Extended Kalman Filter-Based Control of DC-DC Buck Converter

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1 Introduction

DC-DC converters are employed to boost or diminish the level of output voltage. The DC-DC buck converter is used to step down the output voltage and is extensively used in smart grids, renewable sources, etc. [1]. Researchers have used different procedures and control techniques to adjust the output of buck converter. The conduction loss is minimized by creating capacitor paths to maintain average inductor current and ripple current in inductor in [2–4]. Efficient controller is designed for the converters using translinear dynamics in article [5]. To decrease the inrush current, feedback linearization and auxiliary current control technique have been opted for buck converter operating in continuous conduction mode [6, 7]. An auxiliary current control technique is used in [8]. Artificial neural network (ANN)–based control technique is used to control the voltage of DC-DC buck converter in [9]. In this paper, extended Kalman filter (EKF)–based proportional-integral (PI) controller has been designed for buck converter. EKF is used to estimate the state variables of the system and PI controller controls the output voltage. The performance of the controller has been checked for different reference voltages and different load resistances. The results show that the control algorithm fulfills the requirements.

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V. I. George et al. (eds.), *Control and Information Sciences*, Lecture Notes in Electrical Engineering 1140, https://doi.org/10.1007/978-981-99-9554-7_15

2 Buck Converter

The circuit model of DC-DC buck converter is presented in Fig. 1. It contains a MOSFET (S_n), , a diode (D_n), , a capacitor, an inductor, and a load resistor. By controlling the duty ratio (D), the buck converter's output voltage is controlled according to the desired manner. The converter is described by the following set of equations.

$$DV_{\text{in}} - V_{\text{out}} = R_{\text{Lin}} i_{\text{Lin}} + L_n \frac{\mathrm{d}i_{\text{Lin}}}{\mathrm{d}t} \tag{1}$$

$$C_n \frac{\mathrm{d}v_c}{\mathrm{d}t} = i_{\text{Lin}} - \frac{V_{\text{out}}}{R_{\text{out}}} \tag{2}$$

$$V_{\text{out}} = R_{\text{Cin}} \left(i_{\text{Lin}} - \frac{V_{\text{out}}}{R} \right) + v_C \tag{3}$$

where V_{in} and v_{out} are the input voltage and output voltage, respectively, i_{Lin} is the inductor current, and the capacitor voltage is v_C. The value of the inductance and capacitance are L_n, C_n, respectively, and their internal resistances are R_{Lin} and R_{Cin}. The load resistance is R_{out}.

The state space model of the converter is given by

$$\begin{bmatrix} \frac{\mathrm{d}i_{\text{Lin}}}{\mathrm{d}t} \\ \frac{\mathrm{d}v_c}{\mathrm{d}t} \end{bmatrix} = \begin{bmatrix} -\frac{1}{L_n}\left(R_{\text{Lin}} + \frac{R_{\text{out}} R_{\text{Cin}}}{R_{\text{out}} + R_{\text{Cin}}} \right) & \frac{-R_{\text{out}}}{L_n (R_{\text{out}} + R_{Cin})} \\ \frac{R_{\text{out}}}{C_n (R_{\text{out}} + R_{\text{Cin}})} & \frac{-1}{C_n (R_{\text{out}} + R_{\text{Cin}})} \end{bmatrix} \begin{bmatrix} i_{\text{Lin}} \\ v_c \end{bmatrix} + \begin{bmatrix} \frac{V_{in}}{L_n} \\ 0 \end{bmatrix} D \tag{4}$$

$$V_{\text{out}} = \begin{bmatrix} \frac{R_{\text{out}} R_{\text{Cin}}}{R_{\text{out}} + R_{\text{Cin}}} & \frac{R_{\text{out}}}{R_{\text{out}} + R_{\text{Cin}}} \end{bmatrix} \begin{bmatrix} i_{\text{Lin}} \\ v_c \end{bmatrix} \tag{5}$$

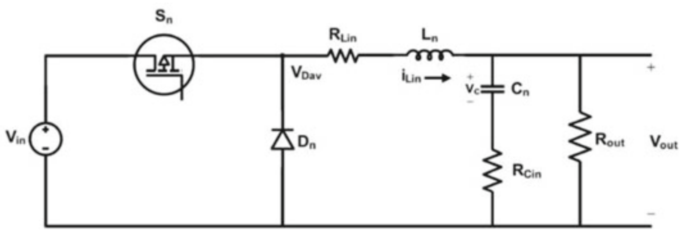

Fig. 1 Circuit model of buck converter

3 Extended Kalman Filter (EKF) Algorithm

Kalman filter is the most extensively used filter to identify parameters, estimate state variables, etc. For the minimization of the effect of sensor and process noises on the output of the system, Kalman filter can also be used [10, 11]. But if the system has some nonlinearity, then Kalman filter does not estimate the state variables accurately. In that case, Extended Kalman filter (EKF) may be used to estimate the state variables. EKF estimates the state variable by linearizing the nonlinear dynamics applying Taylor's series expansion [12]. The state space model of a discrete-time system is given by

$$x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \tag{6}$$

$$y_k = h(x_k) + v_k \tag{7}$$

where w_k is process noise vector and v_k is the measurement noise vector; $f(x_{k-1}, u_{k-1})$ and $h(x_k)$ are nonlinear functions. The EKF algorithm is given below.

