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Published in:
I E E E Transactions on Industrial Electronics

DOI (link to publication from Publisher):
10.1109/TIE.2018.2880666

Publication date:
2019

Document Version
Accepted author manuscript, peer reviewed version

Tracking Control for a DC Microgrid Feeding Uncertain Loads in More Electric Aircraft: Adaptive Backstepping Approach

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***Abstract*—More electric aircrafts (MEAs) comprise a vast amount of power electronic loads, which usually behave as constant power loads (CPLs). The incremental negative impedance of CPLs threatens system stability. To ensure an effective control of power flow in MEAs, eliminating the undesired behavior of CPLs is a necessity. This aim requires spontaneous power estimation of the time-varying uncertain loads. In this paper, an adaptive backstepping controller, which is interconnected to a 3rd degree cubature Kalman filter (CKF), is developed for a DC MG feeding non-ideal CPLs. At first, the load power is considered as an artificial state and augmented into the system states, which enables estimation of not only the DC MG states but also the unknown value of the load power. The estimated load power is then forwarded to a backstepping controller. The systematic approach of this controller allows obtaining the control signal, which is the duty ratio of the switch, to not only system stabilizing but also tracking a desired voltage of the DC bus under the load power variations. The proposed adaptive controller is tested on a DC MG that has one CPL. The conducted experimental results verify the proposed nonlinear control in tracking the desired voltage of the DC bus under slow and fast variations of the load power.**

***Index Terms*—More electric aircraft power system, DC microgrid (MG), Constant power load (CPL), Cubature Kalman filter (CKF), Adaptive backstepping controller.**

I. INTRODUCTION

Nowadays, driven by environmental benefits, improving systems' performance and the high price of fossil fuels, renewable energies have attracted significant research interest. Advancement of power electronic systems has also caused a trend toward the realization of more efficient electric aircrafts [1], electric ships [2], and electric vehicles [3], which are all power electronics intensive technologies. Conventional aircrafts were driven by electrical, mechanical, pneumatic, and hydraulic systems [4]. However, more electric aircraft (MEA) concept was recently introduced by the U.S. air force to encourage the electrification of aircrafts [5]. The transition from conventional aircraft to MEA is expected to increase performance, reduces aerospace ground equipment/ground support equipment, and decreases operation and support costs [5]. Traditional aircrafts contain hydraulic, pneumatic, mechanical and electrical subsystems. The interactions between all these subsystems reduce the efficiency and reliability of the aircraft power systems [6]. Electrification of aircrafts reduces the weight, size, and fuel consumption, and increases the overall efficiency [7].

Microgrids (MG) are systems used to control the power flow of renewable energy sources, which are mainly distributed. Integration and development of MGs in the MEA is one of the challenges to be addressed [8]. Because of the advantages of DC microgrids (MG) over AC MGs, there is a tendency toward using DC MGs in MEA [9]. These advantages include power loss reduction in AC/DC power conversion [10], removing frequency control problems, improving power quality, decreasing the space and weight of transformers [9], and improving fault reconfigurability. DC MGs consist of several interconnected active loads, such as actuators and energy storage systems (ESS), which are commonly controlled by converters. If the bandwidth and control performance of these loads are considerably high, they consume power, which is independent of the bus voltage. In this case, these loads are considered as constant power loads (CPLs). CPLs then behave like incremental negative impedances, which can threaten the stability of DC MGs. Thus, minimizing the undesired effect of CPLs is a necessity to have a successful control of DC MGs.

Several strategies are proposed to mitigate the destructive effects of CPLs in DC MGs. Two basic strategies are passive damping and active damping approaches [11]. Passive damping includes adding damping resistors to the filters. Even though this approach is simple and effective, it causes a lot of dissipation. Active damping involves modifying the control loop, which acts like a virtual resistor [11]. Active damping approaches actively inject the power to the system in order to neutralize the effects of CPLs [12]. In addition, these active damping approaches, which are based on small-signal models, can ensure system stability only in the vicinity of the operating point. Therefore, these linear control methods are not useful in the case of occurrence of large variations in the system [12]. Several nonlinear control approaches have also been studied the stability problems with the DC MGs containing CPLs. In [13], a model predictive control (MPC) is employed, by minimizing a user-defined performance index, to control

