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ROBUST CONVERTER CONTROL APPROACH FOR VELOCITY OF NONLINEAR ELECTRIC MOTOR SYSTEMS WITH PHOTOVOLTAIC POWER SOURCES

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Abstract. *Photovoltaic (PV) generator employed application systems have been widely developed in industrial fields. This paper presents a novel robust converter control approach for DC electric motor systems with PV power generators. Firstly, we mathematically express its nonlinear time-varying system model with a state-space representation and propose a model reference based control approach against random output voltage of PV generators. Next, an adaptive parameter estimation algorithm is analytically derived by using a well-known Lyapunov stability theorem. We carry out numerical simulation to demonstrate reliability of the proposed control approach and superiority with respect to robustness against random PV power excitation through a comparative study in which a conventional state feedback control methodology is applied in the simulation example as well.*
Keywords: PV generator, Robust control, Boost converter, Lyapunov theory, Parameter estimation

1. Introduction.

Photovoltaic (PV) power generators have been widely employed over the world because it is significantly regarded as the best alternative energy system [1,2]. Until now, there are many research issues in terms of PV generator applications including effective power converters, electric power storage systems, high quality solar cell modules, and so on. Qi et al. proposed the global peak area (GPA) methodology which is aimed to improve a management technique against PV modules with temporary shadows [3], and Zhu et al. developed an effective management technique in electric battery charges for stand-alone PV systems and devised a three-port power converter to improve energy equivalent controls of them [4]. Moreover, Simon and Das addressed an incremental conductance concept for power converters in which the inductance and capacitance are additionally installed to improve maximum output power quantity [5]. Sivakumar et al. developed an effective control algorithm for DC-DC converter systems with nonlinear dynamic loads to seek a maximum output power in PV generator applications [6]. More recently, Brenna et al. addressed a control strategy of battery storage systems for dispatching a photovoltaic generation farm and developed a neural network based predictive model to estimate the solar irradiation and load power consumption [7]. We recognize from these literature reviews that they mostly dealt with PV power system as deterministic dynamics. However, this is rarely acceptable practically in that the output power of PV systems is obviously random because it is a function of solar radiation and ambient temperature that are hardly deterministic.

We investigate a novel control approach for DC-DC power converters with PV power excitation. Such control objective is a robust regulation of its velocity under random output power from PV generators. We first express a state-space representation for an integrated system model including the PV generator, the boost converter, and the DC electric motor. Next, we apply a model reference control mechanism to design our proposed control framework and employ a well-known Lyapunov stability theory [8] to derive adaptive control parameter estimation. From this computation, control parameter vector is adjusted based on an error between actual system states and reference system states. Finally, a numerical simulation is carried out to demonstrate reliability of the proposed converter control approach and a comparative study is additionally accomplished to prove its superiority by comparing results from a conventional state feedback control method.

A remainder of this paper is organized as follows. Section 2 presents a state-space representation about integrated DC motor control systems with PV power generators. Section 3 and Section 4 describe the proposed control framework for such dynamic system and its parameter estimation algorithm through mathematical procedures respectively. We provide numerical examples to test reliability of the proposed control approach, and describe comparative study to prove its superiority in Section 5. Lastly, conclusions and future work are respectively offered in Section 6.

2. **System Model.** An electric circuit model of DC-DC boost converter [9] based control systems of DC electric motors with PV power excitation considered in this paper is illustrated in Figure 1. Here, $V_{pv}(t)$ and $i_{pv}(t)$ are the output voltage and current with a continuous time index t from PV generators, $v_o(t)$ is the inverter output voltage regulated by a control input variable $u(t)$, L and C are the inductance and the capacitance in a converter circuit model. In the electric motor system model, R_a and L_a are the resistance and inductance, $i_a(t)$ is the armature current, $\omega(t)$ is its rotor velocity, T_L is a load torque, and J_m is an inertia coefficient. Apparently, this configuration is mainly composed of three system parts including the PV generator, the power inverter, and the electric motor. We simply assume that they are electrically connected in series without any electric loss among its linkages. We mathematically express such integrating system model to a state-space representation as

