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Estimation of parameters of metal-oxide surge arrester models using Big Bang-Big Crunch and Hybrid Big Bang-Big Crunch algorithms

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Abstract
Metal oxide surge arrester accurate modeling and its parameter identification are very important for insulation coordination studies, arrester allocation, and system reliability since quality and reliability of lightning performance studies can be improved with the more efficient representation of the arresters´ dynamic behavior. In this work, the Big Bang - Big Crunch (BB-BC) and Hybrid Big Bang - Big Crunch (HBB-BC) optimization algorithms were used to select the optimum surge arrester model equivalent circuit parameter values, minimizing the error between the simulated peak residual voltage value and that given by the manufacturer. The proposed algorithms were applied to 63 kV and 230 kV metal oxide surge arresters. The results obtained showed that by using this method, the maximum percentage error was below 1.5%.

Keywords: *Surge Arresters, Residual Voltage, Big Bang – Big Crunch (BB-BC) Algorithm, Hybrid Big Bang – Big Crunch (HBB-BC) Algorithm, Parameter Estimation, EMTP.*

1. Introduction

Internal and external overvoltages on high voltage transmission lines are very common causes of interruptions. In order to protect them against overvoltages, surge arresters are implemented to divert the overvoltage current to the ground. Metal oxide surge arresters (MOSAs), due to their good performances, are extensively used in power systems [1]. Proper voltage-current characteristics, low power losses, high-level reliability in the operation time, high-speed response to overvoltages and long lifetime are some advantages of MOSAs [2].

The adequate circuit representation of metal oxide surge arrester characteristics is very important for insulation coordination studies and system reliability. In the case of switching surge studies, the surge arresters can be represented with their non-linear V–I characteristic. However, such a practice would not be suitable for lightning surge studies with fast front waves [3]. This is due to the fact that the surge arresters behave differently in the presence of a fast disturbance. Typically, the predicted residual voltage for an impulse current with the time to peak of 1 μs is about 8-12% higher than that with the time to peak of 8μs.

Also with further increase in the time to peak between 45 and 60 μs, the residual voltage is 2-4% lower than that for the 8μs current impulse [1].

In order to obtain more accurate results and reliable estimation in insulation coordination studies, several frequent dependent models of metal oxide surge arresters such as the IEEE and Pinceti models have been proposed [4,5].

A comparative study of the various existing models in the literature showed that the difficulties with these models reside essentially in the calculation and the adjustment of their parameters. The parameter determinations of each model, in a way that the model simulation results, correspond to the actual behavior of the arrester. Thus many researchers have paid attention to using an appropriate optimization algorithm. This was used to minimize the error between the computed and manufacturer's residual voltage curves [6-10].

In the present work, the transient models of MOSA are simulated using EMTP. The method is based on the use of the measured MOSA terminal voltage obtained from the following injection of the 10 kA, 8/20 µs impulse current. The main issue for the suggested models is the determination of the parameters for each model, in a way that the simulated curve has a good agreement with the real recorded waveform. The simulation results are applied to the Big Bang-Big Crunch (BB-BC) and Hybrid Big Bang-Big Crunch (HBB-BC) algorithms to determine the parameters of different models. The validity and accuracy of the estimated parameters are assessed by comparing the predicted residual voltage with the manufacturer's experimental results [11,12,16,18]. Good agreement of results verifies the ability of the proposed algorithm for estimating the surge arrester parameters.

2. Surge arrester models

Many different models have been presented to describe the transient behavior of surge arresters. IEEE has proposed a model, that shown in figure 1. In the IEEE model, two non-linear resistance of A_0 and A_1 have been separated using R_1L_1 filter [4]. For waves with slow front time, the equivalent impedance of the filter is insignificant, and A_0 and A_1 are parallel. However, in the case of the waves with fast front time, the equivalent impedance is significant, and most of the current passes through the non-linear resistance of A_0.

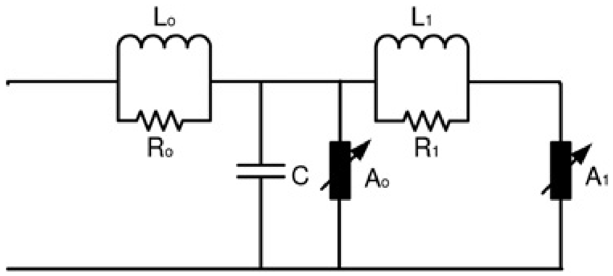

Figure 1. IEEE model.