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIE.2018.2880666, IEEE Transactions on Industrial Electronics

switching of a boost converter sourcing a CPL. However, MPC is not suitable for plant-wide real-time applications, due to its computational burden [14]. In [15], a sliding mode controller is proposed to stabilize a boost converter sourcing a CPL by controlling the duty ratio. This method is able to stabilize the system over the whole operating range even when the load power and supply voltage vary significantly. However, this method requires measuring the capacitor current, which is costly and causes ripple filtering degradation and the output impedance increasing [12]. Backstepping control is a systematic approach to design adaptive controllers with a simple implementation. This method guarantees global or local stabilization and accurate tracking in the presence of uncertainties. In addition, it permits retaining useful nonlinearities, which improves the controller performance [16]. Recently, employing the backstepping controller in the presence of CPLs is considered in [12]. In cases where unknown or time-varying parameters are present in the system, adaptive control approaches, which can regulate the adaptive parameters on-line, have attracted attention [17], [18]. In [19], an adaptive backstepping control is proposed to solve the tracking problem in an electric vehicle. In [12], a deterministic nonlinear disturbance observer is employed to estimate the uncertain power of the load, which is then used in an adaptive backstepping controller to track the DC bus voltage. Nonetheless, the deterministic observer performance may deteriorate in the presence of noisy measurements, which makes it unsuitable for practical applications [20]. Furthermore, the approach of [12] is sensitive to system uncertainty and unmodeled dynamics. Kalman filtering approaches are proved to be optimal in the case of linear dynamics and Gaussian noise [21]. The extended Kalman filter (EKF) applies the Kalman filter to nonlinear systems by linearizing the system model. The EKF exhibits poor performance for highly nonlinear dynamic systems. However, Bayesian sampling methods are alternatives to the EKF. These methods are divided into random sampling and deterministic sampling [22]. Random sampling methods involve a high computational burden, which makes them inappropriate for practical applications where fast estimation is required. Among the deterministic sampling methods, cubature Kalman filters (CKFs) have attracted particular interest recently due to their attractive features such as accuracy, lower computational burden, and good numerical stability properties [22]–[24].

In this paper, to eliminate the undesired effects of CPLs in the MEA operation, a 3rd degree CKF algorithm is developed to solve a joint estimation problem to estimate not only DC MG's states but also the total power of the load. To achieve this goal, the CPL's power is augmented into the state space vector of the system as a virtual state. The estimated load power is then forwarded to a backstepping controller to both stabilize the system and also to track a desired voltage on the DC bus. To this aim, fist the strict-feedback model of the system model is constructed. By following the recursive backstepping controller steps to obtain the intermediate control laws, the main control law, which governs the duty ratio of the switch, is obtained. In comparison to the work in [12], this approach is robust against system uncertainties, unmodeled dynamics, and noisy measurements. Moreover, the backstepping controller is designed based on more simple control Lyapunov functions (CLF), which makes the controller design procedure simpler and easier to be used on the more complex system models. The developed adaptive backstepping controller is then applied to a DC MG connected to an uncertain time-varying CPL. The effectiveness of our proposed CKF to estimate the unknown time-varying power of the total load and the proposed backstepping controller to stabilize the system and track the voltage of the DC bus is verified by experiments.

The outline of this paper is as follows. The modeling of the DC MG is provided in Section II. In Section III, the developed CKF algorithm for the estimation of the unknown power of the load is presented. Section IV presents the nonlinear backstepping controller design, which is interconnected to the estimated power of the load in Section III. To investigate the performance of the proposed adaptive backstepping controller, the illustrative experimental results are presented in sections V. Finally, Section VI concludes the paper.

II. MEA DC MICROGRID DYNAMIC

A typical MEA is shown in Fig. 1 and its simplified electrical schematic is shown in Fig. 2.

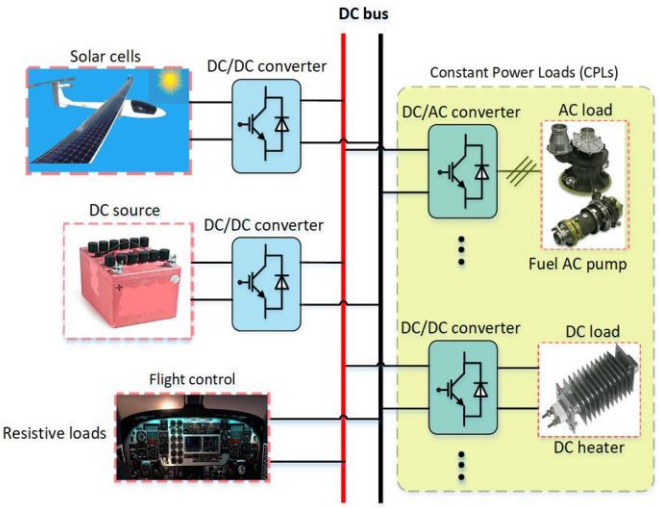

Fig. 1. Power system illustration of an MEA DC MG.

