Research Journal of Engineering Sciences ______________________________________ ISSN 2278 – 9472
Vol. **13(3),** 35-41, September **(2024)** *Res. J. Engineering Sci.*

Review Paper

Extensive Review of Big Bang Big Crunch Optimization Algorithm

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Available online at: www.isca.in, www.isca.me
Received 16th May 2024, revised 10th June 2024, accepted 12th July 2024

Abstract

An updated utilizing an optimization method known for its BB-BC method, produced. It is in accordance with the concepts of the big bang and big crunch, which is among the theory explaining the universe's development. Initially, Big Bang Big Crunch method was introduced address optimization problems with continuous solution spaces. Consequently, among the population-level optimization strategies, the Big Bang –Big Crunch strategies adjusted within this research to handle optimization issues. One of the all issues utilized in the literature, Alternate link to selection of good link by the help of optimization BB-BC dynamic, are utilized for evaluation the efficiency of the recommended methods. BB-BC method control parameter is examined for its influence on performance using the well-known small and medium distance by the link cost like a throughput, Delay, Jitter, Energy, PDR. The results obtained are shown in comparison. The binary version of the BB-BC approach solves by the help of optimization method successfully regarding the standard on the response, according to the experimental results.

Keywords: Big Bang Big Crunch, Optimization, Swarm Intelligence and Application**.**

Introduction

Recently, a variety of swarm intelligence techniques have been presented to address interesting optimization problems due to their straightforward architectures and capacity to produce impactful solutions for issues Heuristic algorithms, which use a straightforward method to provide a workable search result, are growing in strength and sophistication lately. Typical the following can be briefly stated as the reasons for that: They offer general problem-solving procedures that able to apply this collection of choice variables, aim procedures, and restrictions. They function independently of the restrictions, amount of decision variables, and kind of solution space. They make use of random searches with probabilities. Their processing capacity is adequate; therefore they don't require lengthy computation times. Their transformation and adaption techniques for many problem types are straightforward. They also do not require well defined mathematical models; hence they impose fewer mathematical restrictions. Their solutions for the large-scale non-linear and combinatorial challenges are outstanding. They don't need the presumptions that regular algorithms need. As opposed to the presented problem, they do not require modification customary algorithms. They modify themselves to address various kinds of optimization issues.

Several swarm-based evolutionary techniques include genetic algorithms, ant colonies optimizing, and particle swarms optimizer as well artificial bee colonies, have been proposed in recent decades to solve this optimization challenge. To find out more, the data gathered at the conclusion of each iteration (cycle) and the random selection procedure are used optimal outcomes in the ensuing rounds.

One of the swarm intelligence algorithms, the BB-BC algorithm, developed by Erol and Eksin the year 2006 for use in numerical optimization problems. It was predicated on one idea, the massive crunch and big bang theories of the universe's evolution. BB-BC approach similarly creates haphazard points in solution space during the initial Big Bang stage, but during the initial Big Bang stage, it compresses every point because of a centre of mass .down to a single agent point in the search space. It has demonstrated that on numerous benchmark tests, the BB-BC approach performed better than the improved traditional Genetic Algorithm issues.

The literature study states that, the fundamental BB-BC algorithm is a competitive method for resolving optimization issues with a best path of short distance. To tackle this kind of optimization problem, the standard BB-BC algorithm needs to be adjusted if the problem find short best path. One of the primary mathematical operators, the module function what we use to propose a binary version of the BB-BC technique for finding plausible shortest best path. One of the most popular problems in combinatorial optimization is shortest best path. The primary aim in lowering the overall cost is the issue at hand by meeting consumer demand while adhering to the restrictions, which include a fixed facility setup and transportation costs[1].

Big Bang Big Crunch

Erol and Eksin create a new optimization technique called BB-BC. This approach is predicated about the evolution of the universe according to the Big Bang and Big Crunch theories Conceptual Framework, that cheap computing costs as well as a quick rate of convergence. Here are the two steps in this algorithm: Big Bang, in which a chance chaotic condition of the applicant is formed inside allotted Big Crunch comes next, where applicants are ranked and averaged according to quality.

