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An efficient parallel algorithm for the numerical solution for Singularly Perturbed Delay Differential Equations with Layer Behavior

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ABSTRACT

The numerical solution of a Singularly Perturbed Delay Differential Equations (SPDDE) is defined as a very charged problematic of computational because to the non-local nature of this type of differential Equations. Prove that parallelism can be used to overawed these problems for this purpose we suggest the application of parallel processors as the best solution to overcome the difficulties of the perturbed that occurs in Perturbed Delay Differential Equations on a matching processor. Allowing to several latest publications, this process has been effectively applied to a big number of SPDDE rising from a change of application fields. The exact quality of the conception of parallelism is argued in fact and several examples are presented to demonstrate the feasibility of our approach.

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1 . Introduction

A SPDDE is an ordinary differential equation in which the highest derivative is increased by a minor parameter and having delay term. Interest in studying this important topic has increased in recent times due to its great importance in numerical solutions . There are many uses for these important topics, for example, the mathematical modeling used in [1], in the study of bistable plans [2], and variable problems in control theory [3] Which are the only realistic simulations . Lange and Miura [4] Those who studied in this paper studied the problems of perturbed boundary values. Kadalbajoo and Sharma [5, 6], They studied the numerical solutions of perturbed differential equations, which are of great importance to this topic .In [7], they authors studied the numerical solutions of perturbed differential equations of the second degree, with significant delay in the term interaction through the method of integrated characters using exponential functions and quadratic rules with weight and duration remaining in an integrated form. In [8], the authors Juegal Mohapatra, Srinivasan Natesan Create a numerical method for a class of individually disturbed

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perturbed differential equations with minimal delay. The numerical method consists of a finite difference factor in the direction of the wind on an adaptive network, Which is formed by distributing the observation function along the arc . In[9], the authors MK. Kiadalbajoo, Devndra Kumiar Treat the spread with a small delay parameter by presenting a numerical method to a perturbed differential equation .

The goal of this paper is to project feed forward neural network (FFNN) to solve SPDDE. Using a multi-layer with 7 hidden units (neurons) and one linear output unit, the sigmoid activation function of each unit in hidden layer is tan sign function, where the Levenberg – Marquardt training algorithm is used to training the network .

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The goal of this paper is to project feed forward neural network (FFNN) to solve SPDDE. Using a multi-layer with 7 hidden units (neurons) and one linear output unit, the sigmoid activation function of each unit in hidden layer is tan sign function, where the Levenberg – Marquardt training algorithm is used to training the network .

2. Layer on the left side

Consider SPDDE of the form

$$\epsilon \gamma''(x) + h(x)\gamma'(x - \tau) + g(x)\gamma(x) = F(x) , 0 \leq x \leq 1 \tag{1}$$

with boundary conditions

$$\begin{aligned} \gamma(0) &= \alpha , -\tau \leq x \leq 0 && \mathbf{2(a)} \\ \gamma(1) &= \beta && \mathbf{2(b)} \end{aligned}$$

where ϵ is small parameter, $0 < \epsilon \ll 1$ and τ is also small shifting parameter, $0 < \tau \ll 1$; $h(x)$, $g(x)$, $F(x)$ are bc functions in $(0, 1)$ and α, β are finite constants. More, we accept that $h(x) \geq \kappa >$

0 in $[0, 1]$, where \aleph is positive constant. This statement just suggests that the boundary layer will be in the neighborhood of $x = 0$.

3. Right - end boundary layer problem

We now accept that $h(x) \leq \aleph < 1$ in $[0, 1]$, where \aleph is negative constant. This supposition merely suggests that the boundary layer will be in the neighborhood of $x = 1$.