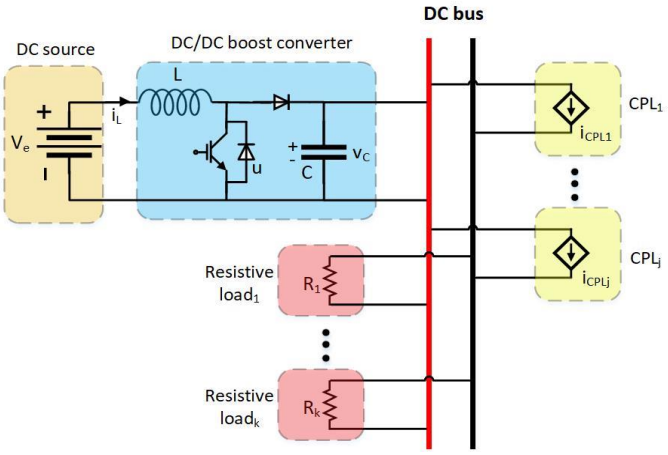

Fig. 2. A simplified illustration of the MEA DC MG shown in Fig. 1 with Q CPLs and K resistive loads.

It has several CPLs, solar cells for providing power during

the day and batteries for providing power during the night. In MEA, most of the closed-loop DC and AC loads behave as CPLs [25]. An example of AC CPLs is a DC/AC converter drives a fuel AC pump when the fuel pump tightly supplies a constant flow of fuel to the engines. Another example of an AC CPL is a DC/AC converter connected to an electric motor that tightly regulates the motor speed [26], [27]. An example of a DC CPL is a heater, for which it is required to keep the dissipated power from the heater constant, in spite of changes in the resistor temperature and process variations. These heaters can have different applications, such as maintaining warmth at high altitudes and in cold weather and food warming.

As can be seen in Fig. 2, all the resistive loads, $R_1, \dots R_K$, are in parallel and the equivalent resistive load, R, is defined as

$$R = \left(\frac{1}{R_1} + \cdots + \frac{1}{R_K}\right)^{-1} \tag{1}$$

The circuit diagram of Fig. 2 is shown in Fig. 3. In this diagram, the CPL current is described as

$$i_{CPL} = \frac{P_{CPL}}{v_{CPL}} = \frac{P_{CPL}}{v_C} \tag{2}$$

where v_{CPL}, P_{CPL} are the CPL voltage and power, respectively, and v_C is the capacitor voltage.

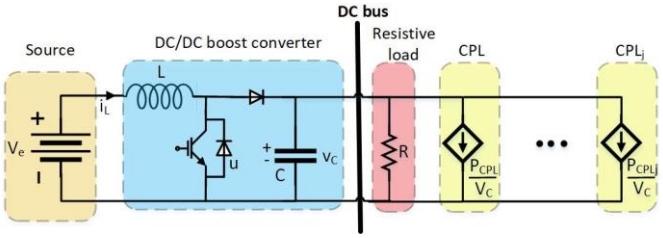

Fig. 3. Circuit Diagram of the DC MG shown in Fig. 2 with Q CPLs and K resistive loads.

The DC/DC boost converter in Fig. 3 can be represented by a switch, as depicted in Fig. 4.

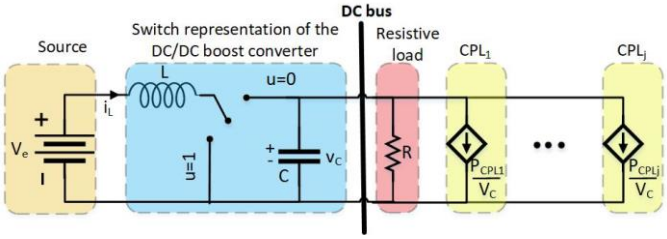

Fig. 4. Switch representation of the simplified power converter load as a CPL.

In Fig. 4, $u \in \{0,1\}$ is the duty cycle of the switch and the control signal of the system. $u = 0$ corresponds to the conducting mode for the switch and $u = 1$ corresponds to the non-conducting mode for the switch. The total load includes the resistive loads and the CPLs. The dynamical model of the system in Fig. 4 is obtained through employing the Kirchhoff's current and voltage laws as follows:

$$\begin{cases} L\dfrac{di_L}{dt} = V_e - (1-u)v_C \\ C\dfrac{dv_C}{dt} = (1-u)i_L - \dfrac{v_C}{R} - \dfrac{P_{CPL1}}{v_C} - \cdots - \dfrac{P_{CPLQ}}{v_C} \end{cases} \tag{3}$$

where L, C are the input inductance and capacitance, respectively, i_L is the inductance current, V_e is the source voltage, and $P_{CPL1}, \dots P_{CPLQ}$ are the power of the CPLs. In the above equations, i_L, v_C are measurable. Also, the total power of the load, P_{load}, as defined below, is estimated using the CKF approach as explained thereafter.

$$P_{load} = P_{CPL1} + \cdots + P_{CPLQ} + \frac{v_C^2}{R} \tag{4}$$

Then, the control signal, u, is obtained by applying the backstepping control as explained in section IV.

