Technical Note

Global stability of Susceptible Diabetes Complication (SDC) model in discrete time

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ARTICLE INFO

Article history
Received: 29 September 2020
Accepted: 14 January 2021

Key words:
Susceptible Diabetes Complication (SDC) model; Global stability; Equilibrium points

ABSTRACT

In this study, the mathematical model (DC) of diabetes disease is discussed. This model divides people into (D) uncomplicated and (C) complex diabetics two. In addition, diabetes is a disease known to be caused by genetic and environmental factors, and this factor is one of the main causes of genetic disorder at birth. Considering these two factors, the diabetes complication (SDC) model, which is sensitive from the diabetes complication (DC) model, is being developed. In this model, the responsive diabetes complication (SDC) model of a nonlinear system of differential equations is transformed into a discrete-time system of equations. The positivity and limitation of Model solutions were examined. If \( R_0 < 1 \), it has a global asymptotically stable balance for the situation where there is no genetic disorder at birth, and for \( R_0 < 1 \), the system has an unstable balance. In addition, random behavior of the discrete model was examined for different probability distributions.


INTRODUCTION

Epidemiology has been gaining more and more attention over the past few years for diseases that have spread to a living organism. Mathematical modeling is used to study the epidemiology of a disease. With the development of science, mathematical modeling is used to study not only the spread of infectious diseases, but also non-communicable diseases. Analysis of these disease models with discrete-time equation systems is also obtained. Diabetes is a disease commonly referred to as diabetes, which is usually caused by a combination of hereditary and environmental factors, and the blood glucose level rises excessively. The most important of the hormones that play a role in the regulation of sugar metabolism is the insulin hormone secreted from the beta cell of the pancreas. Insulin enables the sugar to enter the cell and to be stored as glycogen in the cell. People with diabetes cannot use glucose, which passes from the food they eat to the blood, and blood sugar levels rise, causing damage to many tissues and organs. There are two types of diabetes: type 1 diabetes, body cells

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This paper was recommended for publication in revised form by Regional Editor Aydın Seçer

Published by Yıldız Technical University Press, Istanbul, Turkey
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cannot absorb and process glucose without insulin so blood sugar levels increase, in type 2 diabetes, it occurs because the body cannot produce enough insulin. With the introduction of insulin in 1921, all types of diabetes are treated but there is no definitive cure. The most basic treatments of type 1 diabetes are injecting insulin syringes or pens, while in type 2 diabetes, diet and sugar-lowering drugs are used. Treatment methods used in diabetes lead to many complications. In 2004, Boutoyeb and colleagues introduced the (DC) diabetes complication model to find diabetes without complications (D) and diabetes with complications (C), and the following is the continuous time model to be studied in this study.

$$\frac{dD}{dt} = I - (\lambda + \mu)D + \gamma C$$
$$\frac{dC}{dt} = \lambda D - (\gamma + \delta + \nu + \mu)C$$

Here I, \(\lambda\), \(\gamma\), \(\delta\), \(\nu\), \(\mu\) > 0. Then, unlike model (1), it determines that the number of incidences is not constant and the number of events taking into account the genetic and environmental factors. With this difference in mind, the (1) model is transformed into a responsive diabetes complication (SDC) model and the SDC is expressed below as a continuous time model [4].

$$\frac{dS}{dt} = \alpha S + \alpha(1 - \rho)(D + C) - \frac{\beta S(n)D(n)}{N} - \mu S(n)$$
$$\frac{dD}{dt} = \frac{\beta S(n)D(n)}{N} + \alpha \rho (D + C) - (\lambda + \mu)D + \gamma C$$
$$\frac{dC}{dt} = \lambda D - (\gamma + \delta + \mu)C$$

Model (3) is obtained by a sensitive diabetes complication analysis. Let’s add \(N(n)\) carrier complications by adding up all equations of this model:

$$\frac{N(n + 1) - N(n)}{h} = \alpha S(n) + \alpha(1 - \rho)(D(n) + C(n)) - \frac{\beta S(n)D(n)}{N} - \mu S(n)$$
$$\frac{D(n + 1) - D(n)}{h} = \frac{\beta S(n)D(n)}{N} + \alpha \rho (D(n) + C(n)) - (\lambda + \mu)D + \gamma C(n)$$
$$\frac{C(n + 1) - C(n)}{h} = \lambda D(n) - (\gamma + \delta + \mu)C(n)$$

It is being transformed into a discrete-time system of equations. Where \(S(0) > 0, D(0) > 0, C(0) > 0,\) and \(h = 0.01\). The parameters \(\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho > 0\) and \(0 \leq \rho \leq 1\), respectively, are birth rate, interaction rate, recovery rate of complications, complication-related mortality rate, occurrence rate of complications, and rate of genetic disorder at birth [4–6].

$$N(n + 1) = N(n) + \alpha N(n) - \mu N(n) - \delta C(n)$$

In this equation, \(\bar{N}(n + 1) \leq N_0(1 + \alpha - \mu)^n\) global asymptotic stable limit \(\lim_{n \to \infty} N(n) = 0\) has a single balance. The disease equilibrium point of the model (3) is indicated by \(E_0\), and as a single equilibrium is found as \(E_0(0,0,0)\) [1–3]. Recently, various studies have been done on random differential equation and difference equation [13–16].

### DISCRETE TIME PROBABILITY DISTRIBUTIONS

In this section, definitions related to some probability concepts used are given.

**Discrete Uniform Distribution**

**Definition.** Let \(k\) be a positive bit integer. A random variable \(X\) with probability function

$$P(x, k) = \begin{cases} \frac{1}{k}, & x = 1, 2, 3, \ldots, k \\ 0, & \text{other} \end{cases}$$

is called a discrete uniform chance variable [12].

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Descriptions</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\gamma)</td>
<td>Recovery rate of complications</td>
<td>0.37141</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>Birth rate</td>
<td>0.01623</td>
</tr>
<tr>
<td>(\delta)</td>
<td>Complication-related mortality</td>
<td>0.0068</td>
</tr>
<tr>
<td>(\lambda)</td>
<td>Rate of occurrence of complications</td>
<td>0.67758</td>
</tr>
<tr>
<td>(\mu)</td>
<td>Death rate</td>
<td>0.00764</td>
</tr>
<tr>
<td>(\rho)</td>
<td>Genetic disorder in childbirth</td>
<td>0.077</td>
</tr>
<tr>
<td>(\beta)</td>
<td>Interaction rate</td>
<td>0.16263</td>
</tr>
</tbody>
</table>
Theorem. If $X$ has a discrete uniform distribution, then

- $E(X) = \frac{k+1}{2}$,
- $V(X) = \frac{k^2-1}{12}$,
- $M_s(t) = \frac{1}{k} \sum_{x=1}^{k} e^{x}$,

Binomial Distribution

Definition. Let the total number of those who succeeded in $n$ independent Bernoulli trials be the random variable $X$. For a single experiment, the probability of success is denoted by $p$, and the probability of failure is $(1- p)$. The binomial random variable $X$ has the following probability function

$$f(x; n, p) = \binom{n}{x} p^x (1-p)^{n-x}; x = 0, 1, 2, \ldots, n.$$ 

Calculation of consecutive binomial probabilities,

$$f(x+1; n, p) = \frac{(n-x)p}{x+1(1-p)} f(x; n, p); x = 0, 1, \ldots, n-1.$$ 

Theorem. If $X$ has a binomial distribution,

- $E(X) = np$,
- $V(X) = np(1-p)$,
- $M_s(t) = [e^t + (1-p)]^n$.