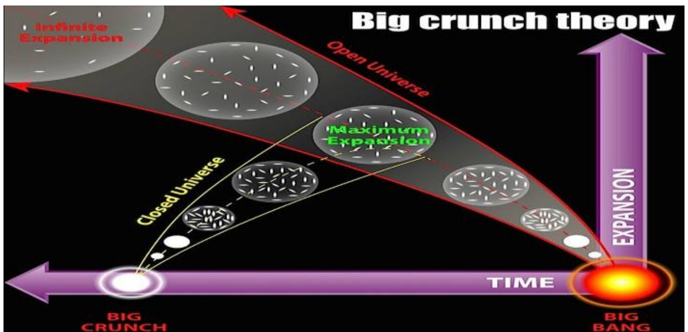

Figure-1: BB- BC[2].

Every time BB-BC methods runs, as fresh population created using the data from the earlier action; conversely, the placement of every fresh potential remedy is generated surrounding the centre in terms estimated after the Great Crunch. When the dispersion of chance in the investigation undergoes several consecutive Big Bangs - Big Crunches, The approach converges to a solution when the area becomes decreasing in size at the Big Bang the average point calculated within Big Crunch.

Description

The primary procedures for putting the algorithm BB-BC into practice in fact briefly explained in this section. As previously noted, the universe evolved according to the BB-BC theory gave rise population-level optimization technique known as the method of huge bang-big crunch.

Considering as suggested by the algorithm, as its name relies on the constant use of two ensuing steps, such as the BB-BC periods. Novel alternatives for solutions, or the parameters influencing the fitness feature, are created at random approximately a "centre of mass" during the phase of the big bang. Their fitness after that estimated during large crunch stage principles. The following is a summary of the processes involved in implementing the BB-BC algorithm. i. Generate uniform starting population through random distributing potential solutions throughout the whole search area (the initial massive boom). This procedure must be used only once. ii. Assign each individual point's fitness value a mass by computing its fitness value; If a minimization is required, either deduct the fitness/cost value from the "mass value from a constant number larger than the original value or by inverting the fitness/cost value greatest value that is feasible. iii. Determine the "centre of mass" by selecting the fittest person among all to serve either by using each person's coordinates and mass value as their centre of mass, or by computing the weighted average (very tight time). iv. Use normal distribution to create additional solution candidates (big bang phase). v. Until a stopping requirement is met Step II follows. Retain the most physically fit person now present in a particular location or as a member of the general public (elitism).

Many BB-BC variations are found in the literature; for example, uses equation (1) to produce the new BB-BC of the algorithm. Being the most physically fit member of the population, applicants are grouped surrounding the mass center[3].

Random selection to create the starting population

This method is similar to the GA in respect to creating an initial population randomly. The creation of the initial population randomly is called the Big Bang. In this step, the candidate solutions are spread all over the search space in an uniform manner.

If there is a limitation for each component of population and any of the components exceeded the boundaries, it is necessary to transfer these values to the adjacent boundaries. The Big Bang is followed by the Big Crunch. The Big Crunch is a convergence operator that has many inputs but only one output, which can be named as the center of 'mass', since the only output has been derived by calculating the center of mass. Here, the term mass refers to the inverse of the fitness function value. The point representing the center of mass that is denoted by x^c is calculated according to.

$$x^c = \frac{\sum_{i=1}^{N} \frac{1}{f^i} x^i}{\sum_{i=1}^{N} \frac{1}{f^i}}$$

Where x^i is a point within an n-dimensional search space generated; f^i is a fitness function value of this point, and N is the population size of algorithm in Big Bang step.

After the Big Crunch, the algorithm must create new members to be used as the Big Bang of the next iteration

$$x^{new} = X^c + \sigma$$

Where σ is calculated using following equation:

$$\sigma = \frac{r\alpha(x_{\max} - x_{\min})}{k}$$

α is the parameter limiting the size of the search space; r is a random number from a standard normal distribution which changes for each candidate; $x_{\max}$ and $x_{\min}$ are the upper and lower limits on the values of the optimization problem variables, and k is the number of Big Bang iterations. After the second explosion, the center of mass is recalculated. These successive explosion and contraction steps are carried repeatedly until a stopping criterion has been met.