The non-linear *V-I* characteristics of A_0 and A_1 are plotted in percent of guaranteed residual voltage at 10 kA, 8/20 µs current impulse in figure 2 [11].

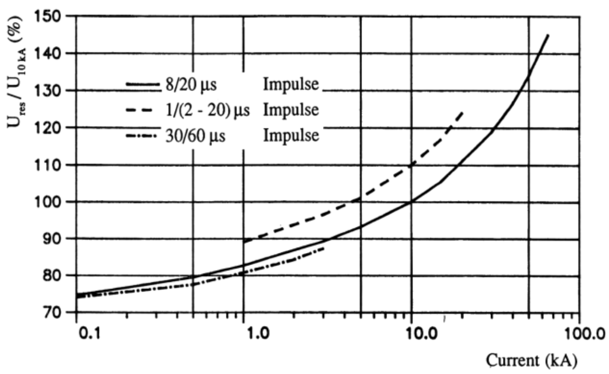

Figure 2. Non-linear characteristics of A_0 and A_1.

The model presented in figure 3 has been presented by Pinceti, and is derived from the IEEE model. In this model, the definition of *V-I* characteristic of A_0 and A_1 non-linear resistances is based on the curves shown in figure 2. The capacitance effect is negligible. The two resistances in parallel with the inductances are replaced by one resistance to avoid numerical troubles. The values for L_0 and L_1 are presented in table 1 [5].

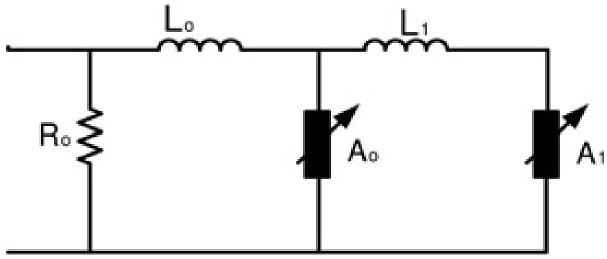

Figure 3. Pinceti model.

The parameters of each model are computed using the electrical characteristic data, obtained from the manufacturers' datasheet. The equations for the parameter computations of the IEEE and Pinceti models are presented in table 1 [4,5].

Table1. Model parameter computations.

	IEEE	Pinceti
R_0	(100d)/n Ω	1 M Ω
R_1	(65d)/n Ω	-
L_0	(0.2d)/n µH	$\frac{1}{12}\cdot\frac{V_{r(1/T2)}-V_{r(8/20)}}{V_{r(8/20)}}\cdot V_n$ µH
L_1	(15d)/n µH	$\frac{1}{4}\cdot\frac{V_{r(1/T2)}-V_{r(8/20)}}{V_{r(8/20)}}\cdot V_n$ µH
C	(100n)/d pF	-

V_n is the arrester's rated voltage, $V_{r(8/20)}$ is the residual voltage for a 10 kA, 8/20 µs lightning current, $V_{r(1/T2)}$ is the residual voltage for a $1/T_2$ 10 kA lightning current, n is a scale factor and d is the length of arrester column in meters. Table 2 and 3 present the electrical and physical characteristic data for the examined surge arrester.

3. Objective function

The surge arrester models were simulated using the EMTP software. The initial parameters for each surge arrester models were calculated. The impulse current of 10 kA, 8/20 µs was applied to the simulated models. Using the BB-BC and HBB-BC algorithms, the residual voltages obtained from the simulation of each model were compared with the measured voltage. The parameters of the MOSA models could be determined by minimizing the following objective function.

Table 2. Electrical and insulation data of arrester for 63 kV [11].

MCOV	48 kV
Rated Voltage	60 kV
Maximum Residual Voltage with lightening current 8/20 µs	137 kV
Height	996 mm
Insulation Material	Porcelain
Creepage	3285 mm

Table 3. Electrical and insulation data of arrester for 230 kV [11].