4. Neural Network [10]

Neural network of this starting It can be run by each and is distributed parallel It is a system that handles a large number of contacts and information with performance numbers with neurological and biological networks. Ann is regularly considered as only or multidimensional. In defining the total of covers, input Units are not totaled as a class, for they do not complete any design. Evenly, number Layers in a network can be definite as the total of covers of weighted links among neuronal plates. In a coated neural network, neurons are prepared into coats. We need at tiniest two covers: input and output. Covers between input and output cover (if any) They are called concealed covers, which in turn are called concealed bulges concealed units. Further concealed neurons upsurge the network's capability to excerpt high-level numbers from (Data Entry. Training is the process of adjusting contact weights and biases b . In the first step, Network output and the difference between actual (obtained) and required (target) outputs Outputs (ie, error) are intended for the weights and biases formed (arbitrary values). Through The second step, the initial weights are adjusted in all connectors and biases in all neurons Reduce the error by propagating the error backwards

5. Description of the method

In this section illustrate how our approach can be used to the approximation solution of the SPDDE is defined in (1) with above boundary layers .The approximate solution can be defined according to the technique described in this paper

$$\gamma_t(x_i, \rho) = \Lambda(x) + \Gamma(x, \Theta(x, \rho)) \tag{3}$$

where $\Theta(x, \rho)$ is a singl-output FFNN with paramters ρ and n input units feed with the input vector x . The term $\Lambda(x)$ contians no adjust able paramters and contents the BCs. The next term Γ is created so as not to contribut to the BCs .And in general can define solution of SPDDE using FFNN.To illustrat the technique, we will reflect the 2nd-order SPDDE:

$$\frac{d^2\gamma}{dx^2} = \Omega(x, \gamma, \gamma', \epsilon, \tau) \tag{4}$$

where $x \in [a, b]$ and the BC: $\gamma(a) = \alpha, \gamma(b) = \beta$; an approximation solution can be written as

$$\gamma_t(x_i, \rho) = \frac{(b\alpha - a\beta)}{(b-a)} + \frac{(\beta - \alpha)}{b-a} x + (x - a)(x - b)\Theta(x, \rho) \tag{5}$$

The our goal in this paper is to design a FFNN $\Theta(x, \rho)$ such that γ_t Fit Informatics unknown function $\gamma(x)$ in any accuracy .Now rewrite (5) to be as following:-

$$\Theta(x, \rho) = \frac{\gamma_t(x) - \frac{x-a}{b-a}\beta - \frac{b-x}{b-a}\alpha}{(x-a)(x-b)} \quad x \neq a, b \tag{6}$$

The error quantety to be minimized is given by

$$E(\rho) = \sum_{i=1}^n \left\{ \frac{d^2 \gamma_t(x_i, \rho)}{dx^2} - \Omega(x_i, \gamma_t(x_i, \rho), \frac{d\gamma_t(x_i, \rho)}{dx}, \epsilon, \tau) \right\}^2 \quad \text{where the } x_i \in [a, b] \quad (7)$$

Since

$$\frac{d\gamma_t(x, \rho)}{dx} = \frac{(\beta - \alpha)}{(b - a)} + \{(x - a) + (x - b)\} \Theta(x, \rho) + (x - a)(x - b) \frac{d\Theta(x, \rho)}{dx}$$

$$\frac{d^2 \gamma_t(x, \rho)}{dx^2} = 2\Theta(x, \rho) + 2\{(x - a) + (x - b)\} \frac{d\Theta(x, \rho)}{dx} + (x - a)(x - b) \frac{d^2 \Theta(x, \rho)}{dx^2} \quad (8)$$

6. Numerical Results and Discussion

To determine the effectiveness of the technique, In this section of the research, we examined four examples of all the different cases with respect to the border layers and different values of the parameters of the perturbed and delay. Some examples did not contain an analytical solution and compared with some numerical solutions and analytical solutions with numbers and graphs, which shows the superiority is clear in relation to the proposed method.

