Preserving non-minimum phase dynamics in model order reduction of fifth-order DC–DC boost converters

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ABSTRACT

In this work, a unified modelling approach is developed for the model order reduction of non-minimum phase systems. An optimized approach is adopted to address the problem. The coordinated hunting behavior of Cuban boa snake is made use of to develop a new optimization strategy. A constrained optimization method is developed to reduce a 5th order boost converter in the unified domain. Comparison is carried out with multiple classical techniques as well as some of the widely known nature inspired algorithms. The step and Bode responses using the proposed method offers closeness to the original responses as compared to the existing techniques. The pole zero mapping reveals the non-minimum nature of the reduced system. The stability of the reduced system is reflected through the Nyquist plot. A second-order proportional-integral-derivative (PID) controller is also synthesized using approximate model matching and Cuban boa snake optimization algorithm (CBSOA), which demonstrates superior transient performance, minimal steady-state error, and enhanced robustness.

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1. INTRODUCTION

DC–DC converters provide efficient energy conversion and voltage level control in many applications, such as embedded electronics, electric vehicles, renewable energy systems, and aeroplanes to making them crucial components of power electronics [1]-[3]. In order to fulfil the increasing demand for electricity, a lot of research has been done recently on power supplies with high step-up conversion ratios that employ non-conventional energy sources, including biofuel cells, solar photovoltaic, and geothermal energy. These energy sources produce low voltages; therefore, a variety of converters are needed to tune them with the battery system or power grid [4], [5]. The boost converter (BC), which must run at a greater duty ratio, is often utilised to obtain a higher voltage. This reduces the efficiency of BC and increases the voltage stress on diodes, electric switches, inductors, and capacitors. As a result, there is always a restriction on the high output voltage in real-world systems [6], [7].

Quadratic boost converter (QBC) [8], [9], cubic boost converter [10], coupled inductor non-isolated converter [11], switched-capacitor converter [12], and super lift boost converter [13] are some of the high-gain DC–DC converters that have recently been introduced. The main goal of these converters is to control the output voltage by altering the duty cycle of the MOSFET switch according to various input supply voltage, demand, parametric uncertainty, and unmodelled dynamics. Owing to their complicated structure and extremely non-linear nature, these converters are challenging to manage [14], [15]. The high-order boost converter models can become computationally demanding and challenging to manage in real-time applications or control system design, despite their value for precise analysis and system identification. To address these issues, engineers are very interested in using reduction of model approaches when working with higher-order converters for evaluation, synthesis, and other various uses. Numerous techniques for model reduction have been proposed in the literature in both the time and frequency domains, including the aggregation approach, Hankel approximation, Pade approximation, Routh approximation, and balanced realization [16].

These traditional methods, however, have a number of drawbacks, including taking a long time, failing to address real-world problems, and lacking robustness. Moreover, there is no escape route for classical approaches if they get trapped in any of the many locally optimum solutions that emerge when dealing with optimisation issues [17]. Recently, optimisation methods for order reduction of both continuous- and discrete-time systems have been employed either alone or in conjunction with traditional methods. These methods include genetic algorithms (GA), particle swarm optimization (PSO), and artificial bee colonies (ABC) [18]-[20].

The coordinated hunting of animals to catch prey is a popular method of optimization used to solve manifold problems in science and engineering [21]. However, it is not so common in reptiles. Few instances [22] are only reported, but their mathematical formulations to project new optimization approaches are still missing in the literature. Hence, an attempt will be made to formulate new optimization algorithms utilizing the concept of coordinated hunting in reptiles. Cuban boa snakes exhibit coordinated hunting to capture the Jamaican fruit bats and have been utilized to develop a new optimization algorithm coined as Cuban boa snake optimization algorithm (CBSOA).

The shift operator parameterization is used in conventional discrete-time system modelling. Unfortunately, at a high sampling frequency, the shift operator parameterization loses its ability to retrieve valuable data from the underlying continuous-time system. An alternative parameterization, known as the delta operator parameterization, is being developed as a solution to this problem by Middleton and Goodwin [23]. Several researchers have successfully on it, particularly in the area of model order reduction and control using this unified framework.

The reduced-order model parameters in optimization-based approaches are determined by minimizing a fitness function, which is frequently the integral square error (ISE) derived by step response matching [24]. Furthermore, it is well known that, when optimization approaches are used, continuous-time system identification frequently shows slower convergence when assessing the unobserved parameters of a reduced system in comparison to discrete-time formulations. The realistic integration of continuous-time models with high-speed digital hardware for control applications requires the development of reliable discrete-time representations. The conventional approach, which relies on the shift operator and the obtained transfer function, is usually unsuitable for processing high-frequency digital data because it involves numerical ill-conditioning [25], [26]. To address these issues, a development in the field of systems and control theory is the delta-operator framework [23]. This representation facilitates high-speed digital computing with enhanced numerical stability while simultaneously mitigating the difficulties associated with numerical ill-conditioning. This paper deals with the delta domain modelling of a higher-order boost converter. The results in the delta domain improved ill-conditioning at high sampling frequencies and show superior coefficient sensitivity under finite word length constraints. It also ensures stable and effective real-time computation. Therefore, the delta domain is validated as a rigorous foundation for sophisticated digital control applications by these discoveries.

