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Designing an Integral LQR Controller for DC-DC X-Converter based on Enhanced Shuffled Frog-Leaping Optimization Algorithm

Power Electronics DC-DC converter plays an important role in different applications, for example, electric vehicles, wind generation and PV systems. This paper addresses the design of DC-DC X-converter with optimal LQR controller combined with integral gain action. Therefore, the proposed controlling scheme for DC-DC converter is very important to make the system stable under different conditions. In order to achieve high performance for DC-DC converter system, the current controller was made first as an inner loop and then an output voltage controller was designed as an outer loop. The behavior of an LQR controller design with integral action is characterized by two parameters: state and control weighting matrices. The problem of finding the semi-optimum weighting matrices has been formulated as an optimization problem. Standard Shuffled Frog-Leaping (SSFL) optimization algorithm is introduced to optimize the selection of the controller s weighting matrices. Furthermore, an Enhanced SFL Optimization Algorithm (ESFLA) is proposed to improve the stability performance of the considered system. The performances of both SSFLA and ESFLA are evaluated in terms of speed of convergence to the global optimum and algorithm accuracy, based on a set of ten benchmark test functions. The simulation results demonstrate that the DC-DC X-converter based on LQR with integral gain tuned by ESFLA outperforms other designs incorporating SSFLA in terms of control effort, stability performance as well as transient response specifications.

Keywords- DC-DC X-converter, LQR, SSFLA, ESFLA, Test functions.

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1. Introduction

Recently, power electronics DC-DC converter has been used in PV applications, wind energy, hybrid-electric vehicle, water pump application and any application that requires output voltage regulation. The efficiency of DC-DC converter is significantly important [1]. X-converter is a combination of buck boost DC-DC converter and this modified converter is like SEPIC, ZETA and CUK converters and have four passive components [2]. Fourth order X-Converter output voltage can be higher or lower than the input voltage, knowing that the output voltage will be negative. The controller of DC - DC X-converter is significantly important to obtain a fixed output voltage for loads under different disturbances. Furthermore, X-converter should operate in the stable region under all operating conditions [1, 2].

Several research works have been carried out for controller design of DC-DC converter based on evolutionary and swarm intelligence (SI) algorithms. In [3] parameters tuning methods based on genetic algorithm (GA) have presented to obtain the system element values for the buck DC-DC converter to minimize the variations in the output voltage under different load conditions. The authors in [4] designed pole placement controller to reduce the voltage ripple of CUK converter using GA and particle swarm optimization (PSO) for adjusting the

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coefficients of the pole placement technique. In [5], PID controller parameters have estimated using GA and bacterial foraging optimization algorithm (BFOA) for the boost converter to improve the performance and observe the time-domain specifications.

The classical tuning approaches of linear quadratic regulator (LQR) are time-consuming and do not guarantee the desired performance. Furthermore, these techniques are only directed to minimize the quadratic objective function and do not consider other control objectives such as improving the time-domain features. In order to improve the accuracy, design criterion and performance of the system, and overcome the drawbacks of classical schemes, bio-inspired optimization paradigms have been introduced. This swarm intelligence based technique is capable of reaching the globally optimal solution within a few numbers of iterations [6]. The main goal of all nature-inspired optimization algorithms is to balance the ability of exploration and exploitation efficiently to find the global optimum [7].

In this paper, shuffled frog-leaping algorithm (SFLA) is presented to tune the LQR with integral action controller. In [8], SFLA technique was used for buck DC –DC Converter to optimize PI controller parameters. In [9], PSO was utilized to optimize the matrices Q and R of the LQR controller, and it was found that the result that this optimization method gives is the best value to enable a system to work with high performance. In [10], LQR and PID controller were adjusted using PSO for two-tank system with the result that the system with LQR tuning using PSO has better performance compared with PID tuning using PSO. In [11, 12], improved SFLA was investigated to optimize PID controller parameters.

In this paper, DC-DC X-converter was designed and simulated in MATLAB environments. The LQR controller with integral action (LQI) was developed for current and voltage DC-DC X-converter. Furthermore, the SSFLA is extended to develop ESFLA for solving the optimization problem to find out the semi-optimal value of weighting matrices R and Q of the system inner current loop and to tune gain parameters of the system outer output voltage loop. In addition, SSFLA was used to tune inner and outer loops of the system. Finally, the comparisons between these approaches were investigated in terms of system stability and performance.

The remainder of this paper is organized as follows: Section 2 establishes the mathematical model of DC-DC X converter. The theoretical basics of the LQI controlling method and the standard SFL algorithm are presented in Section 3. Section 4 describes the proposed enhanced SFL algorithm. The tuning procedure of LQI controller and the proposed objective function are described in Section 5. Section 6 provides the simulation results and discussions. Finally, Section 7 concludes the paper.

2. DC-DC X-Converter Model

X-Converter circuit has four passive components: two inductors and two capacitors. Furthermore, it contains switching power MOSFET device and one diode. Output voltage can be higher or lower than input voltage. Output voltage is inverted not as in boost or buck device converter, and this modified converter can be used in different applications. Circuit Simulink with all current components is shown in Fig. 1.

Figure 1 shows that there are two state operations of X-converter: when the switch is on, L_1 will charge current and C_1 will discharge current via L_2. In the second state of operation, when the switch is off, C_1 will charge current through conducting diode from L_1 and L_2. C_2 is the filter capacitor and R is the load resistance.

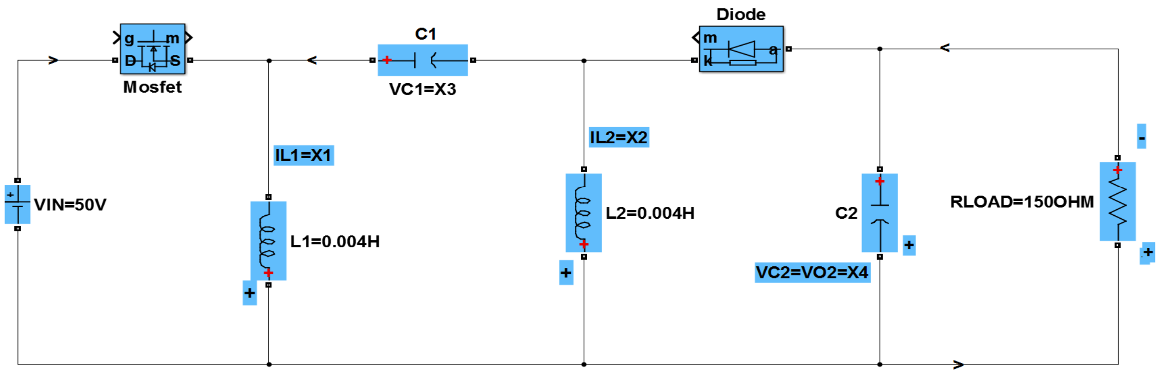

Figure 1: Simulink drawing of DC-DC X-converter

The mathematical model of the DC-DC X-converter is derived using state space approach. The system has two inductors, two capacitors, resistive load, input voltage and two power devices, which are MOSFET and Diode. This converter has four state variables, which are x_1 for i_{L1}, x_2 for i_{L2}, x_3 for v_{c1} and x_4 for v_{O2}. State space and output equations of the system are described below [2].

