

# Some Application for a Fuzzy Differential Equation and Solve by Runge-Kutta Method

Qasim Abd Ali Tayyeh

Department of Mechanical Techniques, Al-Nasiriya Technical Institute, Southern Technical University, Thi-Qar, Al-Nasiriya 64001, Iraq Author correspondence: <u>gassim.tayih@stu.edu.iq</u>

Abstract. In this article, the starting condition was defined using a fuzzy initial value problem (IVP). Additionally, we discussed various methods for solving fuzzy differential equations, including the modified two-step Simpson method and Runge-Kutta of orders (two, three, four, five, and six). For each method, we provided a numerical example and the known convergence rates of the solutions. Then we discussed the comparison of the solutions of all methods, using computer software to offer rough solutions for the Runge Kutta method. And take some application solve by Runge-Kutta in physics and medical

**Keywords:** Fuzzy differential equation, modified two-step Simpson method, Runge-Kutta method, initial value problem.

## 1. INTRODUCTION

Zadeh was the first to introduce the idea of a fuzzy set in [1]. Since then, the theory has developed to the point where it is now acknowledged as a unique discipline of applied mathematics. Because it offers a natural method for expressing dynamical systems under uncertainty, the theory of differential equations with fuzzy coefficients is significant in modeling scientific and engineering challenges. Fuzzy differential equations (FDE) and fuzzy initial value problems (IVP) are studied in [2], [3], and [4]. Theoretical and numerical solutions to FDEs were being discussed by a number of academics [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]. We presented the Runge Kutta technique of order (2, 3, 4, 5 and 6) with a modified 2-step Simpson method to solve some examples of FDE, and ranking from best to least of a solution (sol) of all methods. Throughout this study, we proposed the Runge Kutta technique to solve FDE and employing computer software to supply approximate sols of specific instances.

## 2. METHODOLOGY STUDY

## Fuzzy initial value problem

Take the following first order Fuzzy IVP of DE:

$$\begin{cases} Y'(\mathfrak{t}) = f(\mathfrak{t}, Y(\mathfrak{t})), \mathfrak{t} \in [\mathfrak{t}_0, T] \\ Y(\mathfrak{t}_0) = Y_0 \end{cases}$$

When Y be fuzzy function of  $\mathfrak{t}$ ,  $f(\mathfrak{t}, Y)$  with variable  $\mathfrak{t}$  and a fuzzy var. Y & Y' are fuzzy derivative of Y and  $Y(\mathfrak{t}_0) = Y_0$  be the triangular fuzzy number [17].

A fuzzy function y is written as follows:  $Y = [\underline{Y}, \overline{Y}]$ . So a r-level set on  $Y(\mathfrak{t})$  when  $\mathfrak{t} \in [\mathfrak{t}_0, T]$ was  $[Y(\mathfrak{t})]_{\mathfrak{r}} = [\underline{Y}(\mathfrak{t}; \mathfrak{r}), \overline{Y}(\mathfrak{t}; \mathfrak{r})], [Y(\mathfrak{t}_0)]_{\mathfrak{r}} = [\underline{Y}(\mathfrak{t}_0; \mathfrak{r}), \overline{Y}(\mathfrak{t}_0; \mathfrak{r})], \mathfrak{r} \in (0,1]$ , it is mean  $f(\mathfrak{t}, Y) = [\underline{f}(\mathfrak{t}, Y), \overline{f}(\mathfrak{t}, Y)]$  and  $\underline{f}(\mathfrak{t}, Y) = F[\mathfrak{t}, \underline{Y}, \overline{Y}], \overline{f}(\mathfrak{t}, Y) = G[\mathfrak{t}, \underline{Y}, \overline{Y}]$ , Since  $Y' = f(\mathfrak{t}, Y)$  we get

$$\frac{\mathbf{f}(\mathbf{t}, \mathbf{Y}(\mathbf{t}); \mathbf{r}) = \mathbf{F}[\mathbf{t}, \underline{\mathbf{Y}}(\mathbf{t}; \mathbf{r}), \mathbf{Y}(\mathbf{t}; \mathbf{r})]}{\mathbf{f}(\mathbf{t}, \mathbf{Y}(\mathbf{t}); \mathbf{r}) = \mathbf{G}[\mathbf{t}, \underline{\mathbf{Y}}(\mathbf{t}; \mathbf{r}), \bar{\mathbf{Y}}(\mathbf{t}; \mathbf{r})]$$

And then  $f(t, Y(t))(s) = \sup\{Y(t)(\tau) \setminus s = f(t, \tau)\}, s \in \mathbb{R}$ 

So the fuzzy number f(t, Y(t)) follows that

$$[f(\mathfrak{t}, \Upsilon(\mathfrak{t}))]_{\mathfrak{F}} = [\underline{f}(\mathfrak{t}, \Upsilon(\mathfrak{t}); \mathfrak{r}), \overline{f}(\mathfrak{t}, \Upsilon(\mathfrak{t}); \mathfrak{r})], \mathfrak{r} \in (0, 1]$$
  
where  $\underline{f}(\mathfrak{t}, \Upsilon(\mathfrak{t}); \mathfrak{r}) = \min\{f(\mathfrak{t}, u) \mid u[\Upsilon(\mathfrak{t})]_{\mathfrak{r}}\}$   
 $\overline{f}(\mathfrak{t}, \Upsilon(\mathfrak{t}); \mathfrak{r}) = \max\{f(\mathfrak{t}, u) \mid u[\Upsilon(\mathfrak{t})]_{\mathfrak{r}}\}$ 

The function f:  $R \to R_F$  is known as a F. continuous fun. If for each constant  $t_0 \in R$  with  $\epsilon > 0, \delta > 0$  so  $|t - t_0| < \delta$  implies  $D[f(t), f(t_0)] < \epsilon$  exists [18].

In D, the fuzzy function toke is continuous, as well as the continuity of such  $f(t, Y(t); \tilde{r})$  assures the definition's existence of  $f(t, Y(t); \tilde{r})$  for  $t \in [t_0, T]$  with  $\tilde{r} \in [0,1]$ . So, the functions G and F can also be definitive.