III. Cubature Kalman Filter For Power Estimation

This section presents the design procedure of the developed 3rd degree CKF to estimate the unknown power of the total load [28]. To this aim, the unknown vector of the total load's power, P_{load}, is augmented in the states of the system, in (3) [4]. Thereby, the augmented state vector is defined as:

$$x = [i_L \;\; v_C \;\; P_{load}]^T \tag{5}$$

Since the P_{load} dynamic is unknown, it is assumed that $\dot{P}_{load} = 0$. Using (3), the augmented state-space model for the DC MG is

$$\dot{x} = \left[\dot{i}_L \;\; \dot{v}_C \;\; \dot{P}_{load}\right]^T = f(x,u) \tag{6}$$

Also, the system measurements are described as

$$y = \begin{bmatrix} I & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} [i_L \;\; v_C \;\; P_{load}]^T = Hx \tag{7}$$

Putting (6), (7) together and considering system and measurement noises, w and v, respectively, yields to

$$\begin{cases} \dot{x} = f(x,u) + w \\ y = Hx + v \end{cases} \tag{8}$$

where w and v are assumed independent and normally distributed with zero mean and known covariance matrices Q and R, respectively. The obtained state-space model can be discretized using the forward Euler method as

$$\begin{cases} x_{k+1} = x_k + T_s f(x_k, u_k) + w_k \\ y_k = Hx_k + v_k \end{cases} \tag{9}$$

where T_s is the discretizing time and k is a discrete sample number. The 3rd degree CKF algorithm is done by recursively performing time update and measurement update. After convergence of the filter, the last element of the estimated state is the estimated power of the CPL. The CKF steps are as follows [29]:

- **Time update**

1. Factorize $\mathcal{P}_{k-1|k-1}$ by Cholesky decomposition

$$\mathcal{P}_{k-1|k-1} = S_{k-1|k-1} S_{k-1|k-1}^T \tag{10}$$

2. Calculate cubature points for $i = 1, \dots 2n$

$$X_{i,k-1|k-1} = S_{k-1|k-1}\zeta_i + \hat{x}_{k-1|k-1} \tag{11}$$

3. Propagate cubature points by the nonlinear model

$$X^*_{i,k|k-1} = F(X_{i,k-1|k-1}, u_{k-1}) \tag{12}$$

4. Estimate the predicted states

$$\hat{x}_{k|\,k-1} = \frac{1}{2n}\Sigma_{i=1}^{2n} X^*_{i,k|\,k-1} \tag{13}$$

5. Estimate the predicted covariance of the states

$$\mathcal{P}_{k|k-1} = \frac{1}{2n}\Sigma_{i=1}^{2n}\left(X^*_{i,k|k-1} - \hat{x}_{k|k-1}\right) \times \left(X^*_{i,k|k-1} - \hat{x}_{k|k-1}\right)^T + Q_{k-1} \tag{14}$$

- **Measurement update**

1. Factorize $\mathcal{P}_{k|k-1}$ by Cholesky decomposition

$$\mathcal{P}_{k|k-1} = S_{k|k-1}S_{k|k-1}^T \tag{15}$$

2. Calculate cubature points for $i = 1, \dots 2n$

$$X_{i,k-1|k-1} = S_{k|k-1}\zeta_i + \hat{x}_{k|k-1} \quad for \quad i = 1, \dots 2n \tag{16}$$

3. Propagate cubature points by the measurement model

$$Y_{i,k|\,k-1} = h(X_{i,k|k-1}, u_k) \tag{17}$$

4. Estimate the predicted measurements

$$\hat{y}_{k|\,k-1} = \frac{1}{2n}\Sigma_{i=1}^{2n} Y_{i,k|\,k-1} \tag{18}$$

5. Estimate the auto-covariance matrix:

$$\mathcal{P}_{yy,k|k-1} = \frac{1}{2n}\Sigma_{i=1}^{2n}\left(Y_{i,k|\,k-1} - \hat{y}_{k|k-1}\right) \times \left(Y_{i,k|k-1} - \hat{y}_{k|k-1}\right)^T + R_k \tag{19}$$

6. Estimate the cross-covariance matrix

$$\mathcal{P}_{xy,k|k-1} = \frac{1}{2n}\Sigma_{i=1}^{2n}\left(X_{i,k|\,k-1} - \hat{x}_{k|k-1}\right) \times \left(Y_{i,k|k-1} - \hat{y}_{k|k-1}\right)^T + R_k \tag{20}$$

7. Estimate the Kalman gain

$$K_k = \mathcal{P}_{xy,k|k}\,\mathcal{P}_{yy,k|\,k-1}^{-1} \tag{21}$$

8. Estimate the updated states

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(y_k - \hat{y}_{k|k}\right) \tag{22}$$

9. Estimate the covariance of the states

$$\mathcal{P}_{k|k} = \mathcal{P}_{k|k-1} + K_k\mathcal{P}_{yy,k|k}K_k^T \tag{23}$$

Using the CKF and having i_L, v_C measurements, the estimate of P_{load} is then simply extracted from the estimated state vector $\hat{x}$.