The current i_{L1} is that of the first inductor, i_{L2} is the current of the second inductor, which represents the load current, v_{c1} is the voltage of the first capacitor and v_{O2} is the output voltage of the second capacitor. The system parameters are shown in Table 1.

$$\left.\begin{aligned} \dot{X} &= \begin{bmatrix} 0 & 0 & \frac{D-1}{L_1} & \frac{D-1}{L_1} \\ 0 & 0 & \frac{D}{L_2} & \frac{D-1}{L_2} \\ \frac{1-D}{C_1} & \frac{-D}{C_1} & 0 & 0 \\ \frac{1-D}{C_2} & \frac{1-D}{C_2} & 0 & -\frac{1}{R\,C_2} \end{bmatrix} X + \begin{bmatrix} \frac{1}{L_1} \\ 0 \\ 0 \\ 0 \end{bmatrix} U \\ Y &= [0 \quad 1 \quad 0 \quad 1]\, X \end{aligned}\right\} \qquad (1)$$

Table 1: DC –DC X converter's parameters

Parameters	Values
L_2 and L_1	0.004 H
C_1	1uF
C_2	47 uF
D=duty cycle	0.75
F switching	150 KHZ
R_{Load}	150 Ω
V_o	150 V
V_i	50 V
Power	150 W
MOSFET Power device	0.1 Ω

The responses of load current and output voltage without controlling action are depicted in Fig. 2.

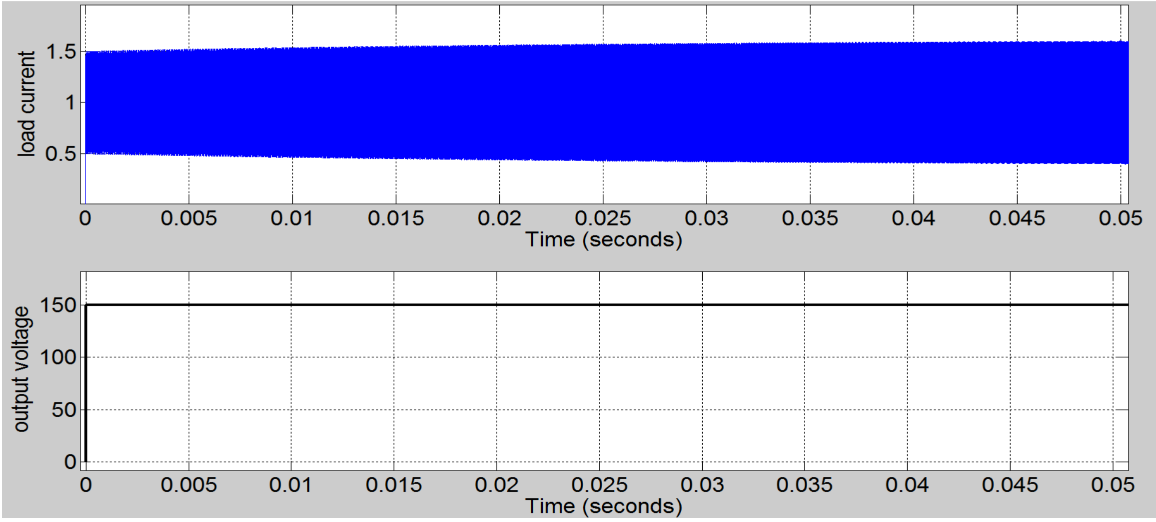

Figure 2: Load current and output voltage of DC-DC X-converter without controller

The results presented in Fig. 2 show that the current system without controller is unstable, with an oscillatory response during the transient period, and did not reach the steady-state region. Load current oscillations can be reduced rendering the system operation very fast by introducing the LQR controller with integral action as well as tuning its parameters using standard and enhanced optimization algorithms. Therefore, DC - DC X-converter should operate in a stable region under all disturbances that occur due to input voltage variation and load change.

3. Theoretical Basics

3.1. Controlling Methods

3.1.1. LQR with Integral (LQI) Action

The state and output equations for a controllable linear time-invariant (LTI) system can be written as follows,

$$\left.\begin{aligned} \dot{X} &= A\,X + B\,U \\ y &= C\,X \end{aligned}\right\} \tag{2}$$

The conventional LQR design problem is to minimize the following quadratic performance index, LQR methodology attempts to balance between a faster response and a low control effort [13]. The goal behind placing an integrator action into the controller is to eliminate the static error between the control reference and the controlled variable.

$$J = \frac{1}{2}\int_0^\infty (X^T Q\, X \;+\; U^T R\, U)\, dt \tag{3}$$

In this method, a feedback and integral action gain matrix are designed, which minimize the performance index in order to achieve a compromise solution between the use of control effort, the magnitude, and the speed of the response that will guarantee a stable system. The quadratic optimal controller aims to find a gain matrix K for the optimal control vector, so that objective function is minimized.

The linear optimal control input for LQR with integral action is,

$$u^* = -K_f\, X + K_i\, Z = -K\,\hat{X}(t)^* = -R^{-1}B^T S\,\hat{X}(t)^* \tag{4}$$

where, $K = R^{-1}B^T S$.

The control law indicated in Eq. (4) minimizes the performance index stated in Eq. (3) where X is an n-dimensional state-space vector, u is an m-dimensional control input vector, y is a p-dimensional output vector, $R \in \Re^{mxm}$ is the square positive definite matrix and $Q \in \Re^{nxn}$ is a positive semi-definite matrix, $Z(t)$ is a new state due to adding integral action, K_f is the inner loop state-feedback gain vector , K_i is the outer loop (forward) integral action error gain, K is the linear optimal feedback and integral gain vector, and S is the solution of matrix differential Riccati equation.

Substituting Eq. (4) in (2) yields,

$$\dot{X} = A\,X + B\,(-K_f\,X + K_i\,Z) = (A - B\,K_f)X + (B\,K_i)Z \tag{5}$$

and $\dot{Z} = r - y = r - C\,X$ (6)

Finally, the overall system with LQR plus integral action representation is as follows,

$$\begin{bmatrix}\dot{X}\\ \dot{Z}\end{bmatrix} = \begin{bmatrix}A - B\,K_f & B\,K_i\\ -C & 0\end{bmatrix}\begin{bmatrix}X\\ Z\end{bmatrix} + \begin{bmatrix}0\\ 1\end{bmatrix} r$$

or, $\dot{\hat{X}} = \hat{A}\,\hat{X} + \hat{B}\,r$ (7)

$$y = \begin{bmatrix}C & 0\end{bmatrix}\begin{bmatrix}X\\ Z\end{bmatrix}$$

or, $\hat{y} = \hat{C}\,\hat{X}$ (8)

The matrix algebraic Riccati equation is represented as follows,

$$S\hat{A} + \hat{A}^T S - S\,\hat{B}\,R^{-1}\hat{B}^T S + Q = 0 \tag{9}$$

The matrix algebraic Riccati equation solution is unique, symmetric and positive semi-definite. The weighting matrices Q and R play an important role in overall system performance, thus they should be chosen appropriately [14]. Basically, the matrix Q modifies the distribution of the control effect over the states, while the matrix R modifies the aggressiveness of the control input [15].

In the process of obtaining the parameters of the LQR with integral action, the trial-and-error scheme has been widely used. Generally, this technique presents satisfactory results after troublesome and time-consuming trials, but it cannot be known whether the achieved results are the global best or not. On the other hand, several classical and swarm based optimization algorithms have been used to find out the parameters of the controller. Although the optimization algorithms increase the computational load, they almost guarantee the semi-optimal results in the specified parameters range [15].

