1**Review Article**2A METHOD FOR COMPUTING INITIAL APPROXIMATIONS FOR A33-PARAMETER EXPONENTIAL FUNCTION

Abstract

This paper proposes a modified method (MM) for computing initial guess values (IGVs) of a 8 single exponential class of transcendental least square problems. The proposed method is an 9 10 improvement of the already published multiple goal function (MGF) method. Current 11 approaches like the Gauss-Newton, Maximum likelihood, Levenbreg-Marquardt e.t.c 12 methods for computing parameters of transcendental least squares models use iteration 13 routines that require IGVs to start the iteration process. According to reviewed literature, 14 there is no known documented methodological procedure for computing the IGVs. It is more 15 of an art than a science to provide a "good" guess that will guarantee convergence and reduce 16 computation time.

To evaluate the accuracy of the MM method against the existing Levenberg-Marquardt (LM) and the MGFmethods, numerical studies are examined on the basis of two problems thats; the growth and decay processes. The mean absolute percentage error (MAPE) is used as the measure of accuracy among the methods. Results show that the modified method acheives higher accuracy than the LM and MGF methods and is computationally attractive. However, the LM method will always converge to the required solution given "good" initial values.

23 The MM method can be used to compute estimates for IGVs, for a wider range of existing

24 methods of solution that use iterative techniques to converge to the required solutions

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Keywords: Initial approximations; Transcendental least squares; Iteration routines;
Exponential problems; Mean absolute percentage error

28 **MSC**: 11D61, 11D72, 11J99

29 **1. Introduction**

Nonlinear problems are regularly encountered in both engineering and physical science
fields. These problems are reformulated into mathematical nonlinear equations which are
solved using existing optimization methods like the Expectation-Maximum (EM) algorithm,

33 Gauss-Newtons methods e.t.c. which employ iteration routines in order to converge to the 34 optimal solution. When practical and theorectical nonlinear problems are formulated, the final 35 step is always finding the solutions of the subsequent simultaneaous nonlinear equations [1]. 36 The equations can not be solved explicitly for exact solutions. However, a sufficiently "good" 37 initial estimate can be provided so that any iterative technique that may be applied will 38 converge to the required optimal solution. It is acknowledged that the word "good" is in itself 39 vague, but theproposed modified method (MM) will provide solutions for initial guess values 40 (IGVs) that will always guarantee convergence to the required optimal solution. Most of the 41 current methods of solution are very sensitive to initialization and this serves as a bench mark 42 for our study to develop systematic and algorithmic procedures for estimating IGVs.

43 Exponential equations are a class of nonlinear problems that are mainly solved by 44 linearisation through algorithmic procedures. Traditional methods for solving nonlinear 45 problems transform the nonlinear function into a linear one using the approximation of the 46 well-known Taylor expansion [2].

47 To solve nonlinear least square problems in the applied sciences and mathematics, numerical 48 iteration methods are usually applied such as the Newton method [3], Gauss-Newton 49 method [2] which transform the integral equations into linear systems of algebraic equations 50 which can be solved by direct or iterative methods. The iterative methods require provision of 51 IGVs to compute the optimal solutions. Other methods in current use are; derivative free 52 methods, direct optimization and the Levenberg-Marquardt (LM) which is more preferred 53 because of it robustness [4] as it always finds a solution even if it starts far from the required 54 minimum. In this paper amethod to the problem of finding IGVs, is presented. The algorithm 55 is described in (modification of the multiple goal function) section and its performance is 56 compared with that of Levenberg-Marquardt [5,6] and the multiple goal function (MGF) 57 [7], methods for a given class of exponential problems. First an analytical nature of the 58 approach is discussed and numerical studies to evaluate the performance of the MM method 59 against the conventional LMand MGF methods is examined.

2. Formulation of the problem 60

2.1.

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General 3-parameterised exponential model

62 We consider a generalised three parameter single exponential model of the form:

$$f(x) = \alpha e^{\beta x} + \gamma, \qquad (2.1)$$

64 where α , β and γ are the unknown parameters, whose initial guess values must be 65 provided.

66 The goal function for the determination of unknown parameters α , β and γ :

67
$$G(\alpha, \beta, \gamma) = \frac{1}{2} \sum_{i=1}^{N} \left\{ \alpha e^{\beta x_i} + \gamma - f(x_i) \right\}^2 \to \min.$$
 (2.2)

Partially differentiating Eq.(2.1) with respect to α , β and γ leads to the following system of equations that are transcendental with respect to the unknown parameters:

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$$\frac{\partial G}{\partial \alpha} = \alpha \sum_{i=1}^{N} e^{2\beta x_i} + \gamma \sum_{i=1}^{N} e^{\beta x_i} - \sum_{i=1}^{N} f(x_i) e^{\beta x_i} = 0.$$
(2.3)

71
$$\frac{\partial G}{\partial \gamma} = \alpha \beta \sum_{i=1}^{N} e^{\beta x_i} + \gamma N - \sum_{i=1}^{N} f(x_i) = 0$$
(2.4)

72
$$\frac{\partial G}{\partial \beta} = \alpha \sum_{i=1}^{N} x_i e^{2\beta x_i} + \gamma \sum_{i=1}^{N} x_i e^{\beta x_i} - \sum_{i=1}^{N} x_i f(x_i) e^{\beta x_i} = 0.$$
(2.5)

The system of Eqs. (2.3–2.5) can not be solved explicitly to give closed form solutions because, each side of the equations contains unknowns in every term. However, their methods of solution are well known like the Newton methods, secant methods, likelihood methods etc, but all these methods demand the use of iterative procedures which require IGVs to start the iteration process.

