

Article

# On stability of Forced van der Pol Equation by control

Hanfeng Zhai <sup>1</sup><sup>1</sup> Sibley School of Mechanical and Aerospace Engineering, Cornell University; hz253@cornell.edu

**Abstract:** Nonlinear dynamics by nature are extremely hard to control, which were usually linearized as implemented in feedback control design. van der Pol oscillatory circuits exhibit such behavior, possess wide engineering applications background. Here, a deterministic algorithm control approach was introduced and investigated on controlling the nonlinear behavior of van der Pol dynamics. Five different scenarios were implemented for controlling the dynamics as for comparison and study the behavior of the deterministic algorithm: the circular trajectory of radius equals zero with no control, the circular trajectory of radius equals five with no control, the circular trajectory of radius equals five with feed-back control, the circular trajectory of radius equals five with feed-forward control, the circular trajectory of radius equals five with both feed-back and feed-forward control. It is observed that the feed-forward control on the targeted radius successfully converges the control algorithm to the desired trajectory. With further emphasis on the controller's behavior, it is observed that as the desired trajectory's radius changes, the stability of the controller may vary. Further investigation on the different radius of desired trajectory one deduce the controller approach to a stable state while the radius is approaching 2, and the CPU computation time increases as radius increases. It is also observed that even for the considered "stable" state the errors still exhibit a sinusoidal fluctuation. The proposed study on nonlinear controllers could proffer insights on microelectronics, system design, and many potential fields.

**Keywords:** Nonlinear system; Control; Linearization; van der Pol dynamics

## 1. Introduction

**Citation:** Zhai, H. On stability of Forced van der Pol Equation by control. *Journal Not Specified* **2021**, *1*, 0. <https://doi.org/>

Received:

Accepted:

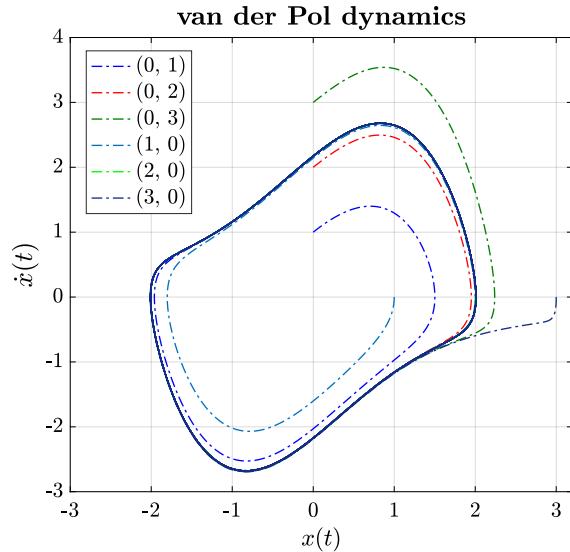
Published:

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

**Copyright:** © 2021 by the authors. Submitted to *Journal Not Specified* for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Controlling nonlinear dynamics and chaos has always been an important goal for scientists and engineers since achieving such can tackle numerous issues in engineering and systems design, i.e., circuits and microelectronics [1], biology and organic systems [2], earth sciences and natural systems [3], etc. Controlling such a complex system usually requires scrutinized systems and model formulation. By 1927, regarding the complex inherent dynamics of oscillating circuits, Balthazar van der Pol sought circuits that oscillated at a fixed frequency for use in signal transmission and receipt [4,5]. The van der Pol equation exhibits strong chaotic dynamics behavior, and the forced van der Pol equation also exhibits chaotic behavior, i.e., global bifurcation [6]. Considering the wide applications background and all these delicate behavior that are extremely hard to control in engineering, proposing methods for controlling such dynamics are hence important and meaningful. In control science, linearizing nonlinear systems for either feedback or feed-forward controls are of common ways to tackle the issue of chaotic system [7]. As of a common practice in control theory, linearization has indeed been applied to many nonlinear chaotic systems such as the Lorenz system [8], the forced Duffing oscillator [9], Poincaré map [10], etc. Considering very little literature truly addressed the issue of controlling van der Pol oscillator, in 2017, Cooper *et al.* study the nonlinear behavior of deterministic algorithm imposing controlled trajectory to forced van der Pol equation [5].