The important two parameters that guide the behavior of LQR controller and influence its performance are as aforesaid: state weighting matrix Q and control weighting value R. Therefore, using an intelligent optimization method for finding Q and R is more effective. In this paper, standard SFL and the proposed enhanced SFL algorithms are utilized as an optimization tool.

3.1.2. Inner and Outer Loops Controllers

Controller of power electronics DC- DC converter is very important. In order to let output voltage of DC-DC Converter work with high efficiency and acceptable performance, a controlling scheme for load current is required. Therefore, the first controller inserted in the system is the current controller, which is the inner loop as illustrated in Fig. 3, while the second controller that is embedded in the system is the output voltage controller, which is the outer loop as demonstrated in Fig. 4.

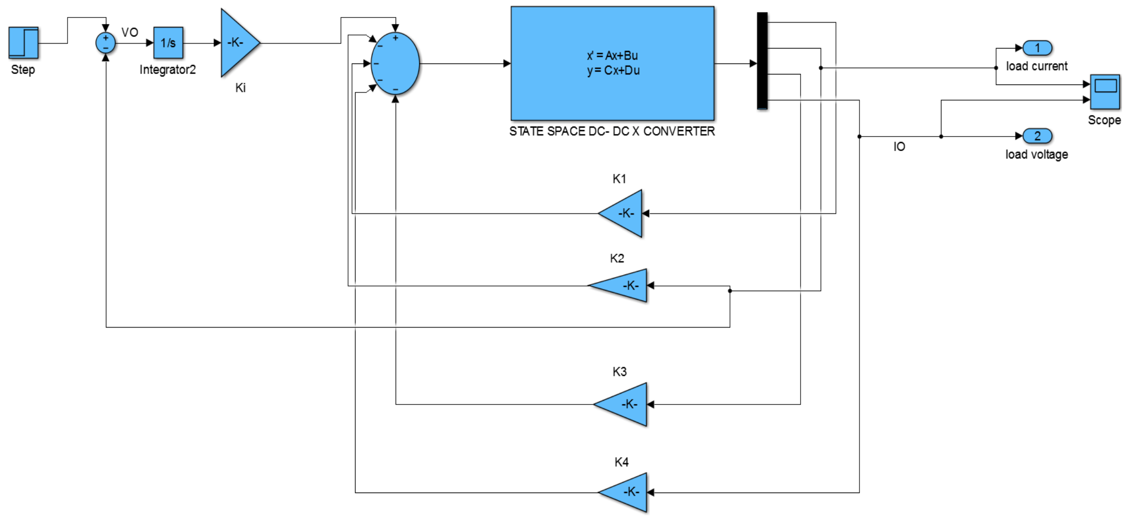

Figure 3: Inner loop LQR with integral action controller for load current of DC -DC X converter

In the inner loop controller illustrated in Fig. 3, five parameters of the inner loop current control were designed using LQR controller with integral action. These parameters are $k_1.k_2.k_3.k_4$ and k_I; where k_1 is for state x_1, k_2 for state x_2 which is load current, k_3 for state x_3, k_4 for state x_4 which is output voltage and k_I is integral action gain parameter.

Regarding Fig. 4, the outer loop of LQR with integral action was designed to get a system output voltage with stable characteristic and that attains the steady state very fast. The controller gain parameters in this figure are the same as in the inner loop controlling scheme, but there is another gain k_5 that is the current steady state, which is represented by x_5.

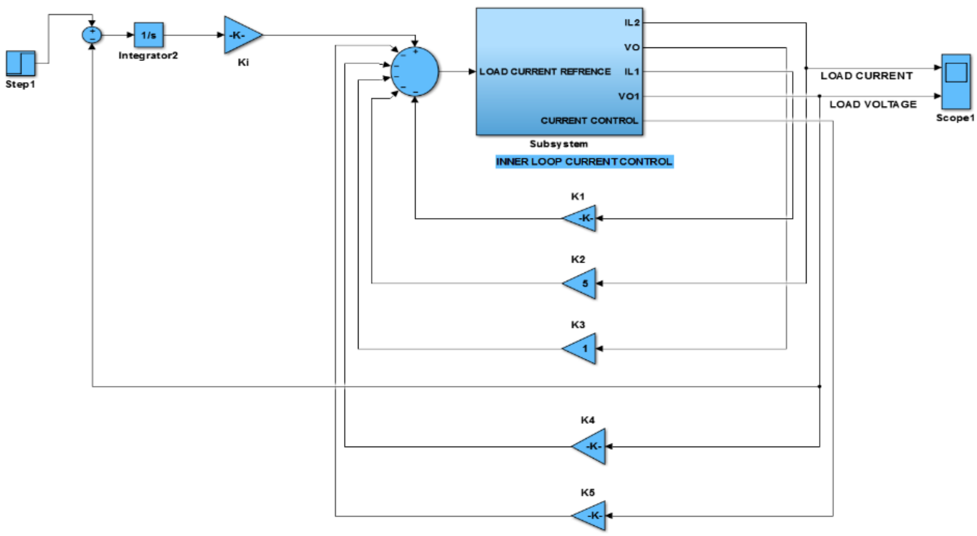

Figure 4: Outer loop LQR with integral action controller for output voltage of DC -DC X converter

3.2. Standard Shuffled Frog-Leaping Algorithm (SSFLA)

Standard Shuffled Frog-Leaping Algorithm (SSFLA) is a metaheuristic approach inspired by the frogs system proposed by M. M. Eusuff and K. E. Lansey in 2003 [16]. Furthermore, the discrete version of the SSFLA was invented by M. M. Eusuff et al. in 2006 for solving discrete optimization problems [17]. It is developed to seek a solution of a complex optimization problem by doing local and global search techniques.

SFLA consists of random frogs called population, which are subdivided into small parts called memeplexes. The utilized algorithm has two search processes, namely, local and global search to find out the optima of the considered application. The main merit of SFLA is its fast convergence speed [18].

The distributions of frogs upon memeplexes are done as follows; the first frog goes to the first memeplex, the second frog goes to the second memplex, the N_mth frog goes to the N_mth memeplex, and the $(N_m + 1)$th frog goes back to the first memeplex and the process continues until the distribution of total number of frogs N_f is accomplished.

The main steps of SSFL algorithm are summarized below [19]:

Step 1 (Initial parameter settings): Initialize the frog population size (N_f), the memeplexes size (N_m), the number of frogs per memeplex (N_n), the number of iterations per memeplex (T_m) and the maximum number of global iterations (T_g).

Step 2 (Generate frog position randomly): Initially generate the random position of individual frogs.

Step 3 (Sort and distribute the frog population): Determine the fitness of each frog according to the proposed performance index. Thereafter, sort them in descending order and distribute them on the N_m memeplexes. Finally, find out the global best position X_g in the population, the local best X_b and the worst X_w for each memeplex.