IV. Adaptive Backstepping Controller

In this section, the procedure of designing the backstepping controller is presented. The control objective is to find the value of the switch position function that stabilizes the output voltage of the converter, v_C, toward its desired value, v_{Cd}. The control signal is then used to generate PWM gate signals for the converter [15]. To implement the backstepping controller, first, the state space of the system in (3) is transformed to the standard strict-feedback form for designing the backstepping controller. The steps for the proposed backstepping controller are provided below:

Step 1: Strict-feedback form of the system

To obtain the strict-feedback form of the system, based on the results of [12], the following diffeomorphism is applied to the dynamical model of the system in (3):

$$z_1 = \frac{1}{2}Li_L^2 + \frac{1}{2}Cv_C^2 \tag{24}$$

where z_1 is the total stored energy in the system. By knowing the fact that the control objective is asymptotic convergence of v_C, toward its desired value, v_{Cd}, the desired values for the inductor current, i_{Ld}, can be obtained as:

$$i_{Ld} = \frac{P_d}{V_e} \tag{25}$$

where P_d is the power of the total load that expressed as

$$P_d = P_{CPL} + \frac{v_{Cd}^2}{R} \tag{26}$$

Therefore, the desired value of z_1 can be expressed as

$$z_{1d} = \frac{1}{2}Li_{Ld}^2 + \frac{1}{2}Cv_{Cd}^2 \tag{27}$$

The tracking error is defined as

$$e_1 = z_1 - z_{1d} \tag{28}$$

which can be simplified as

$$e_1 = \frac{1}{2}L(i_L^2 - i_{Ld}^2) + \frac{1}{2}C(v_C^2 - v_{Cd}^2) \tag{29}$$

The derivative of the tracking error is as

$$\dot{e}_1 = Li_L\frac{di_L}{dt} + Cv_C\frac{dv_c}{dt} \tag{30}$$

which, by using (3), can be simplified as

$$\dot{e}_1 = V_e i_L - \frac{v_C^2}{R} - P_{CPL} \tag{31}$$

Since the total power of the load is estimated using the CKF, (31) is rewritten as

$$\dot{e}_1 = V_e i_L - \frac{v_C^2}{R} - P_{CPL} + \frac{v_C^2}{R_0} - \frac{v_C^2}{R_0} \tag{32}$$

where R_0 is the nominal resistance of the resistive load. Based on (32), the new state z_2 is defined as $z_2 = V_e i_L - \frac{v_C^2}{R_0}$ and the uncertain term $d_1 = -\frac{v_C^2}{R} - P_{CPL} + \frac{v_C^2}{R_0}$. Taking the derivative of z_2 results in

$$\dot{z}_2 = V_e\frac{di_L}{dt} - \frac{2}{R_0}v_C\frac{dv_c}{dt} \tag{33}$$

which can be rewritten as

$$\dot{z}_2 = \frac{{V_e}^2}{L} - (1-u)\left(\frac{V_e v_C}{L} + \frac{2v_C i_L}{R_0 C}\right) + \frac{2}{R_0 C}(P_{CPL} + \frac{v_C^2}{R}) \tag{34}$$

In order to separate the uncertain term of the total power of the load, (34) is rewritten as

$$\dot{z}_2 = \frac{{V_e}^2}{L} - (1-u)\left(\frac{V_e v_C}{L} + \frac{2v_C i_L}{R_0 C}\right) + \frac{2}{R_0 C}(P_{CPL} + \frac{v_C^2}{R} + \frac{v_C^2}{R_0} - \frac{v_C^2}{R_0}) \tag{35}$$

Then, based on (35), d_2 and v are defined as

$$d_2 = \frac{2}{R_0 C}(P_{CPL} + \frac{v_C^2}{R} - \frac{v_C^2}{R_0})$$
$$v = \frac{{V_e}^2}{L} - (1-u)\left(\frac{V_e v_C}{L} + \frac{2v_C i_L}{R_0 C}\right) + \frac{2v_C^2}{R_0^2 C} \tag{36}$$

Hence, the system model in (3) is transformed to the strict-feedback form as

$$\begin{cases}\dot{e}_1 = z_2 + d_1 \\ \dot{z}_2 = v + d_2\end{cases} \tag{37}$$

The intermediate control law, v, can be obtained by solving the equation (37). Then the final control law, u, can be obtained from (36) as

$$u = 1 - (\frac{{V_e}^2}{L} + \frac{2v_C^2}{R^2 C} - v)/(\frac{V_e v_C}{L} + \frac{2v_C i_L}{RC}) \tag{38}$$

Step 2: Backstepping Procedure

Considering (37), the control law, u, can be obtained by employing the following procedure:

i. Finding the virtual control expression z_{2d}

Considering the first equation of (37), i.e. $\dot{e}_1 = z_2 + d_1$, the designed control Lyapunov function (CLF) is as $V_1 = \frac{1}{2}e_1^2$.