Following the work by Cooper *et al.*, the aim of this paper is to investigate how different controlling schemes may variate the behavior of the van der Pol dynamics. The first goal of the paper is to study how different control methods may change the



**Figure 1.** The inherent dynamics of van der Pol equation. The phase was initiated from six different initial points:  $(i, 0)$ ,  $(0, i)$ ,  $i = 1, 2, 3$ , to illustrate the inherent dynamics.

controlled behavior of the van der Pol dynamics. What's more, the stability of the imposed control scheme is also to be discussed since such hasn't been touched much by the field. Different desired trajectories may variate the stability of the controlled scheme, and the variations behavior are also of interest in this paper. To answer these questions, a controlled framework was designed and implemented for comparison with feed-forward, feedback controls of the dynamics. The paper will address how each method changes the controlled scheme of the dynamics.

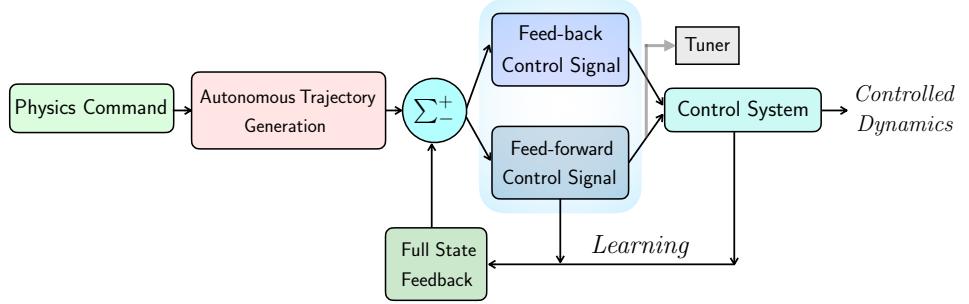
The paper is arranged as follows: In Section 2, the problem for nonlinear van der Pol dynamics control is formulated and the related methods are elicited. In Section 3 the materials and methodology for both nonlinear feed-forward control and linearized feedback control are introduced and explained, in Sections 3 and 3.2, respectively. This is followed by a brief description of the stability analysis of the van der Pol dynamics. Section 4 presented the results on controlled dynamics comparing the five different methods: the circular trajectory of radius equals zero with no control, the circular trajectory of radius equals five with no control, the circular trajectory of radius equals five with feed-back control, the circular trajectory of radius equals five with feed-forward control, the circular trajectory of radius equals five with both feed-back and feed-forward control, in Sections 4.1.1, 4.1.2, 4.1.3, 4.1.4, 4.1.5, respectively. The stability of the controlled schemes is also discussed in Section 4.2. The paper is eventually concluded and summarized in Section 5.

## 2. Problem Formulation

Van der Pol articulated that the oscillatory behavior fit the class of nonlinear equations that are now referred to the van der Pol equation. The equation exhibits an oscillatory behavior, but the amplitude is not constant, it instead represents an invariant set called a "limit cycle" [5]. System trajectories converge to this invariant that is set from any initial conditions, as can be referred in Figure 1.

$$\frac{d^2x}{dt^2} - \mu(1 - x^2) \frac{dx}{dt} + x = 0 \quad (1)$$

Seeking to produce a fixed-amplitude oscillation, forcing functions are added to the nonlinear equation resulting in Equation (2). Typical control design procedures would begin with a linear time-invariant (LTI) feedback controller based on a linearized version



**Figure 2.** Schematic diagrams for both deterministic algorithm control. Note that the tuner can switch and "tune" the choice of feed-forward and feed-back controls.

of the system equation. The paper aim to optimize the feedback control gains via the Riccati equation (linear quadratic regulator, LQR):

$$\frac{d^2x}{dt^2} - \mu(1 - x^2) \frac{dx}{dt} + x = F(t) \quad (2)$$

63 Here, the purpose of this paper is to examine and investigate how different control  
 64 methods can be employed for forced van der Pol equation as for controlling chaos and  
 65 nonlinearities. As referred in Figure 1, the van der Pol equation will converge to a specific  
 66 trajectory given different initial points and difficult to variate the route. The robustness  
 67 of the nonlinearity may also variate the controlled scheme, which may influence the  
 68 stability of the control.