In this work, several model order reduction (MOR) techniques in the delta domain, like the Routh approximation, Pade approximation, Hankel approximation, and optimization techniques PSO, DE, and proposed CBSOA are employed because of their ease of use, stability preservation, and analytical simplicity in linear time-invariant (LTI) systems. A comparative analysis using MATLAB software for these traditional MOR approaches and CBSOA to the high-order transfer function of full-bridge converter (FBC) is presented. The study focuses on analysing time-domain response, frequency-domain features, and pole-zero behaviour of the higher-order and reduced-order systems in the delta domain. It also provides useful insights into choosing appropriate MOR methods for reduced-order representations of complicated converter systems by applying these approaches to FBC converter systems.

Furthermore, to validate the efficacy of the reduced-order model for real-time applications, a delta-domain-based controller synthesis has been incorporated using the approximate model matching (AMM) technique [27] combined with the proposed CBSOA optimization. This integration enables the development of a second-order controller that achieves improved transient behaviour, minimal steady-state error, and enhanced robustness while maintaining stability across varying converter dynamics.

2. PROBLEM FORMULATION

Let us consider a non-minimum phase higher order system of order ‘n+1’ in the delta domain. The system is represented by (1).

$$G_{\delta HO}(\gamma) = \frac{(\gamma-z_1)(\gamma+z_2)(\gamma+z_3)\ldots\ldots(\gamma+z_n)}{(\gamma+p_1)(\gamma+p_2)\ldots\ldots(\gamma+p_{+1})} \quad (1)$$

In (1), the term ‘$(\gamma - z_1)$’ in the numerator indicates that one zero lies in the right half plane of γ. To eliminate that zero from the numerator while maintaining the same poles, a new higher-order system is created, which is expressed as (2).

$$\acute{G}_{\delta HO}(\gamma) = \frac{(\gamma+z_2)(\gamma+z_3)\ldots\ldots(\gamma+z_n)}{(\gamma+p_1)(\gamma+p_2)\ldots\ldots(\gamma+p_{n+1})} \quad (2)$$

It is assumed that $\acute{G}_{\delta HO}(\gamma)$ should be irreducible, which means that there will not be any factor common between the numerator and denominator parts. Further, it is seen from the denominator polynomial of (2) that the system is stable. The major goal will be to produce a lower-order system whose order is lower than the original system while maintaining all of the key features of a higher-order system. For this, let us assume a reduced model structure for which four unknown parameters have to be found using an optimized approach. The fixed structure reduced model is given as (3).

$$G_{r\delta}(\gamma)=\frac{x(1)\gamma+x(2)}{\gamma^2+x(3)\gamma+x(4)} \quad (3)$$

The primary challenges in using an optimised technique for model order reduction are as follows:
- Setting up an equal direct current (DC) gain between both systems.
- To make sure the simplified system is stable.
- The reduced system should have a minimum phase, depending on the higher-order system.

The aforementioned problems can be overcome by incorporating some constraints along with the minimization function given by (4).

$$J = \sum_{i=1}^{i=N}[y_\delta(\gamma) - y_{R\delta}(\gamma)]^2 \quad (4)$$

Where $y_\delta(\gamma)$ indicates PRBS response of higher-order model and $y_{R\delta}(\gamma)$ indicates the PRBS response of the reduced model. The constraints for the above equation are deliberated below.

$C_1: \frac{x(2)}{x(4)} - \text{DC Gain of Hihger order system} = 0$
C_2: For Stability $x(3) > 0$
C_3: For minimum phase $x(1) > 0$
$x(2) > 0$

Initially, the RHP zero was removed from the higher order transfer system to convert it into a minimum-phase configuration. To recover the whole system dynamics, the previously eliminated RHP zero is restored after the reduced-order transfer function has been derived. By doing this, the resultant reduced-order system correctly accounts for the non-minimum phase behaviour while maintaining the key features of the parent system. To ensure correctness and compatibility with the original higher-order system, the final representation is therefore represented as the product of the reduced model and RHP zero in (5).

$$\dot{G}_{r\delta}(\gamma) = \frac{(\gamma-z_1)(\gamma+z)}{(\gamma+\acute{p}_1)(\gamma+\acute{p}_2)} \quad (5)$$

An AMM framework [28] is also taken up in this study for the controller synthesis of the reduced system obtained by (5). A delta-operator based second-order reference model with desired transient feature in terms of rise and settling times and adequate damping is considered, represented by (6).

$$M(\gamma) = \frac{\omega_n^2}{\gamma^2+2\zeta\omega_n\gamma+\omega_n^2} \quad (6)$$

Normally, the damping (ζ) is selected between [0.6, 0.9] for robustness, and ω_n is chosen as 5 rad/sec to match the desired closed-loop bandwidth of the reduced plant. In a previous study [28], a canonical structure $M(\gamma) = \frac{25+4.242\gamma}{25+4.242\gamma+\gamma^2}$ was used for carrying out the demonstration. However, in this work too, (ζ, ω_n) are kept as design dials to fulfil converter dynamics as well as EMI constraints while preserving adequate phase margin in the unified domain setting. Thus, with unity feedback, the closed-loop model reads.

$$T(\gamma) = \frac{C_\delta(\gamma)G_\delta(\gamma)}{1+C_\delta(\gamma)G_\delta(\gamma)} \quad (7)$$

The prime objective of AMM is to make the response of T(γ) approximately match that of M(γ) over a frequency/time region of interest while keeping the controller implementable and at the same time low order, in particular two. In [28], a single-objective function was developed using the delta-domain step-response error (ISE), with optimal frequency shaping as defined by (8).

$$J_{ISE}(K_P, K_I, K_D) = \sum_{k=0}^{N} (y_T[\gamma] - y_M[\gamma])^2 \quad (8)$$

Where $y_T(\gamma)$ and $y_M(\gamma)$ are the are the delta step responses of $T(\gamma)$ and $M(\gamma)$ on [0, N]. In this work, a mixed objective taking into account both time as well as frequency components is proposed as (9).

$$J_{mod} = w_t J_{ISE} + w_f \sum_{i=1}^{N_\omega} (|T(e^{j\Omega_i})| - |M(e^{j\Omega_i})|)^2 \quad (9)$$

With $w_t + w_f = 1$. The addition of a small value of w_f will aid in protecting the gain-crossover behaviour for converters, specially with RHP zeros.