Example 1

Study an example of SPDDE with " left layer":

$$\epsilon Y''(x) + Y'(x - \tau) - Y(x) = 0, \quad 0 \leq x \leq 1$$

with boundary conditions

$$Y(0) = 1$$

$$Y(1) = 1$$

"The exact solution is given by"
$$\gamma(x) = \frac{((1 - e^{\xi_2})e^{\xi_1 x} + (e^{\xi_2} - 1)e^{\xi_2 x})}{(e^{\xi_1} - e^{\xi_2})}$$

Where
$$\xi_1 = \frac{(-1 - \sqrt{1 + 4(\epsilon - \tau)})}{2(\epsilon - \tau)}, \quad \xi_2 = \frac{(-1 + \sqrt{1 + 4(\epsilon - \tau)})}{2(\epsilon - \tau)}$$

compared with results of paper [9].

Table 1: Compare between exact and proposed method forexample 1 for $\varepsilon = 0.001$, $\tau = 0.0001$

| Input x | Exact $y_a(x)$ | suggested method $y_t(x)$ | Numerical solution [9] | $E(x) = y_t(x) - y_a(x) $ |
|---------|----------------|---------------------------|------------------------|----------------------------|
| 0 | 1.000000000000 | 1.000000000000 | 1.0000000 | 0.000000000000E+00 |
| 0.01 | 0.371914090003 | 0.371914090605 | 0.3724909 | 6.016098730299E-10 |
| 0.02 | 0.375641680331 | 0.375641680353 | 0.3753635 | 2.189354253446E-11 |
| 0.03 | 0.379413533243 | 0.379413533619 | 0.3791343 | 3.764627498626E-10 |
| 0.04 | 0.383223259752 | 0.383223259742 | 0.3829441 | 1.038746866300E-11 |
| 0.06 | 0.390957858335 | 0.390957858387 | 0.3906790 | 5.210187836724E-11 |
| 0.08 | 0.398848564392 | 0.398848564926 | 0.3985702 | 5.341356801303E-10 |
| 0.20 | 0.449652021910 | 0.449652021615 | 0.4493791 | 2.954539390920E-10 |
| 0.50 | 0.606803174487 | 0.606803174803 | 0.6065730 | 3.157875072546E-10 |
| 0.60 | 0.670560975535 | 0.670560975574 | 0.6703575 | 3.899758294068E-11 |
| 0.90 | 0.904918712281 | 0.904918712244 | 0.9048500 | 3.727873565396E-11 |
| 1 | 1.000000000000 | 1.000000000000 | 1.0000000 | 0.000000000000E+00 |

Table 2: The performance of the train with epoch and time

| Train Function | Performance of train | Epoch | Time | MSE |
|----------------|----------------------|-------|---------|-------------|
| Trainlm | 2.39-31 | 22 | 0:00:01 | 7.32962E-20 |

Table 3 : Initial Weights and bias for trainlm

| Weights and bias for trainlm | | | |
|------------------------------|-------------|-------------|----------|
| Net.IW{1,1} | Net.IU{1,1} | Net.LW{2,1} | Net.B{1} |
| 0.3548 | 0.6509 | 0.5206 | 0.2609 |
| 0.9674 | 0.9643 | 0.9823 | 0.3598 |
| 0.0963 | 0.6539 | 0.8326 | 0.4764 |
| 0.5234 | 0.8053 | 0.6898 | 0.9635 |
| 0.8710 | 0.3326 | 0.1895 | 0.6529 |