Step 4 (Local search): Within each memeplex, record the frogs with best position X_b and worst position X_w. Apply the following equations to improve the worst frog position using local leaping step size (S).

$$S^{k+1} = \begin{cases} Min\,\{int[r^k(X_b^k - X_w^k)].\ S_{max}\}.\ if\ X_b^k \geq X_w^k \\ Max\,\{int[r^k(X_b^k - X_w^k)]. - S_{max}\}.\ if\ X_b^k < X_w^k \end{cases} \quad (10)$$

$$X_w^{k+1} = X_w^k + S^{k+1} \quad (11)$$

where, X_b denotes the best position; X_w stand for the worst position in submemeplex; S_{max} denotes the maximum step size "leaping"; r is a random number between 0 & 1; k denotes the current iteration number.

If this step "leaping" does not enhance the performance of the worst position, the step distance will be recalculated by using the global best frog X_g instead of X_b. Finally, if the update does not improve X_w^{k+1} then,

$$X_w^{k+1} = \textit{randomly-generated position} \quad (12)$$

Setting S_{max} to a small value reduces the global exploration and tends the SSFLA to local search. On the other hand, a large value of S_{max} may result in missing the actual optima. A preliminary study was carried out for different step size values, and it was found that the success rate of achieving optimal solution was highest at 100 % of the variable range [16, 17, 20].

Step 5 (Memeplexes shuffling): After a defined number of memeplex evolution stages (T_m), the different memeplexes are shuffled by merging all the frogs in each memeplex to form the population again.

Step 6 (Termination condition): If the stopping criterion is satisfied, stop. Otherwise, go to *Step 3* until the maximum number of global iterations (T_g) reached.

Step 7 (Optimum solution): Collect the best solution.

4. Proposed Enhanced Shuffled Frog-Leaping Algorithm (ESFLA)

There are two shortcomings that are usually associated with SSFL algorithm. The first one is that the definition of SFLA tends to be stuck in local minima if the algorithm parameters are not selected well in order to get global minima. The second one is that the SSFL algorithm performs well in exploitation but badly in exploration. This paper proposes an ESFLA to overcome these demerits through introducing several enhancements to achieve a balance between exploitation and exploration as detailed below**:**

A. Enhancing the update strategy

Instead of using $r^k = rand(0.1)$ in *Step 4 (local search)* of the main steps procedure in Section 3.2, which is highly probable that it will stick into local optima, enhanced update strategy is proposed by using:

$$r^k = r_o \exp\left(\frac{-\alpha_d\, k}{T}\right). \quad k=1,2,\ldots\ldots,T \quad (13)$$

where,

r_o : is the initial value.

α_d: is the descending coefficient (selected based on several experiments to suit the considered problem).

B. Enhancing local exploration

To assist the local exploration in *Step 4 (local search)* of the main steps procedure in Section 3.2, the following equation was used to improve the worst frog position in place of Eq. (11).

$$X_w^{k+1} = w^k X_w^k + C^k S^{k+1} \tag{14}$$

where,

w^k: is the inertia weight which is assigned a large value at the initialization step and then linearly decreased from 0.9 to 0.1 to enhance the local exploration [21].

$$w^k = (w_{min} - w_{max})\frac{k}{T} + w_{max}\,\frac{(f_w^k - f_b^k)}{(f_w^k - f_g)} \tag{15}$$

C^k: is a search learning coefficient, a constant greater than 1, and not more than 3, because a large value will lead to premature convergence and prevent unwanted local minima [22].

$$C^k = C_{min} + (C_{max} - C_{min})\,\sin\left(\frac{\pi\,k}{2\,T}\right) \tag{16}$$

C. Adaptive position selection of worst frog

The following equation is developed to be used in *Step 4 (local search)* of the main steps procedure in Section 3.2, to find the new position of the worst frog in case no improvement is obtained by using X_b^k or X_g instead of generation of worst frog position randomly,

$$X_{a\,w}^{k+1} = w^k X_w^k + r^k \left(f_w^k - f_b^k\right) + r^k \left(f_w^k - f_g\right) \tag{17}$$

where,

$X_{a\,w}$: denotes the adaptive worst position in submemeplex.

f_w : The objective function for the worst frog in submemeplex.

f_b : The best value of objective function.

f_g : The global best value of objective function for the whole swarm.

5. Tuning of Controlling Methods

5.1. LQI Controller Tuning

In this research work, an SSFLA and ESFLA are developed in order to determine the elements of Q matrix and R value to attain the satisfactory closed loop response via LQI controller. The assumption criterion of the elements of Q matrix and R value is as follows:

$$\left.\begin{array}{l} Q=\text{diag}\{q_1,\ldots\ldots q_{n+1}\} \\ R=\text{scalar value} \end{array}\right\} \tag{18}$$

The design procedure for finding LQI gains vector:

1. Check the controllability for the system model
2. Assume the initial values for matrix Q *and* R as,

$$Q = \begin{bmatrix} q_1 & 0 & 0 & 0 & 0 \\ 0 & q_2 & 0 & 0 & 0 \\ 0 & 0 & q_3 & 0 & 0 \\ 0 & 0 & 0 & q_4 & 0 \\ 0 & 0 & 0 & 0 & q_5 \end{bmatrix} \& R = [\, R_0 \,] \tag{19}$$

The lower bound of Q matrix diagonal =[0.1 0.1 0.1 1 100]
The upper bound of Q matrix diagonal =[10 10 10 100 10000]
The range for R value is from 0.001 to 1.

3. Solve the algebraic matrix Riccati equation and determine the matrix S.

4. Find the optimal control input $u^*$and then calculate the linear optimal feedback and integral gain vector as follows,

$K = [-k_1 \quad -k_2 \quad -k_3 \quad -k_4 \quad k_I]$

5. Find the overall system state space model ($\hat{A}$. $\hat{B}$ & $\hat{C}$).

6. Determine the system response and therefore obtain the time and frequency domain specifications.

7. Apply the objective function.

8. Go to step 2 to select a new set of values for matrix Q *and* R and repeat the steps using SSFLA or ESFLA, till you find the minimum objective function and thereafter collect the linear optimal feedback and integral gain vector to obtain the state-variable feedback (SVFB) control input with integral action.

5.2. Formulation of the Proposed Objective Function

The objective function can be represented as,

$$f_k = w_1\,(E_{ss}) + w_2\,(P.O) + w_3\,(t_s) + w_4\,(t_r) \tag{20}$$

where $w_1 + w_2 + w_3 + w_4 = 1$

In order to get the optimal values for all time-domain specifications, the weights are assumed to be $w_1 = w_2 = w_3 = w_4 = 0.25$.

6. Simulation Results and Discussions

6.1. Simulation Parameters' Settings

The simulation results are collected based on MATLAB R2014a tool installed on a laptop having 64 bits Windows 7 operating system, Intel Core i5-4210 U (2.4 GHz) CPU, and 6 GB RAM.

The total number of frogs (N_f) is fixed to 24 with 4 memeplexes (N_m) and 6 frogs in each memeplex (N_n). 15 iterations are performed per memeplex (T_m) and 100 generations are utilized as a maximum number of global iterations (T_g). The internal parameters of the SSFLA and ESFLA are assigned as follows; leaping step size $S_{max} = 10$, the main step initial value $r_o = 1$, the descending coefficient $\alpha_d = 1.9$, the inertia weight range $w_{min} = 0.1$ & $w_{max} = 0.9$, and the search learning coefficient range $C_{min} = 1$ & $C_{max} = 3$.

