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Comparative Evaluation of Bio-inspired Controller for a Buck-Boost Converter

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ABSTRACT

This paper compares the performance of Ant colony optimization (ACO) based PI controller, Bacterial foraging optimization (BFO) based PI controller and conventional PI controller applied to a buck boost converter. The Controllers implemented in feedback loop. The design has a feedback-controller for DC-DC boost converter which would maintain a constant output voltage of -24V. The derived design equations are modeled in MATLAB followed by extensive simulation carried out with linear controller parameters and results are published. The controllers are developed to stabilize the output voltage of the converter and improve the performance of the buck-boost converter during transient operations. Simulation results obtained during load and line variations. It shows that the BFO based PI Controller was able to achieve faster transient response and had a stable steady state response.

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INTRODUCTION

The buck-boost converter, a variant of DC-to-DC converter, has an output voltage which could be either lesser than or greater than the input voltage. There is a steady increase in popularity for DC-Power Supply which in the past was limited to electronic devices. Recently, DC Power supply is being widely used in aerospace applications and is proved to be essential for electric vehicles. A DC-DC converter is indispensable to satisfy the DC voltage source level requirements of the DC power supply load. Likewise, the DC-DC converter is vital in applications such as power conditioning of the photovoltaic-alternative electrical energy, wind generator as well as fuel cell systems. For these reasons, DC-DC converter applications are expected to be highly prevalent in the future.

Primarily, the DC-DC converter consists of power semiconductor devices which operate as electronic switches. All such DC-DC converters including Buck-Boost converters function as switching devices that ascribe them to have inherently non-linear characteristics. For this reason, a converter requires a controller with a high degree of dynamic response. Traditionally, Proportional-Integral-Differential (PID) controllers are usually applied to the converters because of their simplicity. However, by implementing this control method to the nonlinear power converters will yield to have dynamic response of the converter's output voltage regulation.

In order to regulate the time-domain behavior among different types of dynamic plants, Proportional-integral-derivative (PID) controllers are the most frequently used in the control system. These controllers gained popularity due to their simple structure and the ability to provide good closed-loop response. However, despite its simple structure, finding a proper PID controller, had always been difficult and various innovations were made by tuning the parameters (Erickson, 1991). Even Standard methods like Ziegler-Nichols tuning method fails to find the optimal PID parameters. Hence many optimization methods were developed to tune the PID controllers such as fuzzy logic is discussed by (Siotine and Li, 1991 and Arulselvi *et al.*, 2004), neural network (Alvarez-Ramirez *et al.*, 2001), neural-fuzzy logic (Cortes *et al.*, 2004), immune algorithm (Tsang *et al.*, 2008), simulated annealing (Sreekumar *et al.*,2007), and pattern recognition (Ioannidis *et al.*, 1998). In the search of optimum tuning PID methods, random search methods such as genetic algorithm (He and Xu *et*

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al.,2007, Ding *et al*., 2007) particle swarm optimization (Guo *et al*., 2002), and ant colony optimization (Oonsivilai *et al*., 2008), Bacterial foraging optimization (Mary Synthia Regis Prabha *et al*., 2011) were also identified to be effective.

Keeping in mind of the above objective, an appropriate function is then derived which proved as evidential in the evolutionary optimization. An evolutionary algorithm powered by the attributes of the small signal model of the power converters yield a feedback controller which is robust enough to reject internal and external disturbances. The optimization technique is expected to provide dynamic and static characteristics at all operating points, and the simulation results are verified through measured results to prove the fact.

This paper focuses on using Bio inspired algorithm based PI controller for a buck-boost converter and comparing the results with conventional PI controller. This paper focuses on using bio intelligent controller for a buck-boost converter and comparing the results with conventional PI controller. The modeling of buck-boost converter is explained in section II. The design of controller is discussed in section III. The simulation results are displayed and discussed in section IV. Section V deals with conclusion.

Modeling of Buck Boost Converter:

A Buck-Boost converter is a step-down and step-up DC-DC converter. The output of Buck-Boost converter's output is controlled by the duty cycle of the Pulse Width Modulation (PWM) input at fixed frequency. Whenever the duty cycle (dc) is less than 0.5, the output voltage of the converter will be lower than the input voltage. However, when the duty cycle is above 0.5 the output voltage of the converter is higher than the input voltage. A Buck-Boost converter's basic power stage is shown in Fig. 1. The following specifications were considered in this paper : input voltage, V_I =12V; switching frequency, Fs=250KHz; Inductance L=220µH; the ESR inductor, L_r =.2Ω; capacitor, C=220µF; equivalent resistance of the capacitor, C_r =0.1Ω, and load resistance, R_L =120Ω.