### 69 3. Methodology

70 In this paper, as introduced in Section 2, both feedback and feed-forward control  
 71 will be implemented in our control scheme as can be tuned on/off in the framework.  
 72 The framework is enabled through SIMULINK in MATLAB®, and the main framework  
 73 is illustrated as in Figure 2. The tuner can turn on/off either feedback or feed-forward  
 74 controllers as to design different control processes for our implementation and compari-  
 75 son. The "learning" of the system is enabled through the full state feedback process as  
 76 reducing errors and passing on commands to the controllers. Note that in the framework  
 77 parameters were picked as  $\mu = 1$  and  $t = 100[s]$ .

#### 78 3.1. Nonlinear Feedforward Control

The basic premise of idealized nonlinear feedforward control design [11] is to define the inherent dynamics as the idealized feedforward control [5], as shown in Equation (3); where the control designer is required to specify the desired trajectory to be followed. In this study, the desired trajectory is a circular route. The controller is idealized only with respect to the assumed parameter estimates as the  $\mu$  in Equation (3) [5]

$$F(t) = u \equiv u_{ff} = \frac{d^2x_d}{dt^2} - \mu(1 - x_d^2) \frac{dx_d}{dt} \quad (3)$$

where  $F(t)$  is the forced term as in Equation (2):

$$\frac{d^2x}{dt^2} - \mu(1 - x^2) \frac{dx}{dt} + x = F(t) \equiv \frac{d^2x_d}{dt^2} - \mu(1 - x_d^2) \frac{dx_d}{dt} \quad (4)$$

#### 79 3.2. Linearized Feedback Control Design

In control theory and sciences, the normal first procedure for control design involves linearizing the nonlinear dynamic equation, and based upon designing the control signal. For the van der Pol dynamics, Equation (1) can be linearized into Equation (5), expressed

in state-variable formulation from which state space trajectories are displayed on phase portraits [5]:

$$\begin{aligned}[A] &= [1 \ -1; 1\ 0]; [B] = [-1; 0]; [C] = [0; 1]; [D] = [0]; \\ [Q] &= [1\ 0; 0\ 1]; [R] = [1]; [S] = [2.6818\ 0.4142; 0.4142\ 3.3784] \\ K_p &= 2.6818; K_d = 0.4142\end{aligned}\quad (5)$$

where the states from  $[A]$  to  $[S]$  are the expressions used in the linear-quadratic optimization leading to a feedback controller with proportional and derivative gains for  $K_p$  and  $K_d$ . The closed loop dynamics are established by Equation (2) where the van der Pol forcing function  $F(t)$  is a proportional-derivative (PD) controller by Sands [12] who's gains are in Equation (5) [5]:

$$\frac{d^2x}{dt^2} - \mu(1 - x^2)\frac{dx}{dt} + x = F(t) \equiv -K_d(\dot{x}_d - \dot{x}) - K_p(x_d - x) \quad (6)$$

which we add the forced term  $F(t)$  back to the original van der Pol equation and obtain:

$$\frac{d^2x}{dt^2} - \mu(1 - x^2)\frac{dx}{dt} + x = F(t) \equiv \frac{d^2x_d}{dt^2} - \mu(1 - x_d^2)\frac{dx_d}{dt} + x_d - K_d(\dot{x}_d - \dot{x}) - K_p(x_d - x) \quad (7)$$