MCOV	160 kV
Rated Voltage	198 kV
Maximum Residual Voltage with lightening current 8/20 µs	451 kV
Height	1625 mm
Insulation Material	Porcelain
Creepage	6570 mm

The proposed algorithm in this work for the surge arrester models is based upon the experimental data [12]. The following equation shows the objective function [15]:

$$F = \int_0^T [V(T,\bar{X}) - Vm(t)]^2 dt \qquad (1)$$

where,

F : sum of the quadratic errors;

T : duration of the impulse current injected;

$V(t,x)$: the residual voltage obtained from simulation results;

$V_m(t)$: measured residual voltage;

x : state variable vector (model parameters).

If the function and variables are discrete, the objective function will be presented as follows:

$$F = \sum_{j=1}^{N} [V(j\Delta t, x) - V_m(j\Delta t)]^2 \, \Delta t \qquad (2)$$

where,

N : Number of discrete points;

$\Delta t = T / N$: computing time step.

The *V-I* characteristic of the surge arrester can be assumed by a non-linear resistance whose variation is exponential, as follows [13]:

$$I = P\left(\frac{V}{V_{ref}}\right)^q \qquad (3)$$

where, V and I are the voltage and current of the surge arrester, respectively, p and q are constant values, and V_{ref} is an arbitrary reference voltage.

4. Big Bang-Big Crunch algorithm

The BB-BC optimization method is one of the evolutionary algorithms presented as a solution for solving an optimization problem. This algorithm is composed of two stages, and is the same as the other evolutionary algorithms from the aspect of population production. The creation of the initial population randomly is called the Big Bang phase. In this stage, the population spreads all over the whole search space randomly and uniformly. The second stage is Big Crunch, which is actually a convergence operator. This operator has a many input but just one output, which is named as the center of mass, since the only output has been derived by calculating the center of mass. The center of mass is calculated using the following formula:

$$X_j^{c(k)} = \frac{\sum_{i=1}^{Np} \frac{1}{f^i} x_j^{(k,i)}}{\sum_{i=1}^{N} \frac{1}{f^i}} \qquad j = 1,2,\dots,D \qquad (4)$$

where, $X_j^c\ (k)$ is j^{th} variable of mass center in k^{th} iteration, $X_j\ (k,i)$ is j^{th} variable of i^{th} population solution in k^{th} iteration, f^i is the fitness function value of i^{th} point, and D and N_p are the number of control variable and the population size in the Big Bang phase, respectively.

After calculating the mass center in the k^{th} iteration and Big Bang stage, the new position of each particle is introduced using a normal distribution around the mass center. This method takes the population members as a whole in the Big-Crunch phase that acts as a squeezing or contraction operator and the algorithm generates new candidate solutions in the next iteration of Big Bang phase using normal distribution around the previous center of mass as follows:

$$x_j^{(k+1,i)} = x_j^{c(k)} + \frac{r_i \alpha\left(x_j^{max} - x_j^{min}\right)}{k+1} \qquad j = 1,2,\dots,D \qquad (5)$$

where r_i is a random number that is obtained using a standard normal distribution. This number is repeated for each member of the population in each iteration; α is a constant to limit the search space; x_j^{max} and x_j^{min} are the maximum and minimum acceptable values for j^{th} variable, respectively. After the Big Crunch phase, the algorithm must create new members to be used as the Big Bang of the next iteration step. "Bang" and "Crunch" will be continued until we reach convergence [16].

5. Hybrid Big Bang-Big Crunch algorithm

The BB-BC algorithm has an effective operation in exploitation, but some problems are observed in the exploration stage such as dependency of the algorithm on the initial population and the possibility of being trapped in local optima.

If all candidates are gathered in a small part of search space, the algorithm is more likely to be trapped in a local optimized point, and may not find the optimum solution. One of the solutions is that a great number of random variables are used to prevent the algorithm from getting stuck in the local optimized points but it causes an increase in the function evaluations, calculation time and finally computational cost. In order to solve these weaknesses and modification of exploration capability, this algorithm is combined with the PSO algorithm which is called "Hybrid Big Bang-Big Crunch" (HBB-BC) [17].

The PSO algorithm is inspired by birds swarm pattern, and operates based on the members of population that are called searching particles for food. Each particle moves through a multiple dimension search space with a constant speed. This speed updates constantly by the best experience of each particle (Pbest) or the best experience of all neighbor particles (Gbest).