### A modified two-step Simpson method

Assuming " $Y = [\underline{Y}, \overline{Y}]$ " is an exact sol with " $Y = [\underline{Y}, \overline{Y}]$ " is the 2-step modified Simpson method's approximate sol initial value Equation [19]. Assume,

$$[Y(\mathfrak{t})]_{\mathfrak{F}} = [\underline{Y}(\mathfrak{t};\mathfrak{F}), \overline{Y}(\mathfrak{t};\mathfrak{F})], [Y(\mathfrak{t})]_{\mathfrak{F}} = [\underline{Y}(\mathfrak{t};\mathfrak{F}), \overline{Y}(\mathfrak{t};\mathfrak{F})]''$$

It's also worth noting that a value  $\mathbf{r}$  be constant during each integration phase. At  $\mathbf{t}_n$ , the precise and approximation sols are indicated by

$$[Y_n]_{\mathfrak{F}} = \left[\underline{Y}_n(\mathfrak{F}), \overline{Y}_n(\mathfrak{F})\right], \ [Y_n]_{\mathfrak{F}} = \left[\underline{Y}_n(\mathfrak{F}), \overline{Y}_n(\mathfrak{F})\right] (0 \le n \le N)"$$

The grid locations are determined, accordingly.

$$h = \frac{T - t_0}{N}, \ t_i = t_0 + ih \ ,"0 \le i \le N"$$

We get the following results using the modified Simpson method:

$$\underline{Y}_{n+1}(\mathbf{r}) = \underline{Y}_{n-1}(\mathbf{r}) + \frac{h}{3}F[\mathbf{t}_{n-1}, \underline{Y}_{n-1}(\mathbf{r}), \overline{Y}_{n-1}(\mathbf{r})] + \frac{4h}{3}F[\mathbf{t}_n, \underline{Y}_n(\mathbf{r}), \overline{Y}_n(\mathbf{r})] + \frac{h}{3}F[\mathbf{t}_{n+1}, \underline{Y}_n(\mathbf{r}) + hF[\mathbf{t}_n, \underline{Y}_n(\mathbf{r}), \overline{Y}_n(\mathbf{r})], \overline{Y}_n(\mathbf{r}) + hG[\mathbf{t}_n, \underline{Y}_n(\mathbf{r}), \overline{Y}_n(\mathbf{r})]] + h^3\underline{A}(\mathbf{r})$$

And

$$\begin{split} \bar{Y}_{n+1}(\mathbf{r}) &= \bar{Y}_{n-1}(\mathbf{r}) + \frac{h}{3}G[\mathfrak{t}_{n-1},\underline{Y}_{n-1}(\mathbf{r}),\bar{Y}_{n-1}(\mathbf{r})] + \frac{4h}{3}G[\mathfrak{t}_n,\underline{Y}_n(\mathbf{r}),\bar{Y}_n(\mathbf{r})] \\ &+ \frac{h}{3}G[\mathfrak{t}_{n+1},\underline{Y}_n(\mathbf{r}) + hF[\mathfrak{t}_n,\underline{Y}_n(\mathbf{r}),\bar{Y}_n(\mathbf{r})],\bar{Y}_n(\mathbf{r}) + hG[\mathfrak{t}_n,\underline{Y}_n(\mathbf{r}),\bar{Y}_n(\mathbf{r})]] \\ &+ h^3\bar{A}(\mathbf{r}) \end{split}$$

When  $A = [\underline{A}, \overline{A}], [A]_{\mathfrak{r}} = [\underline{A}(\mathfrak{r}), \overline{A}(\mathfrak{r})]$  and

$$[A]_{\mathfrak{r}} = \left[\frac{1}{6}f'(\xi_{2}, Y(\xi_{2})) \cdot f_{Y}(\mathfrak{t}_{i+1}, \xi_{3}) - \frac{h^{2}}{90}f^{(4)}(\xi_{1}, Y(\xi_{1}))\right]_{\mathfrak{r}}.$$

$$\Rightarrow \frac{\underline{Y}_{n+1}(\mathfrak{r}) = \underline{Y}_{n-1}(\mathfrak{r}) + \frac{h}{3}F[\mathfrak{t}_{n-1}, \underline{Y}_{n-1}(\mathfrak{r}), \overline{Y}_{n-1}(\mathfrak{r})] + \frac{4h}{3}F[\mathfrak{t}_{n}, \underline{Y}_{n}(\mathfrak{r}), \overline{Y}_{n}(\mathfrak{r})]$$

$$+ \frac{h}{3}F[\mathfrak{t}_{n+1}, \underline{Y}_{n}(\mathfrak{r}) + hF[\mathfrak{t}_{n}, \underline{Y}_{n}(\mathfrak{r}), \overline{Y}_{n}(\mathfrak{r})], \overline{Y}_{n}(\mathfrak{r}) + hG[\mathfrak{t}_{n}, \underline{Y}_{n}(\mathfrak{r}), \overline{Y}_{n}(\mathfrak{r})]]$$

And

$$\bar{Y}_{n+1}(\mathbf{r}) = \bar{Y}_{n-1}(\mathbf{r}) + \frac{h}{3}G[\mathbf{t}_{n-1}, \underline{Y}_{n-1}(\mathbf{r}), \bar{Y}_{n-1}(\mathbf{r})] + \frac{4h}{3}G[\mathbf{t}_n, \underline{Y}_n(\mathbf{r}), \bar{Y}_n(\mathbf{r})] + \frac{h}{3}G[\mathbf{t}_{n+1}, \underline{Y}_n(\mathbf{r}) + hF[\mathbf{t}_n, \underline{Y}_n(\mathbf{r}), \bar{Y}_n(\mathbf{r})], \bar{Y}_n(\mathbf{r}) + hG[\mathbf{t}_n, \underline{Y}_n(\mathbf{r}), \bar{Y}_n(\mathbf{r})]]$$

#### Runge-Kutta of order two

Let an exact sol  $[Y(\mathfrak{t})]_{\mathfrak{r}} = [\underline{Y}(\mathfrak{t};\mathfrak{r}),\overline{Y}(\mathfrak{t};\mathfrak{r})]$ , be approximate by  $[Y(\mathfrak{t})]_{\mathfrak{r}} = [\underline{Y}(\mathfrak{t};\mathfrak{r}),\overline{Y}(\mathfrak{t};\mathfrak{r})]$  [20]. A places on the grid where the sols are computed are  $h = \frac{T-\mathfrak{t}_0}{N}$ ,  $\mathfrak{t}_i = \mathfrak{t}_0 + ih; 0 \le i \le N$ , then we define:

$$\underline{Y}(\mathfrak{t}_{n+1},\mathfrak{r}) - \underline{Y}(\mathfrak{t}_n,\mathfrak{r}) = h \left[ \frac{k_1^2(\mathfrak{t}_n, Y(\mathfrak{t}_n,\mathfrak{r})) + \underline{k_2^2}(\mathfrak{t}_n, Y(\mathfrak{t}_n,\mathfrak{r}))}{\underline{k_1}(\mathfrak{t}_n, Y(\mathfrak{t}_n,\mathfrak{r})) + \underline{k_2}(\mathfrak{t}_n, Y(\mathfrak{t}_n,\mathfrak{r}))} \right]$$