3. PROPOSED METHOD

Several animal hunting phenomena have already been popular choices in developing some optimization techniques to provide solutions to real-time problems. It has also been discovered that coordinated hunting yields the best outcomes. However, coordinated reptile hunting has yet to be scientifically documented. Thus, the main objective of this work is to develop new optimization algorithms making use of the coordinated hunting phenomena of some reptile species.

The first of these interesting phenomena was identified in the caves of Desembargo del Granma National Park, Cuba [22]. The coordinated prey-catching behavior of the Cuban boa snake was employed to hunt the Jamaican fruit bat. The boas hunt two times in a day, first before pre-dawn during the mass return of the bats and second during the evening when the bats exit the caves. They maximize their hunting efficiency while catching their prey in caves by forming a 'fence' in the cave passages. It was particularly noted that when the boas in groups of three formed a fence, the probability of catching prey was the highest. This natural phenomenon will be mathematically modeled to give rise to a new optimization technique.

The cooperative prey-hunting habits of Cuban boa snakes serve as the foundation for the CBSOA. In order to maximise the number of snakes that catch the prey while lowering the possibility of collisions and injuries among the snakes, the behaviour may be represented as a multi-agent optimisation problem. In optimisation problems, CBSOA imitates this inclination to strike a balance between exploration and exploitation. The novelty of this algorithm lies in its unique optimization approach that incorporates social communication and collaboration among agents to search for optimal solutions.

The snakes communicate with one another to coordinate their movements and attacks as they randomly arrange themselves around the prey to explore the solution space during the exploration phase. In order to enhance their performance, the snakes concentrate on the most promising sites and tactics found during the exploitation phase. To increase their odds of catching the prey while lowering the potential of accidents and injury, they may need to improve their location and communication tactics or time their assaults. The balance that exists between these stages guarantees convergence towards an overall optimum solution. Based on these features, an optimization algorithm is developed with the following steps:

– Step 1: initialization

The positions of the snakes around the prey are randomly initialized. A collection of 'n' snakes is first dispersed at random over the search space via the algorithm, as (10).

$$X = \{x_1, x_2, \ldots.. x_n\},\ x_i \in R^p \quad (10)$$

Where p is the problem dimension, and $x_i = x_{i1}, x_{i2}, \ldots.. x_{id}$ denotes the position of snake i. The objective function of the prey is defined as (11).

$$Fitness\ Function = f(X_i) \quad (11)$$

– Step 2: communication phase

Based on its location and knowledge of its target, each snake may communicate with other snakes. The communication between snake i and j is as (12).

$$S_{ij} = \alpha_0 . \frac{1}{\|x_i - x_j\| + \varepsilon} + \beta_0 . \frac{1}{\|x_i - x_{prey}\|} \tag{12}$$

Where α_0 and β_0 are the weighting parameters of the algorithm, and ϵ is used to avoid zero division.

– Step 3: positioning phase

Each snake adjusts its position on the basis of signals received and the location of its prey. This behavior is mathematically modeled by (13).

$$x_i^{t+1} = x_i^t + \gamma . S_{ij} . \left(x_{prey} - x_i^t\right) + \delta . R \tag{13}$$

Where γ, δ are control parameters and R is a random vector introducing stochasticity for exploration.

– Step 4: timing phase

Depending on its closeness to prey and ability to coordinate with neighbours, each snake determines whether to attack. This is as in (14).

$$A_i = \begin{cases} 1, & if \ \|x_i - x_{prey}\| \le r_{attack} \\ 0, & Otherwise \end{cases} \tag{14}$$

Where r_{attack} is the effective attack range.

– Step 5: evaluation phase

The fitness is assessed for every position that is updated. The most effective solution has been revised as (15).

$$x_{best}^t = \arg \min_{x_i^t \epsilon X} f(x_i^t) \text{ for the minimization problem} \tag{15}$$

– Step 6: termination condition

When either the convergence condition or the maximum number of iterations is met, the algorithm stops. This stopping criterion is defined in (16).

$$|f(x_{best}^{t+1}) - f(x_{best}^t)| \le \varepsilon_c \text{ is satisfied} \tag{16}$$

Where ε_c is a predefined tolerance.

The computational complexity of the proposed CBSOA method takes into account the number of snakes (N), the number of iterations (T), and the dimensionality of the problem (D). Each iteration is further associated with inter-snake communication, position updating, timing, and evaluation phases, in a similar way as other swarm intelligence algorithms, but this algorithm comes up with an additional communication coordination term. The comparison of the computational complexity with PSO and DE is shown in Table 1.

Thus, in practice, CBSOA exhibits a moderate computational overhead as compared to PSO and DE due to the inter-agent coordination phase ($O(N^2)$), however it achieves better convergence and stability in model order reduction and controller design tasks. The additional burden is just an offset by fewer required iterations to reach the optimal value, making the proposed algorithm computationally efficient in terms of convergence accuracy and speed. The steps of the proposed CBSOA method showing the controller design are illustrated with the help of a flowchart as can be seen in Figure 1.