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{B}(t)u(t) + \boldsymbol{W}(t) \tag{1}$$

where a state vector $\boldsymbol{x}(t) = [i_{pv}(t)\ v_o(t)\ i_a(t)\ \omega(t)]^T$ and corresponding matrices are given by

$$\boldsymbol{A} = \begin{bmatrix} 0 & -\frac{1}{L} & 0 & 0 \\ \frac{1}{C} & -\frac{1}{C} & 0 & 0 \\ 0 & \frac{1}{L_a} & -\frac{R_a}{L_a} & -\frac{1}{L_a} \\ 0 & 0 & \frac{1}{J_m} & -\frac{1}{J_m} \end{bmatrix}, \quad \boldsymbol{B}(t) = \begin{bmatrix} 1 \\ -\frac{i_L(t)}{C} \\ 0 \\ 0 \end{bmatrix}, \quad \boldsymbol{W}(t) = \begin{bmatrix} \frac{V_{pv}(t)}{L} \\ 0 \\ 0 \\ -\frac{T_L}{J_m} \end{bmatrix}$$

It is obvious that this system model in (1) involves time-varying and nonlinear dynamics because of the input matrix $\boldsymbol{B}(t)$ including the current $i_{pv}(t)$. And the time-varying matrix $\boldsymbol{W}(t)$ contains the output voltage of PV generators which can be regarded as a random

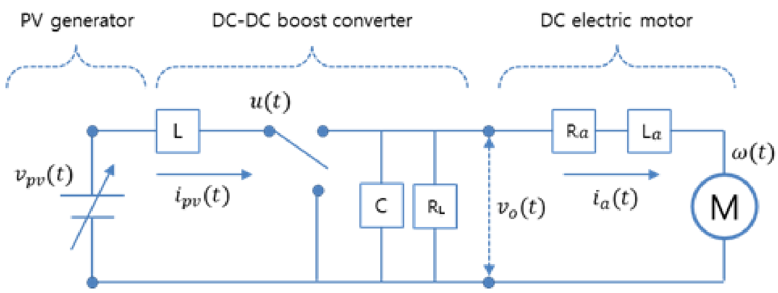

FIGURE 1. An electric circuit model for boost converter based control of DC motor systems with PV generators

variable since its quantity is dependent upon solar radiation and ambient temperature. Consequently, a dynamic behavior of such system requires adaptive robust control strategy to obtain acceptable control performance.

3. **Control Design.** We apply a model reference control approach to our control strategy stated in Section 2. To carry out this task, a reference system model with the same dimension to an actual system model in (1) is first defined as

$$\dot{\boldsymbol{x}}_{\boldsymbol{m}}(t) = \boldsymbol{A}_{\boldsymbol{m}}\boldsymbol{x}_{\boldsymbol{m}}(t) + \boldsymbol{B}_{\boldsymbol{m}}r + \boldsymbol{W}_{\boldsymbol{m}}(t) \tag{2}$$

where $\boldsymbol{x}_{\boldsymbol{m}} \in R^4$ and $r \in R$ are state vector and reference input scalar, and the corresponding matrices are given as $\boldsymbol{A}_{\boldsymbol{m}} \in R^{4\times4}$, $\boldsymbol{B}_{\boldsymbol{m}} \in R^{4\times1}$, and $\boldsymbol{W}_{\boldsymbol{m}} \in R^{4\times1}$. A control objective is that a state vector of an actual system dynamically traces one of a reference system model under a given control law given by

$$u(t) = -\boldsymbol{K}^*\boldsymbol{x}(t) + l^*r \tag{3}$$

where $\boldsymbol{K}^* \in R^{1\times4}$ and $l^* \in R$ are optimal control parameter matrix and scaler respectively. With an assumption that $\boldsymbol{W}_{\boldsymbol{m}} = \boldsymbol{W}$, we substitute (3) to (1) and then have

$$\dot{\boldsymbol{x}}(t) = (\boldsymbol{A} - \boldsymbol{B}\boldsymbol{K}^{\boldsymbol{*}})\boldsymbol{x}(t) + \boldsymbol{B}(t)l^*r + \boldsymbol{W}_{\boldsymbol{m}}(t) \tag{4}$$