6.2. Benchmark Test Functions Details

There are many optimization algorithms claiming predominance over other techniques. Hence, to specify the most reliable methods, benchmark test functions can be used as an indicator to check their effectiveness. The performance of the proposed ESFL algorithm has been examined based on 10 test functions [23, 24]. The selected benchmark functions illustrated in Table 2, have different characteristics such as; multimodality, unimodality, non-separable and separable to explore the exploitation and exploration capabilities.

Table 2: Benchmark test functions' used in proposed algorithm's verification

No.	Function Name	Dim. (n)	Domain	Function Formulation
1	Ackley	30	[-32, 32]	$f(x) = 20 + \exp(1) - 20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right)$
2	Dixon-Price	30	[-10, 10]	$f(x) = (x_1 - 1)^2 + \sum_{i=2}^{n} i\,(2\,x_i^2 - x_{i-1})^2$
3	Extended Tridiagonal	20	[-100, 100]	$f(x) = \sum_{i=1}^{\frac{n}{2}} [(x_{2i-1} + x_{2i} - 3)^2 + (x_{2i-1} - x_{2i} + 1)^4]$
4	Perm	30	[-4, 4]	$f(x) = \sum_{k=1}^{4}[\sum_{i=1}^{4}(i^k + 50)\{(x_i/i)^k - 1\}]^2$
5	Powell Second Singular	20	[-4, 5]	$f(x) = \sum_{i=1}^{n-2}[(x_{i-1} + 10\,x_i)^2 + 5\,(x_{i+1} - x_{i+2})^2 + (x_i - 2\,x_{i+1})^4 + 10\,(x_{i-1} - x_{i+2})^4]$
6	Rastrigin	30	[-5.12, 5.12]	$f(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10]$
7	Rosenbrock	30	[-100, 100]	$f_1(x) = \sum_{i=1}^{n-1}[100\,(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$
8	Salomon	20	[-100, 100]	$f(x) = 1 - \cos\left(2\pi\sqrt{\sum_{i=1}^{n} x_i^2}\right) + 0.1\sqrt{\sum_{i=1}^{n} x_i^2}$
9	Sphere	30	[-100, 100]	$f(x) = \sum_{i=1}^{n} x_i^2$
10	Zakharov	20	[-5, 10]	$f(x) = \sum_{i=1}^{n} x_i^2 + (\sum_{i=1}^{n} 0.5\,i\,x_i)^2 + (\sum_{i=1}^{n} 0.5\,i\,x_i)^4$

Note: All the selected benchmark test functions with global optima $(f(x^*))$ =0.

6.3. Proposed Algorithm Validation

The proposed ESFL algorithm has been validated using ten benchmark test functions. In order to compare the SSFLA with ESFLA for various selected test functions, the algorithms are executed in MATLAB R2014a environment. Afterward each algorithm has been run at least 30 times, with each run, the maximum number of global iterations is 100 to collect meaningful statistical results. The obtained statistical results are demonstrated in Table 3, which contains the average best (AB), the median best (MB) and the standard deviation (SD).

Table 3: Comparison of optimization results based on benchmark test functions

Function	Criteria	SSFLA	ESFLA
Ackley	AB	0.2058	5.25E-7
	MB	2.69	6.935E-6
	SD	5.23	1.24E-5
Dixon-Price	AB	6.45E-4	9.44E-5
	MB	0.4462	0.0375
	SD	0.035	0.0021
Extended Tridiagonal	AB	0.0148	0.0037
	MB	2.57	0.4401
	SD	0.3838	0.135
Perm	AB	0.0902	0.0076
	MB	0.818	0.67
	SD	2.8322	0.2233
Powell Second Singular	AB	0.0215	1.206E-6
	MB	4.157	1.114E-4
	SD	0.687	4.257E-5
Rastrigin	AB	0.0207	2.3E-4
	MB	3.272	0.0053
	SD	0.2661	0.0065
Rosenbrock	AB	0.0764	2.5E-4
	MB	6.06	0.0199
	SD	2.5	0.0091
Salomon	AB	0.07	6.303E-4
	MB	0.2148	7.567E-3
	SD	2.299	0.02
Sphere	AB	0.0334	3.866E-5
	MB	0.9655	9.87E-4
	SD	1.04	0.0012
Zakharov	AB	2.49	1.7313E-6
	MB	0.0269	8.83E-5
	SD	0.6277	5.823E-5

For all the benchmark test functions, ESFLA has outperformed on SSFLA. Furthermore, from the obtained results, the optimum solution can be found easily with high accuracy using the proposed algorithm. Finally, the enhanced SFL algorithm can meet the desired requirements with an average running time of about 1.5 s.

6.4. Results and Discussion

LQI controller for load current and output voltage DC –DC X converter were designed to excite the system to work in a stable region. In addition, SSFLA was used for tuning parameters of LQI controller for load current and output voltage. Moreover, ESFLA was applied for tuning parameters of LQI controller for load current and output voltage. The results of three tuning methods for load current and load voltage as well as the comparison results are clarified below.

6.4.1. Results of LQR with Integral Action

The responses of the system with LQI controller for current and voltage control are shown in Fig. 5 and Fig. 6, respectively.