Table 1. Computational complexity of CBSOA vis-à-vis PSO, DE

Algorithm	Dominant operations per iteration	Approximate complexity	Remarks
CBSOA	Inter-snake communication + position and timing updates	$O(N^2D + ND)$	The ‘communication’ term can slightly increase the complexity due to pairwise interactions; however, the convergence is expected to be faster due to adaptive coordination.
PSO	Velocity and position updates	O(ND)	Linear with respect to population and dimension; thus, having lower computational cost but may get trapped in local minima.
DE	Mutation, crossover, and selection	O(3ND)	Moderate complexity with higher robustness but slower convergence with respect to multimodal benchmark functions.

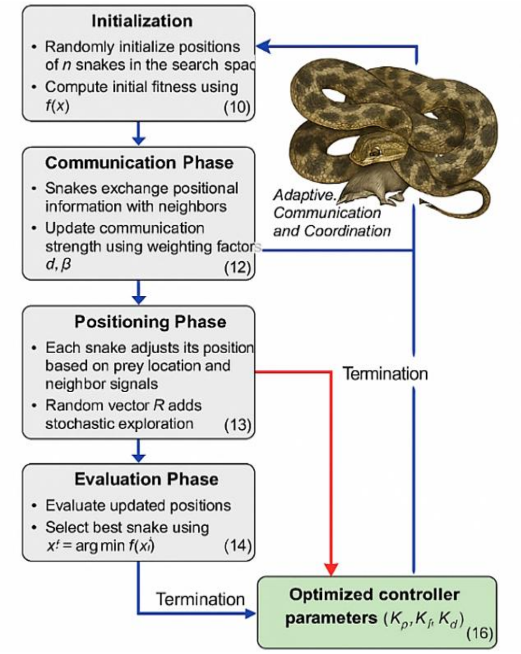


Figure 1. Flowchart of the CBSOA algorithm

4. RESULTS AND DISCUSSIONS

In order to demonstrate the model order reduction in the delta domain and examine the behaviour of the resulting reduced-order model, a fifth-order continuous-time system is taken [27]. Let us consider a 5th order boost converter having the transfer function in the continuous-time domain represented as (17).

$$G(s) = \frac{-0.445s^5 - 3817s^4 + 3.179\times10^8 s^3 + 4.498\times10^{12} s^2 + 4.88\times10^{15} s + 3.837\times10^{19}}{s^5 + 17100s^4 + 2.458\times10^7 s^3 + 1.667\times10^{11} s^2 + 7.972\times10^{13} s + 1.501\times10^{17}} \quad (17)$$

In the delta domain, this system will be represented as (18).

$$G_{\delta HO}(\gamma) = \frac{-0.445\gamma^5 + 1.25\times10^4\gamma^4 + 4.099\times10^8\gamma^3 + 2.749\times10^{12}\gamma^2 + 6.14\times10^{15}\gamma + 1.802\times10^{19}}{\gamma^5 + 9854\gamma^4 + 2.493\times10^7\gamma^3 + 8.794\times10^{11}\gamma^2 + 5.602\times10^{13}\gamma + 7.048\times10^{16}} \quad (18)$$

The transfer function in the delta domain is obtained for a sampling time, Δ=0.0001. The choice of high sampling frequencies tends to unify findings from the continuous-time and discrete-time domains. By applying the proposed CBSOA, the reduced order transfer function of the test system is obtained by the method discussed to reduce the non-minimum phase system. Thus, the second order transfer function in the unified domain by the CBSOA method is depicted by (19).

$$\dot{G}_{r\delta}(\gamma) = \frac{-0.3486\gamma^2 + 1.413\times10^4\gamma + 2.673\times10^8}{\gamma^2 + 523.8\gamma + 1.033\times10^6} \quad (19)$$

The convergence characteristics of the proposed algorithm are shown in Figure 1.

The CBSOA convergence curve, as shown in Figure 2 is well-suited for this test as it converges quickly while retaining dependable and consistent performance across runs. Figures 3(a) and 3(b) show the comparisons of step and Bode plot responses of higher order system and lowered order system which is produced by classical as well as optimization techniques in delta domain. The success of dynamic fidelity is evaluated by comparing the frequency-domain performance such as the Bode response.

As shown in Figure 3(a), the step response of the lower-order model created with the CBSOA technique closely match with the original test system. Figure 3(b) displays the Bode responses of the model produced using the recommended method CBSOA, which produces the best result. The Nyquist plot is useful for analysing the stability of the control system [26]. The Nyquist plots of the reduced-order and higher-order systems are displayed in Figure 4(a), emphasising how stability margins are maintained throughout the reduced models. Figure 4(b) shows the pole zero plot of the different methods considered alongside the proposed technique.