### 80 3.3. Stability Analysis

81 As per Cooper *et al.* [5] discussed, directly implementing the feedforward control  
 82 signal make converge the desired trajectory pretty successfully. But during the numerical  
 83 experiments it is found that as the trajectory radius varies, the controlled scheme some-  
 84 times does not converge well. Hence, an estimation of effect of radius to the stability  
 85 of the controlled signal was carried out by investigating four different desired radius:  
 86  $r = 1$  to  $4$ , implemented with idealized nonlinear feedforward control. The trajectories  
 87 are to be analyzed considering both trajectory history, CPU computation time and errors  
 88 of the controlled trajectories.

## 89 4. Results and discussion

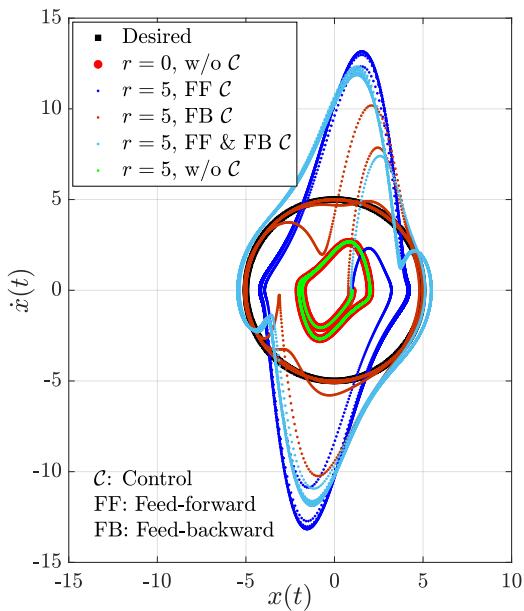
### 90 4.1. Control analysis with different methods

91 The overall results of trajectories were accumulated into one graph for concise visu-  
 92 alization as in Figure 3. It can be observed in Figure 3 that for both uncontrolled signal  
 93 with  $r = 5$  and  $r = 0$  the trajectories converged to a same route: the inherent dynamics  
 94 of van der Pol equation. The algorithm of pure feedback control does not successfully  
 95 impose the desired trajectory, howbeit a pure feed-forward control successfully enforce  
 96 the circuits to the desired trajectory: a circle with radius equals to five. Such results agree  
 97 with Cooper *et al.*'s findings [5]. The combined feedback - feed-forward control scheme  
 98 also seems not to successfully enforce the desired trajectory, as in the light blue dots in  
 99 Figure 3.

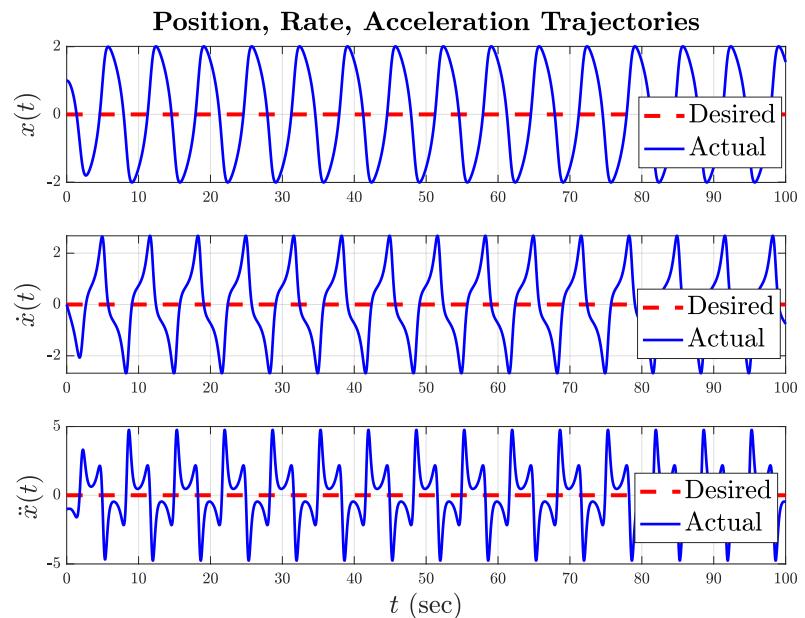
100 Now, to characterize how different control signals and frameworks alternate the  
 101 trajectories in details, a full position, rate, acceleration trajectories ( $x(t)$ ,  $\dot{x}(t)$ ,  $\ddot{x}(t)$ )  
 102 estimation in comparison with the desired control phase are analyzed as follows.