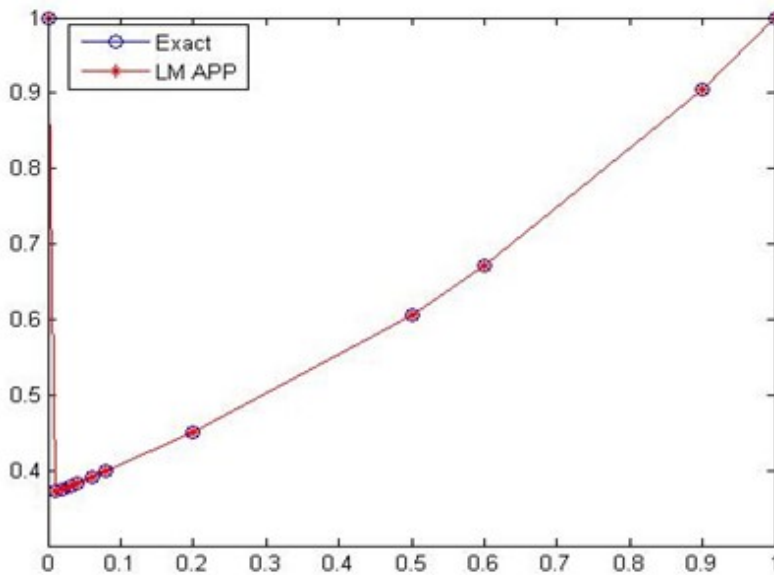


Figure 1. Exact and Approximate solution of example1 for $\varepsilon = 0.001$, $\tau = 0.0001$

Table 4 : Compare between exact and proposed method for example 1 for $\epsilon = 0.0001$, $\tau = 0.00001$

| Input x | Exact $y_a(x)$ | suggested method $y_t(x)$ | $E(x) = y_t(x) - y_a(x) $ |
|---------|----------------|---------------------------|----------------------------|
| Input | Exact $y_a(x)$ | suggested method | $E(x) = y_t(x) - y_a(x) $ |
| 0.1 | 0.406899055265 | 0.406899055496 | 2.310537317030E-10 |
| 0.2 | 0.449652539205 | 0.449652587774 | 4.856917357188E-08 |
| 0.3 | 0.496898194767 | 0.496898194766 | 5.044853423897E-13 |
| 0.4 | 0.549108021049 | 0.549108021045 | 3.535061132709E-12 |
| 0.5 | 0.606803610791 | 0.606803618671 | 7.880012309336E-09 |
| 0.6 | 0.670561361253 | 0.670561361756 | 5.034846983776E-10 |
| 0.7 | 0.741018232602 | 0.741018232998 | 3.960383132551E-10 |
| 0.8 | 0.818878111353 | 0.818878111362 | 9.330314298950E-12 |
| 0.9 | 0.904918842412 | 0.904918842798 | 3.857814068198E-10 |
| 1.0 | 1.000000000000 | 1.000000000000 | 0.000000000000E+00 |

Table 5: The performance of the train with epoch and time

| Train Function | Performance of train | Epoch | Time | MSE |
|----------------|----------------------|-------|---------|-------------|
| Trainlm | 4.6534 | 50 | 0:00:02 | 2.20124E-16 |

Table 6 : Initial weight and bias of the network for different training algorithm

| Weights and bias for trainlm | | | |
|------------------------------|-------------|-------------|----------|
| Net.IW{1,1} | Net.IU{1,1} | Net.LW{2,1} | Net.B{1} |
| 0.5997 | 0.2964 | 0.9329 | 0.4496 |
| 0.7838 | 0.8987 | 0.5983 | 0.6112 |
| 0.0834 | 0.2331 | 0.7001 | 0.7889 |
| 0.9804 | 0.6435 | 0.6492 | 0.3297 |
| 0.0388 | 0.6932 | 0.3445 | 0.1165 |

Example 2

Study an example of SPDDE with right-end boundary layer [12]

$$\epsilon \gamma''(x) - \gamma'(x - \tau) - \gamma(x) = 0, \quad 0 \leq x \leq 1, \quad -\tau \leq x \leq 0$$

with b.c $\gamma(0) = 1, \quad \gamma(1) = -1$

"The exact solution is given by" $\gamma(x) = \frac{((1+e^{\xi_2})e^{\xi_1 x} - (e^{\xi_1+1})e^{\xi_2 x})}{(e^{\xi_2} - e^{\xi_1})}$