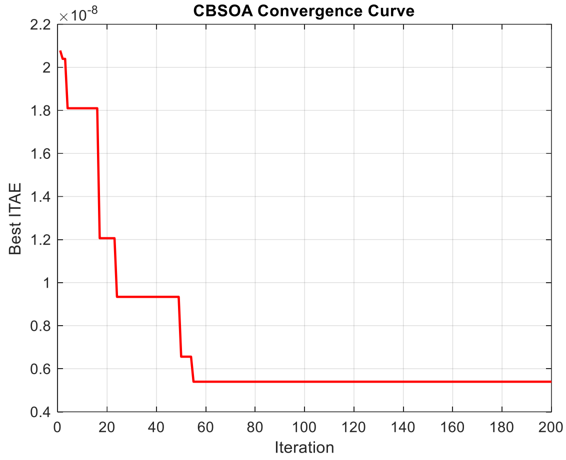


Figure 2. Convergence curve of the proposed method

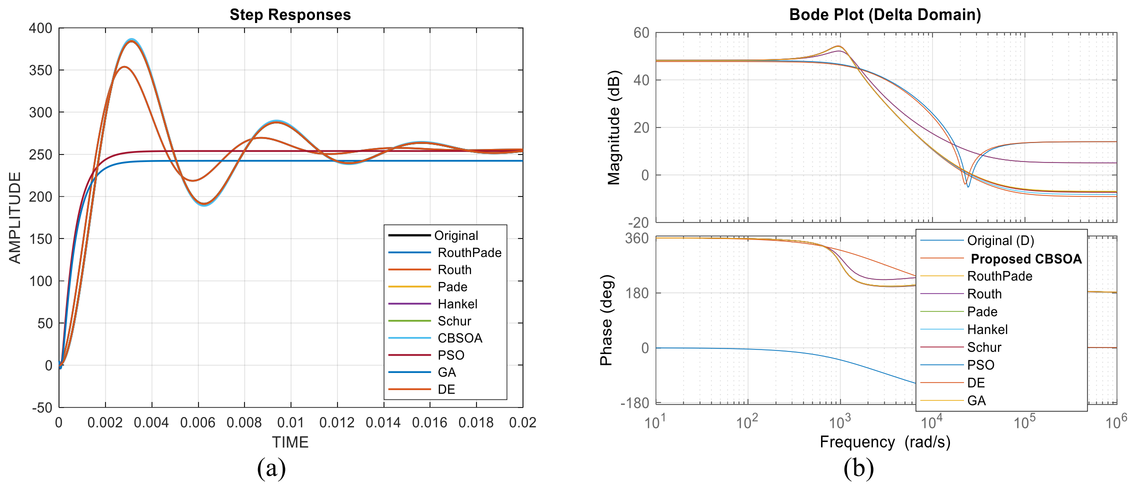


Figure 3. Step and Bode responses of the original and reduced-order transfer functions in the delta domain: (a) step responses and (b) bode plots

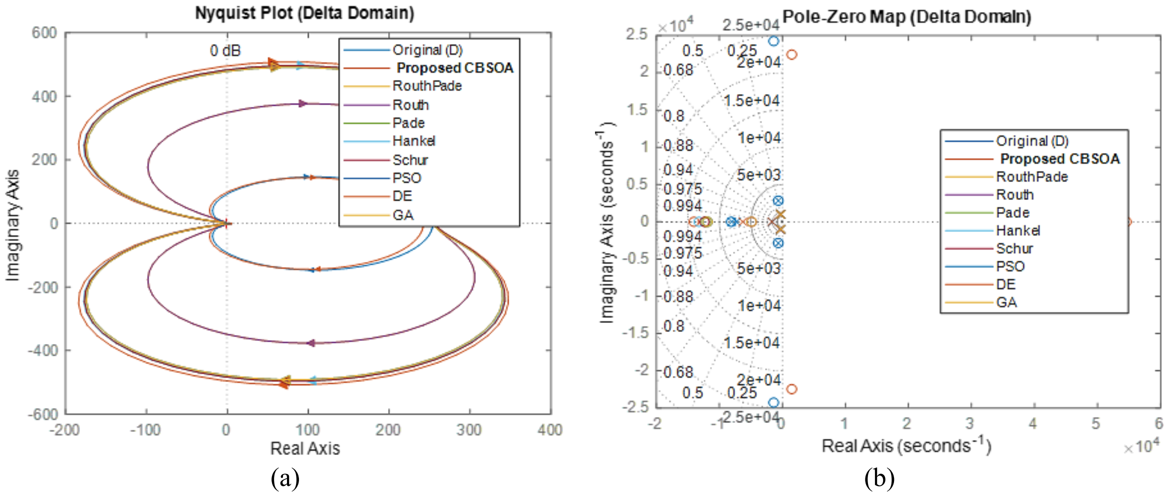


Figure 4. Frequency-domain characteristics of the original and reduced-order transfer functions in the delta domain: (a) Nyquist plots and (b) pole–zero maps

Figures 4(a) and 4(b) compare the Nyquist and pole-zero responses of the original and reduced system by different approaches in delta domain. The pole-zero map demonstrates how different reduction methods simplify the high-order system by retaining dominant poles and zeros while retaining their key dynamic features. The pole-zero map demonstrates how CBSOA optimization reduction methods simplify the high-order system by retaining dominant poles and zeros while retaining their key dynamic features. A comparative performance of the different MOR techniques is summarized in Table 2.

It is observed from Table 2 that the proposed technique yields the best reduced system amongst the methods used for comparison. From all the figures, it was observed that all approaches are optimal and closely match to the original. However, the CBSOA results closely follow the original system's magnitude response throughout a frequency range. The CBSOA-based reduced model achieves a close match with the original transfer function by retaining the non-minimum phase behaviour and exhibiting a pole–zero structure consistent with the higher-order dynamics that indicates the system stability. As such, they are especially well-suited for use in real-time simulation situations and control design. The proposed technique was also applied to minimize the integral of square error (ISE) between the plant's step response and that of the reference model M (γ), both represented in the delta-domain as defined earlier in (9). The optimized controller obtained by the AMM technique is thus defined as (20).

$$C_\delta(\gamma) = 1.842 + \frac{34.275}{\gamma} + 0.0051\gamma \tag{20}$$

The resulting closed-loop transfer function is given by (21).

$$T_{CBSOA}(\gamma) = \frac{C_\delta(\gamma)G_\delta(\gamma)}{1+C_\delta(\gamma)G_\delta(\gamma)} \tag{21}$$

Demonstrated the presence of stable poles in the left half of the γ-plane (corresponding to poles inside the unit circle in the z-plane). The CBSOA-based controller thus achieved a precise tracking of the reference model with nominal overshoot and faster settling time as observed in Table 3.