When

$$\begin{aligned} k_{1} &= hF \big[ \mathfrak{t}_{n}, \underline{Y}(\mathfrak{t}_{n}, \mathfrak{r}), \overline{Y}(\mathfrak{t}_{n}, \mathfrak{r}) \big] \\ k_{2} &= hF \Big[ \mathfrak{t}_{n} + h, \underline{Y}(\mathfrak{t}_{n}, \mathfrak{r}) + \underline{k_{1}} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}) \big), \overline{Y}(\mathfrak{t}_{n}, \mathfrak{r}) + \overline{k_{1}} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}) \big) \Big] \\ \text{And } \overline{Y}(\mathfrak{t}_{n+1}, \mathfrak{r}) - \overline{Y}(\mathfrak{t}_{n}, \mathfrak{r}) &= h \left[ \frac{\overline{k_{1}^{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \overline{k_{2}^{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))}{\overline{k_{1}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \overline{k_{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))} \right] \end{aligned}$$

When

en  $k_{1} = hG[t_{n}, \underline{Y}(t_{n}, \mathbf{r}), \overline{Y}(t_{n}, \mathbf{r})]$   $k_{2} = hG[t_{n} + h, \underline{Y}(t_{n}, \mathbf{r}) + \underline{k_{1}}(t_{n}, Y(t_{n}, \mathbf{r})), \overline{Y}(t_{n}, \mathbf{r}) + \overline{k_{1}}(t_{n}, Y(t_{n}, \mathbf{r}))]$ 

So can be define  $G(\mathfrak{t}_n, Y(\mathfrak{t}_n, \mathfrak{r})) = h\left[\frac{\overline{k_1^2}(\mathfrak{t}_n, Y(\mathfrak{t}_n, \mathfrak{r})) + \overline{k_2^2}(\mathfrak{t}_n, Y(\mathfrak{t}_n, \mathfrak{r}))}{\overline{k_1}(\mathfrak{t}_n, Y(\mathfrak{t}_n, \mathfrak{r})) + \overline{k_2}(\mathfrak{t}_n, Y(\mathfrak{t}_n, \mathfrak{r}))}\right]$ 

So we get:

$$\underline{\underline{Y}}(\mathfrak{t}_{n+1},\mathfrak{r}) = \underline{\underline{Y}}(\mathfrak{t}_n,\mathfrak{r}) + \overline{F}[\mathfrak{t}_n,\overline{Y}(\mathfrak{t}_n,\mathfrak{r})]$$

$$\overline{\overline{Y}}(\mathfrak{t}_{n+1},\mathfrak{r}) = \overline{\overline{Y}}(\mathfrak{t}_n,\mathfrak{r}) + \overline{G}[\mathfrak{t}_n,\overline{Y}(\mathfrak{t}_n,\mathfrak{r})]$$

$$and$$

$$\underline{\underline{Y}}(\mathfrak{t}_{n+1},\mathfrak{r}) = \underline{\underline{Y}}(\mathfrak{t}_n,\mathfrak{r}) + \overline{F}[\mathfrak{t}_n,\overline{Y}(\mathfrak{t}_n,\mathfrak{r})]$$

$$\overline{\overline{Y}}(\mathfrak{t}_{n+1},\mathfrak{r}) = \overline{\overline{Y}}(\mathfrak{t}_n,\mathfrak{r}) + \overline{G}[\mathfrak{t}_n,\overline{Y}(\mathfrak{t}_n,\mathfrak{r})]$$

clearly  $Y(t; \mathbf{F})$  and  $\overline{Y}(t; \mathbf{F})$  converge to  $\underline{Y}(t; \mathbf{F})$  and  $\overline{Y}(t; \mathbf{F})$  whenever  $h \to 0$ 

ъ

### **Runge-Kutta of order three**

Let that we have a fuzzy IVP  $Y'(t) = f(t, Y(t))Y(t_0) = Y_0$  [21]. All Runge-Kutta techniques are based on expressing the difference between the value of y at  $t_{n+1}$  and  $t_n$  as  $Y_{n+1} - Y_n = \sum_{i=0}^m w_i k_i$ 

When  $w_i$  's are constant for all i and  $k_i=hf\bigl(\iota_n+a_ih,Y_n+\sum_{j=1}^{i-1}c_{ij}k_j\bigr)$ 

Assume 
$$Y(t_{n+1}) = Y(t_n) + \frac{h}{2} \left[ \frac{k_1^2 + k_2^2}{k_1 + k_2} + \frac{k_2^2 + k_3^2}{k_2 + k_3} \right]$$
, When  
 $k_1 = hf(t_n, Y(t_n))$   
 $k_2 = hf(t_n + a_1, Y(t_n) + a_1k_1)$   
 $k_3 = hf(t_n + a_2, Y(t_n) + a_2k_2)$ 

With the parameters  $a_1, a_2$  were selected to produce  $Y_{n+1}$  closer to  $Y(t_{n+1})$ . The parameter values  $a_1 = \frac{2}{3}, a_2 = \frac{2}{3}$ Assume that an exact sol  $[Y(t)]_{\vec{r}} = [\underline{Y}(t; \vec{r}), \overline{Y}(t; \vec{r})]$ , be approximated by  $[Y(t)]_{\vec{r}} = [\underline{Y}(t; \vec{r}), \overline{Y}(t; \vec{r})]$ . A places on the grid where the sols are computed are  $h = \frac{T-t_0}{N}, t_i = t_0 + ih; 0 \le i \le N$ . Now can be define:

$$\begin{split} \underline{Y}(\mathfrak{t}_{n+1},\mathfrak{r}) &- \underline{Y}(\mathfrak{t}_{n},\mathfrak{r}) \\ &= \frac{h}{2} \bigg[ \frac{k_{1}^{2}(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})) + \underline{k}_{2}^{2}(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r}))}{\underline{k_{1}}(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})) + \underline{k}_{2}(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r}))} \\ &+ \frac{\underline{k}_{2}^{2}(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})) + \underline{k}_{3}^{2}(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r}))}{\underline{k_{2}}(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})) + \underline{k}_{3}(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r}))} \bigg] \end{split}$$

