 0,0.01];%model covariance
13 R = [4 0;0 1];%measurement covariance
14 Z = zeros(2,300); %measurment
15 turnOn = 0;%comand to turn on an off air conditioner
16 u_k = 0;%control input
17 P(:, :, 1)= eye(2);%initialize estimate covariance to some big
    value
18 U_k = zeros(300,1);%hold command history
19 B = [-1,0]';%B
20 meanEstimateInternal = zeros(300,1);
21 varianceEstimate = zeros(300,1);
22 alpha = 0.25;%contol the MC
23 beta = 0.5;%control the MC
24 mcP = [1-alpha, alpha; beta, 1-beta];%markov chain transition
    matrix
25 state = 1;%start state of MC
26 Ztrue = zeros(2,300);
27 Xtrue = Ztrue;
28 Xtrue(:,1) = [23,20];
29 ZtrueNoConditioner = zeros(2,300);
30 XtrueNoConditioner = ZtrueNoConditioner;
31 XtrueNoConditioner(:,1) = [23,20];
32
33 for n=1:numberOfTimeSteps
34     u_k = turnOn;
35     U_k(n) = u_k;
36     [Xtrue(:,n+1),Ztrue(:,n+1)] = get_measurment(Xtrue(:,n),u_k,
n);%get measurement at constant rate
37
38     [XtrueNoConditioner(:,n+1),ZtrueNoConditioner(:,n+1)] =
get_measurment(XtrueNoConditioner(:,n),0,n);%get measurement
at constant rate
39     if state==1%if in prediction state
40
41

```

```

42
43     Xh(:,n+1) = A*Xh(:,n) + 0.1*sin((2*pi/300)*n) + B*u_k ;
44     %prediction
45     P(:, :, n+1) = A*P(:, :, n)*A' + Q;%predicted covariance
46     state = discrete(mcP(state, :));%get next state
47     fprintf('prediction\n');
48
49 end
50 while state==2%while measurment is available update
51
52     %get measurement
53     [Xtrue(:,n+1),Ztrue(:,n+1)] = get_measurment(Xtrue(:,n),
54     u_k,n);%get measurement at constant rate
55     [XtrueNoConditioner(:,n+1),ZtrueNoConditioner(:,n+1)] =
56     get_measurment(XtrueNoConditioner(:,n),0,n);%get measurement
57     at constant rate
58
59     Z(:,n) = Ztrue(:,n) + [normrnd(0,4); normrnd(0,1)];
60
61     K = P(:, :, n+1) * H' * ((H*P(:, :, n+1)*H' +R)) ^(-1);
62     P(:, :, n+1) = (eye(2)-K*H)*P(:, :, n+1);
63     Xh(:,n+1)= Xh(:,n+1)+K*(Z(:,n)-H*Xh(:,n+1));
64
65     fprintf('fusion\n');
66     state = discrete(mcP(state, :));
67
68 end
69
70 meanEstimateInternal(n) = Xh(1,n+1);
71 varianceEstimate(n) = P(1,1,n+1);
72 %if prob. temp>28 is >10%=0.1
73 if qfunc((28-meanEstimateInternal(n))/sqrt(varianceEstimate(
74 n)))>0.1
75     turnOn = 1;
76 else
77     turnOn = 0;
78 end
79 end
80
81 internalTempError = sqrt(P(1,1,:));%error matrix
82 externalTempError = sqrt(P(2,2,:));
83 figure;
84 errorbar(1:300,Xh(1,:),internalTempError(:));
85 hold on;
86 %plot(Z(1,:));
87 %hold on;
88 plot(Xtrue(1,:), 'r');
89 %plot(Ztrue(1,:), 'b--');
90 plot(U_k(:,1));
91 title('Kalman filter Internal Temperature');
92 xlabel('Time step')
93 ylabel('Temperature')
94 legend('Internal Temperature Estimate','True Internal
95 Temperature.','Control Input');

```

```

90 figure;
91 plot(XtrueNoConditioner(1,:), 'DisplayName', 'Actual internal temp
    . no air conditioner');
92 hold on;
93 plot(Xtrue(1,:), 'DisplayName', 'Actual internal temp. with air
    conditioner');
94 plot(Xtrue(2,:), 'DisplayName', 'Actual external temp. ');
95 legend('show')

1 function [X_k, Z_k] = get_measurment(X_k_1, u_k, n)
2 A = [0.96, 0.04; 0, 1];
3 H = eye(2);
4 B = [-0.2; 0];
5 V = [normrnd(0, 1.5); normrnd(0, 1.5)];
6 W = [normrnd(0, 0.03); normrnd(0, 0.02)];
7
8 X_k = A*X_k_1 + [0; 0.14*sin((2*pi/300)*n)] + B*u_k + W;
9 Z_k = H*X_k + V;
10
11 end

```