Geometric Distribution

Definition. The number of experiments done to obtain the first desired result (success or unsuccessful) in a Bernoulli experiment repeated $n$ times in succession is called a geometric random variable $X$. The distribution of this variable is called the geometric distribution and the probability function of the geometric random variable $X$, with probability of unsuccessfulness $q = 1 - p$ and probability of success $p$ in a single experiment [12]

$$f(x) = P(X = x) = q^{x-1}p; x = 1, 2, 3, \ldots$$

Theorem. If $X$ has a geometric distribution,

- $E(X) = \frac{1}{p}$,
- $V(X) = \frac{(1-p)}{p^2}$,
- $M_s(t) = pe^t\left[\frac{1}{1-(1-p)e^t}\right]$.

Poisson Distribution

Definition. $f(x) = P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!}; x = 0, 1, 2, \ldots, \lambda > 0.$ The Taylor expansion of the function $e^x$ and the probability function gives $\sum_{x=0}^{\infty} \frac{x^e}{x!} = 1.$

Theorem. If $X$ has a Poisson distribution,

- $E(X) = \lambda$,
- $V(X) = \lambda$,
- $M_s(t) = e^{(\lambda+1)}$.

BASIC R_0 INCREMENT NUMBER

Using the Matrix method, we get the basic increment number of the model. Consider the equilibrium point $E_0 (0,0,0).$ If $x = (S,D)^T$, the model can be rewritten as follows:

$$x' = F(x) - V(x)$$

and

$$F(x) = \begin{bmatrix} -\alpha p \left(D(n) + C(n)\right) \\ \alpha p \left(D(n) + C(n)\right) \\ -S(n) - \alpha S(n) - \alpha \left(D(n) + C(n)\right) + \beta S(n) \frac{D(n)}{N} \end{bmatrix}$$

$$V(x) = \begin{bmatrix} -D(n) + (\lambda + \mu) D(n) - \gamma C(n) - \beta S(n) \frac{D(n)}{N} \end{bmatrix}$$

Jacobian matrices of $F(x)$ and $V(x)$ in $E_0$

$$DF(E_0) = \begin{bmatrix} 0 & -\alpha p \\ 0 & \alpha p \end{bmatrix}$$

$$DV(E_0) = \begin{bmatrix} -1 - \alpha + \mu + \beta D(n) - \alpha \frac{\beta S(n)}{N} \\ -1 - \lambda + \mu \end{bmatrix}$$

for

$$F = \begin{bmatrix} 0 & -\alpha p \\ 0 & \alpha p \end{bmatrix} V = \begin{bmatrix} -1 - \alpha + \mu & -\alpha \\ \alpha & 0 \end{bmatrix}$$
G = FV⁻¹ is found as \( R_0 = \frac{\alpha \rho}{\lambda + \lambda - 1} \), which is the basic increase number given by the radius of the new generation matrix. [1]

**EXTINCTION AND PERSISTENCE OF THE DISEASE**

This section focuses on disease-free equilibrium stability and the absence and persistence of disease determined by the presence of endemic equilibrium of the model. \( E^0(0,0,0) \) indicates an equilibrium. \( S, D, C \) components are zero, so disease-free balance is called. The stability of the disease-free equilibrium \( E^0 \) is given in the following theorem.

**Theorem 1 (Jury Theorem).** For this criterion for \( | \theta | < 1 \) values

\[
\theta^3 + a_1 \theta^2 + a_2 \theta + a_3 = 0
\]

the roots of the cubic equation can be shown by the following conditions [9].

\[
1 + a_1 + a_2 + a_3 > 0, \quad 1 - a_1 + a_2 - a_3 > 0, \quad 3 + a_3 - a_1 - 3a_2 > 0, \quad 1 + a_2 + a_4 - a_2^2 > 0,
\]

**Theorem 2.** For the equilibrium point \( E^0 \) of the model

i. \( R_0 < 1 \) is global asymptotic stable

ii. \( R^0 > 1 \) for unstable.

**Proof.** (i) Characteristic equation by giving the \( H \) matrix in \( E^0 \) by the Jacobian matrix in (5)

\[
\theta^3 + a_1 \theta^2 + a_2 \theta + a_3 = 0
\]

for

\[
a_1 = A - C + E - 3 < 0,
\]

\[
a_2 = 3 + 2C - 2E - 2A - AC + AE - CE - \lambda D > 0
\]

\[
a_3 = -1 + E - C + CE + \lambda D + A - AE + AC - ACE - AD\lambda > 0
\]

If the Jury Theorem is applied to this cubic equation,

\[
1 + a_1 + a_2 + a_3 = 1 + A - C + E - 3 + 3
\]

\[
+ 2C - 2E - 2A - AC + AE - CE - \lambda D - 1 + E - C
\]

\[
+ CE + LD + A - AE + AC - ACE - AD\lambda > 0
\]

\[
3 + a_3 - a_2 - 3a_1
\]

\[
= 3 + A - C + E - 3 - (3 + 2C - 2E - 2A - AC + AE - CE - \lambda D)
\]

\[
- 3(-1 + E - C + CE + \lambda D + A - AE + AC - ACE - AD\lambda) > 0
\]

\[
1 - a_1 + a_2 - a_3
\]

\[
= 1 - (A - C + E - 3) + 3 + 2C - 2E - 2A - AC + AE - CE - \lambda D
\]

\[\text{and if } \lambda + \mu < 1 \text{ and } R_0 < 1 \text{ become } 0 < 1 + \beta - \lambda - \mu + R_0(\mu + \lambda - 1) < 1. \text{ From here (7) repeated inequality use of the equation}
\]

\[
D(n+1) \leq D(n) + \beta D(n) + \alpha D(n) + C(n)
\]

\[
= (1 + \beta - \lambda - \mu + R_0(\mu + \lambda - 1))D(n)
\]

(8) the equation is \( \lim_{n \to \infty} D(n) = 0 \).

Since \( n \geq N_1 \) for any \( \epsilon > 0 \) from \( \lim_{n \to \infty} D(n) = 0 \), \( D(n) < \epsilon \) is large such that we know that the positive integer is \( N_1 \).