In HBB-BC algorithm, each parameter updates using three parameters which belong to the previous iteration; these parameters are the center of mass, the best position of each solution, and the best position of all particles. Equation (6) shows the procedure of this updating.

$$x_j^{(k+1,i)} \beta_1 x_j^{c(k)} + \left(1-\beta_1\right)\left(\beta_2 x_j^{gbest(k)} + \left(1-\beta_2\right) x_j^{pbest(k,i)}\right) + \frac{r_i \alpha (x_j^{max} - x_j^{min})}{k+1} \qquad j = 1,2,\ldots,D \,, i = 1,2,\ldots,Np \tag{6}$$

In this equation, $x_j^{pbest(k,i)}$ is the best experience of i^{th} particle in k^{th} iteration, $x_j^{gbest(k)}$ is the best experience of all particles in k^{th} iteration, and β_1 and β_2 are the adjustable control coefficients related to the penetration of the best collective experience and the best individual experience for the new solution positions, respectively.

Mutation is used to prevent the HBB-BC from trapping into the local optimum as follows:

$$x_j^{(k+1,i)} = x_j^{min} + rand().\left(x_j^{max} - x_j^{min}\right) \quad if\ rand(\ \ ) > P_m \tag{7}$$

where, P_m is the mutation probability and *rand* () is a random number generated for each particle at each iteration[18].

6. Simulation results and analysis

The surge arrester different models with the rated voltage of 63 kV and 230 kV were simulated using EMTP. The IEEE model has 5 parameters (R_0 ، R_1 ، L_0 ، L_1 ، C_0), and the pinceti model has 3 parameters (R_0 ، L_0 ، L_1).

$$x = [x_1, x_2, x_3, x_4, x_5]^T = [R_0, R_1, L_0, L_1, C]^T \quad \text{(IEEE model)} \tag{8}$$

$$x = [x_1, x_2, x_3]^T = [R_0, L_0, L_1]^T \quad \text{(Pinceti model)} \tag{9}$$

Application of an optimization algorithms determines the optimal values for x_i. The BB-BC and HBB-BC optimization methods are applied to minimize the relative error. The initial parameter values for each model are computed by the procedures described in the references [4, 5].

The applied algorithms change the values for the parameters and calculate the objective function value according to the new residual voltage obtained.

The surge arrester parameters are determined using the BB-BC and HBB-BC algorithms. An impulse current of 10 kA, $8/20\,\mu s$ are applied to the models. The residual voltage obtained by the simulation are compared with the measured one obtained by the manufacturer [12]. The initial computed parameters and the optimum parameters for each model obtained using the BB-BC and HBB-BC algorithms are listed in tables 6-9.

The optimized peak value for the residual voltage and the relative errors for each model are given in tables 4 and 5. The relative error was calculated using the following equation as follows;

$$Error\ \% = \frac{X_{sim} - X_{meas}}{X_{meas}} \times 100 \tag{10}$$

In the above equation, X_{sim} and X_{meas} are the peak residual voltage obtained by the simulation and experimental data reported by the manufacturers, respectively. As it can be seen, these algorithms are capable of estimating different parameters, and can effectively model the dynamic characteristic of surge arresters.

Table 4. Residual voltages and relative errors for 63 kV.

Algorithms	10 kA 8/20 μs Models	Peak of Residual voltage (kV)	Error (%)	Standard deviation
BB-BC	IEEE	138.485	1.084	0.51708
	Pinceti	137.028	0.02	
HBB-BC	IEEE	137.849	0.62	
	Pinceti	137.023	0.0173	

Table 5. Residual voltages and relative errors for 230 kV.

Algorithms	10 kA 8/20 μs Models	Peak of Residual voltage (kV)	Error (%)	Standard deviation
BB-BC	IEEE	444.579	-1.42	0.6813
	Pinceti	451.035	0.0077	
HBB-BC	IEEE	447.862	-0.69	
	Pinceti	451.02	0.0046	

The relative error of the residual voltage peak values for the initial and optimized parameter values compared with the values given by manufacturer are presented in figure 4 and 5.