From this dynamic equation in (4), we recognize that if we have $\boldsymbol{A} - \boldsymbol{B}\boldsymbol{K}^{\boldsymbol{*}} = \boldsymbol{A}_{\boldsymbol{m}}$ and $\boldsymbol{B}(t)l^* = \boldsymbol{B}_{\boldsymbol{m}}$, a state $\boldsymbol{x}(t)$ dynamically traces a reference state $\boldsymbol{x}_{\boldsymbol{m}}(t)$ and an equilibrium value of $\boldsymbol{x}$ becomes $\boldsymbol{x}_{\boldsymbol{m}}(\infty)$ under assumption that a reference system model is stable. This simple concept is realized by estimating proper parameters $\boldsymbol{K}$ and l through numerical method.

4. **Adaptive Parameter Estimation.** This section describes a mathematical procedure to derive adjustment rules for control parameters $\boldsymbol{K}$ and l. We rewrite a control law composed of these two parameters as

$$u(t) = -\boldsymbol{K}(t)\boldsymbol{x}(t) + l(t)r \tag{5}$$

A proper estimation algorithm should be accomplished for which the parameters $\boldsymbol{K}(t)$ and $l(t)$ become the optimal parameters $\boldsymbol{K}^*$ and l^* against given system environment. Likewise, we substitute (5) to (1) and then expand as

$$\begin{aligned}\dot{\boldsymbol{x}} &= \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}(-\boldsymbol{K}\boldsymbol{x} + lr) + \boldsymbol{W}\\ &= (\boldsymbol{A} - \boldsymbol{B}\boldsymbol{K})\boldsymbol{x} + \boldsymbol{B}lr + \boldsymbol{B}(\boldsymbol{K}^*\boldsymbol{x} - l^*r + u) + \boldsymbol{W}\\ &= \boldsymbol{A}_{\boldsymbol{m}}\boldsymbol{x} + \boldsymbol{B}_{\boldsymbol{m}}r + \boldsymbol{B}(\boldsymbol{K}^*\boldsymbol{x} - l^*r + u) + \boldsymbol{W}\end{aligned} \tag{6}$$

Next, we define a state error $\boldsymbol{e}_{\boldsymbol{x}}$ between actual and reference states, and two parameter errors $\boldsymbol{e}_{\boldsymbol{K}}$ and e_l between estimated and optimal values, mathematically are expressed as

$$\boldsymbol{e}_{\boldsymbol{x}} = \boldsymbol{x} - \boldsymbol{x}_{\boldsymbol{m}}, \quad \boldsymbol{e}_{\boldsymbol{K}} = \boldsymbol{K} - \boldsymbol{K}^{\boldsymbol{*}}, \quad e_l = l - l^* \tag{7}$$

We apply a well-known Lyapunov stability theory for this parameter estimation rule. Thus, a positive definite Lyapunov function should be necessarily defined including error variables in (7) as

$$V = \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}}\boldsymbol{P}\boldsymbol{e}_{\boldsymbol{x}} + tr\left[\boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}}\gamma\boldsymbol{e}_{\boldsymbol{K}} + e_l^T\gamma e_l\right] \tag{8}$$

where tr denotes the matrix trace, $\boldsymbol{P} \in R^{4\times4}$ is a positive definite matrix, and γ is a non-negative scalar. To designate a positive parameter γ, we let its inverse as

$$\gamma^{-1} = l^*sgn(l^*) \tag{9}$$

where $sgn(l^*)$ denotes a sign of the variable l^*. Next, we differentiate a Lyapunov function in (8) and then have

$$\dot{V} = \dot{\boldsymbol{e}}_{\boldsymbol{x}}^{\boldsymbol{T}}\boldsymbol{P}\boldsymbol{e}_{\boldsymbol{x}} + \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}}\boldsymbol{P}\dot{\boldsymbol{e}}_{\boldsymbol{x}} + tr\left[\dot{\boldsymbol{e}}_{\boldsymbol{K}}^{\boldsymbol{T}}\gamma\boldsymbol{e}_{\boldsymbol{K}} + \boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}}\gamma\dot{\boldsymbol{e}}_{\boldsymbol{K}} + \dot{e}_l^T\gamma e_l + e_l^T\gamma\dot{e}_l\right] \tag{10}$$