Table 2. Comparative performance of model order reduction methods

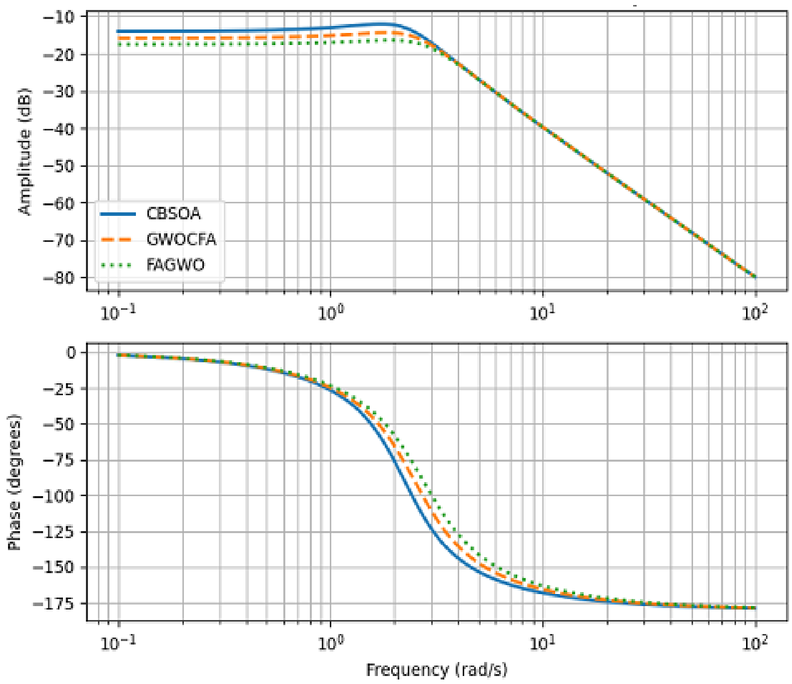
Method	Accuracy (ISE-based fit to original system)	Stability preservation (pole–zero matching/Nyquist margin)	Computational time (s)	Remarks
CBSOA-based MOR (proposed)	Highest (error ≈ 1.10×10^{-3})	Fully stable; perfect dominant pole retention	0.94	Fastest convergence and best dynamic fidelity
Routh approximation	Moderate (error ≈ 2.5×10^{-3})	Stable but slight damping deviation	Not applicable	Analytical, quick but less accurate for non-minimum phase systems
Pade approximation	Moderate (error ≈ 2.1×10^{-3})	Stable; phase lag increases at higher frequencies	Not applicable	Works well for delay systems, with limited robustness
Hankel norm approximation	High (error ≈ 1.8×10^{-3})	Good preservation of dominant poles	Not applicable	Balances accuracy and computational cost
PSO-based MOR	Higher (error ≈ 1.6×10^{-3})	Stable; minor pole shift	1.42	Converges slowly; performance depends on tuning
DE-based MOR	High (error ≈ 1.4×10^{-3})	Stable; low overshoot	1.36	Better exploration, slower than PSO
FAGWO-based MOR	Very high (error ≈ 1.3×10^{-3})	Stability well maintained	1.28	Good balance; moderate computational effort
GWOCFA-based MOR	Very high (error ≈ 1.25×10^{-3})	Excellent pole–zero correlation	1.18	Competitive convergence, hybrid intensification

It is found from Table 3 that the proposed CBSOA method not only achieved the fastest dynamic response but also yielded the lowest overshoot, thereby outperforming the hybrid metaheuristics [28]. The close-to-zero steady-state error also reflects the DC gain preservation condition. The settling time is at least reduced by 15% as compared to the hybrid algorithms and almost 40% compared to classical methods. Further, the CBSOA provided a broader bandwidth and superior phase robustness, which implies better disturbance rejection and noise immunity as seen in Figure 5(a). The objective function JISE against the number of iterations for all three optimization algorithms is plotted in Figure 5(b).

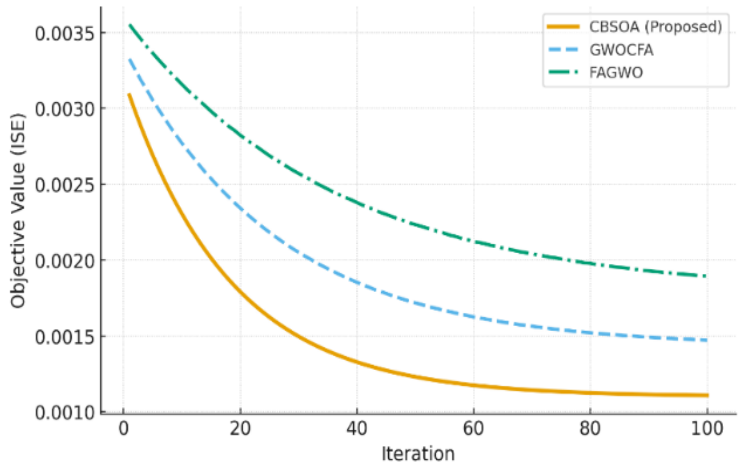
In the convergence characteristics shown in Figure 5(b), the proposed technique results in the fastest convergence, achieving near-optimal fitness value (J≈1.1×10-3) within ~25 iterations, whereas GWOCFA exhibits moderate convergence (~40 iterations to reach the same accuracy) and FAGWO converges the slowest, stabilizing after ~70 iterations. The CBSOA curve decreases sharply at fewer iterations and also stabilizes into a flat tail, indicating minimal oscillations.