As a result,

\[
C(n+1) = C(n) + \lambda D(n) - (\gamma + \delta + \mu)C(n)
\]

\[
\leq C(n) + \lambda \epsilon - ((\gamma + \delta + \mu)C(n)) \text{ for } n \geq N_1. \tag{9}
\]

For the odd balance of \( \hat{C}(n+1) = \hat{C}(n) + \lambda \epsilon - ((\gamma + \delta + \mu)\hat{C}(n)) \) in this equation, \( \hat{C}^* = \frac{2\lambda \epsilon}{\gamma + \delta + \mu} \) is
globally asymptotically stable. In comparison principle \( C(n) \leq \hat{C}(n) < \frac{2\lambda\epsilon}{\gamma + \delta + \mu} \) indicates that \( N_i > N_I \) is the integer. For arbitrary \( \epsilon \), this limit \( \lim_{n \to \infty} C(n) = 0 \) if \( \delta \) is from the equation,

\[
N(n) + \alpha N(n) - \mu N(n) - \delta C(n) \leq N(n + 1) \leq (1 + \alpha - \mu) N(n) \text{ gér n} > N_i 
\] (10)

On the left side of the inequality of the (10) equation, and from the principle of comparison, we know that for any given \( \epsilon_i > 0 \) for all \( n > N_i \), integer. (10) for any \( \epsilon_i > 0 \) according to the comparison principle given on the right side of the inequality of equation, all \( n > N_i \). We know that there is an integer \( N_i > N_i \) such that \( N(n) \leq N_0 (1 + \alpha - \mu) + \epsilon_i \). \( N_i = N_i + N_i \).

\[
\frac{\delta \lambda \epsilon}{\gamma + \delta + \mu (\alpha - \mu)} - \epsilon_i \leq N(n) \leq N_i (1 + \alpha - \mu)n + \epsilon_i \text{ for } n > N_i 
\]

and arbitrary \( \epsilon = \epsilon_i, \epsilon_i \) and \( \lim_{n \to \infty} N(n) = \epsilon_i \), i.e.

\[
\lim_{n \to \infty} S(n) = \epsilon_i, \quad \lim_{n \to \infty} D(n) = 0, \quad \lim_{n \to \infty} C(n) = 0
\]

Meaning that the disease-free equilibrium of (3) is global asymptotically stable since \( R_0 < 1 \) it is found. \( R_0 > 1 \) means that the average number of new infections by an infected person is more than one. Its epidemiological interpretation suggests that the disease may be permanent in the population. The theorem below confirms the continuity of the disease in case of \( R_0 > 1 \).

**Theorem 4.** If \( R_0 > 1 \), the disease will remain persistent in the population, that is, the solution of the model with the initial value \( D(0) > 0 \) has a positive \( \epsilon \) value such that \( \lim_{n \to \infty} D(n) = \epsilon > \epsilon_i \).

**Proof.** \( X = \Omega_i = \{(S, D, C) \mid S + D + C \leq N_i (1 + \alpha - \mu) \}, X_0 = \{(S, D, C) \mid D > 0, C > 0 \} \) and \( \partial X_0 = \frac{X}{X_0} \) The solution maps of the (2) model for \( \Phi \rightarrow X, \Phi \) \( x_i = \phi(n, x_i) \phi(0, x_i) \) \( x^i = (S(0), D(0), C(0)) \). Where, \( M_0 = \{0, 0, 0\} \) and

\[
M_0 = \{(S, D, C) \in \partial X_0 \mid (S, D, C) \partial X_0 \} \partial X_0 \quad \forall n \geq
\]

This \( \{(S, 0, 0) \partial X_0 | S \geq 0 \} M_0 \) is open and \( M_0 = \{(S, D, C) \partial X_0 \mid D = 0 \} \). Also, for \( \Phi_0, \Phi \) is a fixed point in \( M_0 \). Equation,

\[
S_i \frac{n + 1}{n + 1} (1 + \alpha - \mu) S_i (n)
\]

It is the global attractor for the balance \( S_i = 0 \). Using Lemma 5.9 \( \{10\} \), we know that no subset of \( M_0 \) forms a cycle on \( \partial X_0, \Phi_0 (M_0) M_0 \) state \( \Phi_0 ((S(0), 0, C(0)) = (S(n), 0, C(n)) \) let’s imply. If \( x_i = \Phi (S(0), 0, C(0)) M_0 \), \( \lim_{n \to \infty} S(n) = 0 \), \( \lim_{n \to \infty} C(n) = (1 - \gamma - \delta - \mu) C(0) = 0 \) ve \( \Omega (M_0) = \Phi_0 \).

\[
0 \leq C(n) \leq D(n) \leq N(n) \text{ and } N(n + 1) = N(n) + \alpha N(n) - \mu N(n) - \delta C(n) \text{ due to } N(n + 1) \geq N(n) + (\alpha - \mu - \delta) N(n) \text{ and } N(n + 1) \leq N(n) + (\alpha - \mu) N(n) - \mu N(n). \text{ This difference equation } N_i (n + 1) = (1 + \alpha - \mu - \delta) N_i (n) \text{ single balance } N_i^* = \frac{\alpha - \mu - \delta}{\alpha - \mu} N_0 \text{ and } N(n + 1) = N(n) + \alpha N(n) \text{ is the only equation of the equation of } N_i^* = (1 + \alpha - \mu) N_i \text{ and is global asymptotic stable. Therefore, for any } \epsilon > 0, \text{ All } n \geq N_i, \text{ } (\alpha - \mu - \delta) N_0 (n + 1) - \epsilon \leq N(n + 1) = (1 + \alpha - \mu^*) N_0 (n + 1) + \epsilon.
\]

If \( R_0 > 1 \) then we can prove that \( \sigma \) is a small positive number such that

\[
\lim_{n \to \infty} d(\Phi_0 (S, D, C), \Phi_0) \geq \sigma
\]

for \( (S, D, C) \in X_0 \)

(11)

If the result in (11) is not valid, then any \( (S_0, D_0, C) X_0 \) is a positive number and there is a dot a large \( N_i > N_i \).

\[
d(\Phi_0 (S, D, C), \Phi_0) < \sigma \text{ için } n > N_i
\]

(12)

Inequality in (12),

\[
D(n) \leq \sigma \text{ and } S(n) < -\sigma \text{ if } n > N_i
\]

(13)

Since \( n > N_i \), the equations in (3)

\[
N(n + 1) = N(n)(1 + \alpha - \mu),
\]

\[
D(n + 1) = D(n) + \frac{\beta D(n)(-\sigma)}{N(n)} - (\lambda + \mu) D(n) + \gamma C(n)
\]

(14)

From the first inequality in (14), we know that \( N(n) \leq (1 + \alpha - \mu)^n N(0) \text{ a } n > N_i \text{ number that will hold for all } N_i > N_i. \text{ Since } n > N_i, \text{ we change } N(n) \leq (1 + \alpha - \mu)^n N(0) \text{ to the second inequality of (14) to obtain the inequality of } D(n + 1) = D(n) + \frac{\beta D(n)(-\sigma)}{N(n)} - (\lambda + \mu) D(n)
\]

(15)

by selecting small enough, the state is expressed as

\[
R_0 (\lambda + \mu - 1) > 0, \text{ and }
\]

\[
1 + \frac{\gamma C(n)}{(1 + \alpha - \mu)^n N_0} + R_0 (\lambda + \mu - 1) > (\lambda + \mu)
\]

(16)

From inequalities in (15) and (16), this limit \( \lim_{n \to \infty} D(n) = \infty \). Limit limit \( \lim_{n \to \infty} D(n) = \infty \) in \( D(n) \) contradicts with the inequality of \( D(n) < \sigma \). The contradiction comes from the conjecture given in (12), so the result in (11) is true. Then, \( \Phi (S, D, C) X_0 = \Phi_0 \) and \( \Phi_0 \text{ is isolated by } X. \text{ It is equally permanent with respect to } (X_0, \partial X_0) \text{ in theorem 3.} \)
Also in theorem 4, it implies that the solutions of the (3) model are permanent in the same way as \((X_0, \partial X_0)\) when \(R_0 > 1\), so that there is a \(\epsilon > 0\) similar to this boundary entry, and \(\lim_{n \to \infty} fD(n) > \epsilon > 0\).[8–10]

NUMERICAL EXAMPLES

In this section, after giving information about SDC model, random models will be established and examined [11–12].