#### 103 4.1.1. Zero desired trajectory with no control

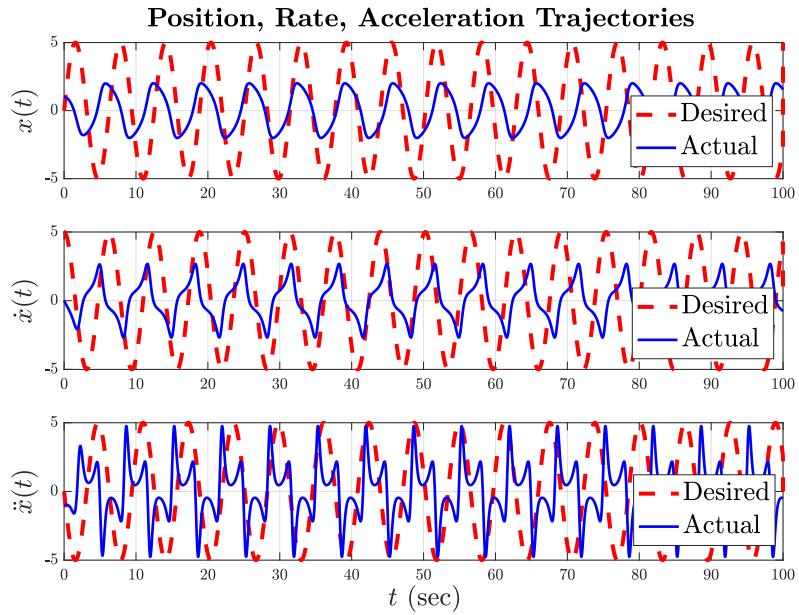
104 As can be observed in Figure 4, with the desired control of circular trajectory  $r = 0$   
 105 as shown in the red dotted lines, the systematic response (blue solid lines) doesn't  
 106 seem to change much along the time, which is explained as no control signals were  
 107 implemented. As indicated by Cooper *et al.*, this simulation can be considered as a  
 108 baseline for further controlled schemes. The first and second order derivatives of  $x(t)$   
 109 increases the oscillation along with time.



**Figure 3.** The phase portrait of the van der Pol equations by five different control methods. Note that the black solid squares are the desired trajectory; the light red dots are the trajectory given no control with circular radius  $r = 0$ ; the dark blue dots are the trajectory with feed-back control with circular radius  $r = 5$ ; the dark red dots are the trajectory with feed-forward control with circular radius  $r = 5$ ; the light blue dots are the trajectory combined feed-back and feed-forward control with circular radius  $r = 5$ ; the green dots are the trajectory given no control with circular radius  $r = 5$ . In the figure,  $\mathcal{C}$  stands for the term control and FB & FF are abbreviations for feed-back and feed-forward.



**Figure 4.** The trajectory comparison of  $x(t)$ ,  $\dot{x}(t)$ ,  $\ddot{x}(t)$ , for desired trajectory:  $r = 0$  with no control activated.



**Figure 5.** The trajectory comparison of  $x(t)$ ,  $\dot{x}(t)$ ,  $\ddot{x}(t)$ , for desired trajectory:  $r = 5$  with no control activated.

#### 110 4.1.2. Circular desired trajectory with no control

111 In Figure 5 it can be observed that the actual trajectories as in the blue solid lines are  
 112 same as in Figure 4,  $r = 0$ , corresponding to Figure 3. As the imposed circular trajectory  
 113 of  $r = 5$  (red dotted line) the systematic does not displayed the any response signals,  
 114 which can be accounted to the no control blocks were implemented in the framework.