In this controller, it is necessary to compare the Vref (reference value, sometimes called as demand voltage) to the output voltage and then appropriate remedial action is required to ensure Vout = Vref. Ideally this is accomplished by generating an error signal e=Vref-Vout which is minimized by the controller (sometimes referred to as a compensator). Morever then it manipulates to adjust Vout by varying the duty cycle (dc).

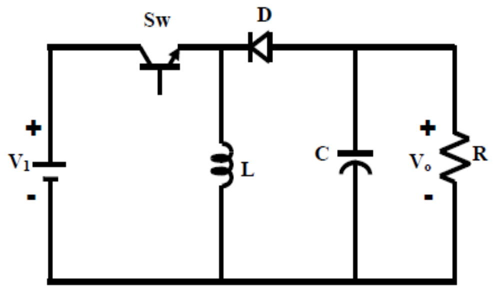

Fig. 1: Buck-Boost Converter

The converter contains two independent ac inputs, the control $\hat{d}(s)$ & line $\hat{v}_I(s)$ and an output $\hat{v}_o(s)$.

The control-to-output transfer function can be defined as

$$G_{vd}(s) = \left(-\frac{V_I - V_O}{D'^2}\right)\frac{\left(1 - s\frac{LI}{V_I - V_O}\right)}{1 + s\frac{L}{D'^2 R} + s^2\frac{LC}{D'^2}} \qquad (1)$$

To assess the dynamic performance of the buck-boost converter, the above explained equations are modeled using matlab/simulink.

Design of controller:

In this work, more emphasis is given for improving the dynamic response of the DC-DC buck-boost by identifying proper controller parameter. The following dynamic parameters are considered in this work.

i) Rise Time (T_r)
ii) Settling Time (T_s)
iii) Peak Overshoot (P_o)
iv) Steady State Error (E_{ss})

The objective of improved dynamic response of DC-DC buck-boost converter is perceived as an optimization task and solved. Therefore the optimization problem is formulated as:

Minimize:

$$F(\phi) = \left((1+T_r)*(1+T_s)*(1+E_{ss})*(1+P_o)\right) \qquad (2)$$

Subject to constraints:

$$K_{p(\min)} < K_p < K_{p(\max)}$$
$$K_{I(\min)} < K_I < K_{I(\max)} \qquad (3)$$

A. ***Design of PI controller:***

In a controller it is necessary to compare the output voltage to a reference value V_{ref} (sometimes called a demand voltage) and then take appropriate remedial action to ensure that $V_{out} = V_{ref}$. Usually, this is achieved by generating an error signal $e=V_{ref} - V_{out}$ which is minimized by the controller (sometimes referred to as a compensator) which then manipulates in such a manner so as to adjust V_{out} by varying the duty cycle (dc).

Referring to Fig. 2, the output voltage is compared to a reference producing an error signal, (e). The error signal is individually applied to each term of the compensator after which they are combined forming the duty cycle input command to the buck- boost converter. The proportional gain Kp acts as a feed-forward term allowing any changes in the error to be passed to the compensator output without delay. Kp must be carefully chosen because large values tend to induce instabilities in the system response. The integral term Ki is used to reduce the steady-state error at the expense of reducing the dynamic response.

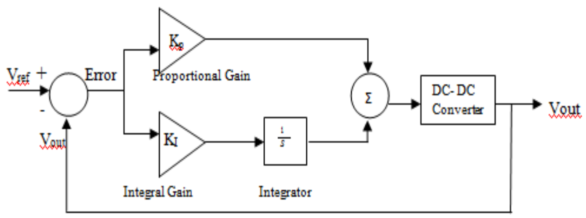

Fig. 2: Block diagram of PI control system.

The PI controller designed for a buck-boost converter is given in equation. The controllers can be introduced in either feed-back or feed-forward path which will control the steady state error and transient performance. In most of the practical control systems, the input to the controlling device is error.