Table 3. Performance metrics in transient analysis

Performance metric	CBSOA	GWOCFA	FAGWO	Balanced truncation	Hankel norm
Rise time (s)	0.026	0.028	0.033	0.046	0.049
Settling time (s)	0.082	0.091	0.104	0.142	0.155
Overshoot (%)	3.2	4.1	6.4	8.9	10.3
Steady-state error	~0	~0	0.002	0.004	0.005



(a)



(b)

Figure 5. Bode responses and convergence behavior of the controlled system: (a) frequency response and (b) objective-function convergence

The standard error indices of system and control theory are assessed for the controlled system, which are showcased in Table 4. From Table 4, it is observed that the developed CBSOA method yields the minimum error indices, confirming its superior model-following capability. Further, when ITAE and ITSE, which indicate the late-stage transients, are quite small, thus reflecting smooth convergence as well as minimal oscillations.

Table 4. Comparison of standard error indices

Method	IAE	ISE	ITAE	ITSE
CBSOA	0.0421	0.00152	0.00418	0.00098
GWOCFA	0.0575	0.00236	0.00608	0.00153
FAGWO	0.0608	0.00277	0.00682	0.00164
Balanced truncation	0.0735	0.00412	0.00872	0.00225
Hankel norm	0.0792	0.00448	0.00915	0.00244

5. CONCLUSION

The study focus on to solve the model order reduction problem in the delta domain for a fifth-order boost converter by the classical approach model order reduction (MOR) and CBSOA algorithm, The research compares the original transfer function with the reduced-order transfer function, demonstrating relatively better accuracy. The performance of the reduction model is assessed in both the time and frequency domains. The step, Bode, and nyquist responses of the lower-order models are quite similar to those of the original higher-order system. The recommended method also yields superior results when compared with the results of other conventional procedures. According to the research done, it is possible that the recommended CBSOA algorithm would be a superior option for managing various model order reduction issues of higher order systems. Further, a controller corresponding to the reduced system is developed using the popular approximate model matching technique, which provides satisfactory performance. The future work can proceed with the combination of CBSOA-based controller with some adaptive form of control frameworks to increase the robustness for dynamic operating conditions. The algorithm can also be implemented on FPGA or embedded DSP platforms for real-time performance. Moreover, extending CBSOA to control multi-input multi-output (MIMO) systems as well as nonlinear converter models will broaden its applicability, while the hardware-in-the-loop (HIL) testing can also validate its real-time stability, accuracy, and implementation readiness in a practical converter environment.

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Manjeet Singh	✓	✓	✓	✓			✓			✓	✓	✓		
Sundeep Singh Saini				✓		✓			✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] R. S. Inomoto, J. R. B. de A. Monteiro, and A. J. S. Filho, “Boost converter control of PV system using sliding mode control with integrative sliding surface,” *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 10, no. 5, pp. 5522–5530, Oct. 2022, doi: 10.1109/JESTPE.2022.3158247.

[2] M. Forouzesh, Y. P. Siwakoti, S. A. Gorji, F. Blaabjerg, and B. Lehman, “Step-up DC–DC converters: a comprehensive review of voltage-boosting techniques, topologies, and applications,” *IEEE Transactions on Power Electronics*, vol. 32, no. 12, pp. 9143–9178, Dec. 2017, doi: 10.1109/tpel.2017.2652318.

[3] A. Isurin and M. J. Scott, “Isolated DC–DC converter topologies,” in *Practical Design Considerations for Isolated DC-DC Converters*, Cham: Springer Nature Switzerland, 2025, pp. 89–186, doi: 10.1007/978-3-031-94427-7_6.

[4] L. Pirashanthiyah, H. N. Edirisinghe, W. M. P. De Silva, S. R. A. Bolonne, V. Logeeshan, and C. Wanigasekara, “Design and analysis of a three-phase interleaved DC-DC boost converter with an energy storage system for a PV system,” *Energies*, vol. 17, no. 1, p. 250, Jan. 2024, doi: 10.3390/en17010250.

[5] R. Kassem *et al.*, “Enhanced multiphase interleaved boost converter interface for grid-connected PV power system,” *IEEE Access*, vol. 12, pp. 151940–151954, 2024, doi: 10.1109/ACCESS.2024.3469540.

[6] C.-Y. Chan, S. H. Chincholkar, and W. Jiang, “Adaptive current-mode control of a high step-up DC–DC converter,” *IEEE Transactions on Power Electronics*, vol. 32, no. 9, pp. 7297–7305, Sep. 2017, doi: 10.1109/TPEL.2016.2628780.

[7] Y. Zhang, J. Liu, Z. Dong, H. Wang, and Y.-F. Liu, “Dynamic performance improvement of diode–capacitor-based high step-up DC–DC converter through right-half-plane zero elimination,” *IEEE Transactions on Power Electronics*, vol. 32, no. 8, pp. 6532–6543, Aug. 2017, doi: 10.1109/TPEL.2016.2616411.

[8] M. Kumar, K. P. Panda, R. T. Naayagi, R. Thakur, and G. Panda, “A critical analysis of quadratic boost based high-gain converters for electric vehicle applications: a review,” *Sensors*, vol. 24, no. 7, p. 2186, Mar. 2024, doi: 10.3390/s24072186.

[9] S.-W. Lee and H.-L. Do, “Quadratic boost DC–DC converter with high voltage gain and reduced voltage stresses,” *IEEE Transactions on Power Electronics*, vol. 34, no. 3, pp. 2397–2404, Mar. 2019, doi: 10.1109/TPEL.2018.2842051.