In this paper a method thatcould be used to estimate IGVs which guarantee convergence to the required solutionsand lead to a shorter computation time is formulated. According to the reviewed literature, there exists no known algorithms and systematic approaches for computing the IGVs. The method of trial and error is oftenly employed and in some cases the underlying problem is estimated as a linear model and identified using the ordinary least squares techniques ignoring the nonlinearities in the model. The computed parameters are then used as IGVs [<u>8</u>].

85 **3. Methodology**

The main idea is to transform the original transcendental problem into a new problem which is linear with respect to new unknown parameters. Differential methods are applied in order to linearise the problem and the problem solved using ordinary least squares techniques via integral methods. The multiple goal function method proposed by [7], is modified to a single goal function to estimate some of the required parameters.

91 **3.1.** The Multiple goal function (MGF) method

92 Under this section, we examine the MGF, this method provides solutions of transcendental 93 problems via two stages of optimisation of the initial problem. Optimisation is achieved by 94 formulating an objective function at each stage and subsequently solving the normal 95 equationsfor the unknown set of parameters using ordinary least squares techniques. To 96 improve on the accuracy of estimatability of this method (MGF), a new method is proposed 97 that applies optimisation of an objective function at one stage to obtain some of the unknown 98 parameters and continues to solve for the rest of the unknown parameters using simple 99 algebraic formulations of the initial problem. The solutions are then applied as IGVs to start 100 the iteration process to a range of existing optimisation methods that use iteration procedures 101 to estimate the required solution.

102 Considering the first and second derivatives of Eq.(3.1):

$$f'(x) = \eta e^{\beta x}$$
, with $\eta = \alpha \beta$, (3.1)

taking the second derivative and making approprate substitutions, we have;

$$f''(x) = \beta f'(x).$$
 (3.2)

106 Integrating Eq.(3.2) over the region [a; x] yields:

107
$$f'(x) - \beta f(x) - f'(a) + \beta f(a) = 0.$$
 (3.3)

108 Letting $\lambda = \beta f(a) - f'(a)$ in Eq.(3.3), we obtain:

109
$$f'(x) - \beta f(x) + \lambda = 0.$$
 (3.4)

110 Integrating Eq.(3.4), over the region [a; x] again yields:

111
$$f(x) = \beta I(x) - \lambda x + f(a) \text{ with } I(x) = \int_a^x f(\xi) d\xi.$$
(3.5)

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112 When a dataset $(x_i, f(x_i))$ for i = 1,..., n is available, it is possible to obtain a system of linear 113 equations represented by Eq. (3.6);

$$Y = \beta X_1 - \lambda X_2 + C, \tag{3.6}$$

115 where $Y = f(x_i)$, $X_1 = I(x_i)$, $X_2 = x_i$ and $C = f(a) + \lambda(a)$; parameters β , λ and C are 116 estimated by solving the system of equations represented by Eq. (3.6) using ordinary least 117 squares methods.

118 FortheMGFmethod estimates $\hat{\lambda}$ and \hat{C} are considered as nuisance parameters and 119 subsequently ignored, only $\hat{\beta}$ is considered for further analyses. After estimating $\hat{\beta}$ from 120 Eq. (3.6), the original problem can be reformulated as a system of linear regression equations:

121
$$f(x_i) = \alpha X_3 + C_1 \text{ for } X_3 = e^{\beta x_i} \text{ and } C = \gamma.(3.7)$$

122 The unknwon parameters α and C_1 are as well estimated using the ordinary least squares 123 methods.

4. Modification of the Multiple goal function algorithm (MM)

The MGF method is based on the idea that the unknown parameters are estimated from two formulated objective functions of Eqs. (3.6&3.7) from which normal equations that have closed form solutions are formed.

One major disadvantage of the MGF method is that numerical differentiation procedures are done several times which leads to greater loss of information or data at these subsequent stages. This eventual loss of data compromises the accuracy of the MGF method. The copious differentiation procedures may be minimised as follows.