The derivative of the considered CLF is as

$$\dot{V}_1 = e_1\dot{e}_1 = e_1(z_2 + d_1) \tag{39}$$

For asymptotic convergence of e_1 toward the origin, it is required that $\dot{V}_1 < 0$ when $z_1 \neq 0$. Considering $z_{2d} = -d_1 - \zeta e_1$where k is a positive gain matrix, results in $\dot{V}_1 = -\zeta e_1^2 < 0$. The new state variable e_2 is defined as

$$e_2 = z_2 - z_{2d} = z_2 + d_1 + \zeta e_1 \tag{40}$$

which gives

$$z_2 = e_2 - d_1 - \zeta e_1 \tag{41}$$

Substituting (41) in $\dot{e}_1 = z_2 + d_1$ yields

$$\begin{cases} \dot{e}_1 = e_2 - \zeta e_1 \\ \dot{e}_2 = \dot{z}_2 + \dot{d}_1 + \zeta\dot{e}_1 = v + d_2 + \dot{d}_1 + k(e_2 - \zeta e_1) \end{cases} \tag{42}$$

Defining

$$v' = v + d_2 + \dot{d}_1 \tag{43}$$

results in

$$\begin{cases} \dot{e}_1 = e_2 - \zeta e_1 \\ \dot{e}_2 = v' + \zeta e_2 - \zeta^2 e_1 \end{cases} \tag{44}$$

The next step is finding the control expression v'; then, the intermediate control law, v, can be obtained from (43) as

$$v = v' - d_2 - \dot{d}_1 \tag{45}$$

ii. Finding the control expression v'

Based on (44), the considered CLF is as $V_2 = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2$. The derivative of V_2 along its trajectory can be obtained as

$$\dot{V}_2 = e_1\dot{e}_1 + e_2\dot{e}_2 = -\zeta e_1^2 + e_2(v' + \zeta e_2 - \zeta^2 e_1 + e_1) \tag{46}$$

For asymptotic convergence of e_2 toward the origin, it is needed that $\dot{V}_2 < 0$ when $e_2 \neq 0$. Considering

$$v' = -(m + \zeta)e_2 + (\zeta^2 - 1)e_1 \tag{47}$$

where m is a positive gain matrix, yields to

$$\dot{V}_2 = -\zeta e_1^2 - me_2^2 < 0 \tag{48}$$

Using (29) and (40), (47) can be simplified as

$$v' = -(m + \zeta)(z_2 + d_1) - (1 + m\zeta)\left(\frac{1}{2}L(i_L^2 - i_{Ld}^2) + \frac{1}{2}C(v_C^2 - v_{Cd}^2)\right) \tag{49}$$

The final step is finding v, and consequently, u from the obtained expression for v'.

iii. Finding the control input u

Considering (45) and (49), the intermediate control law, v, can be obtained as

$$v = -(m + \zeta)(z_2 + d_1) + (-1 - m\zeta) \times \left(\frac{1}{2}L(i_L^2 - i_{Ld}^2) + \frac{1}{2}C(v_C^2 - v_{Cd}^2)\right) - d_2 - \dot{d}_1 \tag{50}$$

In the above equation, v_C and i_{Ld} are measurable and their instantaneous values are estimated using the CKF. Also, the only unknown quantity in d_1 and d_2 is P_{load}, which is estimated during operation using the CKF, and the derivative of d_1 is a known value too. Therefore, all parameters in (50) are known and u can be obtained based on (38).

Also, (48) indicates the negative definiteness of the time derivative of the Lyapunov function V_2. Therefore, the errors e_1 and e_2 asymptotically converge to zero. Consequently, from the diffeomorphism variable changes z_1 and z_2, one can infer that if the artificial states z_1 and z_2 converge to their desired values, then the actual system states i_L and v_c will also converge to their desired references. Thereby, the tracking of the overall closed-loop system is assured.

V. Experimental Results

In this section, the results of the proposed adaptive backstepping controller are provided. The controller is integrated to the CKF algorithm, which estimates the uncertain time-varying total power of the load. The general configuration of the experimental setup is shown in Fig. 5.

Fig. 5. The experimental setup

At first, the total power of the load, P_{load}, is estimated using the CKF. Then, the estimated P_{load} serves as an input to the backstepping controller. A block diagram of the suggested approach is shown in Fig. 6.