When

$$\begin{aligned} \mathbf{k}_{1} &= \mathbf{h} \mathbf{F} \Big[ \mathbf{t}_{n}, \underline{Y}(\mathbf{t}_{n}, \mathbf{r}), \bar{Y}(\mathbf{t}_{n}, \mathbf{r}) \Big] \\ \mathbf{k}_{2} &= \mathbf{h} \mathbf{F} \left[ \mathbf{t}_{n} + \frac{2}{3}, \underline{Y}(\mathbf{t}_{n}, \mathbf{r}) + \frac{2}{3} \mathbf{k}_{1} \big( \mathbf{t}_{n}, Y(\mathbf{t}_{n}, \mathbf{r}) \big), \bar{Y}(\mathbf{t}_{n}, \mathbf{r}) + \frac{2}{3} \overline{\mathbf{k}_{1}} \big( \mathbf{t}_{n}, Y(\mathbf{t}_{n}, \mathbf{r}) \big) \Big] \\ \mathbf{k}_{3} &= \mathbf{h} \mathbf{F} \left[ \mathbf{t}_{n} + \frac{2}{3}, \underline{Y}(\mathbf{t}_{n}, \mathbf{r}) + \frac{2}{3} \mathbf{k}_{2} \big( \mathbf{t}_{n}, Y(\mathbf{t}_{n}, \mathbf{r}) \big), \bar{Y}(\mathbf{t}_{n}, \mathbf{r}) + \frac{2}{3} \overline{\mathbf{k}_{2}} \big( \mathbf{t}_{n}, Y(\mathbf{t}_{n}, \mathbf{r}) \big) \Big] \end{aligned}$$

With

$$\begin{split} \bar{Y}(\mathfrak{t}_{n+1},\mathfrak{r}) &- \bar{Y}(\mathfrak{t}_{n},\mathfrak{r}) \\ &= \frac{h}{2} \bigg[ \frac{\overline{k_{1}^{2}} \big(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})\big) + \overline{k_{2}^{2}} \big(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})\big)}{\overline{k_{1}} \big(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})\big) + \overline{k_{2}} \big(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})\big)} + \frac{\overline{k_{2}^{2}} \big(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})\big) + \overline{k_{3}^{2}} \big(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})\big)}{\overline{k_{2}} \big(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})\big) + \overline{k_{3}} \big(\mathfrak{t}_{n},Y(\mathfrak{t}_{n},\mathfrak{r})\big)} \bigg] \end{split}$$

When

$$\begin{aligned} \mathbf{k}_{1} &= \mathrm{hG}\big[\mathbf{t}_{\mathrm{n}}, \underline{Y}(\mathbf{t}_{\mathrm{n}}, \mathbf{r}), \bar{Y}(\mathbf{t}_{\mathrm{n}}, \mathbf{r})\big] \\ \mathbf{k}_{2} &= \mathrm{hG}\left[\mathbf{t}_{\mathrm{n}} + \frac{2}{3}, \underline{Y}(\mathbf{t}_{\mathrm{n}}, \mathbf{r}) + \frac{2}{3}\mathrm{k}_{1}\big(\mathbf{t}_{\mathrm{n}}, Y(\mathbf{t}_{\mathrm{n}}, \mathbf{r})\big), \bar{Y}(\mathbf{t}_{\mathrm{n}}, \mathbf{r}) + \frac{2}{3}\overline{\mathrm{k}_{1}}\big(\mathbf{t}_{\mathrm{n}}, Y(\mathbf{t}_{\mathrm{n}}, \mathbf{r})\big)\big] \\ \mathbf{k}_{3} &= \mathrm{hG}\left[\mathbf{t}_{\mathrm{n}} + \frac{2}{3}, \underline{Y}(\mathbf{t}_{\mathrm{n}}, \mathbf{r}) + \frac{2}{3}\mathrm{k}_{2}\big(\mathbf{t}_{\mathrm{n}}, Y(\mathbf{t}_{\mathrm{n}}, \mathbf{r})\big), \bar{Y}(\mathbf{t}_{\mathrm{n}}, \mathbf{r}) + \frac{2}{3}\overline{\mathrm{k}_{2}}\big(\mathbf{t}_{\mathrm{n}}, Y(\mathbf{t}_{\mathrm{n}}, \mathbf{r})\big)\big] \end{aligned}$$

We also define:

$$\begin{split} F(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) &= \frac{h}{2} \begin{bmatrix} \frac{k_{1}^{2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \underline{k}_{2}^{2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))}{\underline{k_{1}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \underline{k}_{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))} + \frac{k_{2}^{2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \underline{k}_{3}^{2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))}{\underline{k_{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \underline{k_{3}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))} \end{bmatrix} \\ G(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) &= \frac{h}{2} \begin{bmatrix} \overline{k_{1}^{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \overline{k_{2}^{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))}{\underline{k_{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))} + \frac{k_{2}^{2}}{\underline{k_{3}}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))} \end{bmatrix} \\ G(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) &= \frac{h}{2} \begin{bmatrix} \overline{k_{1}^{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \overline{k_{2}^{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))}{\underline{k_{2}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))} \end{bmatrix} \\ + \frac{k_{2}^{2}}{\underline{k_{2}}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})) + \underline{k_{3}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))}{\underline{k_{3}}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r}))} \end{bmatrix} \\ So we get \frac{Y(\mathfrak{t}_{n+1}, \mathfrak{r})}{\overline{Y}(\mathfrak{t}_{n+1}, \mathfrak{r})} &= \underline{Y}(\mathfrak{t}_{n}, \mathfrak{r}) + F[\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})] \\ = \overline{Y}(\mathfrak{t}_{n}, \mathfrak{r}) + F[\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})] \\ With \frac{Y(\mathfrak{t}_{n+1}, \mathfrak{r})}{\overline{Y}}(\mathfrak{t}_{n+1}, \mathfrak{r}) &= \overline{Y}(\mathfrak{t}_{n}, \mathfrak{r}) + G[\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}, \mathfrak{r})] \\ \end{bmatrix}$$