#### 115 4.1.3. Circular desired trajectory with feedback control

116 By adding up a feedback control signal, one can observe that the data of  $x(t)$  are  
 117 fitted with good approximation as on the top sub figure in Figure 6. However, for the  
 118 terms of  $\dot{x}(t)$  and  $\ddot{x}(t)$  the errors grows evidently, which are accounted for the increasing  
 119 erroneous trajectory in Figure 3.

#### 120 4.1.4. Circular desired trajectory with feed-forward control

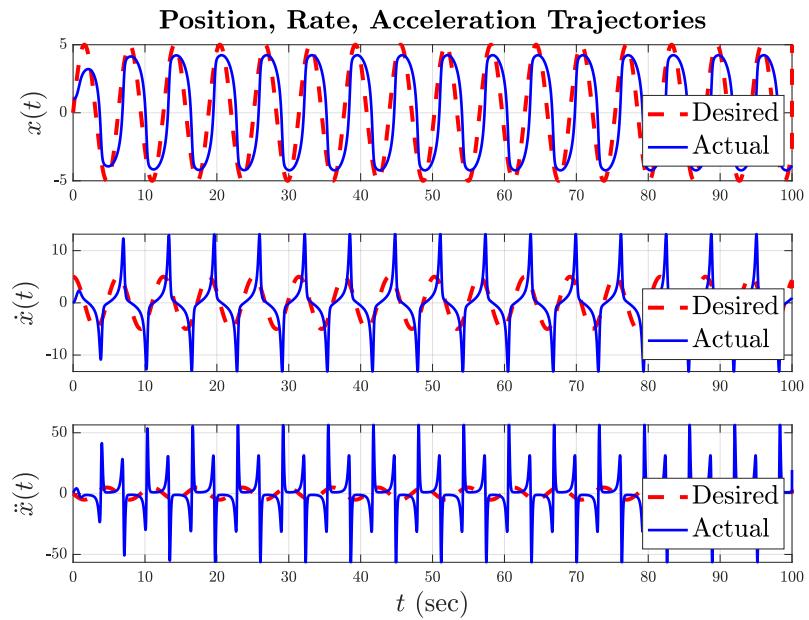
121 If only impose a feed-forward control, the systematic response, as shown in Figure  
 122 7, will converge to the desired trajectory following the executed signals. The results in  
 123 Figure 7 agrees with what's been observed in Figure 3. Also, the rate and accelerations  
 124 reveals how the signals been implemented for control: fluctuations happened at the  
 125 initial stage later converged to the desired trajectory at approximately 10s.

#### 126 4.1.5. Circular desired trajectory with both controls

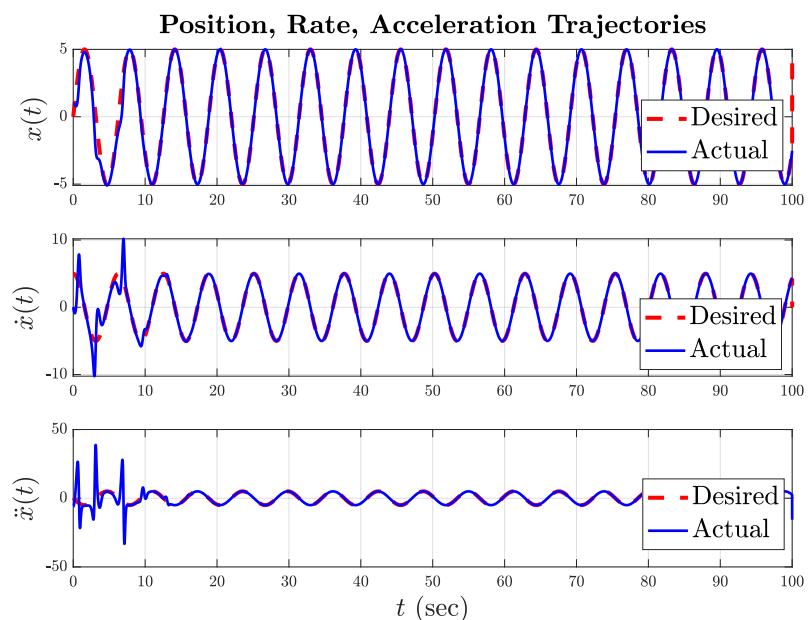
127 If both feedback and feed-forward controls were implemented to the system, Figure  
 128 8 indicates that the position and the rate were fitted pretty well, yet the accelerations  
 129 display higher error.