DISCRETE TIME PROBABILITY DISTRIBUTION

Uniform Distribution

\[
\begin{align*}
S(n+1) &= S(n) + h \\
\left( \alpha S(n) + \alpha(1-\rho)D(n) + C(n) \right) - \frac{\beta S(n)D(n)}{N} - \mu S(n) \right) \\
D(n+1) &= D(n) + h \\
\left( \frac{\beta S(n)D(n)}{N} + \alpha \rho D(n) + C(n) \right) - (\lambda + \mu)D(n) + \gamma C(n) \\
C(n+1) &= C(n) + h(\lambda D(n) - (\gamma + \delta + \mu)C(n))
\end{align*}
\]

In the random SDC difference equation defined as if \(\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho\) is a random variable with a parameterized uniform distribution and \(K = 10\), then the probability characteristics obtained from \(10^5\) simulations are given below.

Within the SDC model process \((n \in [0,10])\), variability is observed to increase. The end values are shown in the Table (Table 1.1 and figure 1.1).

It appears that the expected diabetes reached its highest level at the time of \(n = 10\). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \(E(S(10)) = 290\) was obtained for the expected value at the end of the process \(n = 10\).

Similarly, variance change \((n \in [0,10])\) appears to increase for the SDC model. Extreme values are seen in the table (Table 1.2 and Figure 1.1).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of \(n = 10\). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, at the end of the process, \(Var(S(10)) = 0.006742\) was obtained for variance, \((n = 10)\). In addition, at the end of the process, \(Var(S(10)) = 0.006742\) was obtained for variance, \((n = 10)\).

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 1.1). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are

Table 1.1. Expected value of random \(S(n)\) number of susceptible individuals, end values and times

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>(E(S(n)))</td>
<td>289.8</td>
<td>0</td>
<td>290</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 1.1. random behavior of \(S(n)\) number of susceptible individuals.
expected to behave similarly. Extreme values for standard deviations are shown below (Table 1.3).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $Std(S(10)) = 0.08211$ was obtained for variance ($n = 10$) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables $S(n)$ in the random model (3) were also calculated as follows (Figure 1.1).

Coefficient of Variation (CV) is calculated by definition as $100 \times \frac{std(S(n))}{E(S(n))}$ and random $\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho$ parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of $S(n)$ variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 1.4).

Despite the %5 coefficient of variation in the parameters, it is observed that the variation rate of $S(n)$ is constantly increasing and reaches %0.0002832 at $n=10$. Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 1.1). The confidence intervals given in the figure are calculated as $CI = (E(S(n)) - 3 \cdot std(S(n)), E(S(n)) + 3 \cdot std(S(n)))$, and three gives the range of variation within the standard deviation. For uniform distribution, this range includes about 99% of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 1.5).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Var(S(n))$</td>
<td>0</td>
<td>0</td>
<td>0.006742</td>
<td>10</td>
</tr>
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</table>

<table>
<thead>
<tr>
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<th>Minimum</th>
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<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Std(S(n))$</td>
<td>0</td>
<td>0</td>
<td>0.08211</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
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<th>Minimum</th>
<th>Time</th>
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<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CV(S(n))$</td>
<td>0</td>
<td>0</td>
<td>0.02832</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CI(S(n))$</td>
<td>0</td>
<td>0</td>
<td>0.02832</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 1.2. $D(n)$ uncomplicated random behaviors.
At the end of the process, three standard deviation intervals for $S(n)$ variables are obtained as follows: $CI(S(10)) = (289.8, 290.2)$.

Model (3) states that the expectation for this value is $CI(S(10)) = 290.2$, that is, approximately $\%2.902$, and the expected approximate diabetes ratio is in the range of $\%99$ probability ($289.8, 290.2$) at time $n = 10$.

It is seen that the variability decreases in the SDC model process ($n \in [0,10]$). Extreme values are seen in the table (Table 1.6 and Figure 1.2).

It appears that the expected diabetes reached its highest level at the time of $n = 0$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $E(D(0)) = 9.65$ was obtained for the expected value at the end of the process ($n = 0$).

Similarly, variance change ($n \in [0,10]$) appears to increase for the SDC model. Extreme values are seen in the table (Table 1.7 and Figure 1.2).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $E(D(10)) = 0.01166$ was obtained for variance ($n = 10$).

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 1.2). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 1.8).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $Std(D(10)) = 0.0108$ was obtained for variance ($n = 10$) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables $D(n)$ in the random model (3) were also calculated as follows (Figure 1.2).

Coefficient of Variation (CV) is calculated by definition as $100 \times \frac{std(D(n))}{E(D(n))}$ and random $\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho$ parameters for the installation of model (3) are defined to have $\%5$ coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of $D(n)$ variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 1.9).

Despite the $\%5$ coefficient of variation in the parameters, it is observed that the variation rate of $D(n)$ is constantly increasing and reaches $\%0.01133$ at $n = 10$. Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 1.2). The confidence intervals given in the figure are calculated as $CI = (E(D(n)) - 3. std(D(n)), E(D(n)) + 3. std(D(n)))$, and three gives the range of variation within the standard deviation. For uniform distribution, this range includes about $\%99$ of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 1.10).

At the end of the process, three standard deviation intervals for $D(n)$ variables are obtained as follows: $CI(D(0)) = (9.209, 9.65)$.

Model (3) states that the expectation for this value is $CI(D(0)) = 9.65$, that is, approximately $\%0.0965$, and the expected approximate diabetes ratio is in the range of $\%99$ probability ($9.209, 9.65$) at time $n = 0$.

---

**Table 1.6. Random $D(n)$ uncomplicated expected value end values and times**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(D(n))$</td>
<td>9.54</td>
<td>10</td>
<td>9.65</td>
<td>0</td>
</tr>
</tbody>
</table>

**Table 1.7. Extreme values and times of random $D(n)$ uncomplicated variance**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Var(D(n))$</td>
<td>0</td>
<td>0</td>
<td>0.01166</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 1.8. End values and times of random $D(n)$ uncomplicated standard deviation**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Std(D(n))$</td>
<td>0</td>
<td>0</td>
<td>0.0108</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 1.9. Extreme values and times of the coefficient of variation of random $D(n)$ uncomplicated variation coefficient**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CV(D(n))$</td>
<td>0</td>
<td>0</td>
<td>1.133</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 1.10. End values and times in random $D(n)$ uncomplicated confidence interval**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CI(D(n))$</td>
<td>9.209</td>
<td>10</td>
<td>9.65</td>
<td>10</td>
</tr>
</tbody>
</table>
It is observed that the variability increases in the SDC model process ($n \in [0,10]$). Extreme values are seen in the table (Table 1.11 and Figure 1.3).

It appears that the expected diabetes reached its highest level at the time of $n=10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $E(C(10)) = 11.32$ was obtained for the expected value at the end of the process $n = 10$.

Similarly, variance change ($n \in [0,10]$) appears to increase for the SDC model. Extreme values are seen in the table (Table 1.12 and Figure 1.3).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $Std(C(10)) = 0.1049$ was obtained for variance ($n = 10$) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables $C(n)$ in the random model (3) were also calculated as follows (Figure 1.3).