The controller transfer function is given in equation (4)

$$G_C(s) = K_P + \frac{K_I}{s} \quad (4)$$

The phase margin ϕ_m at ω is determined from the settling time. Phase and Magnitude response equation is given in (5) and (6)

$$\phi_m + \angle G(j\omega)H(j\omega)G_C(j\omega) = \angle 180 \quad (5)$$

ϕ_m is desired phase margin at ω

$$\left|G(j\omega)H(j\omega)G_C(j\omega)\right| = 1 \quad (6)$$

Solving these two equation (5) and (6) we get the K_I and K_P value.

$$G_C(s) = 0.125 + \frac{0.157}{s} \quad (7)$$

B. ***ACO based PI controller:***

Ant colony optimization algorithms are especially suited for finding solutions to difficult optimization problems. A colony of artificial ants helps to find good solutions, by using the emergent property of the ant's cooperative interaction. Ant colony algorithms are adaptive and robust in nature due to their similarities with ant. This property can be applied to different optimization problems as well as different versions of the same problem.

The main traits of artificial ants are derived from their natural model. Such borrowed traits include: (1) Cooperative existence in colonies with other ants, (2) Indirect information transmission by depositing pheromone (stigmergic communication), (3) repetitive local moves in a sequence to find the shortest path to a destination point, and (4) applying a stochastic decision policy using local information alone to find the best solution. In order to a particular optimization problem, artificial ants are enriched with additional capabilities which are not present in real ants.

For a given optimization problem, the best solution is searched by finite sized ant colony. Each ant can find a solution or at least part of the solution to the optimization problem on its own, but the optimal solution can be achieved only when many ants work together. Since the optimal solution can only be achieved through global cooperation of all the ants in a colony, it is a promising result of such cooperation. The ants do not communicate directly while searching for a solution, but they communicate indirectly by adding pheromone to the environment. The ant finds the shortest path for a particular problem from a given starting state by moving through a sequence of neighboring states. It moves based on a non-deterministic local search policy influenced by its own internal state (private information), the pheromone trails, and local information encoded in the environment (together public information). Ants use this private and public information to decide when and where to deposit pheromones. The amount of pheromone deposited by an ant is proportional to the quality of the movement made by an ant. It concludes more the pheromone, the better the solution, obtained. Once an ant has found a solution; it dies, that is, it is deleted from the system.

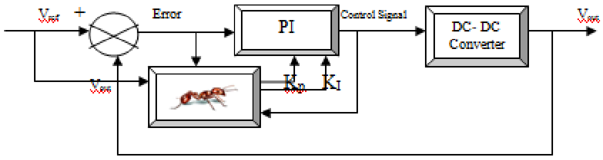

Fig. 3: PI Control System

The PI controller is implemented to improve the dynamic response in addition to reducing or eliminating the steady state error. To characterize the performance of the PI controller systems, performance of the transient response such as rise time (t_r), the integral square error (ISE), overshoot (O_s), settling time (t_s), Integral Absolute Error (IAE), Integral Time Absolute Error (ITAE), Integral Time square Error (ITSE) are computed. Tuning the parameters of the PI controllers using the multiobjective ant colony optimization is indicated in Fig.3.

The basic step in applying optimization method is to choose the optimization criteria that are used to evaluate fitness. Since the PI controller has many performance indexes of the transient response, then they can be combined into one objective function composed of the weighted sum of objectives.

The objective function must be set:

$$L^A = \min(\phi F) \tag{8}$$

where F = [f1 f2 f3 f4 f5 f6 f7]^T: vector of objective functions, f1: settling time (T_s), f2: overshoot (O_S), f3: rise time (T_r), f4: integral absolute error (IAE), f5: integral square error (ISE), f6: integral time absolute error (ITAE), Φ = [λ1 λ2 λ3 λ4 λ5 λ6 λ7]: vector of nonnegative weights and f7: integral time square error (ITSE).

ACO uses a pheromone matrix $\tau = \{\tau_{ij}\}$ for the construction of potential good solutions. The initial values of τ are set $\tau_{ij} = \tau_0$ for all (i, j), where $\tau_0 > 0$.

The probability P_{ij}^A (t) of choosing a node j at node i is defined in (9). At each evolution of the algorithm, the ant constructs a complete solution using (9), starting at source node.

$$P_{ij}^A(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\Sigma_{i,j\in T^A}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}, \; if\ i, j \in T^A \tag{9}$$

where η_{ij} representing heuristic functions, constant α - determine the relative influence of pheromone values where constant - β determine the relative influence of the heuristic values and at a given time, T^A: is the path effectuated by the ant A.

The pheromone evaporation is a way to elude unlimited increase of pheromone trails and it allows the forgetfulness of the poor decisions

$$\tau_{ij}(t) = \rho\tau_{ij}(t-1) + \sum_{A=1}^{NA}\Delta\tau_{ij}^A(t) \tag{10}$$

Where the quantity of pheromone on each path, NA represents number of ants, ρ indicates the evaporation rate. Evaporation rate lies between zero and one ($0 < \rho \leq 1$).