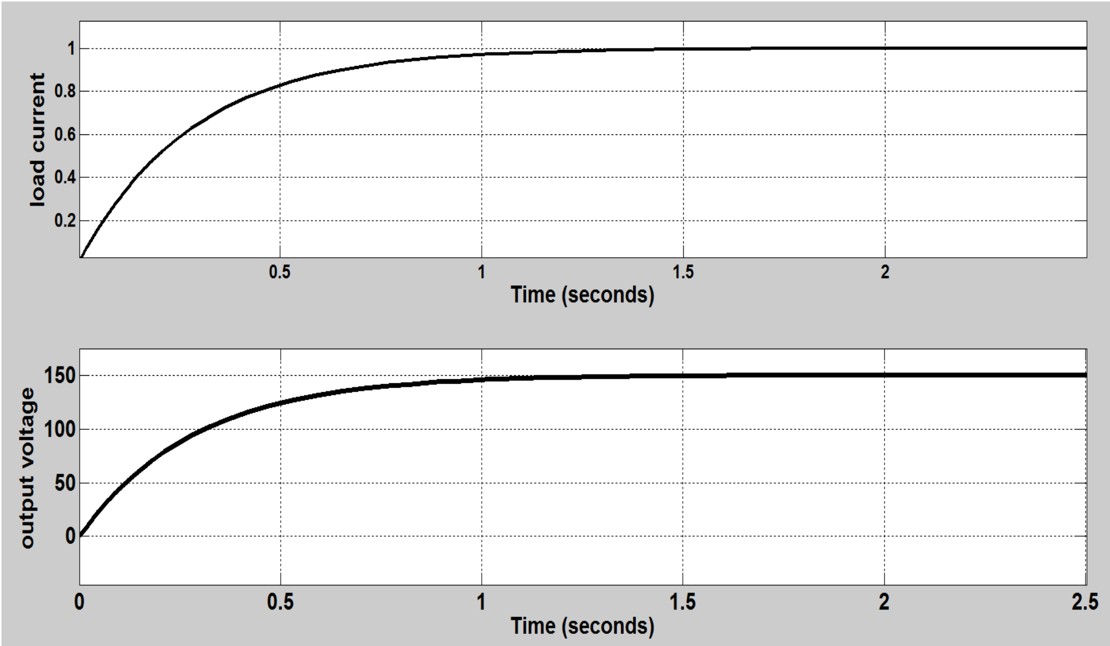

Figure 5: The response for inner loop current control scheme with LQI controller

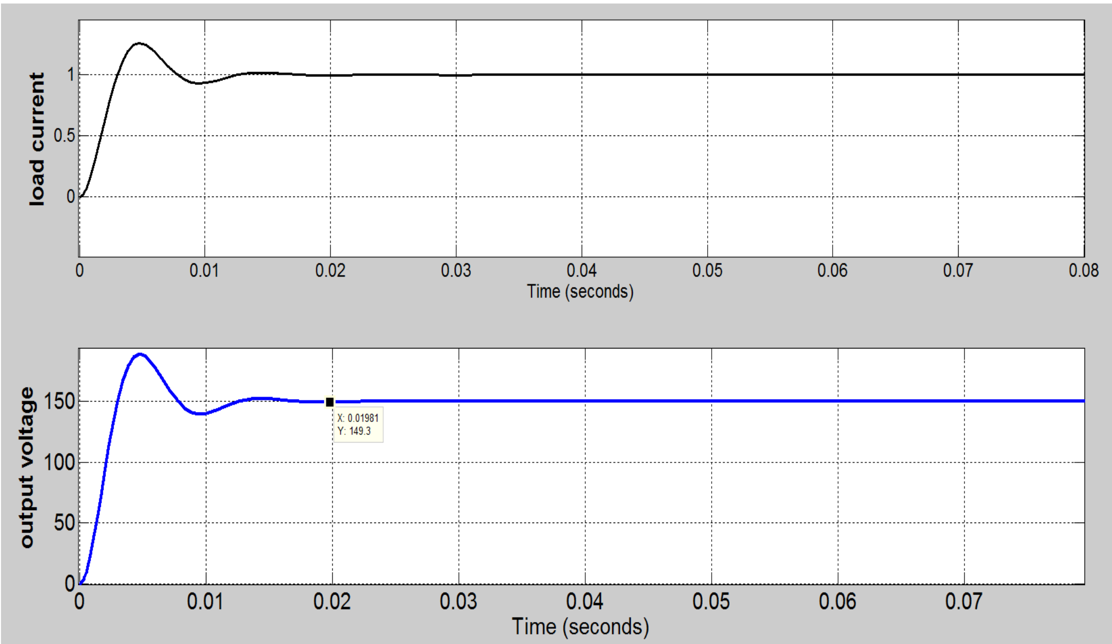

Figure 6: The response for outer loop voltage control scheme with LQI controller

In Fig. 5, it can be seen that the inner loop of the system, which is a load current control, is stable and reaches a steady state at 1.3 s. In addition, inner loop output voltage of the system without control attained the steady state as well at 1.3 s as shown in Fig. 5. That means that the system is very slow whereas the requirement is to get a very fast system response. Therefore, it is very important to let the system reach the steady state faster when achieving control over the output voltage. In Fig. 6, the controller for output voltage of the system was made, whereby the output voltage of the system reached a steady state by 0.017 s faster than output voltage at inner loop current control. Furthermore, load current arrived at the settling point by 0.016 s faster than an inner loop current control after making controller for load voltage.

6.4.2. Results of LQR with Integral Action with SSFLA

In this part, SSFL algorithm is used to tune gain parameters of LQI controller for DC – DC X converter. Therefore, the inner loop of current controller and outer loop of output voltage controller responses are shown below in Fig. 7 and Fig. 8, respectively.

In Fig. 7, the inner loop of the system, which is a load current control, has stable response and reaches the steady state at 0.18 s, while the load voltage of the system arrived at steady state slower than the load current at 0.2 s as shown in Fig. 7. Therefore, it is very important to let the system reach the steady state faster when achieving control for output voltage. In Fig. 8, also, SSFLA was used to tune gain parameters of LQI of outer loop output voltage control. It can be seen that the load voltage settled at the steady state by 3*E-3 s faster than output voltage at inner loop control for load current. Moreover, load current arrived at the settling point by 2.6*E-3 s faster than the inner loop current control after making controller for load voltage. Obviously, the load voltage of the system became faster after using SSFLA to find the semi-optimal values of LQI controller gain parameters. Moreover, the output voltage of a system with tuning gain parameters using SSFLA has arrived at steady state faster than output voltage of a system with LQI controller without an optimization algorithm.

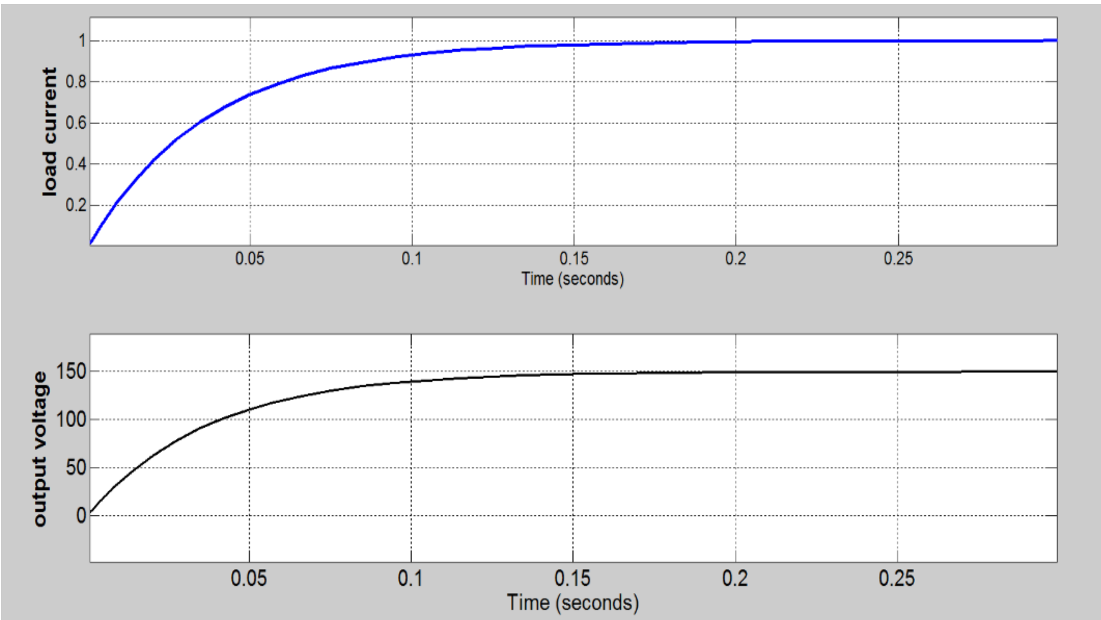

Figure 7: The response for inner loop current control scheme with LQI based on SSFLA