By employing (2) and (6), we calculate a derivative of the state error function in (7) as

$$\begin{aligned}\dot{\boldsymbol{e}}_{\boldsymbol{x}} &= \dot{\boldsymbol{x}} - \dot{\boldsymbol{x}}_{\boldsymbol{m}} = \boldsymbol{A_m x} + \boldsymbol{B_m} r + \boldsymbol{B}(\boldsymbol{K}^*\boldsymbol{x} - l^* r + u) + \boldsymbol{W_m} - \boldsymbol{A_m x_m} - \boldsymbol{B_m} r - \boldsymbol{W_m} \\ &= \boldsymbol{A_m e_x} + \boldsymbol{B}(\boldsymbol{K}^*\boldsymbol{x} - l^* r - \boldsymbol{Kx} + lr) = \boldsymbol{A_m e_x} + \boldsymbol{B}(-\boldsymbol{e_K x} + e_l r) \\ &= \boldsymbol{A_m e_x} + \boldsymbol{B_m} l^{*-1}(-\boldsymbol{e_K x} + e_l r)\end{aligned} \tag{11}$$

We simply substitute the resulting equation in (11) to the first two terms in the right part of (10) and then obtain

$$\begin{aligned}&\dot{\boldsymbol{e}}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P e_x} + \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P} \dot{\boldsymbol{e}}_{\boldsymbol{x}} \\ =\ & [\boldsymbol{A_m e_x} + \boldsymbol{B_m} l^{*-1}(-\boldsymbol{e_K x} + e_l r)]^T \boldsymbol{P e_x} + \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P}[\boldsymbol{A_m e_x} + \boldsymbol{B_m} l^{*-1}(-\boldsymbol{e_K x} + e_l r)] \\ =\ & \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P}^{\boldsymbol{T}}[\boldsymbol{A_m e_x} + \boldsymbol{B_m} l^{*-1}(-\boldsymbol{e_K x} + e_l r)] + \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P}[\boldsymbol{A_m e_x} + \boldsymbol{B_m} l^{*-1}(-\boldsymbol{e_K x} + e_l r)] \\ =\ & \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \left(\boldsymbol{P}^{\boldsymbol{T}} + \boldsymbol{P}\right)[\boldsymbol{A_m e_x} + \boldsymbol{B_m} l^{*-1}(-\boldsymbol{e_K x} + e_l r)] \\ =\ & \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \left(\boldsymbol{P A_m} + \boldsymbol{A}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P}\right) \boldsymbol{e_x} + 2\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P B_m} l^{*-1}(-\boldsymbol{e_K x} + e_l r)\end{aligned} \tag{12}$$

From a well-known Lyapunov stability theory, if we select $\boldsymbol{P} = \boldsymbol{P}^{\boldsymbol{T}}$, the Lyapunov equation in (12) is expressed as

$$\boldsymbol{P A_m} + \boldsymbol{A}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P} = -\boldsymbol{Q} \tag{13}$$

where a matrix $\boldsymbol{Q} = \boldsymbol{Q}^{\boldsymbol{T}}$ is positive definite. By applying (13) to the last term of (12), we rewrite

$$\dot{\boldsymbol{e}}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P e_x} + \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P} \dot{\boldsymbol{e}}_{\boldsymbol{x}} = -\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{Q e_x} + 2\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P B_m} l^{*-1}(-\boldsymbol{e_K x} + e_l r) \tag{14}$$

where $l^{*-1} = \gamma sgn(l^*)$ from (9). Thus, Equation (14) is rewritten as

$$\dot{\boldsymbol{e}}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P e_x} + \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P} \dot{\boldsymbol{e}}_{\boldsymbol{x}} = -\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{Q e_x} - 2\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P B_m} \gamma \boldsymbol{e_K x} sgn(l^*) + 2\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P B_m} \gamma e_l r sgn(l^*) \tag{15}$$