Two additional steps implemented to improve computational efficiency and performance. First, positions of candidate solutions at the beginning of each Big Bang are normally distributed around a new point located between the center of mass, X^c, and the best global solution, X^{gbest}, using the following:

$$X^{(k+1,i)} = \beta X^{c(k)} + (1-\beta) X^{gbest(k)} + \sigma$$

Where β is the parameter for controlling the influence of the $X^{gbest(k)}$ on the location of new candidate solutions; $X^{gbest(k)}$ is the position of the best global solution. Numerical studies indicate that there is significant improvement. In the quality of the solutions and the computational efficiency of the BB-BC algorithm using Eq. over the original equation developed by Erol and Eksin. In some sense, the weighted average of X^{gbest} and X^c, controlled by β, may be viewed as equivalent to an elitist strategy, wherein the best solution is allowed to influence the directionof the search over many iterations of the technique. Second, for continuous design variables, a multi Phase search is applied to potentially improve the overall search performance. In a two-phase search, the BB-BC algorithm is initially applied to the entire search space and after convergence, a Phase 2 search is conducted in a reduced searchspace center around X^{gbest} from Phase 1.

Subsequent Big Bangs and Big Crunches are repeated until the global best solution, has not changed for a number of consecutive iterations; with this condition reached, the BB-BC algorithm is considered to have converged to a solution. At this point, Phase 1 of the BB-BC search is complete. To encourage a refined local search, a Phase 2 BB-BC search is initiated in the region surrounding X^{gbest}. In Phase 2, the search space is redefined around the values encoded in X^{gbest} from Phase 1 and a fraction of the search space immediately smaller and larger than globalbest values. Therefore boundary of variables in Phase 2 is defined as

$$X_{\min} = X^{gbest} - 0.5 \times \eta \times (\text{overall search space})$$
$$X_{\max} = X^{gbest} + 0.5 \times \eta \times (\text{overall search space})$$

Which η = size of search space in Phase 2.

Also, at the beginning of Phase 2, the X^{gbest} solution from Phase 1 can be either maintained or reset. In this paperis assumed the best global solution which obtained from Phase 1, be kept[4].

Architecture of the BB-BC Algorithm

The Big Bang Big Crunch (BB-BC) optimization method is inspired through the cosmos concepts within the world' evolution - the Big Bang and the Big Crunch. In this algorithm, the efficiency problem is framed a dynamic system where solutions evolve over time. Here's a simplified layout of the procedure BB-BC.

Initialization: Initialize a population of potential solutions solve fixing the enhancement issue. These solutions are often represented points in multidimensional search space. Define factors include The amount of repetitions and the dimension of sample size, mutation rate, convergence criteria.

Big Bang Phase: During this stage, the population undergoes an explosive expansion, similar to the rapid Following the BB, the cosmos expanded. Randomly perturb solutions in look around space to explore new regions. Assess a population-wide health for every approach.

Evaluation: Determine everyone's health status solution according to the aim function an efficiency issue. This performance measures as good or bad a fix.

The Big Crunch Stage: During this stage, that population contracts towards favourable areas inside looking for area, analogous toward the gravitational collapse leading to the Big Crunch. Select a subset of the best-performing solutions based on their fitness. Apply optimization techniques such as mutation, crossover, or local search to improve the selected solutions[5].

Application of Big Bang Big Crunch optimization Algorithm

The BB-BC Mechanism for Management is inspired by the cosmological phenomenon within cosmos' expansion and contraction. It's a population-based met heuristic optimization technique to identify the best course of action given complex optimization problems. Here are some potential uses of the BB-BC[6].