It's obvious Y(t; r),  $\overline{Y}(t; r)$  converge to  $\underline{Y}(t; r)$ ,  $\overline{Y}(t; r)$ , respectively where  $h \rightarrow 0$ 

### **Runge-Kutta of order four**

The first-order FDE is written in the following form:  $\dot{Y}(\mathfrak{t}) = f(\mathfrak{t}, Y)$   $Y(\mathfrak{t}_0) = Y_0$  [22]. An exact sol would be:  $[Y(\mathfrak{t}_n)]_{\mathfrak{r}} = [\underline{Y}(\mathfrak{t}_n; \mathfrak{r}), \overline{Y}(\mathfrak{t}_n; \mathfrak{r})]$  an approximate sol is as follows:  $[Y(\mathfrak{t}_n)]_{\mathfrak{r}} = [Y(\mathfrak{t}_n; \mathfrak{r}), \overline{Y}(\mathfrak{t}_n; \mathfrak{r})].$ 

The Runge-Kutta technique of order four was used.

$$[Y(\mathfrak{t}_{n})]_{\mathfrak{r}} = \underline{[Y}(\mathfrak{t}_{n};\mathfrak{r}), \bar{Y}(\mathfrak{t}_{n};\mathfrak{r})$$

$$\underline{Y}(\mathfrak{t}_{n+1};\mathfrak{r}) = \underline{Y}(\mathfrak{t}_{n};\mathfrak{r}) + \sum_{j=1}^{4} w_{j}k_{j,1}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n},\mathfrak{r}))$$

$$\bar{Y}(\mathfrak{t}_{n+1};\mathfrak{r}) = \bar{Y}(\mathfrak{t}_{n};\mathfrak{r}) + \sum_{j=1}^{4} w_{j}k_{j,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n},\mathfrak{r}))$$

When  $k_{j,1}$ ,  $k_{j,2}$  describe the following:

$$k_{1,1}(\mathfrak{t}_n, Y(\mathfrak{t}_n; \mathfrak{r})) = \min \left\{ Y(\mathfrak{t}_n, u) \mid u \in \left( \underline{Y}(\mathfrak{t}_n; \mathfrak{r}), \overline{Y}(\mathfrak{t}_n; \mathfrak{r}) \right) \right\}$$

$$\begin{aligned} k_{1,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \max \left\{ Y(\mathfrak{t}_{n}, u) : u \in \left( \underline{Y}(\mathfrak{t}_{n}; \mathbf{r}), \overline{Y}(\mathfrak{t}_{n}; \mathbf{r}) \right) \right\} \\ k_{2,1}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \min \left\{ Y\left(\mathfrak{t}_{n} + \frac{h}{2}, u\right) : u \in \left( q_{1,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})), q_{1,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) \right) \right\} \\ k_{2,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \max \left\{ Y\left(\mathfrak{t}_{n} + \frac{h}{2}, u\right) : u \in \left( q_{1,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})), q_{1,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) \right) \right\} \\ k_{3,1}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \min \left\{ Y\left(\mathfrak{t}_{n} + \frac{h}{2}, u\right) : u \in \left( q_{2,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})), q_{2,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) \right) \right\} \\ k_{3,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \max \left\{ Y\left(\mathfrak{t}_{n} + \frac{h}{2}, u\right) : u \in \left( q_{2,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})), q_{2,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) \right) \right\} \\ k_{4,1}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \max \left\{ Y\left(\mathfrak{t}_{n} + \frac{h}{2}, u\right) : u \in \left( q_{3,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})), q_{3,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) \right) \right\} \\ k_{4,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \min \left\{ Y\left(\mathfrak{t}_{n} + \frac{h}{2}, u\right) : u \in \left( q_{3,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})), q_{3,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) \right) \right\} \\ k_{4,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \min \left\{ Y\left(\mathfrak{t}_{n} + \frac{h}{2}, u\right) : u \in \left( q_{3,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})), q_{3,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) \right) \right\} \\ k_{4,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) &= \max \left\{ Y\left(\mathfrak{t}_{n} + \frac{h}{2}, u\right) : u \in \left( q_{3,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r}), q_{3,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) \right) \right\} \\ q_{1,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) &= \underline{Y}(\mathfrak{t}_{n}, \mathbf{r}) + \frac{h}{2} k_{1,1}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) \\ q_{1,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) &= \underline{Y}(\mathfrak{t}_{n}, \mathbf{r}) + \frac{h}{2} k_{1,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) \\ q_{2,1}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) &= \underline{Y}(\mathfrak{t}_{n}, \mathbf{r}) + \frac{h}{2} k_{2,1}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) \\ q_{2,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) &= \overline{Y}(\mathfrak{t}_{n}, \mathbf{r}) + \frac{h}{2} k_{2,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) \\ q_{2,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) &= \overline{Y}(\mathfrak{t}_{n}, \mathbf{r}) + \frac{h}{2} k_{2,2}(\mathfrak{t}_{n}, Y(\mathfrak{t}_{n}; \mathbf{r})) \\ q_{2,2}(\mathfrak{t}_{n}; Y(\mathfrak{t}_{n}, \mathbf{r})) &= \overline{Y}(\mathfrak{t}_{n}, \mathbf{r})$$

$$q_{2,2}(\mathfrak{t}_{n}; \Upsilon(\mathfrak{t}_{n}, \mathfrak{r})) = \overline{\Upsilon}(\mathfrak{t}_{n}, \mathfrak{r}) + \frac{h}{2} k_{2,2}(\mathfrak{t}_{n}, \Upsilon(\mathfrak{t}_{n}; \mathfrak{r}))$$

$$q_{3,1}(\mathfrak{t}_{n}; \Upsilon(\mathfrak{t}_{n}, \mathfrak{r})) = \underline{\Upsilon}(\mathfrak{t}_{n}, \mathfrak{r}) + \frac{h}{2} k_{3,1}(\mathfrak{t}_{n}, \Upsilon(\mathfrak{t}_{n}; \mathfrak{r}))$$

$$q_{3,2}(\mathfrak{t}_{n}; \Upsilon(\mathfrak{t}_{n}, \mathfrak{r})) = \overline{\Upsilon}(\mathfrak{t}_{n}, \mathfrak{r}) + \frac{h}{2} k_{3,2}(\mathfrak{t}_{n}, \Upsilon(\mathfrak{t}_{n}; \mathfrak{r}))$$