Furthermore, we apply a matrix trace theory to the second and third terms in the right part of (15) and then expand respectively as

$$\begin{aligned}-2\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P B_m} \gamma \boldsymbol{e_K x} sgn(l^*) &= -2tr\left[\boldsymbol{x}^{\boldsymbol{T}} \boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \gamma \boldsymbol{B}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P e_x}\right] sgn(l^*) \\ &= -2tr\left[\boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \gamma \boldsymbol{B}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P e_x x}^{\boldsymbol{T}}\right] sgn(l^*)\end{aligned} \tag{16}$$

and

$$2\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P B_m} \gamma e_l r sgn(l^*) = 2tr\left[r e_l \gamma \boldsymbol{B}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P e_x}\right] sgn(l^*) = 2tr\left[e_l \gamma \boldsymbol{B}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P e_x} r\right] sgn(l^*) \tag{17}$$

By substituting the last terms in (16) and (17) to (15), we rewrite

$$\begin{aligned}&\dot{\boldsymbol{e}}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P e_x} + \boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{P} \dot{\boldsymbol{e}}_{\boldsymbol{x}} \\ =\ & -\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{Q e_x} - 2tr\left[\boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \gamma \boldsymbol{B}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P e_x x}^{\boldsymbol{T}}\right] sgn(l^*) + 2tr\left[e_l \gamma \boldsymbol{B}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P e_x} r\right] sgn(l^*)\end{aligned} \tag{18}$$

Note from (7) that $\dot{\boldsymbol{e}}_{\boldsymbol{K}} = \dot{\boldsymbol{K}}$ and $\dot{e}_l = \dot{l}$ because of constant parameters $\boldsymbol{K}^*$ and l^*. Likewise, we employ a matrix trace theory to rewrite the third term of (10) as

$$\begin{aligned}&tr\left[\dot{\boldsymbol{e}}_{\boldsymbol{K}}^{\boldsymbol{T}} \boldsymbol{\gamma} \boldsymbol{e_K} + \boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \boldsymbol{\gamma} \dot{\boldsymbol{e}}_{\boldsymbol{K}} + \dot{e}_l^T \gamma e_l + e_l^T \gamma \dot{e}_l\right] \\ =\ & tr\left[\boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \boldsymbol{\gamma} \dot{\boldsymbol{e}}_{\boldsymbol{K}} + \boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \boldsymbol{\gamma} \dot{\boldsymbol{e}}_{\boldsymbol{K}} + e_l^T \gamma \dot{e}_l + e_l^T \gamma \dot{e}_l\right] \\ =\ & 2tr\left[\boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \boldsymbol{\gamma} \dot{\boldsymbol{e}}_{\boldsymbol{K}} + e_l^T \gamma \dot{e}_l\right] = 2tr\left[\boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \boldsymbol{\gamma} \dot{\boldsymbol{K}} + e_l^T \gamma \dot{l}\right]\end{aligned} \tag{19}$$

By substituting the resulting equations in (18) and (19) to (10), we finally obtain a derivative of the Lyapunov function as

$$\begin{aligned}\dot{V} =\ & -\boldsymbol{e}_{\boldsymbol{x}}^{\boldsymbol{T}} \boldsymbol{Q e_x} - 2tr\left[\boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \gamma \boldsymbol{B}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P e_x x}^{\boldsymbol{T}}\right] sgn(l^*) + 2tr\left[e_l \gamma \boldsymbol{B}_{\boldsymbol{m}}^{\boldsymbol{T}} \boldsymbol{P e_x} r\right] sgn(l^*) \\ & +2tr\left[\boldsymbol{e}_{\boldsymbol{K}}^{\boldsymbol{T}} \gamma \dot{\boldsymbol{K}} + e_l^T \gamma \dot{l}\right]\end{aligned} \tag{20}$$

We know from a Lyapunov stability theory that the derivative function $\dot{V}$ should be negative to guarantee asymptotical stability of the error $\boldsymbol{e_x}$ for a given time interval $t \in [t_0, t_f]$. Such stable dynamic behavior involves that the state error $\boldsymbol{e_x}$ is bounded for $t \in [t_0, t_f]$ and consequently, dynamics of an actual state vector $\boldsymbol{e_x}$ matches one of a reference state vector $\boldsymbol{e_m}$. To assure $\dot{V} < 0$ in (20), we have a feasible condition as

$$-2tr\left[\boldsymbol{e_K^T}\gamma \boldsymbol{B_m^T P e_x x^T}\right] sgn(l^*) + 2tr\left[e_l \gamma \boldsymbol{B_m^T P e_x} r\right] sgn(l^*) + 2tr\left[\boldsymbol{e_K^T}\gamma \dot{\boldsymbol{K}} + e_l^T \gamma \dot{l}\right] = 0 \tag{21}$$