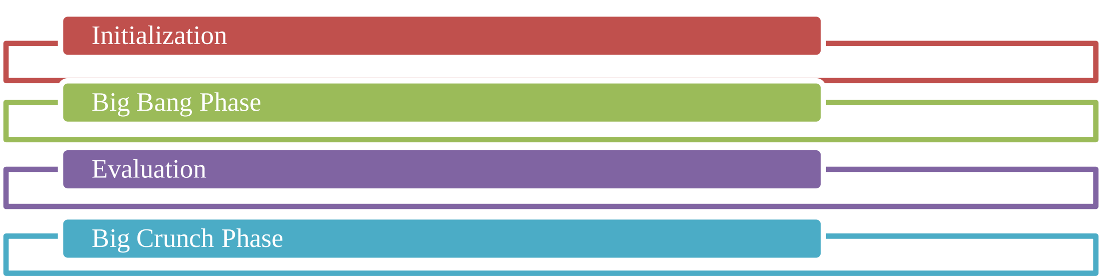

Figure-2: Architecture of the BB-BC algorithm.

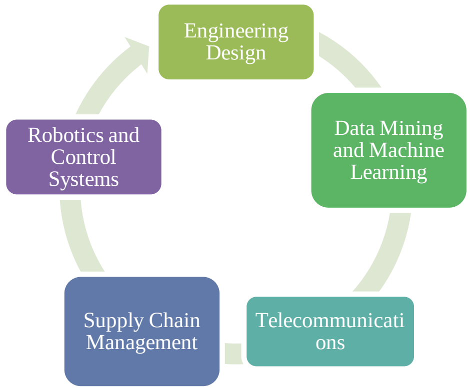

Figure-3: Application of BB-BC.

Engineering Designee: BB-BC it is possible to maximize the design characteristics of complex engineering systems such as aircraft, automobiles, or mechanical structures. It can help in minimizing weight, maximizing strength, or optimizing other performance metrics[7].

Here are several specific applications of the Engineers use the BB-BC method for designing:

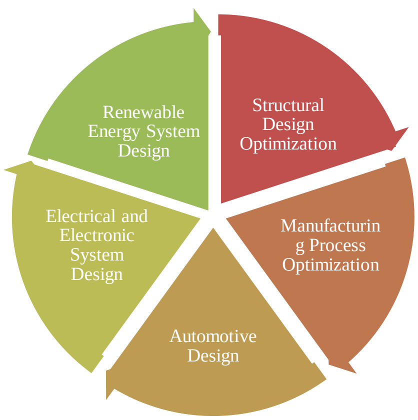

Figure-4: Engineering Design.

Structural Design Optimization: BB-BC can optimize the design of constructions like skyscrapers, roads, even palaces to meet performance criteria while minimizing weight, material usage, or cost. It can consider factors such as stress distribution, deformation, and stability constraints to find the most efficient design configurations[8].

Automotive Design: BB-BC can optimize the design of automotive systems, including vehicle body structures, chassis, suspension systems, and power trains. It can help improve vehicle performance, fuel efficiency, safety, and comfort while considering factors such as vehicle dynamics, crashworthiness, and manufacturing constraints[9].

Electrical and Electronic System Design: BB-BC can optimize the design of electrical and electronic systems, including circuits, antennas, sensors, and communication systems. It can help improve system performance, power efficiency, signal integrity, and electromagnetic compatibility while considering design constraints and specifications[10].

Heat Exchanger and HVAC System Design: BB-BC can optimize the design of HVAC (heating, ventilation, and air conditioning) platforms, heating elements and thermal management systems to improve energy efficiency, temperature control, and thermal comfort. It can consider factors such as heat transfer rates, pressure drop, and fluid flow characteristics[11].

Renewable Energy System Design: BB-BC can optimize the design of devices that use energy from renewable sources, such hydropower power plants, windmills, and solar cells to increase the generation of energy, efficiency as well reliability. It can consider factors such as geographic location, environmental conditions, and energy output variability[12].

Manufacturing Process Optimization: BB-BC can optimize manufacturing processes such as casting, machining, welding, and additive manufacturing to improve productivity, quality, and cost-effectiveness. It can consider factors such as material properties, process parameters, and production constraints[13].

By applying the BB-BC Optimization Algorithm to these engineering design applications, designers and engineers can efficiently explore large design spaces, identify optimal solutions, and achieve better-performing, cost-effective, and innovative designs[14].

Data Mining and Machine Learning

BB-BC can be utilized to optimize the parameters of machine learning algorithms or neural networks. It can help in improving model accuracy, reducing over fitting or optimizing hyper parameters.