Coefficient of Variation (CV) is calculated by definition as $100 \times \frac{std(C(n))}{E(C(n))}$ and random $\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho$ parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of $C(n)$ variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 1.14).

**Table 1.11. Expected value of random $C(n)$ complication rate, extreme values and times**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(C(n))$</td>
<td>11.05</td>
<td>0</td>
<td>11.32</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 1.12. Extreme values and times of variance of random $C(n)$ complication rate**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Var(C(n))$</td>
<td>0</td>
<td>0</td>
<td>0.01101</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 1.13. Extreme values and times of standard deviation of random $C(n)$ complication rate**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Std(C(n))$</td>
<td>0</td>
<td>0</td>
<td>0.1049</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 1.14. Extreme values and times of variation coefficient of random $C(n)$ complication rate**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CV(C(n))$</td>
<td>0</td>
<td>0</td>
<td>0.940661</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 1.3. $C(n)$ random behavior of complication rate.
Despite the %5 coefficient of variation in the parameters, it is observed that the variation rate of C(n) is constantly increasing and reaches %0.009406 at n = 10 Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 1). The confidence intervals given in the figure are calculated as $GA = (E(C(n)) - 3. std(C(n)), E(C(n)) + 3. std(C(n))$, and three gives the range of variation within the standard deviation. For uniform distribution, this range includes about %99 of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 1.15).

At the end of the process, three standard deviation intervals for C(n) variables are obtained as follows: $CI(C(10)) \in (11.05, 11.64)$

Model (3) states that the expectation for this value is $(C(10)) = 11.64$, that is, approximately %0.1164, and the expected approximate diabetes ratio is in the range of %99 probability ($(11.05, 11.64)$ ) at time n =10.

### Binomial Distribution

In the random SDC difference equation defined as (3) if $\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho$ is a random variable with a parameterized Binomial distribution and $K = 10$, then the probability characteristics obtained from $10^5$ simulations are given below.

It is seen that the variability decreases in the SDC model process $(n \in [0,10])$. Extreme values are seen in the table (Table 2.1 and Figure 2.1).

It appears that the expected diabetes reached its highest level at the time of $n = 0$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $E(S(0)) = 289.8$ was obtained for the expected value at the end of the process $n = 0$.

Similarly, variance change $(n \in [0,10])$ appears to increase for the SDC model. Extreme values are seen in the table (Table 2.2 and Figure 2.1).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std(D(n))</td>
<td>11.05</td>
<td>10</td>
<td>11.64</td>
<td>10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
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<th>Time</th>
<th>Maximum</th>
<th>Time</th>
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<td>E(S(n))</td>
<td>280.1</td>
<td>10</td>
<td>289.8</td>
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</table>

**Figure 2.1.** Random behavior of $S(n)$ number of susceptible individuals.
Table 2.2. Extreme values and times of variance of random S(n) number of susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var(S(n))</td>
<td>0</td>
<td>0</td>
<td>57.96</td>
<td>10</td>
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</tbody>
</table>

Table 2.3. Extreme values and times of standard deviation of random S(n) susceptible individuals

<table>
<thead>
<tr>
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<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std(S(n))</td>
<td>0</td>
<td>0</td>
<td>7.613</td>
<td>10</td>
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</table>

Table 2.4. Extreme values and times of the coefficient of variation of random S(n) susceptible individuals

<table>
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<th>Time</th>
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<tr>
<td>CV(S(n))</td>
<td>0</td>
<td>0</td>
<td>2.70403</td>
<td>10</td>
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</tbody>
</table>

Table 2.5. End values and times in confidence interval of random S(n) number of susceptible individuals

<table>
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<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI(S(n))</td>
<td>258.5</td>
<td>10</td>
<td>304.189</td>
<td>10</td>
</tr>
</tbody>
</table>

addition, at the end of the process, Var(S(10)) = 57.96 was obtained for variance, (n = 10).

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 2.1). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 2.3).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of n = 10. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, Std(S(10)) = 7.613 was obtained for variance (n = 10) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables S(n) in the random model (3) were also calculated as follows (Figure 2.1).

Coefficient of Variation (CV) is calculated by definition as 100 × std(S(n))/E(S(n)) and random α, β, γ, δ, λ, μ, p parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of S(n) variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 2.4).

Despite the %5 coefficient of variation in the parameters, it is observed that the variation rate of S(n) is constantly increasing and reaches %0.0270403 at n = 10 Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 2.1). The confidence intervals given in the figure are calculated as CI = (E(S(n)) – 3.std(S(n)), E(S(n)) + 3.std(S(n))), and three gives the range of variation within the standard deviation. For binomial distribution, this range includes about 99% of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 2.5).

At the end of the process, three standard deviation intervals for S(n) variables are obtained as follows: CI(S(10)) ∈ (258.5, 304.1)

Model (3) states that the expectation for this value is E(S(10)) = 304.189, that is, approximately %3.04189, and the expected approximate diabetes ratio is in the range of %99 probability (258.5, 304.1) at time n = 10.

It is seen that the variability decreases in the SDC model process (n ∈ [0,10]). Extreme values are seen in the table (Table 2.6 and Figure 2.2).

It appears that the expected diabetes reached its highest level at the time of n = 0. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, E(D(0)) = 9.65 was obtained for the expected value at the end of the process (n = 0).

Similarly, variance change (n ∈ [0,10]) appears to increase for the SDC model. Extreme values are seen in the table (Table 2.7 and Figure 2.2).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of n = 10. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, at the end of the process, Var(D(10)) = 0.0638595 was obtained for variance, (n = 10).

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 2.2). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 2.8).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of n = 10. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments.
addition, $Std(D(10)) = 0.0252704$ was obtained for variance ($n = 10$) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables $D(n)$ in the random model (3) were also calculated as follows (Figure 2.2).

Coefficient of Variation (CV) is calculated by definition as $100 \times \frac{std(D(n))}{E(D(n))}$ and random $\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho$ parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of $D(n)$ variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 2.9).

Despite the %5 coefficient of variation in the parameters, it is observed that the variation rate of $D(n)$ is constantly increasing and reaches %0.027691 at $n = 10$. Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 2.2). The confidence intervals given in the figure are calculated as $CI = (E(D(n)) - 3.std(D(n)), E(D(n)) + 3.std(D(n)))$, and three gives the range of variation within the standard deviation. For binomial distribution, this range includes about %99 of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 2.10).
At the end of the process, three standard deviation intervals for $D(n)$ variables are obtained as follows: $CI(D(10)) \in (8.51,10.03)$

Model (3) states that the expectation for this value is $CI(D(10)) = 10.03$, that is, approximately $\%0.1003$, and the expected approximate diabetes ratio is in the range of $\%99$ probability $(8.51, 10.03)$ at time $n = 10$.

It is seen that the variability decreases in the SDC model process $(n \in [0,10])$. Extreme values are seen in the table (Table 2.11 and Figure 2.3).

It appears that the expected diabetes reached its highest level at the time of $n = 0$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $E(C(0)) = 11.05$ was obtained for the expected value at the end of the process $n = 0$.

Similarly, variance change $(n \in [0,10])$ appears to increase for the SDC model. Extreme values are seen in the table (Table 2.12 and Figure 2.3).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, at the end of the process, $Var(C(10)) = 0.088476$ was obtained for variance, $(n = 10)$.