We obtain solutions of Equation (21) with respect to the parameters $\dot{\boldsymbol{K}}$ and $\dot{l}$. Simply, Equation (21) is divided to two equations as

$$tr\left[\boldsymbol{e_K^T}\gamma \dot{\boldsymbol{K}}\right] = -tr\left[\boldsymbol{e_K^T}\gamma \boldsymbol{B_m^T P e_x x^T}\right] sgn(l^*), \quad tr\left[e_l^T \gamma \dot{l}\right] = -tr\left[e_l \gamma \boldsymbol{B_m^T P e_x} r\right] sgn(l^*) \tag{22}$$

As a result, we have its solutions respectively as

$$\dot{\boldsymbol{K}} = \boldsymbol{B_m^T P e_x x^T} sgn(l^*), \quad \dot{l} = -\boldsymbol{B_m^T P e_x} r sgn(l^*) \tag{23}$$

These parameters adjustments rules are expressed as ordinary differential functions with respect to a state error vector. We mathematically integrate these differential functions to update parameter values through a suitable numerical method.

5. **Numerical Simulation.** We carry out numerical simulation to test reliability of the proposed control approach. For this simulation experiment, system parameters values in (1) are selected as follows: $L = 1.5$[mH], $C = 500[\mu\text{F}]$, $R_L = 10[\Omega]$, $J_m = 0.02[\text{Nm/rad/sec}^2]$, $T_L = 1$[Nm], $L_a = 50$[mH], $R_a = 1[\Omega]$. And to construct a reference system model in (2), we let $\boldsymbol{B_m} = \boldsymbol{B}$, $\boldsymbol{W_m} = \boldsymbol{W}$, $r = 10$, and

$$\boldsymbol{A_m} = \begin{bmatrix} 0 & -1.3 & 0 & 0 \\ 4 & -0.4 & 0 & 0 \\ 0 & 0.4 & -0.4 & -0.4 \\ 0 & 0 & 100 & -0.1 \end{bmatrix} \times 10^3$$

A control objective in this simulation is that the rotor velocity of the electric motor keeps to the reference level, $r = 10$[rad/sec] under random output voltage from the PV generator. Particularly, we consider that this random voltage is excited from Gaussian distribution with 20 voltage mean and unit variance, i.e., $v_{pv} \sim N(20, 1)$. Under this simulation topology, we iteratively accomplish the proposed control parameter estimation algorithm in (22) until the best control performance is achieved in the control point of view. Figure 2 shows time-histories of the control parameters estimation for the best control performance. We observe from these curves that the parameters have transient behaviors until about 0.2sec and since then these keep steady state responses with almost equilibrium levels. From this simulation result in Figure 2, we obtain its final values as $\boldsymbol{K} = [0.055, 0.012, 0.143, 0.221]$ and $l = 0.125$. We apply these parameter values to the control law in (5) and carry out numerical simulation about dynamics of the system model