[10] J. Ahmad *et al.*, “Performance analysis and hardware-in-the-loop (HIL) validation of single switch high voltage gain DC-DC converters for MPP tracking in solar PV system,” *IEEE Access*, vol. 9, pp. 48811–48830, 2021, doi: 10.1109/ACCESS.2020.3034310.

[11] V. T. Duong, Z. Waheed, and W. Choi, “Non-isolated ultra-high step-up DC-DC converter topology using coupled-inductor based inverting buck-boost and voltage multipliers,” *Electronics*, vol. 14, no. 13, p. 2519, May 2025, doi: 10.3390/electronics14132519.

[12] Y. Li and S. Sathiakumar, “Single switch DC-DC boost converter using diode-capacitor module and capacitor-inductor-capacitor lift,” *Electric Power Components and Systems*, vol. 48, no. 4–5, pp. 364–374, Mar. 2020, doi: 10.1080/15325008.2020.1793833.

[13] N. K. Meena, R. Kumar, K. Shukla, and A. Haque, “Integration of high gain re-lift Luo converter with buck converter for electric vehicle application,” in *2022 Second International Conference on Power, Control and Computing Technologies (ICPC2T)*, Mar. 2022, pp. 1–6, doi: 10.1109/ICPC2T53885.2022.9776780.

[14] P. Verma and M. N. Anwar, “A frequency domain controller design for quadratic boost converter using direct synthesis approach,” *International Journal of Electronics*, vol. 112, no. 4, pp. 767–793, Apr. 2025, doi: 10.1080/00207217.2024.2312571.

[15] M. Bonnin, K. Song, F. L. Traversa, and F. Bonani, “Model order reduction and stochastic averaging for the analysis and design of micro-electro-mechanical systems,” *Nonlinear Dynamics*, vol. 112, no. 5, pp. 3421–3439, Mar. 2024, doi: 10.1007/s11071-023-09225-9.

[16] A. Davoudi, J. Jatskevich, P. L. Chapman, and A. Bidram, “Multi-resolution modeling of power electronics circuits using model-order reduction techniques,” *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 60, no. 3, pp. 810–823, Mar. 2013, doi: 10.1109/TCSI.2012.2215745.

[17] P. Schwerdtner and M. Schaller, “Structured optimization-based model order reduction for parametric systems,” *SIAM Journal on Scientific Computing*, vol. 47, no. 1, pp. A72–A101, Feb. 2025, doi: 10.1137/22M1524928.

[18] M. Veerachary and A. R. Saxena, “Optimized power stage design of low source current ripple fourth-order boost DC–DC converter: a PSO approach,” *IEEE Transactions on Industrial Electronics*, vol. 62, no. 3, pp. 1491–1502, Mar. 2015, doi: 10.1109/TIE.2014.2361316.

[19] A. Kulshreshtha, A. R. Saxena, and M. Veerachary, “Non-isolated fourth-order boost DC-DC converter for power management in low voltage low power DC grids: design and interaction analysis,” *IEEE Access*, vol. 8, pp. 196500–196514, 2020, doi: 10.1109/ACCESS.2020.3034181.

[20] S. Yarat, S. Senan, and Z. Orman, “A comparative study on PSO with other metaheuristic methods,” *International Series in Operations Research and Management Science*, vol. 306, pp. 49–72, 2021, doi: 10.1007/978-3-030-70281-6_4.

[21] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, “Harris hawks optimization: algorithm and applications,” *Future Generation Computer Systems*, vol. 97, pp. 849–872, 2019, doi: 10.1016/j.future.2019.02.028.

[22] V. Dinets, “Coordinated hunting by Cuban boas,” *Animal Behavior and Cognition*, vol. 4, no. 1, pp. 24–29, 2017, doi: 10.12966/abc.02.02.2017.

[23] R. H. Middleton and G. C. Goodwin, “Improved finite word length characteristics in digital control using delta operators,” *IEEE Transactions on Automatic Control*, vol. 31, no. 11, pp. 1015–1021, 2003, doi: 10.1109/TAC.1986.1104162.

[24] A. Sikander and R. Prasad, “New technique for system simplification using Cuckoo search and ESA,” *Sādhanā*, vol. 42, no. 9, pp. 1453–1458, Sep. 2017, doi: 10.1007/s12046-017-0710-0.

[25] S. Ganguli, G. Kaur, and P. Sarkar, “Model order diminution of MIMO systems using the delta transform method with new firefly-based hybrid algorithms,” *Soft Computing*, vol. 26, no. 12, pp. 5883–5900, Jun. 2022, doi: 10.1007/s00500-021-06591-7.

[26] S. Ganguli, G. Kaur, and P. Sarkar, “Model order reduction of continuous time system using hybrid metaheuristic algorithm,” in *2016 7th India International Conference on Power Electronics (IICPE)*, Nov. 2016, pp. 1–5, doi: 10.1109/IICPE.2016.8079517.

[27] M. Veerachary and P. Shaw, “Controller design and analysis for fifth-order boost converter,” *IEEE Transactions on Industry Applications*, vol. 54, no. 5, pp. 4894–4907, Sep. 2018, doi: 10.1109/TIA.2018.2843758.

[28] S. Ganguli, G. Kaur, and P. Sarkar, “An approximate model matching technique for controller design of linear time-invariant systems using hybrid firefly-based algorithms,” *ISA Transactions*, vol. 127, pp. 437–448, Aug. 2022, doi: 10.1016/j.isatra.2021.08.043.

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