130 In fine, the implementation and comparison of the five different control schemes  
 131 imply using directly a feed-forward nonlinear adaptive control will best impose the  
 132 desired signal (trajectory), same as reported by Cooper *et al.* [5]; Yet linearized feedback  
 133 control do have fair dynamics implementation for position  $x$ , yet the errors increases  
 134 evidently for rate (velocity) controls.

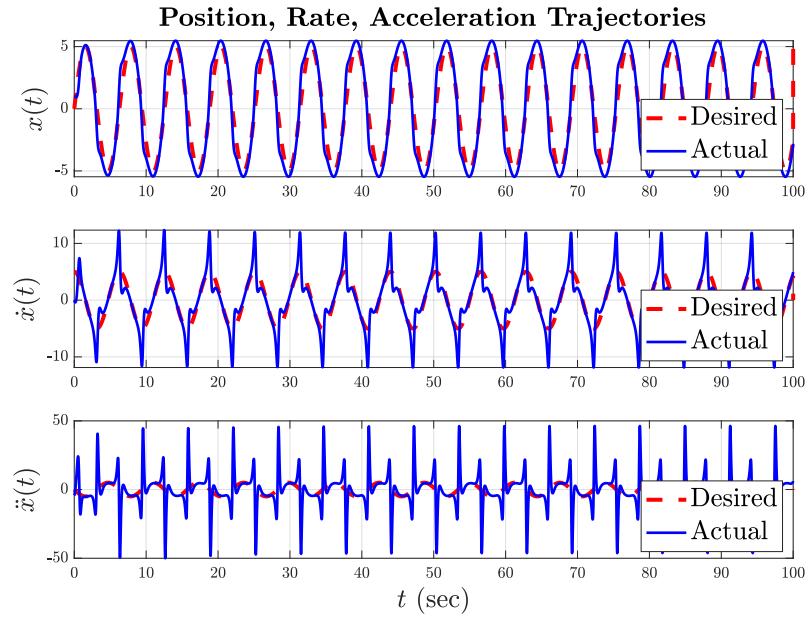
135 Also, Cooper *et al.* [5] reported how the standard deviation and the mean errors  
 136 variate compared with three of the methods we implemented: Unforced, indicating  
 137 given a desired trajectory with no control; Forced by linear feedback control and forced



**Figure 6.** The trajectory comparison of  $x(t)$ ,  $\dot{x}(t)$ ,  $\ddot{x}(t)$ , for desired trajectory:  $r = 5$  with feed-back control.