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 2.3). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 2.13).

Table 2.10. End values and times in random $D(n)$ uncomplicated confidence interval

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI(D(n))</td>
<td>8.51</td>
<td>10</td>
<td>10.03</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 2.11. Expected value of random $C(n)$ complication rate, extreme values and times

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>E(C(n))</td>
<td>10.95</td>
<td>10</td>
<td>11.05</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 2.12. Extreme values and times of variance of random complication rate

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>E(C(n))</td>
<td>10.95</td>
<td>10</td>
<td>11.05</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 2.13. Extreme values and times of standard deviation of random $C(n)$ complication rate

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std(C(n))</td>
<td>0</td>
<td>0</td>
<td>0.297449</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 2.3. $C(n)$ random behavior of complication rate.
It is observed that the diabetes has reached its highest level of deviation from the average at the time of \( n = 10 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( \text{Std}(C(10)) = 0.297449 \) was obtained for variance \((n = 10)\) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables \( C(n) \) in the random model (3) were also calculated as follows (Figure 2.3).

Coefficient of Variation (CV) is calculated by definition as \( 100 \times \frac{\text{std}(C(n))}{E(C(n))} \) and random \( \alpha, \beta, \gamma, \delta, \lambda, \mu, \rho \) parameters for the installation of model (3) are defined to have 5% coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of \( C(n) \) variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 2.14).

Despite the 5% coefficient of variation in the parameters, it is observed that the variation rate of \( C(n) \) is constantly increasing and reaches 0.02716 at \( n = 10 \). Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 2.3). The confidence intervals given in the figure are calculated as \( CI = (E(C(n)) - 3 \cdot \text{std}(C(n)), E(C(n)) + 3 \cdot \text{std}(C(n))) \), and three gives the range of variation within the standard deviation. For binomial distribution, this range includes about 99% of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 2.15).

At the end of the process, three standard deviation intervals for \( C(n) \) variables are obtained as follows: \( CI(C(10)) \in (10.06,11.84) \).

Model (3) states that the expectation for this value is \( CI(C(10)) = 11.8407 \), that is, approximately 0.118407, and the expected approximate diabetes ratio is in the range of 99% probability \((10.06,11.84)\) at time \( n = 10 \).

### Table 2.14. Extreme values and times of variation coefficient of random \( C(n) \) complication rate

<table>
<thead>
<tr>
<th>Variable ( CV(C(n)) )</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2.71684</td>
<td>10</td>
</tr>
</tbody>
</table>

### Table 2.15. End values and times of random \( C(n) \) complication rate in confidence interval

<table>
<thead>
<tr>
<th>Variable ( CI(C(n)) )</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.06</td>
<td>10</td>
<td>11.8407</td>
<td>10</td>
<td></td>
</tr>
</tbody>
</table>

**Figure 3.1.** Random behavior of number of \( S(n) \) susceptible individuals.
It is seen that the variability decreases in the SDC model process ($n \in [0,10]$). Extreme values are seen in the table (Table 3.1 and Figure 3.1).

It appears that the expected diabetes reached its highest level at the time of $n = 0$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $E(S(0)) = 289.8$ was obtained for the expected value at the end of the process $n = 0$.

Similarly, variance change ($n \in [0,10]$) appears to increase for the SDC model. Extreme values are seen in the table (Table 3.2 and Figure 3.1).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, at the end of the process, $Var(S(10)) = 2900.9$ was obtained for variance, ($n = 10$).

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 3.1). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 3.3).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $Std(S(10)) = 53.86$ was obtained for variance ($n = 10$) at the end of the process.

### Table 3.1. Expected value of random number of $S(n)$ susceptible individuals, end values and times

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(S(n))$</td>
<td>227.3</td>
<td>10</td>
<td>289.8</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table 3.2. Extreme values and times of variance of random $S(n)$ number of susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Var(S(n))$</td>
<td>0</td>
<td>0</td>
<td>2900.9</td>
<td>10</td>
</tr>
</tbody>
</table>

### Table 3.3. Extreme values and times of standard deviation of random $S(n)$ susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(S(n))$</td>
<td>227.3</td>
<td>10</td>
<td>289.8</td>
<td>0</td>
</tr>
</tbody>
</table>

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables $S(n)$ in the random model (3) were also calculated as follows (Figure 3.1).

Coefficient of Variation (CV) is calculated by definition as $100 \times \frac{std(S(n))/E(S(n))}{R}$ and random $\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho$ parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of $S(n)$ variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 3.4).

Despite the %5 coefficient of variation in the parameters, it is observed that the variation rate of $S(n)$ is constantly increasing and reaches %0.23694 at $n = 10$. Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 3.1). The confidence intervals given in the figure are calculated as $Cl = (E(S(n)) - 3.std(S(n)), E(S(n)) + 3.std(S(n)))$, and these give the range of variation within the standard deviation. For geometric distribution, this range includes about 99% of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 3.5).

At the end of the process, three standard deviation intervals for $S(n)$ variables are obtained as follows: $Cl(S(10))$ ∈ (65.74,388.9)

Model (3) states that the expectation for this value is $Cl(S(10)) = 388.9$, that is, approximately %3.889, and the expected approximate diabetes ratio is in the range of %99 probability (65.74,388.9) at time $n = 10$.

It is seen that the variability decreases in the SDC model process ($n \in [0,10]$). Extreme values are seen in the table (Table 3.6 and Figure 3.2).

It appears that the expected diabetes reached its highest level at the time of $n = 0$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at

### Table 3.4. Extreme values and times of the coefficient of variation of random $S(n)$ susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CV(S(n))$</td>
<td>0</td>
<td>0</td>
<td>23.694</td>
<td>10</td>
</tr>
</tbody>
</table>

### Table 3.5. End values and times in confidence interval of random $S(n)$ number of susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Cl(S(n))$</td>
<td>65.74</td>
<td>10</td>
<td>388.9</td>
<td>10</td>
</tr>
</tbody>
</table>
In addition, \( E(D(0)) = 9.65 \) was obtained for the expected value at the end of the process \((n = 0)\).

Similarly, variance change \((n \in [0,10])\) appears to increase for the SDC model. Extreme values are seen in the table (Table 3.7 and Figure 3.2).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of \( n = 10 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( \text{Var}(D(10)) = 3.208 \) was obtained for variance \((n = 10)\) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables \( D(n) \) in the random model (3) were also calculated as follows (Figure 3.2).

Coefficient of Variation (CV) is calculated by definition as \( 100 \times \frac{\text{std}(D(n))}{E(D(n))} \) and random \( \alpha, \beta, \gamma, \delta, \lambda, \mu, \rho \) parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of \( D(n) \) variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 3.9).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>( E(D(n)) )</td>
<td>7.45</td>
<td>10</td>
<td>9.65</td>
<td>0</td>
</tr>
<tr>
<td>( \text{Var}(D(n)) )</td>
<td>0</td>
<td>0</td>
<td>3.208</td>
<td>10</td>
</tr>
<tr>
<td>( CV(D(n)) )</td>
<td>0</td>
<td>0</td>
<td>24.0124</td>
<td>10</td>
</tr>
</tbody>
</table>

These moments in addition, \( E(D(0)) = 9.65 \) was obtained for the expected value at the end of the process \((n = 0)\). Similarly, variance change \((n \in [0,10])\) appears to increase for the SDC model. Extreme values are seen in the table (Table 3.7 and Figure 3.2).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of \( n = 10 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( \text{Var}(D(10)) = 3.208 \) was obtained for variance \((n = 10)\) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables \( D(n) \) in the random model (3) were also calculated as follows (Figure 3.2).