- **Initialization:** The initial value of state is considered as x_{in} and the error covariance matrix is chosen as $P_{\text{in}} = E\left[(x_{\text{in}} - \hat{x}_{\text{in}})(x_{\text{in}} - \hat{x}_{\text{in}})^T\right]$. Usually, P_{in} is chosen as diagonal matrix.
- **The prediction step:** The estimated state is $\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1})$ and error covariance matrix is $P_{k|k-1} = \hat{F}_k \hat{P}_{k-1|k-1} \hat{F}_k^T + Q_k$ where process noise covariance matrix is Q_k is and $F_k = \frac{\partial f}{\partial x}\Big|\hat{x}_{k|k-1,u_k}$.
- **Measurement step:**

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{y}_k \tag{8}$$

$$P_{k|k} = \left(I - K_k \hat{H}_k\right) P_{k|k-1} \tag{9}$$

where $\tilde{y}_k = Z_k - h\left(\hat{x}_{k|k-1}\right)$; $H_k = \frac{\partial h}{\partial x}\Big|\hat{X}_{k|k-1}$

- Innovation covariance $S_k = \hat{H}_k P_{k|k-1} \hat{H}_k^T + R_k$ where R_k is covariance of v_k.

The gain of EKF is given by

$$K_k = \hat{P}_{k|k-1} \hat{H}_s^T S_k^{-1} \tag{10}$$

Sometimes EKF faces stability issue, suffered from low track accuracy, and does not estimate state variables accurately for highly nonlinear systems.

4 EKF-Based Control Algorithm

The block diagram of the buck converter with EKF and proportional-integral (PI) controller is shown in Fig. 2. The values of the parameters of buck controller are considered as [9] and those are as follows: $V_{\text{in}} = 42$ V; $L_n = 5.63$ mH; $R_{\text{Lin}} = 0.3\ \Omega$; $R_{\text{Cin}} = 0.02\ \Omega$; $C_n = 5\ \mu F$; $R_{\text{out}} = 10\ \Omega$; switching frequency $f = 20$ kHz.

For the design of the EKF, the sensor and process noise covariances are considered as 0.01 and 0.000001, respectively. When initial states are known, the initial value of error covariance matrix may be chosen as small. But for unknown initial states, the initial value of covariance matrix may be chosen as high. In this study, initial covariance matrix is chosen as $\begin{bmatrix} 0.0000001 & 0 \\ 0 & 0.0000001 \end{bmatrix}$ as initial states are known. The resulting noise error covariance matrix becomes $P = \begin{bmatrix} 1.182e^{-5} & 8.081e^{-5} \\ 8.081e^{-5} & 0.0007039 \end{bmatrix}$. The estimated state variable (v_C) of the system along with the measured state variables are shown in Fig. 3. From the figures, it is clear that EKF almost eliminates the effect of noise.

In present study, the proportional-integral (PI) controller is designed by comparing the characteristic equations. The design specifications are taken as settling time 0.005 s and maximum overshoot 0.2%. In order to meet these specifications, the closed-loop poles are placed at $-\zeta\omega_n \pm j\omega_d$ and $-5\zeta\omega_n$. The PI controller gain that

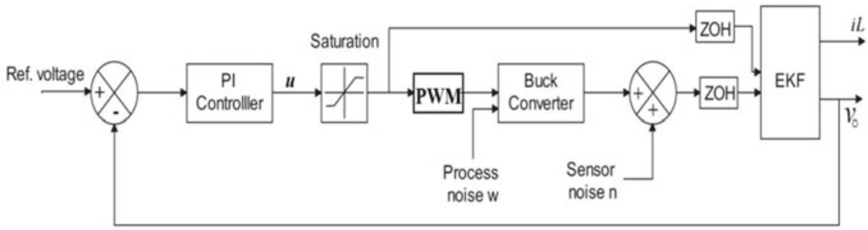

Fig. 2 Buck converter with EKF and PI controller

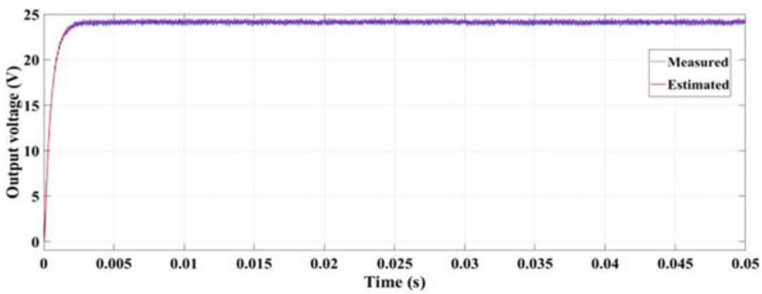

Fig. 3 Estimated and measured output voltage

is obtained is $\left(0.0435 + \frac{21.7}{s}\right)$. The output voltages of the closed-loop system with EKF and PI controller and with only PI controller are displayed in Fig. 4 for reference voltage 20 V, and the performance measures are given in Table 1. The responses show that EKF-based controller minimizes the effect of noise.