Where $\xi_1 = \frac{(1 - \sqrt{1+4(\epsilon+\tau)})}{2(\epsilon+\tau)}, \quad \xi_2 = \frac{(1 + \sqrt{1+4(\epsilon+\tau)})}{2(\epsilon+\tau)}$

Table 7 : Compare between exact and proposed method for example for $\varepsilon = 0.01$, $\tau = 0.001$

| Input x | Exact $y_a(x)$ | suggested method $y_t(x)$ | $E(x) = y_t(x) - y_a(x) $ |
|---------|-----------------|---------------------------|----------------------------|
| 0 | 0.000000000000 | 0 | 0.000000000000E+00 |
| 0.1 | -0.100000000000 | -0.100000000220 | 2.199999904473E-10 |
| 0.2 | -0.200000000000 | -0.200000000983 | 9.829999869648E-10 |
| 0.3 | -0.300000000000 | -0.300000000084 | 8.400002915465E-11 |
| 0.4 | -0.400000000000 | -0.400000000567 | 5.670000025049E-10 |
| 0.5 | -0.500000000000 | -0.500000000934 | 9.339999884617E-10 |
| 0.6 | -0.600000000000 | -0.600000000034 | 3.400002501763E-11 |
| 0.7 | -0.700000000000 | -0.700000000972 | 9.720000360147E-10 |
| 0.8 | -0.800000000000 | -0.800000000884 | 8.839999843246E-10 |
| 0.9 | -0.900000000000 | -0.900000000000 | 0.000000000000E+00 |
| 1 | -1.000000000000 | -0.010000000000 | 9.900000000000E-01 |

Table 8: The performance of the train with epoch and time

| Train Function | Performance of train | Epoch | Time | MSE |
|----------------|----------------------|-------|---------|-------------|
| Trainlm | 2.7689 | 33 | 0:00:01 | 2.63461E-19 |

Table 9 : Initial weight and bias of the network for different training algorithm

| Weights and bias for trainlm | | | |
|------------------------------|-------------|-------------|----------|
| Net.IW{1,1} | Net.IU{1,1} | Net.LW{2,1} | Net.B{1} |
| 0.8046 | 0.7959 | 0.4665 | 0.4888 |
| 0.9375 | 0.8574 | 0.9898 | 0.1444 |
| 0.9402 | 0.2363 | 0.8788 | 0.8995 |
| 0.6870 | 0.4858 | 0.5768 | 0.4858 |
| 0.3848 | 0.6566 | 0.5477 | 0.4758 |

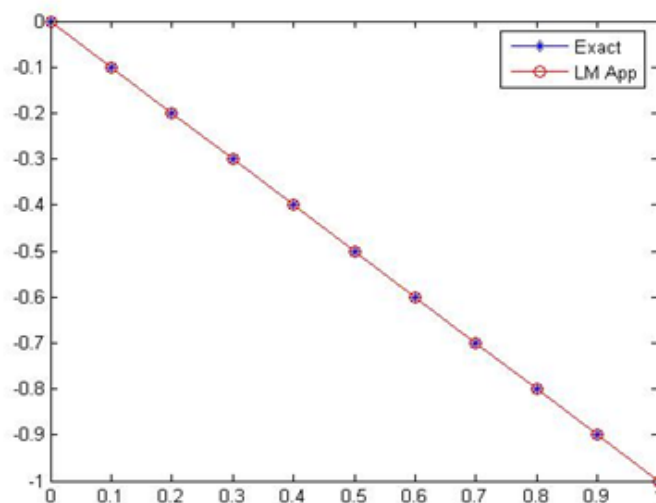


Figure 2. Exact and Approximate solution of example1 for $\varepsilon = 0.01$, $\tau = 0.001$

Example 3

Study an example of nonlinear SPDDE [11]

$$\varepsilon\gamma'' + \gamma(x)\gamma'(x - \tau) - \gamma(x) = 0$$

under the interval with B.C $\gamma(x) = 1, -\tau \leq x \leq 0, \gamma(1) = 1$
 The exact solution is not known.