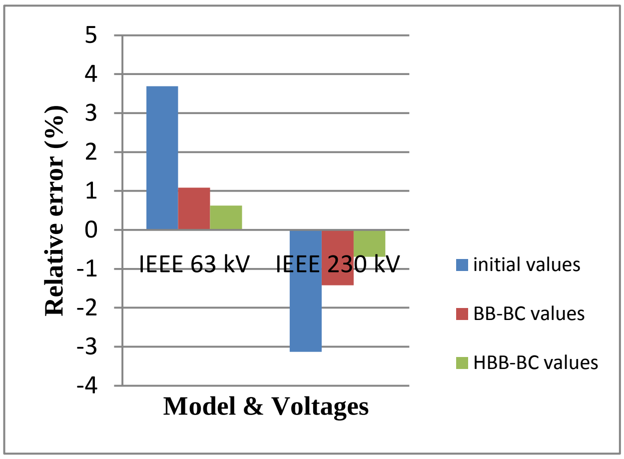

Figure 4. Relative error for a 10 kA (8/20 µs) injected impulse current using the values in tables 4 and 5.

Tables 6-9 show the initial computed parameters for each model, according to the computation described in section 2, as well as the optimum parameter values obtained using the BB-BC and HBB-BC algorithms described in sections 4 and 5. In tables 4 and 5 the peak value of the simulated residual voltage for each one model and relative errors are given, comparing them with the manufacturer′s datasheet. As it can be seen, the pinceti model gives a lower error due to its simplicity in comparison to the IEEE model.

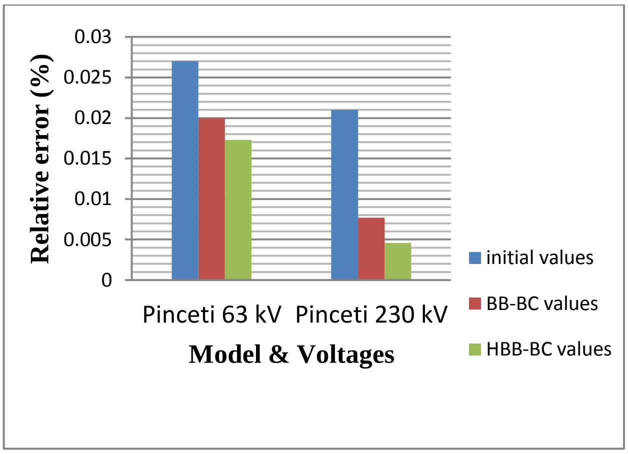

Figure 5. Relative error for a 10 kA (8/20 µs) injected impulse current using the values in tables 4 and 5.

Residual voltage peak values with optimized parameter value using BB-BC was compared to those obtained using HBB-BC; they are higher, and more accurate. It is obvious that the use of the HBB-BC algorithm gives more optimum parameters values for the equivalent circuit models.

The results obtained show that the use of the proposed algorithms cause high accuracy and low error between the manufacturer′s and the simulated residual voltage. The methods are capable of estimating different parameters, and can effectively model dynamic characteristic of MOV surge arresters.

Table 6. Initial and estimated parameters using BB-BC algorithm for 63 kV.

	IEEE Model		Pinceti Model	
	Initial parameters	**Optimized parameters**	**Initial parameters**	**Optimized parameters**
R_0	99.6 Ω	120.5782 Ω	1 MΩ	1.1473 MΩ
R_1	64.744 Ω	66.7165 Ω	-	-
L_0	0.1992 µH	0.2103 µH	0.365 µH	0.3299 µH
L_1	14.94 µH	11.1919 µH	1.095 µH	1.0847 µH
C	0.1004 nF	0.0673 nF	-	-

Table 7. Initial and estimated parameters using BB-BC algorithm for 230 kV.

	IEEE Model		Pinceti Model	
	Initial parameters	**Optimized parameters**	**Initial parameters**	**Optimized parameters**
R_0	162.5 Ω	173.4655 Ω	1 MΩ	1.1546 MΩ
R_1	105.625 Ω	116.8947 Ω	-	-
L_0	0.325 µH	0.3524 µH	1.17 µH	1.2427 µH
L_1	24.375 µH	28.8533 µH	3.51 µH	3.1519 µH
C	0.0615 nF	0.0839 nF	-	-

Table 8. Initial and estimated parameters using HBB-BC algorithm for 63 kV.