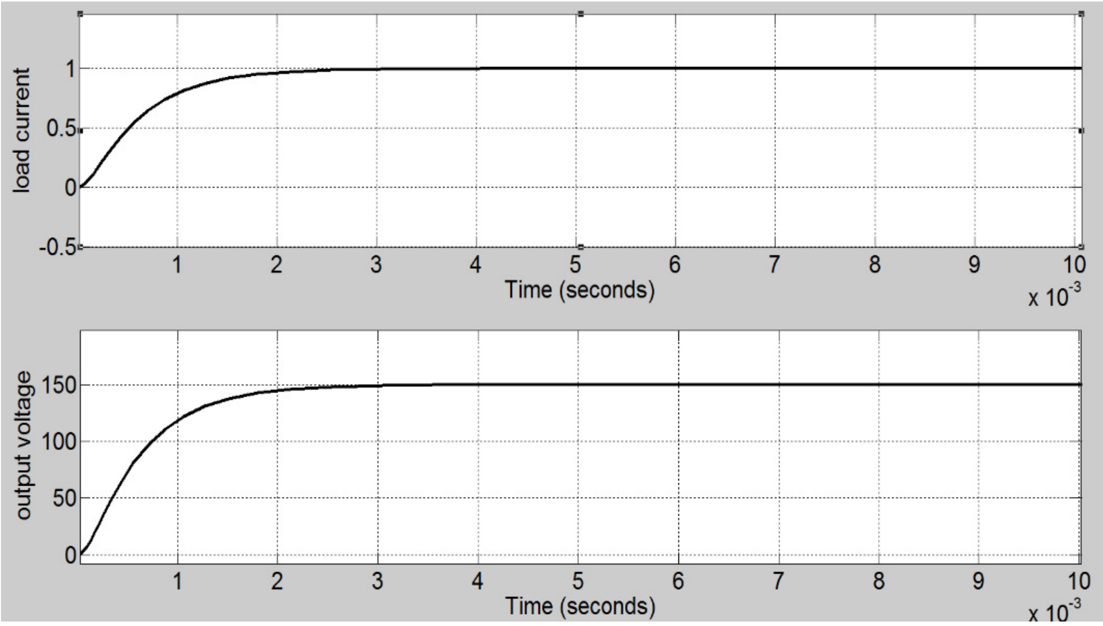

Figure 8: The response for outer loop voltage control scheme with LQI based on SSFLA

6.4.3. Results of LQR with Integral Action with ESFLA

The responses of the system with LQI controller based on ESFL algorithm for both current and voltage control are depicted in Fig. 9 and Fig. 10, respectively.

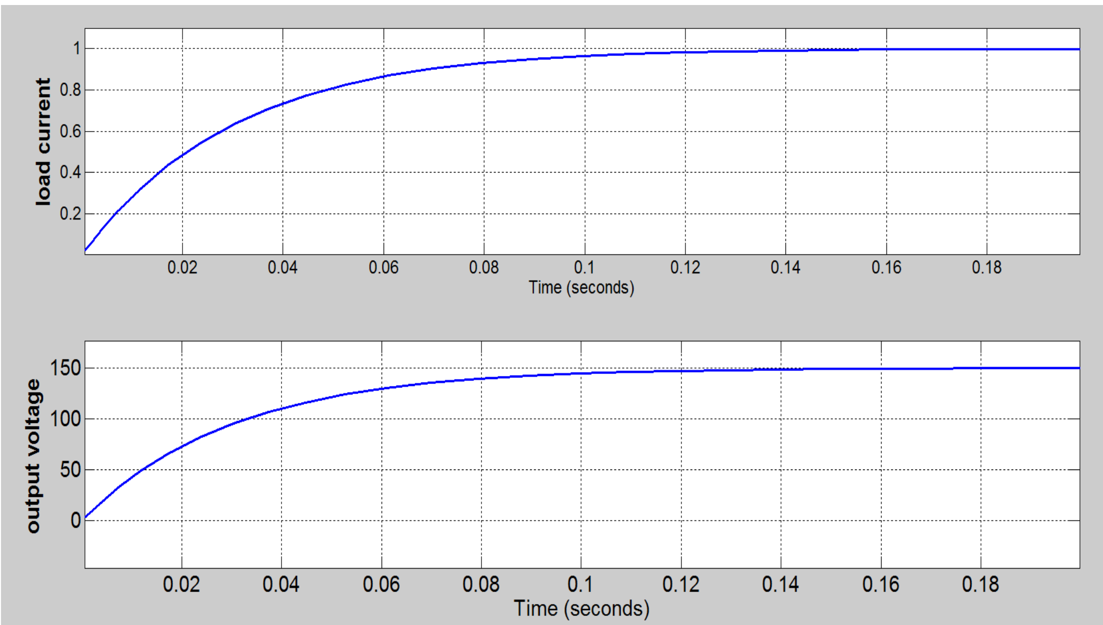

Figure 9: The response for inner loop current control scheme with LQI based on ESFLA

In Fig. 9, it can be seen that after improving SSFLA to get the optimum values of LQI gain parameters, the system load current with controller becomes stable and reaches a steady state at 0.14 s, which is faster than current control with LQI, and LQI based on SSFLA. On the other hand, the load voltage of the system arrived at the steady state at 0.15 s.

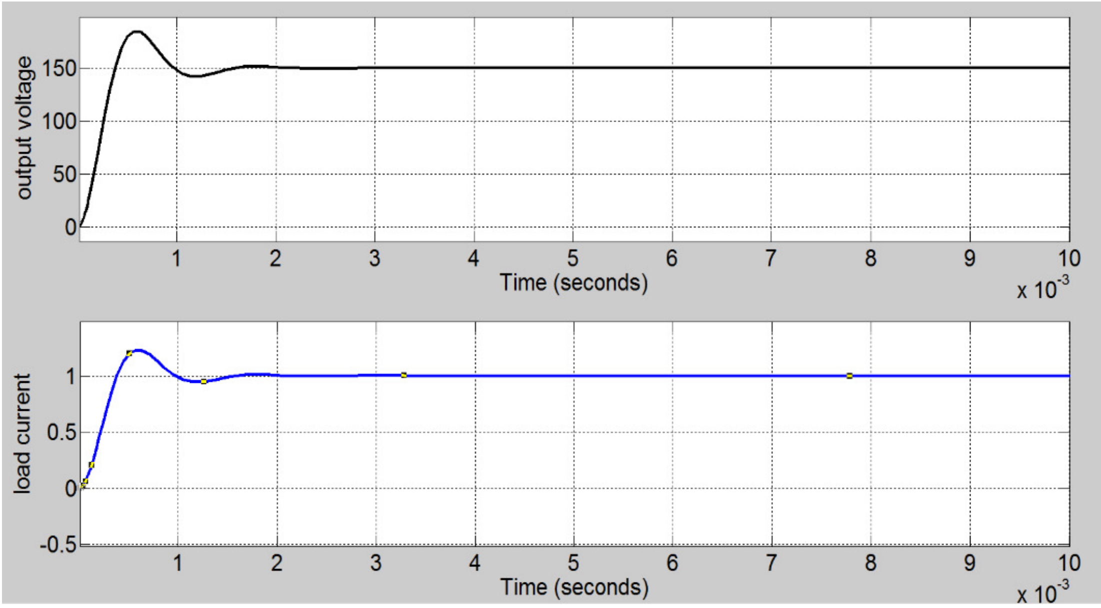

Figure 10: The response for outer loop voltage control scheme with LQI based on ESFLA

In Fig. 10, also, ESFLA was used to tune parameters of LQI controller for output voltage of the system. It is obvious that the load voltage settled at the steady state by 2*E-3 s faster than output voltage when control was made for load current. Also, load current arrived at the settling point by 2*E-3 s faster than inner loop current control after making control over load voltage. It is noticeable that the load voltage of the system became faster after using ESFLA for selecting gain parameters of LQI controller in comparison with the system with LQI controller and with LQI tuned by SSFL algorithm.