When it comes to artificial intelligence as well as crunching, the BB-BC Technique for Optimize can be utilized to address variety in efficiency tasks involved in model training, parameter tuning, feature selection, and model selection[15].

Feature Selection and Dimensionality Reduction: BB-BC can optimize feature selection techniques and dimensionality reduction algorithms to identify the most informative subset of features or principal components that contribute to model prediction accuracy. It can explore different feature combinations or projection matrices to improve model interpretability and generalization performance[16].

Model Training and Tuning: BB-BC can optimize the training process of machine learning models by tuning model parameters, optimization algorithms, and convergence criteria. It can optimize the model training pipeline to minimize training time, resource utilization, and computational cost while maximizing model performance on training and validation data[17].

Ensemble Model Optimization: BB-BC can optimize ensemble learning techniques such as bagging, boosting, and stacking to improve model ensemble diversity, stability, and predictive accuracy. It can optimize choosing of beginning students, group weights, and aggregation strategies to construct highly effective group structures for problems involving grouping, regression, or categorization[18].

Telecommunication: BB-BC can optimize the placement of telecommunication towers or antennas to maximize coverage and minimize interference. It can also be used to optimize network routing or resource allocation in telecommunications networks[19]. In the telecommunications domain, the BB-BC Optimization method is applicable to address various optimization related to network planning, resource allocation, routing, and performance optimization.

Network Planning and Design: BB-BC can optimize Development as well as layout of telecommunications Systems networks, including that placement of base stations, antennas, and network infrastructure elements. It can consider factors such as coverage requirements, capacity constraints, interference mitigation, and cost optimization to design efficient and scalable network architectures[20].

Distributing Resources in cellular network: BB-BC can optimize resource allocation strategies in wireless networks, including time, frequency, and Distribution of energy in cellular networks, additionally resource distribution hoc and mesh networks. It can optimize resource allocation algorithms to improve network capacity, throughput, and fairness while meeting quality of service (QoS) requirements[21].

Supply Chain Management

BB-BC can optimize supply chain networks by determining the best locations for warehouses, distribution centres, and transportation routes to minimize costs and delivery times while maximizing efficiency.

In supply chain management, the BB-BC Efficiency Technique can be utilized to address various optimization challenges related to inventory management, production planning, logistics, distribution, and supply chain coordination[22].

Inventory Optimization: BB-BC can optimize inventory levels and reorder points in supply chains to minimize holding costs while ensuring adequate stock availability to meet customer demand. It can consider variables such timelines, performance objectives, as well as fluctuating demand and supply chain uncertainties to optimize inventory policies and reduce stock outs and excess inventory[23].

Production Planning and Scheduling: BB-BC can optimize production planning and scheduling processes in manufacturing facilities to improve production efficiency, resource utilization, and on-time delivery performance. It can optimize production schedules, job sequencing, and machine allocations to minimize production lead times, setup costs, and idle times while meeting production targets and customer requirements.

Logistics and Transportation Optimization: BB-BC can optimize logistics and transportation operations in supply chains to minimize transportation costs, lead times, and carbon emissions while maximizing service levels and delivery reliability. It can optimize vehicle routing, fleet management, mode selection, and shipment consolidation to improve transportation efficiency and sustainability[24].

Warehousing and Distribution Optimization: BB-BC can optimize warehousing and distribution operations in supply chains to improve storage capacity utilization, order picking efficiency, and inventory turnover rates. It can optimize warehouse layouts, storage policies, and order fulfilment processes to minimize handling costs and order processing times while maximizing customer satisfaction[25].

Figure-5: Data Mining and Machine Learning.

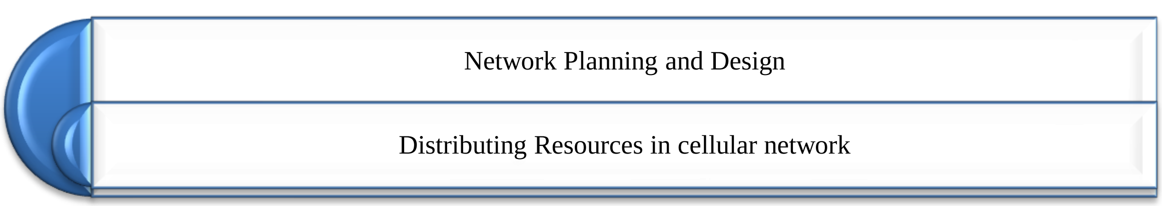

Figure-6: Telecommunication.