Using just the initial condition, we can now calculate:

$$\begin{split} \underline{Y}(\mathfrak{t}_{n+1};\mathfrak{r}) &= \underline{Y}(\mathfrak{t}_{n};\mathfrak{r}) \\ &+ \frac{1}{6} \left( k_{1,1} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n};\mathfrak{r}) \big) + 2k_{2,1} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n};\mathfrak{r}) \big) + 2k_{3,1} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n};\mathfrak{r}) \big) \\ &+ k_{4,2} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n};\mathfrak{r}) \big) \\ \bar{Y}(\mathfrak{t}_{n+1};\mathfrak{r}) &= \bar{Y}(\mathfrak{t}_{n};\mathfrak{r}) \\ &+ \frac{1}{6} \big( k_{1,2} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n};\mathfrak{r}) \big) + 2k_{2,2} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n};\mathfrak{r}) \big) + 2k_{3,2} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n};\mathfrak{r}) \big) \\ &+ k_{4,2} \big( \mathfrak{t}_{n}, Y(\mathfrak{t}_{n};\mathfrak{r}) \big) \end{split}$$

A sol at  $\mathfrak{t}_n$  where:  $0 \le n \le N$ ,  $a = \mathfrak{t}_0 \le \mathfrak{t}_1 \le \mathfrak{t}_2 \le \cdots \le \mathfrak{t}_n = b$ , and  $h = \frac{b-a}{N} = \mathfrak{t}_{n+1} - \mathfrak{t}_n$ ,

$$\underline{Y}(\mathfrak{t}_{n+1};\mathfrak{r}) = \underline{Y}(\mathfrak{t}_{n};\mathfrak{r}) + \frac{1}{6}F[\mathfrak{t}_{n},Y(\mathfrak{t}_{n};\mathfrak{r})]$$

$$\overline{Y}(\mathfrak{t}_{n+1};\mathfrak{r}) = \overline{Y}(\mathfrak{t}_{n};\mathfrak{r}) + \frac{1}{6}G[\mathfrak{t}_{n},Y(\mathfrak{t}_{n};\mathfrak{r})],$$

$$\underline{Y}(\mathfrak{t}_{n+1};\mathfrak{r}) = \underline{Y}(\mathfrak{t}_{n};\mathfrak{r}) + \frac{1}{6}F[\mathfrak{t}_{n},Y(\mathfrak{t}_{n};\mathfrak{r})]$$

$$\overline{Y}(\mathfrak{t}_{n+1};\mathfrak{r}) = \overline{Y}(\mathfrak{t}_{n};\mathfrak{r}) + \frac{1}{6}G[\mathfrak{t}_{n},Y(\mathfrak{t}_{n};\mathfrak{r})]$$

The proposed Runge-Kutta approach (by MATLAB) is depicted in the Figure 1.

#### 3. RESULT AND DISCUSSION

**Appllication in Radio Nuclides :** Let be considered a first-order ordinary differential equation

$$y'(w) = -x. y(w), y(w_0) = y_0, w \in I = [w_0, a]$$

Where x stands for the decay constant,  $y_{0}$ , is the quantity of radionuclides in the mixture at the beginning of the operation, and y(w) is the quantity of radionuclides in each radioactive material. Given that nuclear disintegration is a stochastic process, the quantity of radionuclides can be unpredictable. Assuming that the starting value  $y_{0}$ , in this scenario is unclear. However there are some circumstances in which it may not be known exactly how many radionuclides are in the radioactive material under investigation. In this case, the starting value $y_{0}$  is regarded as an intuitionistic fuzzy number with a triangular form.

Let x = 1, I = [0, 1] and  $y_0 = (5, 7, 9; 3, 7, 11) \cdot (\alpha, \beta) - \text{cut of } y(w_0) = y_0$  is given by:  $y(w_{0,r}) = y_0(r) = \{ [y_{\alpha}, \overline{y_{\alpha}}], [y_{\beta}, \overline{y_{\beta}}] \}$ ,  $r \in [0, 1]$  and  $0 \le r = \alpha + \beta \le 1$ . That means  $y(w_{0,r}) = y_0(r) = \{ [5 + 2\alpha, 9 - 2\alpha], [3 + 4\beta, 11 - 4\beta] \}$ ,  $r \in [0, 1]$  and  $0 \le r = \alpha + \beta \le 1$ .

In this problem Three methods can be used to approximate solutions for both membership and non-membership functions: the Runge-Kutta technique, the modified Euler method, and the Euler method.

#### Case 1: (1, 2) Differentiability

Using equation (1.1) and the idea of (1, 2)-Differentiability, the following are the membership function's precise solutions:

$$y_{\alpha}(w) = (5 + 2\alpha)e^{-w}; \overline{y_{\alpha}} = (9 - 2\alpha)e^{-w}$$

and the following provides the precise non-membership function solutions:

$$y_b(w) = (3 + 4b)e^{-w}; \overline{y_B(w)} = (11 - 4B)e^{-w}$$

Table 1 displays the total error between the approximate and exact solutions for the

membership	function a	t various r-	levels.
------------	------------	--------------	---------

Table. 1. Absolute Error for Membership function			
r	Error by Euler Method	Error by Modified Euler	Error by Runge-Kutta
		Method	Method
0.0	0.4 <i>0</i> 9 <i>0</i> 15747 <i>7</i>	0.0 <i>0</i> 16 <i>3</i> 03928	8.3 <i>0</i> 48E-06
0.22	0.3 <i>0</i> 9 <i>5</i> 52597 <i>8</i>	0.0013343142	6.6 <i>0</i> 49E-06
0.42	0.2 <i>0</i> 9 <i>4</i> 894484	0.0 <i>0</i> 10 <i>3</i> 82356	5.0 <i>0</i> 42E-06
0.61	0.2063814014	0.0009461612	4.6 <i>0</i> 46E-06
0.81	0.2 <i>0</i> 6 <i>5</i> 814015	0.000126161	4.6 <i>0</i> 45E-06
1.0	0.2062814014	0.00 <i>01</i> 261612	4.6 <i>0</i> 45E-06

The total difference between the exact and approximate solutions for the nonmembership function at different r-levels is shown in Table 2.