6.4.4. Results Comparison

The comparison between the collected responses based on different controlling criteria is discussed with reference to Fig. 11 and Fig. 12 shown below.

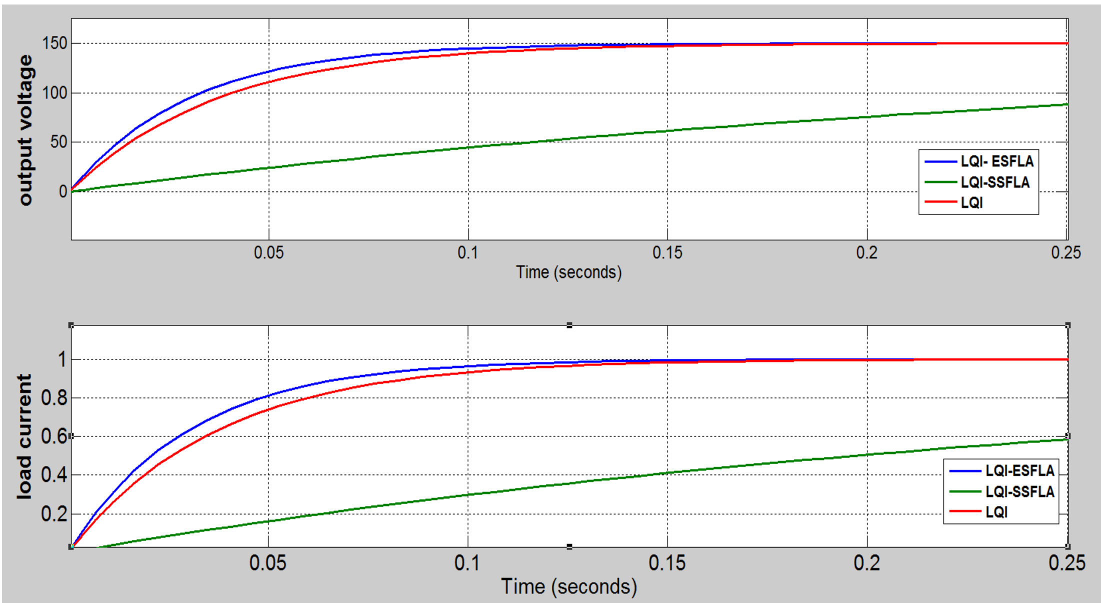

Figure 11: The response of inner loop current control based on different controlling techniques

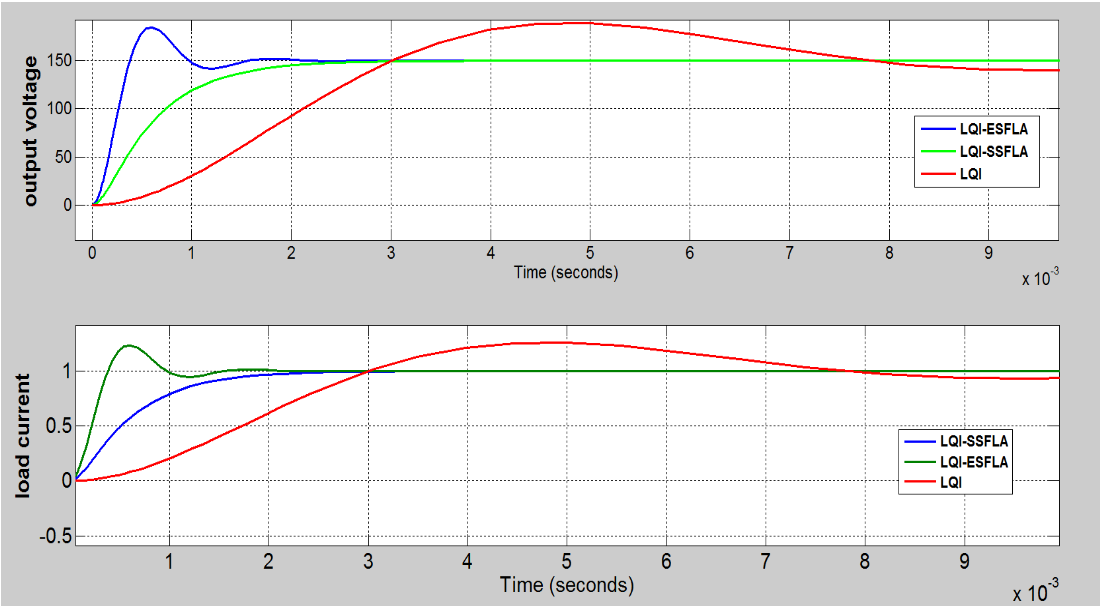

Figure 12: The response of outer loop voltage control based on different controlling techniques

In Fig. 11, it is obvious that inner loop load current using LQI-ESFLA has the best performance and the system settled at the steady state very fast as compared to the system inner loop load current using LQI and LQI-SSFLA as shown in Table 4. In Fig. 12, after implementing the load voltage controller as outer loop, the system using LQI-ESFLA arrived at the steady state faster than system outer loop using LQI-SSFLA and LQI controller. Furthermore, Table 4 shows the comparison between the three different types of tuning methods. Finally, it can be seen that LQI-ESFLA- output voltage /outer loop has arrived at the steady state by 2E-3 s faster than outer loop LQI output voltage and LQI-SSFLA- output voltage.

Table 4: Comparison of collected results for different controlling techniques with their settling time index.

Controlling techniques	Settling time
LQI –load current/ inner loop	1.3 s
LQI-output voltage/ outer loop	0.017 s
LQI-SSFLA-load current /inner loop	0.18 s
LQI-SSFLA- output voltage/ outer loop	3E-3 s
LQI-ESFLA-load current /inner loop	0.14 s
LQI-ESFLA- output voltage /outer loop	2E-3 s

7. Conclusions

In this research work, the problem of finding the optimum values of LQI's parameters in order to control the DC-DC X-converter has been regarded as an optimization problem. Global optimization of the weighting matrices of the LQI controller is performed based on the standard and enhanced SFL algorithms in order to achieve the best response requirements. The SSFLA has been enhanced to improve the reliability in providing the better-quality solutions with a minimum number of generations to finally avoid premature convergence. To demonstrate the efficiency of the proposed ESFL algorithm, a set of ten-benchmark test functions with different dimensions and types are utilized and then compared with results obtained by SSFL algorithm. The collected results reveal that the proposed algorithm is more reliable, more robust and more efficient than the standard algorithm. The considered system has an unstable load current response with high oscillation property. Therefore, two controllers are designed for the system, one for current loop control (inner loop) and the second one for voltage loop control (outer loop). The LQI controller is designed as an inner and outer controller for the system. In addition, gain parameters of LQI controller are tuned using SSFLA and ESFLA. The comparisons between three types of tuning controllers of the system are investigated. The simulation results show that the outer loop output voltage with LQI controller arrived at a steady state at 0.017s and the outer loop output voltage with LQI based on SSFLA reached the steady state at 3E-3s. In addition, outer loop output voltage of the system arrived very fast to the steady state at 2E-3 s after using LQI controller based on ESFLA in comparison with outer loop output voltage of the system using LQI controller and LQI based on SSFLA. Moreover, the inner loop load current of the system arrived very fast to steady state at 0.14 s after using ESFLA for tuning of LQI gain parameters in comparison with inner loop of the system load current using LQI controller and LQI based on SSFLA.

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