132 Consider Eq. (3.6), rewritten as:

133
$$f(x) - \beta I(x) + \lambda x - C = 0.$$
 (4.1)

Estimation of the parameters β , λ and *C* was done in Eq. (3.6)using ordinary least squares methods. Now considering that:

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$$f(a) + \lambda a = C, \text{ for } \lambda = \beta f(a) - f'(a)$$
(4.2)

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138 It is then clear that:

139
$$\beta(C - \lambda a) - f'(a) = \lambda, \qquad (4.3)$$

140 solving for f'(a) from Eq. (4.3), we obtain:

141
$$f'(a) = \beta C - \lambda \beta a - \lambda. \tag{4.4}$$

142 Therefore, f'(a) and f(a) are now known.

143 Taking the first derivative of the original problem inEq. (2.1), we have:

144
$$f'(x)\Big|_{x=a} = \frac{d\left[\alpha e^{\beta x} + \gamma\right]}{dx} = \alpha \beta e^{\beta a}, \qquad (4.5)$$

145 implying;

146
$$f'(a) = \alpha \beta e^{\beta a}.$$
 (4.6)

147 Equating Eq. (4.4) and Eq. (4.6), and solving for α we obtain:

148
$$\alpha = (C - \lambda a - \frac{\lambda}{\beta})e^{-\beta a}.$$
 (4.7)

149 For x = a in Eq. (2.1) and equating the result with Eq. (4.2) yields:

150
$$\gamma = C - \lambda a - \alpha e^{\beta a} \,. \tag{4.8}$$

151 Substituting for α in Eq. (4.8) from Eq. (4.7), and simplifying, we obtain:

152
$$\gamma = \frac{\lambda}{\beta}$$
 (4.9)

Hence the unknown parameters (α , β and γ) in Eq. (2.1) are identified from Eqs. (4.7, 3.6, 44.9) respectively. The estimated parameters could then be used as initial guess values to a wider range of the single exponential class of problems.

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5. Performance of the algorithms

The criterion used to evaluate the performance of the methods (i.e LM, MGF and MM) was that; two datasets were generated which simulated the growth and decay processes. The

160 methods were then applied to estimate the known theoretical models in each case. The 161 measure of performance was the mean absolute percentage error (MAPE). This is a measure of accuracy commonly prefered because of its suitability in many practical and theoretical 162 163 instances [9,10]. Table 2& 4summarise the performance of the three methods on the basis of the known models considered, and Tables 1& 2 show the estimated parameters from the 164 respective methods. The main focus on the performance of the three methods was on how 165 166 well each of them estimated the already known (exact) model parameters ($\alpha, \beta \& \gamma$) in either 167 problem.

parameter	Exact values	Modified Multiple goal function (MGF)		Levenberg- Marquardt	
		Method (MM)		Method (LM)	
α	0.2	0.219092	0.177825	0.156527	
β	1.1	1.095585	1.114730	1.135970	
γ	15	14.98090	16.43410	17.03950	

168 Table 1: Comparison of the parameter estimates using the Modified, the Multiple goal function and the169 Levenberg-Marquardt methods with the Exact values for the growth model.

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171

MAPE for the Modified	MAPE for the Multiple goal	MAPE	for	the
Method	function	Levenberg-Marquardt		
3.36	7.33	12.87		

Table 2: The mean absolute percentage errors of the Modified Method, the Multiple Goal Function and the
 Levenberg-Marquardt method on growth model.

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parameter	Exact values	Modified	Multiple goal	Levenberg-
		Method (MM)	function (MGF)	Marquardt Method (LM)
α	10.2	10.19991	10.18640	10.06450
β	-1.1	-1.095585	-0.104719	-1.029130

γ	15	15.00009	14.91630	14.89790

Table 3: Comparison of the parameter estimates using the Modified, the Multiple goal function and the
 Levenberg-Marquardt methods with the Exact values for the decay model.

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MAPE for the Modified	MAPE for the Multiple goal	MAPE	for	the
Method	function	Levenberg-Marquardt		
0.13	30.39	2.82		

Table 4: The mean absolute percentage errors of the Modified Method, the Multiple Goal Function and theLevenberg-Marquardt method on the decay model.

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181 6. Discussion and conclusion

182 From a comparision of the current MM method and results obtained on the same problems 183 (growth and dacay models) by the existing and general methods (i.e MGF and LM), it is 184 clear that the MM method has a comparative advantage over the other methods see Tables 185 2& 4. The MM method has an accuracy of about 2 and 4 times that of the MGF and the 186 commonly applied and more robust LM methodrespectively on estimating the growth model. 187 We also examined the performance of the MM method on the decay model, and it was found 188 that its performance was far more appealing on identification of the decay model than the 189 growth model parameters. It exhibited an accuracy of about 234 and 22 times that of the 190 MGF and LM methods respectively. The authors have compared the MM method with their 191 earlier work using the MGF and the existing LM methods and found that the MM performs 192 better in estimating solutions (IGVs) than other methods. It is thus recommended that results 193 from the modified method be used as initial guess values to a broader range of exponential 194 models which fall in the class of 3-parameter problems.

195 COMPETING INTERESTS

196 The author has declared no competing interests

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