For different reference voltages and different load resistances, output voltage responses are shown in Figs. 5 and 6, respectively. It can be observed from the figures that the controller tracks the different reference voltages and also give satisfactory result in the presence of different load resistances. For different load resistances, the inductor current is shown in Fig. 7.

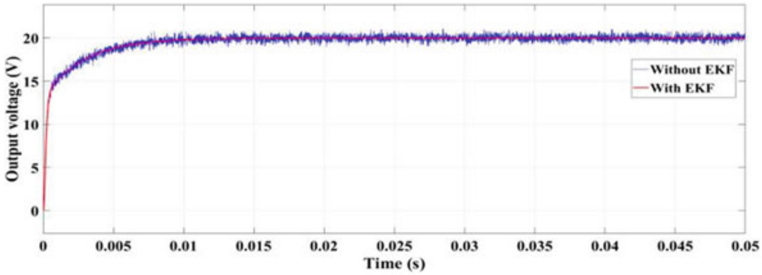

Fig. 4 Output voltage with EKF and without EKF

Table 1 Performance measures of closed-loop system

Controller	ISE (integral square error)	IAE (integral absolute error)	ITAE (integral time absolute error)
With EKF and PI	0.1298	0.02996	0.001918
With PI only	0.1806	0.1503	0.03263

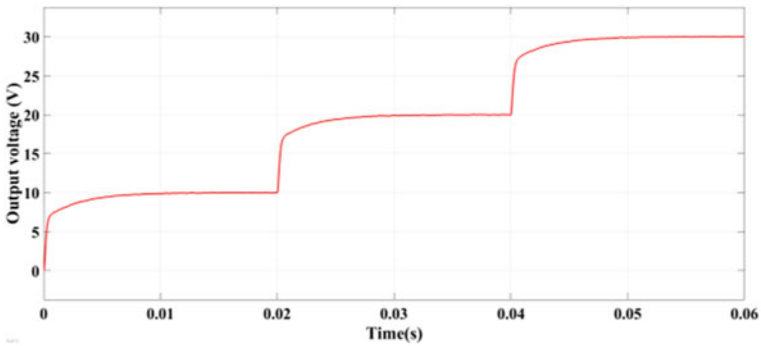

Fig. 5 Output voltage for different reference voltages (10 V at $t = 0$ s, 20 V at $t = 0.02$ s and 30 V at $t = 0.04$ s)

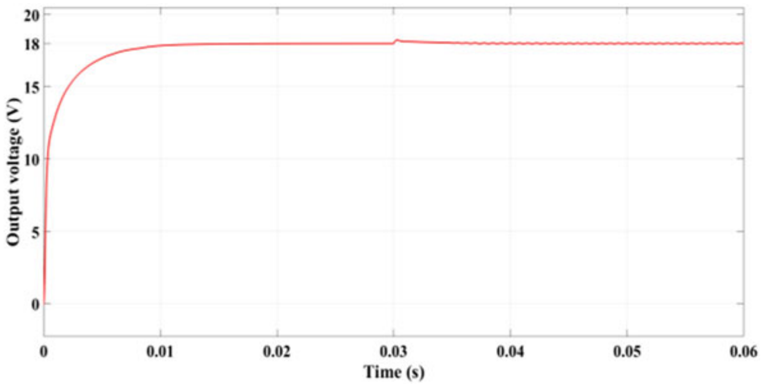

Fig. 6 Output voltage for different load resistance (5 Ω from time 0 s to 0.03 s and 30 Ω from time 0.03 s to 0.06 s)

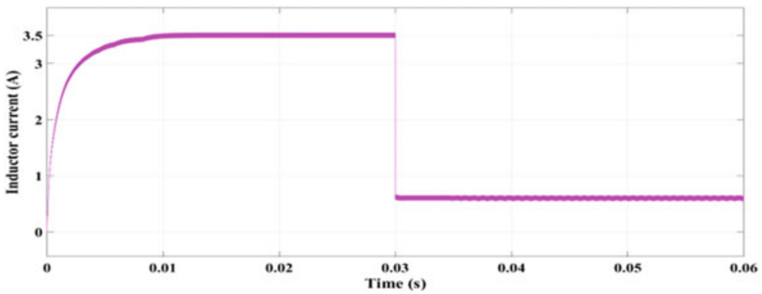

Fig. 7 Inductor current for different load resistance (5 Ω from time 0 s to 0.03 s and 30 Ω from time 0.03 s to 0.06 s)

5 Conclusion

In the present study, EKF and PI controller are designed to estimate state variables and to control output voltage PI controller of the DC-DC buck converter. The responses of EKF-based PI controller track the different output voltages of the DC-DC converter accurately and give good transient responses. In future, more efficient controller like fuzzy logic–based PID controller, fractional order-based PI or PID controller may be designed for the improvement of the output of the system. The control algorithm may be tested in real-time buck converter.

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