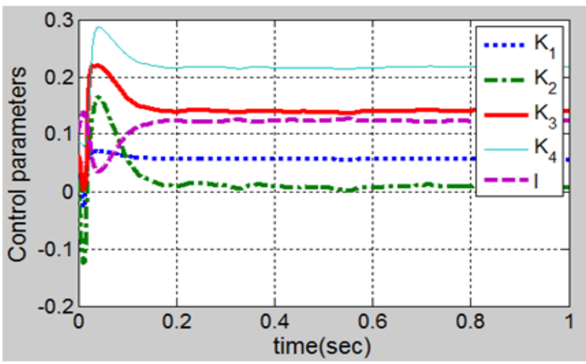

Figure 2. Control parameters estimation

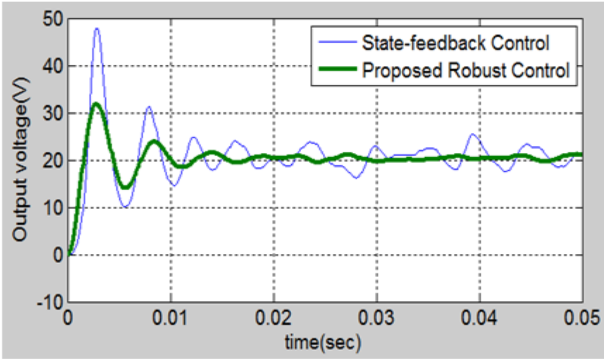

FIGURE 3. Converter output voltage

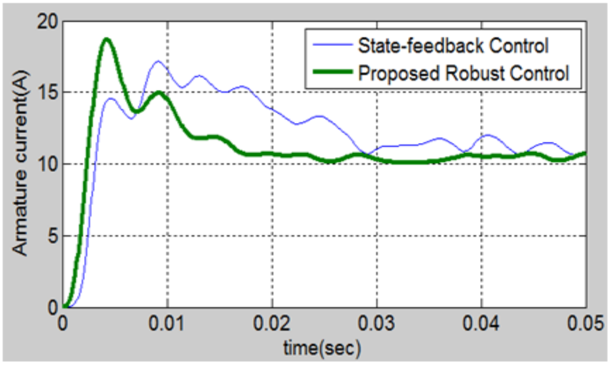

FIGURE 4. Armature current

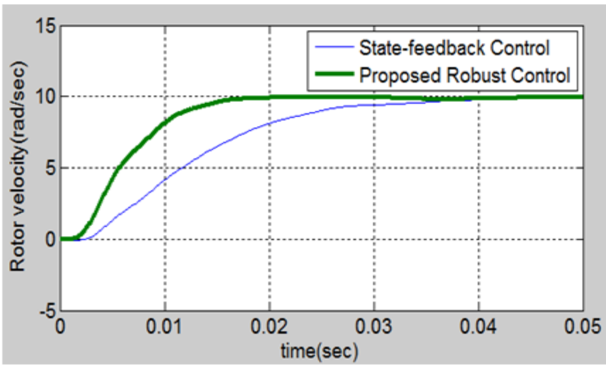

FIGURE 5. Rotor velocity

in (1). For a comparative study, an additional simulation by using a conventional state-feedback control [8] is similarly accomplished under the same simulation environments. As well known, a state-feedback control is easily constructed for somewhat excellent control performances in nonlinear systems. Figures 3, 4, and 5 illustrate simulation results from conventional control and the proposed control methods. Figure 3 shows time-histories of the converter output voltage for two control methods. We observe that the converter voltage from a conventional control method has larger overshoots and longer transient time period than one of the proposed control methods. From Figure 4, the armature current of the electric motor in a case of the conventional control rarely approaches steady-state response during a given time period. However, our proposed control system has an equilibrium current level around 0.02sec with few ripples. Since such ripple is obviously due to the random output voltage from the PV generator, such dynamic behavior is quite acceptable. Lastly, Figure 5 plots time-histories of the rotor velocity against the two control methods. Similarly, we recognize that dynamic performance of our proposed control system is superior in that its steady-state response time is rather fast although there are almost no overshoot behaviors in a transient region for both of the two control systems. In conclusion, from this comparative simulation study, we prove reliability and superiority of the proposed control methodology for DC motor control systems with PV generator based power converters.

6. **Conclusions.** This paper investigates a boost converter control method for rotor velocity of DC motor systems with PV power excitation by employing Lyapunov stability theory to realize adaptive robust control performance. We mathematically present adaptive parameter estimation algorithm to seek a best parameter value for DC-DC power converters. Simulation experiment was carried out to test its reliability and superiority through a comparative study in which a conventional state feedback control method was applied under the same simulation topology as well. From the simulation results, we demonstrate that the proposed control system is superior for transient dynamics in that a maximum overshoot is less and a steady-state arriving time becomes faster than a conventional control method. Moreover, we prove that our control method is outstandingly robust against random PV output voltage. Future work includes real-time experiments to demonstrate practicability of the proposed converter control systems excited from PV power generators.

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