Table. 2. Absolute Error for Non - Membership function			
r	Error by Euler Method	Error by Modified Euler	Error by Runge-Kutta
		Method	Method
0.0	0.264 <i>3</i> 814016	0.30275884	0.309390333
0.22	0.264 <i>2</i> 814015	0.242807073	0.247332268
0.42	0.264 <i>4</i> 814015	0.181855305	0.185374201
0.61	0.264 /814014	0.122903536	0.123316134
0.81	0.264 /814014	0.062951768	0.061358067
1.0	0.2642814014	0.003261612	4.663 <i>4</i> E-06

### Case 2: (2, 1) Differencing

Equation (1.1) can be solved precisely for the membership function by using the

concept of (2, 1)-Differentiability. The solutions are as follows:

 $y_{\alpha}(w) = (5 + 2\alpha)e^{-w}; \overline{y_{\alpha}} = (9 - 2\alpha)e^{-w}$ 

and the exact solutions of non-membership function are given by:

$$y_{b}(w) = (3 + 4b)e^{-w}; \overline{y_{B}(w)} = (11 - 4B)e^{-w}$$

The total difference at different r-levels between the exact and approximate

membership function solutions is shown in Table 3.

Table 3. Absolute Error for Membership function			
r	Error by Euler Method	Error by Modified Euler	Error by Runge-Kutta
		Method	Method
0.0	0.2 <i>1</i> 62814016	0.1 <i>9</i> 53379421	0.15 <i>3</i> 1895167
0.22	0.2162814021	0.1 <i>9</i> 23903536	0.12 <i>4</i> 1916134
0.42	0.2 <i>1</i> 62814015	0.0 <i>9</i> 93427653	0.09 <i>3</i> 1937101
0.61	0.2162814014	0.0 <i>9</i> 63951768	0.06 <i>47</i> 3958067
0.81	0.2162814015	0.0 <i>9</i> 33475884	0. <i>1</i> 033 <i>3</i> 979033
1.0	0.2162814014	0.0903261612	4. <i>3</i> 636E-06

Table 4 displays the overall error of the approximate and exact solutions for the non-

membership function at various r-levels.

Table 4. Absolute Error for Non-Membership function			
r	Error by Euler Method	Error by Modified Euler	Error by Runge-Kutta
		Method	Method
0.0	0. <i>1</i> 993314947	0.034607855	1.6175E-05
0.22	0. <i>1</i> 793051957	0.024886284	1.134E-05
0.42	0.1593788968	0.024164713	1.100E-05
0.61	0.1393525979	0.014443142	6.269E-06
0.81	0.1263814014	0.004261612	4.266E-06
1.0	0.1263814014	0.004261612	4.266E-06

## Case 3: (1, 1) Differencing

Equation (1.1) can be solved precisely for the membership function using the concept of (1, 1)-Differentiability using the following formula:

$$y_{\alpha}(w) = (5+2\alpha)e^{-w}; \overline{y_{\alpha}} = (9-2\alpha)$$

and the specific responses for the non-membership function are as follows:

$$y_b(w) = (3+4b)e^{-w}; \overline{y_B(w)} = (11-4B)e^{-w}$$

The errors made by the numerical methods described in this article are contrasted in the following graphic. Data was imported into MATLAB (Version R2021) to construct the figure.



### Case 4: (2, 2) Differentiability

The exact answers of the membership function are given by:

$$y_{\alpha}(w) = (5 + 2\alpha)e^{-w}; \overline{y_{\alpha}} = (9 - 2\alpha)$$

and the precise responses for the non-membership function are as follows:

$$y_b(w) = (3 + 4b)e^{-w}; \overline{y_B(w)} = (11 - 4B)e^{-w}$$

An example of comparing the errors between the accurate and approximate solutions for the membership and non-membership functions may be seen in the figure below.



It is evident that the lengths of the supports of the equation (4.1) solutions under (1,1)-Differentiability, (1,2)-Differentiability, and (2,1)-Differentiability will all increase as the independent variable "w" rises. This indicates that as time passes, the system's radioactivity increases and its.

There could even be a negative radionuclide population. Nonetheless, it is commonly recognized that a material's radioactivity never increases above zero and always decreases with time. Thus, for problems of this kind, (2, 2)-Differentiability makes sense. The numerical

solutions to equation (1.1) obtained by the Runge-Kutta method are substantially superior to those obtained by the other two methods in each of the four cases. However, by utilizing a smaller minimum step size, the inaccuracy could be reduced.

#### **Application for COVID-19**

Figures 2.3 and 2.4 show that the number of affected individuals was at least 200,000, reaching a high on Day 20. After that, the curvature started to progressively flatten. The government's protective measures, which mandate that everyone exercise social distancing and isolation at home, are most likely to blame for this. An increase in the number of impacted individuals who recovered from COVID-19 is seen in Figures 2.5 and 2.6. It is estimated that 400000 people are still alive. This could be as a result of the fact that more infected individuals are treated in quarantine centers with isolation and other therapies.

Figures 2.7 and 2.8 display the graph of all three SIR model classes, with starting parameters of 1.63 10-7 and 0.125, respectively, indicating that the immunization has not yet been administered in this simulation. The basic reproduction number (R\_0) for the simulation model seen in Figures 2.7 and 2.8 is provided below. Consequently, we can state that the output computation fits the Euler's technique with SIR model flawlessly.







Figure 2.

Simulation of Susceptible (S) in Euler's calculation of population









Figure 4

Simulation of Infected (I) in Euler's calculation of population

Simulation of Infected (I) in SIR calculation of population



Figure 5



Simulation of Recovered (I) in Euler's calculation of population



Figure 7





Figure 8

Simulation of the Susceptible (S), Infected (I), Recovered (R) in Euler's

Simulation of the Susceptible (S), Infected (I), Recovered (R) in SIR



Figure 9

Simulation of Recovered (I) in Runge Kutta fourth order calculation of population



#### Figure 10

Simulation of Recovered (I) in Runge Kutta fourth order calculation of population







### 4. CONCLUSION

Through this article we apply the sol of Runge-Kutta method of order (2, 3, 4, 5 and 6) utilizing a modified 2-step Simpson technique to numerical method of FDEs. We have ranking of the best to least (Rung Kutta of order six, Rung Kutta of order five, Rung Kutta of order four, Rung Kutta of order three, Rung Kutta of order two and a modified of 2-step Simpson) respectively. The researcher attempted to apply some of the problems in physics and medicine that the Runge-Kutta mothed was used to solve.