	IEEE Model		Pinceti Model	
	Initial parameters	**Optimized parameters**	**Initial parameters**	**Optimized parameters**
R_0	99.6 Ω	119.5121 Ω	1 MΩ	0.7690 MΩ
R_1	64.744 Ω	68.9275 Ω	-	-
L_0	0.1992 µH	0.1329 µH	0.365 µH	0.3228 µH
L_1	14.94 µH	10.7021 µH	1.095 µH	1.0726 µH
C	0.1004 nF	0.3616 nF	-	-

Table 9. Initial and estimated parameters using HBB-BC algorithm for 230 kV.

	IEEE Model		Pinceti Model	
	Initial parameters	**Optimized parameters**	**Initial parameters**	**Optimized parameters**
R_0	162.5 Ω	158.3645 Ω	1 MΩ	0.8364 MΩ
R_1	105.625 Ω	112.4447 Ω	-	-
L_0	0.325 μH	0.3348 μH	1.17 μH	1.0453 μH
L_1	24.375 μH	31.0672 μH	3.51 μH	3.2849 μH
C	0.0615 nF	0.0374 nF	-	-

7. Conclusion

Metal-oxide surge arresters (MOSAs) are extensively used in power systems due to good performance in over-voltage protection. The correct and adequate modeling of MOSAs characteristics is very important for insulation coordination studies and system reliability. In this work, the mostly used equivalent circuit IEEE and Pinceti models were simulated in EMTP, and then their parameters were optimized using the BB-BC and HBB-BC optimization algorithms. In these methods, the MOSA parameters were estimated based on the comparison between the residual voltage obtained by simulating it with the manufacturer´s results. One of the most advantages of the proposed methods is required only manufacturer data for estimating the initial parameters of MOSA models.

The two models used in this study, simulate and reproduce adequately the ferequency-dependent behavior of MOSAs, giving a very small error after the application of the optimization procedures. The simulation results obtained showed that after an application of the optimization procedures, the error between the simulated and manufacturer´s residual voltage for a given 10 kA, 8/20 µs input impulse current was less than 1.5 percent.

Considering the accuracy of these two optimization algorithms, the results showed that the HBB-BC algorithm is more accurate. Therefore, in order to optimize the parameters of the MOSA models, it is proposed to use the HBB-BC algorithm.

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نشریه هوش مصنوعی و داده کاوی

تخمین پارامترهای مدل‌های برقگیر اکسید فلزی با استفاده از الگوریتم‌های بهینه‌سازی بیگ بنگ- بیگ کرانچ و هیبرید بیگ بنگ- بیگ کرانچ

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چکیده:

مدل دقیق برقگیر اکسید فلزی و تعیین دقیق پارامترهای آن برای مطالعات هماهنگی عایقی، مطالعات قابلیت اطمینان و جایابی بهینه برقگیر از اهمیت بالایی برخوردار است. کیفیت و مطالعات قابلیت اطمینان در برابر عملکرد صاعقه با شناخت موثر رفتار دینامیکی برقگیرها بهبود می‌یابد. در این مقاله برای تخمین بهینه پارامترهای مدل‌های مختلف برقگیر از الگوریتم‌های بیگ بنگ- بیگ کرانچ و هیبرید بیگ بنگ- بیگ کرانچ استفاده شده است. در این روش، پارامترهای برقگیر براساس مقایسه ولتاژ پسماند شبیه‌سازی شده مدل‌ها با ولتاژ اندازه‌گیری شده کارخانه تخمین زده می‌شود و با حداقل رساندن خطا بین این دو مقدار پارامترهای بهینه شده مدار معادل برقگیر تعیین می‌گردد. این روش برای دو سطح ولتاژ ۶۳ و ۲۳۰ کیلوولت انجام گرفته است. نتایج اعمال پارامترهای بهینه برقگیر بیانگر کاهش خطا بین پیک ولتاژ باقیمانده حاصل از شبیه‌سازی با مقادیر اعلام شده توسط سازنده می‌باشد به طوری‌که حداکثر خطا کمتر از ۱/۵ درصد می‌باشد.

کلمات کلیدی: برقگیر، ولتاژ باقیمانده، الگوریتم بیگ بنگ-بیگ کرانچ، الگوریتم هیبرید بیگ بنگ-بیگ کرانچ، تخمین پارامتر، EMTP.