The following general algorithm can describe the proposed algorithm.

Begin:

Step1. Initialize randomly potential solutions of the parameters (K_i, K_p) by using uniform distribution.

Initialize the heuristic value and the pheromone trail.

Initialize the Pareto set to an empty set.

Step 2. Place the Ath ant on the node.

Compute the heuristic value associated in the multiobjective L^A.

Choose the successive node with probability:

$$P_{ij}^A(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]\beta}{\Sigma_{i,j\in T^A}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}, \qquad if\ i, j \in T^A \tag{11}$$

where $\eta_{ij} = 1/K_j$, j = [P,I]: representing heuristic functions, at a given time T^A: represents the path effectuated by the ant A. The quantity of pheromone on each path may be defined as:

$$\Delta\tau_{ij}^A = \begin{cases} \frac{L^{\min}}{L^A}, & ifi,\ j \in T^A, \\ 0, & else \end{cases} \tag{12}$$

where L^A is the value of the objective function found by the ant A. Till the current iteration, L min is the best optimal solution brought out by the set of the ants.

Step3. Use pheromone evaporation given by (10) to avoid an infinite progression of pheromone trails and allow the forgetfulness of bad choices:

$$\tau_{ij}(t) = \rho\tau_{ij}(t-1) + \Sigma\sum_{A=1}^{NA}\Delta\tau_{ij}^A(t) \tag{13}$$

where NA: number of ants and ρ: the evaporation rate $0 < \rho \leq 1$

Step 4. Evaluate the obtained solutions according to the different objectives.

Update the Pareto archive with the non-dominated ones.

Reduce the size of the archive if necessary.

Step 5. Display the optimum values of the optimization parameters.

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Step 6. Globally update the pheromone, according to the optimum solutions calculated at Step 5.

Iterate from Step 2 until we reach the maximum number of iterations.

End:

C. ***BFO based PI controller:***

Bacterial Foraging Algorithm mimics how bacteria forage over a landscape of nutrients to perform parallel non gradient optimization. This algorithm is inspired by the social foraging behavior of Escherichia Coli. The bacteria moves by taking small steps while searching for nutrients to maximize its energy, known as chemotaxis.

Table I: Controller parameter

Method	Controller Parameters	
	Kp	K_I
Conventional PI controller	0.125	0.157
ACO based PI	0.45	1.2
BFOA based PI	0.214	1.7678

- *Fitness Evaluation*: Evaluate objective function for the entire population.
- *Sorting:* Arrange population according to fitness.
- *Store:* keep a record of the Best fitness value at the end of iteration out of the 10 values generated to know the convergence.
- *Run &tumble:* Bacteria take small steps in any direction in order to search for food. They take n steps in same direction till they can minimize their energy.
- *Reproduction:* Bacteria split into two and again each individual tries to find nutrients.
- *Elimination & Dispersal:* the bottom 50% population previously obtained is now replaced by the new bacteria formed.

The above steps are repeated till the termination criteria are met. A dedicated matlab code is written for the bacterial foraging algorithm.

The values obtained for the controller parameters using ACO, BFOA and conventional controller are shown in the Table 1. The flowchart corresponding of BFOA is shown in Fig. 4.

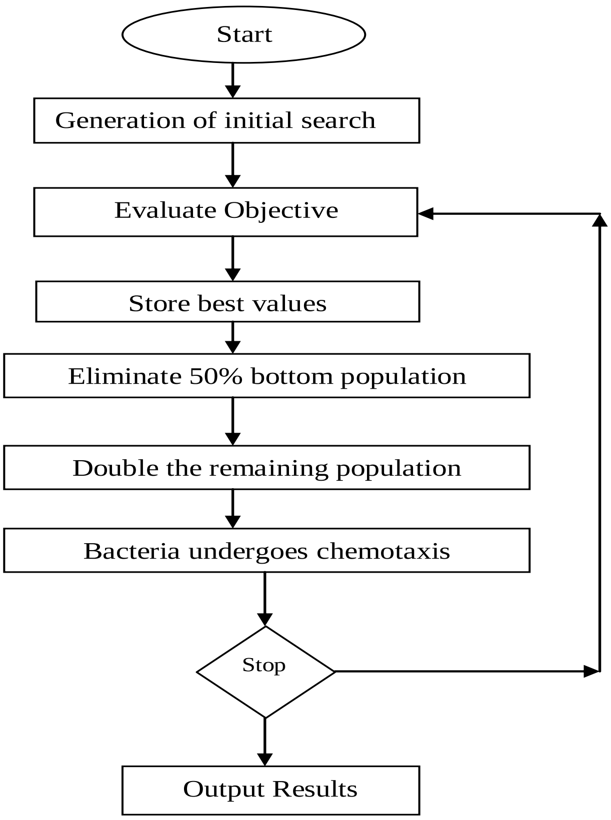

Fig. 4: Flow chart of BFOA

RESULT AND DISCUSSION

The response of the converter with the conventional PI controller is shows in Fig.5. From this plot various time domain parameters like rise time, settling time, peak overshoot, steady state error can be analyzed