### REFERENCES

- Abbasbandy, S., & Viranloo, T. A. (2002). Numerical solution of fuzzy differential equation. *Mathematical and Computational Applications*, 7(1), 41-52. <u>https://doi.org/10.3390/mca7010041</u>
- Allahviranloo, T., Ahmady, E., & Ahmady, N. (2008). Nth-order fuzzy linear differential equations. *Information Sciences*, 178(5), 1309-1324. <u>https://doi.org/10.1016/j.ins.2007.10.013</u>
- Allahviranloo, T., Ahmady, N., & Ahmady, E. (2007). Numerical solution of fuzzy differential equations by predictor-corrector method. *Information Sciences*, *177*(7), 1633-1647. https://doi.org/10.1016/j.ins.2006.09.015
- Barkhordari Ahmadi, M., & Khezerloo, M. (2011). Fuzzy bivariate Chebyshev method for solving fuzzy Volterra-Fredholm integral equations. *International Journal of Industrial Mathematics*, *3*(2), 67-77.
- Dhayabaran, D. P., & Kingston, J. C. (2016). Solving fuzzy differential equations using Runge-Kutta second order method for two stages contra-harmonic mean. *International Journal of Engineering Science and Innovative Technology*, 5(1), 154-161.

- Dhayabaran, D. P., & Kingston, J. C. (2016). Solving fuzzy differential equations using Runge-Kutta third order method with modified contra-harmonic mean weights. *International Journal of Engineering Research and General Science*, 4(1), 292-300.
- Fard, O. S., & Bidgoli, T. A. (2011). The Nyström method for hybrid fuzzy differential equation IVPs. *Journal of King Saud University-Science*, 23(4), 371-379. https://doi.org/10.1016/j.jksus.2010.07.020
- Ghayyib, M. N., Fuleih, A. I., & Adnan, F. A. (2023). A statistical analysis of the effects of afforestation on the environment in Iraq (Northern Iraq). *IOP Conference Series: Earth* and Environmental Science, 1215(1), 012039. https://doi.org/10.1088/1755-1315/1215/1/012039
- Ghazanfari, B., & Shakerami, A. (2012). Numerical solutions of fuzzy differential equations by extended Runge-Kutta-like formulae of order 4. *Fuzzy Sets and Systems*, 189(1), 74-91. <u>https://doi.org/10.1016/j.fss.2011.06.018</u>
- Jayakumar, T., Maheskumar, D., & Kanagarajan, K. (2012). Numerical solution of fuzzy differential equations by Runge-Kutta method of order five. *Applied Mathematical Sciences*, *6*(60), 2989-3002.
- Jehad, R. K., & Manar, N. G. (2019). Properties of a general fuzzy normed space. *Iraqi Journal* of Science, 60(4), 847-855. https://doi.org/10.24996/ijs.2019.60.4.18
- Jehad, R. K., & Manar, N. G. (2019). Properties of the space GFB(V, U). Journal of AL-Qadisiyah for Computer Science and Mathematics, 11(1). https://doi.org/10.29304/jqcm.2019.11.1.478
- Jehad, R. K., & Manar, N. G. (2021). Properties of the adjoint operator of a general fuzzy bounded operator. *BSJ*, *18*(1). https://doi.org/10.21123/bsj.2021.18.1(Suppl.).0790
- Kaleva, O. (1987). Fuzzy differential equations. *Fuzzy Sets and Systems*, 24(3), 301-317. https://doi.org/10.1016/0165-0114(87)90029-7
- Kaleva, O. (1990). The Cauchy problem for fuzzy differential equations. *Fuzzy Sets and Systems*, 35(3), 389-396. https://doi.org/10.1016/0165-0114(90)90010-4
- Khaki, M., & Ganji, D. D. (2010). Analytical solutions of nano boundary layer flows by using He's homotopy perturbation method. *Mathematical and Computational Applications*, 15(5), 962-966. <u>https://doi.org/10.3390/mca15050962</u>
- Kim, H., & Sakthivel, R. (2012). Numerical solution of hybrid fuzzy differential equations using improved predictor-corrector method. *Communications in Nonlinear Science and Numerical Simulation*, 17(10), 3788-3794. <u>https://doi.org/10.1016/j.cnsns.2012.02.003</u>
- Ma, M., Friedman, M., & Kandel, A. (1999). Numerical solutions of fuzzy differential equations. *Fuzzy Sets and Systems*, 105(1), 133-138. https://doi.org/10.1016/S0165-0114(97)00233-9
- Malinowski, M. T. (2010). Existence theorems for solutions to random fuzzy differential equations. *Nonlinear Analysis: Theory, Methods and Applications*, 73(6), 1515-1532. https://doi.org/10.1016/j.na.2010.04.049

- Radhy, Z. H., Maghool, F. H., & Abed, A. R. (2017). Numerical solution of fuzzy differential equation (FDE). *International Journal of Mathematics Trends and Technology*, 52(9), 596-602. <u>https://doi.org/10.14445/22315373/IJMTT-V52P585</u>
- Raja, N., & Suganya, K. (2018). Numerical solution of fuzzy differential equation by comparison of Runge-Kutta sixth order method and Adam's fifth order predictorcorrector method. *International Journal of Science and Engineering Development Research*, 3(7), 176-181.
- Salahshour, S., Allahviranloo, T., & Abbasbandy, S. (2012). Solving fuzzy fractional differential equations by fuzzy Laplace transforms. *Communications in Nonlinear Science and Numerical Simulation*, 17(3), 1372-1381. https://doi.org/10.1016/j.cnsns.2011.07.005
- Salahshour, S., Allahviranloo, T., Abbasbandy, S., & Baleanu, D. (2012). Existence and uniqueness results for fractional differential equations with uncertainty. Advances in Difference Equations, 2012(1), 1-12. <u>https://doi.org/10.1186/1687-1847-2012-112</u>
- Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X
- Ziari, S., Ezzati, R., & Abbasbandy, S. (2012). Numerical solution of linear fuzzy Fredholm integral equations of the second kind using fuzzy Haar wavelet. In Advances in Computational Intelligence (pp. 79-89). Berlin, Heidelberg.