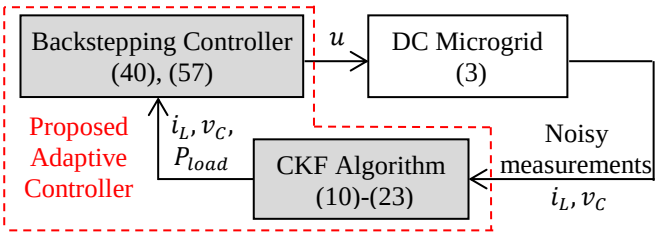

Fig. 6. A simple block diagram illustration of the proposed controller.

As can be seen in Fig. 6, the CKF algorithm is utilized to estimate P_{load} online. Then, this estimation alongside the measurements, i.e. i_L, v_C, is used in the backstepping controller to compute the optimal value of the duty cycle of the switch, i.e. u. The MG parameters are listed in Table I. The initial condition of the CKF $\hat{x}_0 = [1 \;\; 55 \;\; 80]^T$.

TABLE I
PARAMETERS FOR THE DC MG WITH ONE CPL

$L = 1\ mH$	$v_{Cd} = 270\ V$
$C = 470\ \mu F$	$V_e = 200\ V$

Remark 1: The process noise covariance matrix, i.e. Q, corresponds to both system noise covariance and the uncertainty that is expected in the state-space equations. If one is very confident in the model, Q can be small. However, there is typically some uncertainty in the model equations, such as discretization, approximations in the derivation, etc. Additionally, larger (smaller) values of Q correspond to faster (slower) convergence at the expense of larger (smaller) steady-state error [30]. Since the last element correspond to P_{load}, for which the dynamics is unknown, a larger value of system noise covariance is required. Therefore, $R = diag(10^{-2}, 10^{-2})$ and $Q = diag(10^{-3}, 10^{-3}, 0.3)$. Usually, the initial value of p is chosen as a diagonal matrix whose diagonal elements are related to the expected variance of the corresponding state. Since i_L, v_C are measurable, one can choose small corresponding covariance values. On the other hand, P_{load} is unknown. Consequently, its corresponding

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIE.2018.2880666, IEEE Transactions on Industrial Electronics

elements of p should have a larger value. Therefore, the initial value of p is chosen as $p_0 = diag(1,1,10^3)$.

Remark 2: Since the estimation of P_{load} through the CKF algorithm is fed to the controller, the CKF should be faster than the controller. As can be seen in (38) and (50), since the sum of the backstepping controller parameters, i.e. m, ζ, appears in the control signal, the control parameters have the same effect on the control signal. Larger parameters lead to a smaller settling time. However, since $m + \zeta$ is multiplied to the measurement signals, larger values of $m + \zeta$ tend to amplify the noise in these signals. Nonetheless, some part of the amplified noise can be compensated for by the measurement covariance matrix, R, in the CKF. In addition, very high values of $m + \zeta$ cause system overshoot. Overall, in tuning the controller alongside the CKF parameters, there is a trade-off between a faster response, less overshoot, and more robustness to noise. Considering all these facts, m, ζ are chosen in the subsequent experiments as $m + \zeta = 400$.

To show the merits of the proposed nonlinear controller, two scenarios are provided. In the first one, the power of the total load, P_{load}, changes in a stepwise manner; meanwhile, in the second scenario, the power of the total load varies slightly and periodically. In the following, the experimental results for both scenarios are presented. In both scenarios, the CKF algorithm is used to estimate the unknown load power and then the adaptive backstepping controller regulated the voltage of the DC MG to the desired reference of 270 (V). The scale of each figure is given together with it and the horizontal axis shows the time in the interval $t \in [0, 6]$ seconds.

Scenario 1 (Stepwise varying P_{load}): In this scenario, P_{load} changes promptly at some moments. These sudden changes can be reasonable in practice, when the characteristics of the loads connected to inverters changes very fast. By applying the CKF, the currents and voltages of the filter, as well as the total load's power are estimated. Fig. 7 shows the actual values and the estimations of the augmented states using the CKF. As can be seen in Fig. 7, the suggested observer can estimate the P_{load} value fast and precisely. From Fig. 7, one concludes that by promptly changing the power of the CPL, a sudden error is produced in the CKF estimation, which however is attenuated very fast. After that, since the power is constant, the estimation error of the states becomes smaller. Then, the estimated states using the CKF are employed in the backstepping controller.

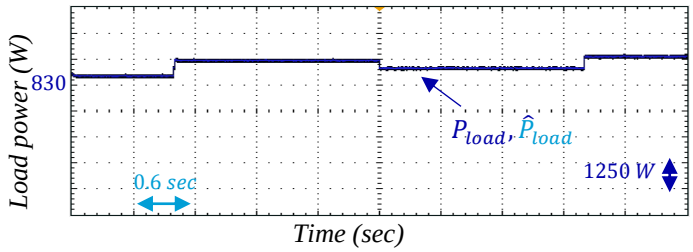

Fig. 7. The actual value and the estimation of the load's power using the CKF of Scenario 1.