The various dynamic response parameters found for the controller gain parameters obtained from BFO algorithms in before are summarized in the table2 below. From this table BFOA based PI controller has best time domain specification.

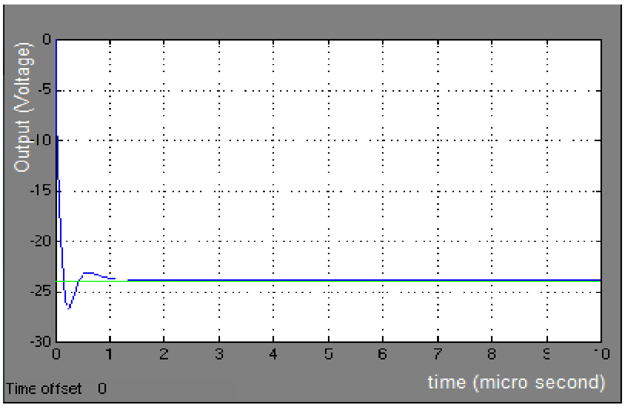

Fig. 5: Response of converter under conventional PI controller

Fig.6 shows the response of the converter that plotted with the ACO based PI controller. From this plot various time domain parameters can be analyzed.

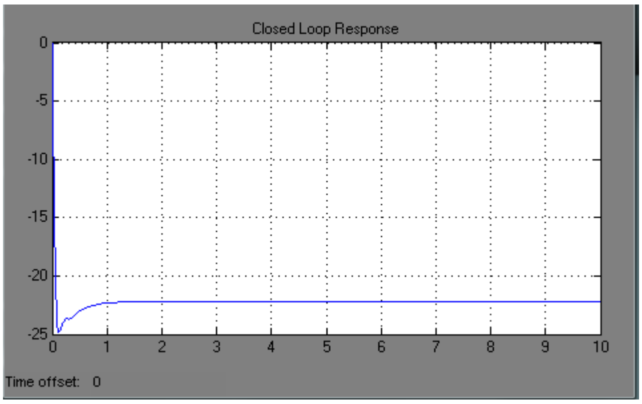

Fig. 6: Response of converter under ACO based PI controller

Table II: Time domain specifications

Method	Time domain Specifications			
	T_r *(sec)*	T_s*(sec)*	P_o *(%)*	E_{ss} *(V)*
Conventional PI controller	0.56	1.5	10	0.8
ACO based PI	0.45	1.25	4.1	0.4
BFOA based PI	0.13	.75	4.2	0.3

Fig.7 shows the response of the converter that plotted with the BFOA based PI controller. From this plot various time domain parameters can be analyzed.

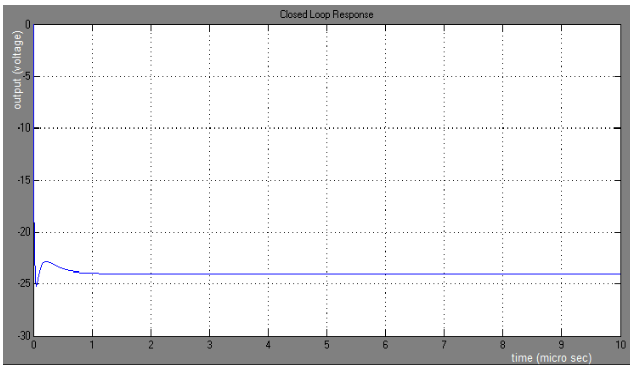

Fig. 7: Response of converter under BFO based PI controller

Conclusion:

The design of controller for the buck-boost converter is perceived as an optimization task and the controller constants are estimated through evolutionary search algorithms. The designs of PI controller parameters for the buck-boost converter were designed based on ACO and BFOA. By observing the rise time, settling time, peak overshoot from the step response curves which are obtained by using the controller parameters from the table it can be concluded that BFOA based parameter gives better results. The output of the Converter is stable and less steady state error.

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