Table 10: Numerical results of Example 3 for $\varepsilon = 0.001$ and different values of τ

| Numerical results | | | |
|-------------------|-------------------|-------------------|--------------------|
| x | $\tau_1 = 0.0002$ | $\tau_2 = 0.0006$ | $\tau_3 = 0.00009$ |
| 0 | 1.000000000000 | 1.000000000000 | 1.000000000000 |
| 0.1 | 0.3947646663542 | 0.3947646666396 | 0.3947646663553 |
| 0.2 | 0.449379653098 | 0.449379653054 | 0.449379658923 |
| 0.3 | 0.411296485522 | 0.411296485296 | 0.411296485526 |
| 0.4 | 0.544886359863 | 0.544886359174 | 0.544886359811 |
| 0.5 | 0.526599731324 | 0.526599739362 | 0.526599731358 |
| 0.6 | 0.671276386097 | 0.671276386032 | 0.671276386087 |
| 0.7 | 0.634824163797 | 0.634824163732 | 0.634824155231 |
| 0.8 | 0.823957234665 | 0.823957234669 | 0.823957234880 |
| 0.9 | 0.915851135426 | 0.915851132865 | 0.915851135451 |
| 1 | 1.000000000000 | 1.000000000000 | 1.000000000000 |

Table 11: The performance of the train with epoch and time

| Train Function | Performance of train | Epoch | Time |
|----------------|----------------------|-------|---------|
| Train τ_1 | 1.4327 | 20 | 0:00:01 |
| Train τ_2 | 2.9832 | 55 | 0:00:02 |
| Train τ_3 | 2.1232 | 12 | 0:00:00 |

Example 4

Study an example of nonlinear SPDDE [11]

$$\varepsilon\gamma'' + 2\gamma'(x - \tau) + e^{\gamma(x)} = 0$$

under the interval with b.c $\gamma(x) = 0, -\tau \leq x \leq 0, \gamma(1) = 0$

"The exact solution is not known".

Table 12: Numerical results of Example 3 for $\varepsilon=0.0001$ and different values of τ

| Numerical results | | | |
|-------------------|-------------------|-------------------|--------------------|
| x | $\tau_1 = 0.0001$ | $\tau_2 = 0.0004$ | $\tau_3 = 0.00008$ |
| 0 | 0.000000000000 | 0.000000000000 | 0.000000000000 |
| 0.1 | -0.189388733852 | -0.189388799527 | -0.189388732597 |
| 0.2 | -0.048362098365 | -0.048362098366 | -0.048362097759 |
| 0.3 | -0.139655972443 | -0.139655972034 | -0.139655972482 |
| 0.4 | -0.049812338768 | -0.049812995632 | -0.049812338777 |
| 0.5 | -0.039655972443 | -0.039655972086 | -0.039655972491 |
| 0.6 | -0.073784286498 | -0.073784286495 | -0.073784286494 |
| 0.7 | -0.048630716853 | -0.048630716822 | -0.048630717734 |
| 0.8 | -0.035049432073 | -0.035049432116 | -0.035049432882 |
| 0.9 | -0.017086866521 | -0.017086866595 | -0.017086866623 |
| 1 | 0.000000000000 | 0.000000000000 | 0.000000000000 |

Table 13: The performance of the train with epoch and time

| Train Function | Performance of train | Epoch | Time |
|------------------|----------------------|-------|---------|
| Trainlm τ_1 | 7.6643 | 63 | 0:00:04 |
| Trainlm τ_2 | 4.0433 | 32 | 0:00:02 |
| Trainlm τ_3 | 3.7743 | 43 | 0:00:03 |

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