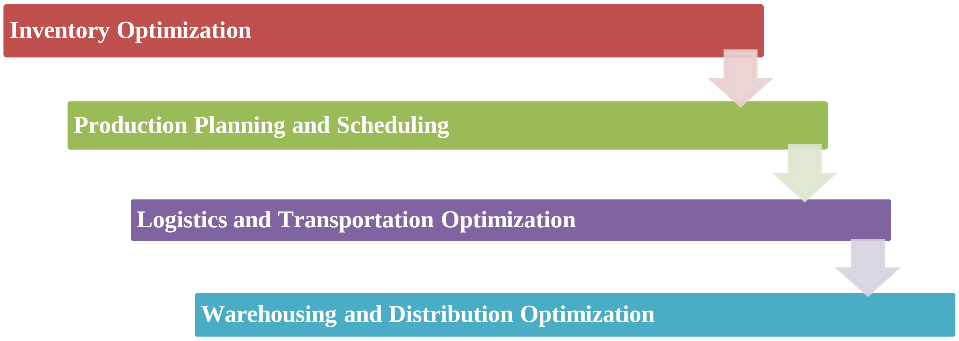

Figure-7: Supply chain Management.

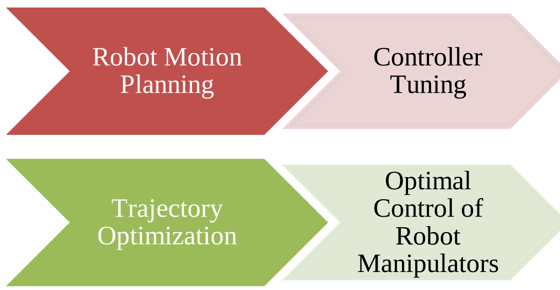

Figure-8: Robotics and Control System.

Robotic and Control system

BB-BC can optimize the control parameters of robotic systems or industrial processes to improve performance, efficiency, and safety. In the field of robotics and control systems, BB-BC Optimization method can be applied to address various optimization issue related to robot motion planning, trajectory optimization, controller tuning, and system design[26].

Robot Motion Planning: BB-BC can optimize robot motion planning algorithms to generate collision-free paths for robots to navigate in complex environments. It can optimize path planning strategies, obstacle avoidance techniques, and motion primitives to minimize path length, execution time, and energy consumption while ensuring safe and efficient robot motion.

Trajectory Optimization: BB-BC can optimize robot trajectory generation and tracking algorithms to achieve smooth and accurate robot motions. It can optimize trajectory parameters such as velocity profiles, acceleration profiles, and jerk profiles to minimize trajectory errors, vibration, and settling time while meeting performance specifications and constraints.

Controller Tuning: BB-BC can optimize controller parameters for feedback control systems to improve system stability, performance, and robustness. It can optimize proportional-integral-derivative (PID) controller gains, filter coefficients, and control loop parameters to achieve desired control objectives such as monitoring of limits, denial of disturbances, with safety limits.

Optimal Control of Robot Manipulators: BB-BC can optimize the control strategies for robot manipulators to achieve optimal motion and manipulation tasks. It can optimize control algorithms such as inverse kinematics, inverse dynamics, and model predictive control (MPC) to minimize energy consumption, end-effectors error, and task execution time while maximizing manipulation accuracy and efficiency[27].

Conclusion

In this paper, we studied BB-BC Optimization method a promising Meta heuristic enhancement technique combines their principles between enlargement and contracting to efficiently explore and converge towards optimal solutions in complex optimization problems. Despite its advantages and versatility, the algorithm may exhibit limitations such as parameter sensitivity and premature convergence, requiring careful consideration and adaptation to specific problem domains. Nevertheless, BB-BC holds great potential for addressing a wide range of optimization challenges across diverse application areas, making it a useful resource for users, technicians, and scholars across a range of disciplines.

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