As can be seen in Fig. 8, the proposed controller (38) tracks the desired value of the output voltage of the converter.

Scenario 2 (periodic slowly varying P_{load}): In this scenario, the total power of the load changes slowly and periodically. In practice, the slowly variation of P_{load} is occurred because the efficiency of practical converters is not constant and the controller of the converters has a limited bandwidth. Fig. 9 shows the actual values and estimations of the augmented states of the CKF.

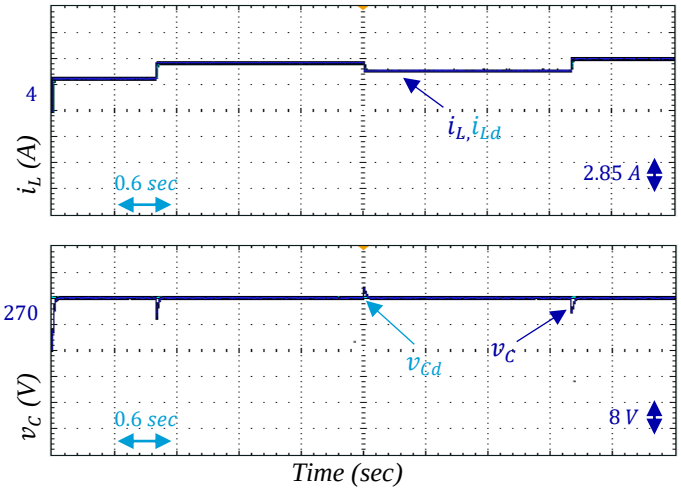

Fig. 8. The desired values of v_c and i_l and their obtained value using the backstepping controller of Scenario 1.

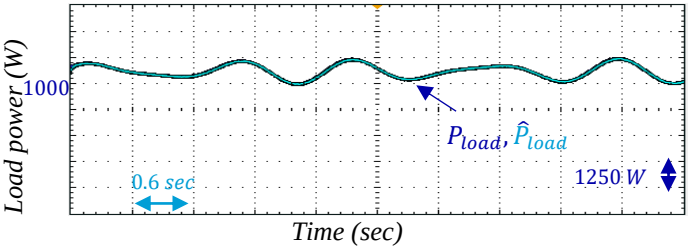

Fig. 9. The actual value and the estimation of the load's power using the CKF of Scenario 2.

As can be seen in Fig. 9, the suggested observer estimates the value of P_{load} effectively. The CKF captures the varying behavior of the DC MG with continuously varying power load and results in a smal estimation error. Then, the estimated states using the CKF are employed in the backstepping controller. As can be seen in Fig. 10, the proposed controller tracks the desired value of the output voltage of the converter.

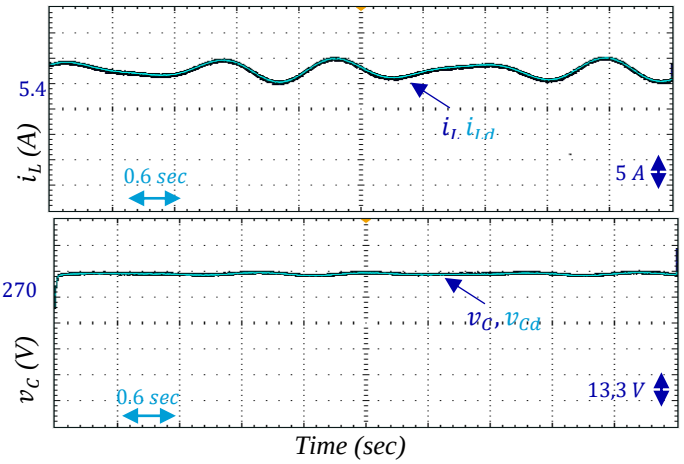

Fig. 10. The desired values of v_c and i_l and their obtained value using the backstepping controller of Scenario 2.

VI. Conclusion

The goal of this research was to stabilize a DC MG that has uncertain time-varying loads and to make the DC voltage of the bus to track the desired voltage. To this aim, the uncertain load power was augmented to the system states vector and its spontaneous value is estimated using a cubature Kalman filter (CKF). The estimated load power is then feedforwarded to a backstepping controller to obtain the duty ratio of the switch. To implement the controller, first, the strict-feedback model of the system is obtained. Then, the virtual control signals are obtained step by step, by constructing suitable control Lyapunov functions (CLF) and providing the stability conditions, until the desired control signal is obtained. To illustrate the effectiveness of the proposed controller, two scenarios including fast changes and slow periodically changes of the load power are provided. The real-time implementation results showed the ability of the proposed adaptive controller in tracking the desired voltage of the bus for sudden and continuous changes of the load power.

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