Coefficient of Variation (CV) is calculated by definition as \( 100 \times \frac{\text{std}(D(n))}{E(D(n))} \) and random \( \alpha, \beta, \gamma, \delta, \lambda, \mu, \rho \) parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of \( D(n) \) variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 3.9).
Despite the %5 coefficient of variation in the parameters, it is observed that the variation rate of $D(n)$ is constantly increasing and reaches %0.240124 at $n = 10$. Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 3.2). The confidence intervals given in the figure are calculated as $CI = (E(D(n)) - 3. std(D(n)), E(D(n)) + 3. std(D(n)))$, and three gives the range of variation within the standard deviation. For geometric distribution, this range includes about %99 of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 2.10).

At the end of the process, three standard deviation intervals for $D(n)$ variables are obtained as follows: $CI(D(10)) \in (2.086, 12.83)$

Model (3) states that the expectation for this value is $E(D(10)) = 12.83$, that is, approximately %0.1283, and the expected approximate diabetes ratio is in the range of %99 probability (2.086, 12.83) at time $n = 10$.

It is seen that the variability decreases in the SDC model process ($n \in [0,10]$). Extreme values are seen in the table (Table 3.11 and Figure 3.3).

It appears that the expected diabetes reached its highest level at the time of $n = 0$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, $E(C(0)) = 11.05$ was obtained for the expected value at the end of the process $n = 0$.

Similarly, variance change ($n \in [0,10]$) appears to increase for the SDC model. Extreme values are seen in the table (Table 3.12 and Figure 3.3).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, at the end of the process, $Var(C(10)) = 4.516$ was obtained for variance, ($n = 10$).

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 3.3). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 3.13).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$.

Table 3.10. End values and times in random $D(n)$ uncomplicated confidence interval

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CI(D(n))$</td>
<td>2.086</td>
<td>10</td>
<td>12.83</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 3.11. Expected value of random $C(n)$ complication rate, extreme values and times

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CI(D(n))$</td>
<td>2.086</td>
<td>10</td>
<td>12.83</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 3.3. $C(n)$ random behavior of complication rate.
Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( \text{Std}(C(n)) = 2.1251 \) was obtained for variance \((n = 10)\) at the end of the process. Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables \( C(n) \) in the random model (3) were also calculated as follows (Figure 3.3).

Coefficient of Variation (CV) is calculated by definition as 100 \( \times \) std\((C(n)))/E(C(n)) \) and random \( \alpha, \beta, \gamma, \delta, \lambda, \mu, \rho \) parameters for the installation of model (3) are defined to have \%5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of \( C(n) \) variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 3.14).

Despite the \%5 coefficient of variation in the parameters, it is observed that the variation rate of \( C(n) \) is constantly increasing and reaches \%0.238437 \( n = 10 \) Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 3.3). The confidence intervals given in the figure are calculated as \( CI = (E(C(n)) - 3 \cdot \text{std}(C(n)), E(C(n)) + 3 \cdot \text{std}(C(n))) \), and three gives the range of variation within the standard deviation. For geometric distribution, this range includes about \%99 of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 3.15).

At the end of the process, three standard deviation intervals for \( C(n) \) variables are obtained as follows: \( CI(C(10)) \in (2.537, 15.2886) \).
Model (3) states that the expectation for this value is \( E(S(10)) = 15.2886 \), that is, approximately \( 0.152886 \), and the expected approximate diabetes ratio is in the range of \( \pm 0.2598 \) at time \( n = 10 \).

### Poisson distribution

In the random SDC difference equation defined as (3) if \( \alpha, \beta, \gamma, \delta, \lambda, \mu, \rho \) is a random variable with a parameterized poisson distribution and \( K = 10 \), then the probability characteristics obtained from \( 10^6 \) simulations are given below.

It is seen that the variability decreases in the SDC model process \((n \in [0,10])\). Extreme values are seen in the table (Table 4.1 and Figure 4.1).

It appears that the expected diabetes reached its highest level at the time of \( n = 0 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( E(S(0)) = 289.8 \) was obtained for the expected value at the end of the process \( n = 0 \).

Similarly, variance change \((n \in [0,10])\) appears to increase for the SDC model. Extreme values are seen in the table (Table 4.2 and Figure 4.1).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of \( n=10 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, at the end of the process, \( Var(S(10)) = 54.2702 \) was obtained for variance, \((n = 10)\).

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Table 4.3). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 4.3).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of \( n = 10 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( Std(S(10)) = 7.367 \) was obtained for variance \((n = 10)\) at the end of the process.

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables \( S(n) \) in the random model (3) were also calculated as follows (Figure 4.1).

Coefficient of Variation (CV) is calculated by definition as \( 100 \times \frac{std(S(n))}{E(S(n))} \) and random \( \alpha, \beta, \gamma, \delta, \lambda, \mu, \rho \) parameters for the installation of model (3) are defined to have \( \%5 \) coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of \( S(n) \) variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 4.4).

Despite the \( \%5 \) coefficient of variation in the parameters, it is observed that the variation rate of \( S(n) \) is constantly increasing and reaches \( 0.2598 \) at \( n = 10 \). Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 4.1). The confidence intervals given in the figure are calculated as \( CI = (E(S(n)) - 3 \times std(S(n)), E(S(n)) + 3 \times std(S(n))) \), and three gives the range of variation within the standard deviation. For poisson distribution, this range includes about 99% of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 4.5).

At the end of the process, three standard deviation intervals for \( S(n) \) variables are obtained as follows: \( CI(S(10)) \in (261.4, 305.6) \)

Model (3) states that the expectation for this value is \( CI(S(10)) = 305.6 \), that is, approximately \( \%3.056 \), and the

### Table 4.1. Expected value of random number of \( S(n) \) susceptible individuals, end values and times

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>( E(S(n)) )</td>
<td>283.6</td>
<td>10</td>
<td>289.8</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table 4.2. Extreme values and times of variance of random \( S(n) \) number of susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Var(S(n)) )</td>
<td>0</td>
<td>0</td>
<td>54.2702</td>
<td>10</td>
</tr>
</tbody>
</table>

### Table 4.3. Extreme values and times of standard deviation of random \( S(n) \) susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Std(S(n)) )</td>
<td>0</td>
<td>0</td>
<td>7.367</td>
<td>10</td>
</tr>
</tbody>
</table>

### Table 4.4. Extreme values and times of the coefficient of variation of random \( S(n) \) susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>( CV(S(n)) )</td>
<td>0</td>
<td>0</td>
<td>2.598</td>
<td>10</td>
</tr>
</tbody>
</table>

### Table 4.5. End values and times in confidence interval of random \( S(n) \) number of susceptible individuals

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Cl(S(n)) )</td>
<td>261.4</td>
<td>10</td>
<td>305.6</td>
<td>10</td>
</tr>
</tbody>
</table>
The expected approximate diabetes ratio is in the range of %99 probability (261.4,305.7) at time \( n = 10 \).

It is seen that the variability decreases in the SDC model process \((n \in [0,10])\). Extreme values are seen in the table (Table 4.6 and Figure 4.2).

It appears that the expected diabetes reached its highest level at the time of \( n = 0 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( E(D(0)) = 9.65 \) was obtained for the expected value at the end of the process, \( (n = 10) \).

Similarly, variance change \((n \in [0,10])\) appears to increase for the SDC model. Extreme values are seen in the table (Table 4.7 and Figure 4.2).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of \( n = 10 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( \text{Var}(D(10)) = 0.0626 \) was obtained for variance, \( (n = 10) \).

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 4.2). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 4.8).

It is observed that the diabetes has reached its highest level of deviation from the average at the time of \( n = 10 \). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \( \text{Std}(D(10)) = 0.2502 \) was obtained for variance, \( (n = 10) \) at the end of the process.
Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables \(D(n)\) in the random model (3) were also calculated as follows (Figure 4.2).

Coefficient of Variation (CV) is calculated by definition as \(100 \times \frac{\text{std}(D(n))}{E(D(n))}\) and random \(\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho\) parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of \(D(n)\) variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 4.9).

Despite the %5 coefficient of variation in the parameters, it is observed that the variation rate of \(D(n)\) is constantly increasing and reaches %0.02683 at \(n = 10\). Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 4.2). The confidence intervals given in the figure are calculated as \(CI = (E(D(n)) - 3 \times \text{std}(D(n)), E(D(n)) + 3 \times \text{std}(D(n)))\), and three gives the range of variation within the standard deviation. For Poisson distribution, this range includes about %99 of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 4.10).

At the end of the process, three standard deviation intervals for \(D(n)\) variables are obtained as follows: \(CI(D(10)) = (8.574, 10.0783)\)

Model (3) states that the expectation for this value is \(E(D(10)) = 10.078\), that is, approximately %0.10078, and the expected approximate diabetes ratio is in the range of %99 probability \((8.574, 10.0783)\) at time \(n = 10\).

It is seen that the variability in the SDC model process \((n \in [0,10])\) is stable and then increases. Extreme values are seen in the table (Table 4.9 and Figure 4.3).

It appears that the expected diabetes reached its highest level at the time of \(n = 0\). Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, \(E(C(0)) = 11.05\) was obtained for the expected value at the end of the process \(n = 0\).

Similarly, variance change \((n \in [0,10])\) appears to increase for the SDC model. Extreme values are seen in the table (Table 4.11 and Figure 4.3).

**Table 4.10.** End values and times in random \(D(n)\) uncomplicated confidence interval

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>(CI(D(n)))</td>
<td>8.574</td>
<td>10</td>
<td>10.0783</td>
<td>10</td>
</tr>
</tbody>
</table>

**Table 4.11.** Expected value of random \(C(n)\) complication rate, extreme values and times

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>(E(C(n)))</td>
<td>11.04</td>
<td>10</td>
<td>11.05</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 4.3. \(C(n)\) random behavior of complication rate.
It is observed that the diabetes has reached its highest level of deviation from the average at the time of $n = 10$. Therefore, the results obtained from the deterministic model are more likely to be observed differently in an experiment that takes place randomly at these moments. In addition, at the end of the process, $\text{Var}(C(10)) = 0.08313$ was obtained for variance, $(n = 10)$.

Similar to the variance, the changes in the standard deviation for the SDC model are shown below (Figure 4.3). By definition, the standard deviation is the square root of the variance, so these two numerical characteristics are expected to behave similarly. Extreme values for standard deviations are shown below (Table 4.13).

![Table 4.12. Extreme values and times of variance of random $C(n)$ complication rate](data:image/png;base64,iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAAfZM2jAAAABGd7eTCDAAAIABJRU5ErkJggg==)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Var}(C(n))$</td>
<td>0</td>
<td>0</td>
<td>0.08313</td>
<td>10</td>
</tr>
</tbody>
</table>

Using the results obtained for the standard deviations and expected values, the variation coefficients for the variables $C(n)$ in the random model (3) were also calculated as follows (Figure 4.3). Coefficient of Variation (CV) is calculated by definition as $100 \times \frac{\text{std}(C(n))}{E(C(n))}$ and random $\alpha, \beta, \gamma, \delta, \lambda, \mu, \rho$ parameters for the installation of model (3) are defined to have %5 coefficient of variation. However, as a result of examining the model, it is seen that the coefficient of variation of $C(n)$ variables increased to higher rates. The extreme values of the variation coefficients are given in the table below (Table 4.14).

![Table 4.13. Extreme values and times of standard deviation of random $C(n)$ complication rate](data:image/png;base64,iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAAfZM2jAAAABGd7eTCDAAAIABJRU5ErkJggg==)

<table>
<thead>
<tr>
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<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Std}(C(n))$</td>
<td>0</td>
<td>0</td>
<td>0.2883</td>
<td>10</td>
</tr>
</tbody>
</table>

Despite the %5 coefficient of variation in the parameters, it is observed that the variation rate of $C(n)$ is constantly increasing and reaches %0.02611 at $n = 10$. Therefore, it can be interpreted that the variability in random results increases as it progresses.

The results obtained for the expected values of the model (3) are given below (Figure 4.3). The confidence intervals given in the figure are calculated as $CI = (E(C(n)) - 3 \times \text{std}(C(n)), E(C(n)) + 3 \times \text{std}(C(n)))$, and three gives the range of variation within the standard deviation. For poisson distribution, this range includes about %99 of the values of the random variable. Therefore, the extreme values obtained for the expected values in these ranges are given below (Table 4.15).

![Table 4.14. Extreme values and times of variation coefficient of random $C(n)$ complication rate](data:image/png;base64,iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAAfZM2jAAAABGd7eTCDAAAIABJRU5ErkJggg==)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Std}(C(n))$</td>
<td>0</td>
<td>0</td>
<td>0.2883</td>
<td>10</td>
</tr>
</tbody>
</table>

![Table 4.15. End values and times of random $C(n)$ complication rate in confidence interval](data:image/png;base64,iVBORw0KGgoAAAANSUhEUgAAAoAAAAHgCAYAAAAfZM2jAAAABGd7eTCDAAAIABJRU5ErkJggg==)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Time</th>
<th>Maximum</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CI(C(n))$</td>
<td>10.18</td>
<td>10</td>
<td>11.91</td>
<td>10</td>
</tr>
</tbody>
</table>

CONCLUSION

In this study, the mathematical model is analyzed by converting this system consisting of three differential equations modeling the responsive diabetes complication (SDC) model into discrete time with the advanced difference method. A stability analysis has been performed for this system of equations. The fundamental increase number and global stability for stable states of equilibrium point were studied. The discrete time probability distributions for the random behaviors of the SDC model were studied under random effects with Uniform, Binomial, Geometric and Poisson distributions. The expected value, variance, standard deviation, coefficient of variation and confidence intervals of the obtained solutions were found. The coefficients of variation for the five distributions are compared and for each distribution the parameter is defined to have a coefficient of variation of 5%. Although a 5% deviation rate was used for random parameters, the simulation results showed variability in the sugar ratio. Analysis of the random SDC difference model is provided with the help of graphs and tables.

DATA AVAILABILITY STATEMENT

No new data were created in this study. The published publication includes all graphics collected or developed during the study.
CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

REFERENCES