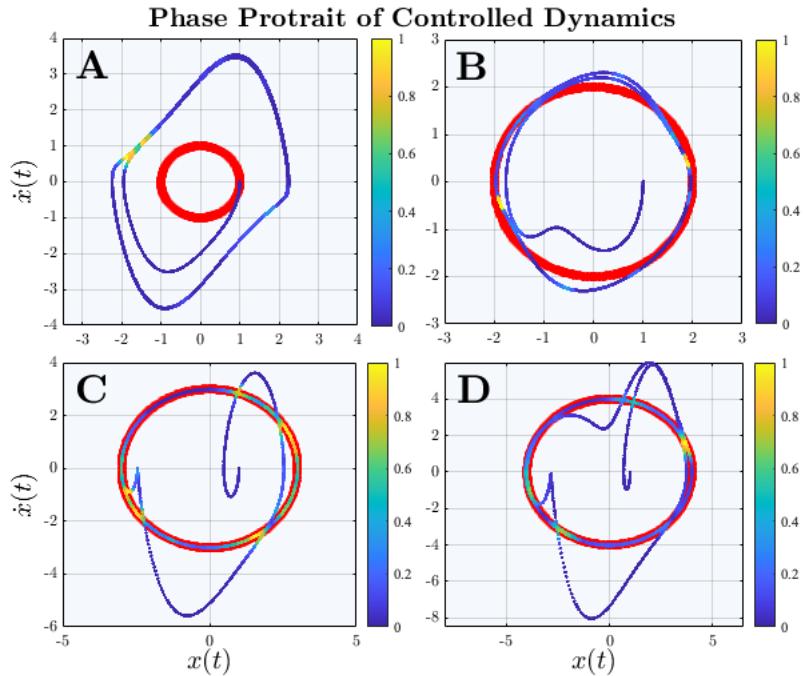
**Figure 7.** The trajectory comparison of  $x(t)$ ,  $\dot{x}(t)$ ,  $\ddot{x}(t)$ , for desired trajectory:  $r = 5$  with feed-forward control.



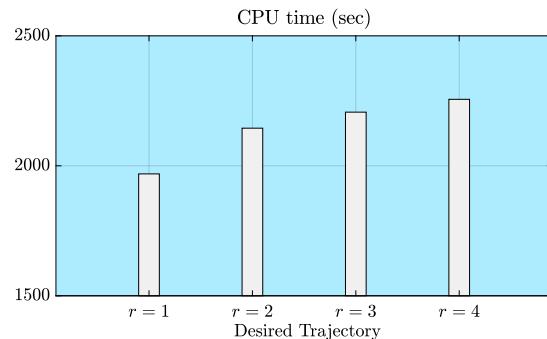
**Figure 8.** The trajectory comparison of  $x(t)$ ,  $\dot{x}(t)$ ,  $\ddot{x}(t)$ , for desired trajectory:  $r = 5$  with both feed-back and feed-forward control.

Initial Position	Unforced	Forced by LQR Linear Feedback		Forced only by Idealized Nonlinear Feedforward
		$K_p = 1.1913$	$K_d = 0.9050$	
(0,0)	$\mu = 2.858$ $\sigma = 3.357$	$\mu = 0.28163$ $\sigma = 1.41$		$\mu = 0.083008$ $\sigma = 0.30951$
(5,0)	$\mu = 2.2539$ $\sigma = 4.4174$	$\mu = 0.15107$ $\sigma = 2.0607$		$\mu = -0.5283$ $\sigma = 1.2645$
(1,0)	$\mu = 2.8491$ $\sigma = 3.4741$	$\mu = 0.28427$ $\sigma = 1.4116$		$\mu = 0.092108$ $\sigma = 0.33885$
(0,1)	$\mu = 2.8756$ $\sigma = 3.1283$	$\mu = 0.2784$ $\sigma = 1.3977$		$\mu = 0.066252$ $\sigma = 0.24343$
(6,0)	$\mu = 1.7929$ $\sigma = 4.62$	$\mu = 0.0041396$ $\sigma = 2.9392$		$\mu = -1.0166$ $\sigma = 2.0182$
(0,6)	$\mu = 2.7794$ $\sigma = 3.7424$	$\mu = 0.26159$ $\sigma = 1.3979$		$\mu = 0.01697$ $\sigma = 0.067415$

Table 1: Comparison of forcing method (non-optimal observers). LQR.  $\mu$  and standard deviation  $\sigma$  for comparison. Note that the table is reproduced from Cooper *et al.* [5]



**Figure 9.** The stability of the van der Pol dynamics regarding four different desired trajectory with radius:  $r = 1$  to 4 from subfigures **A** to **D**.

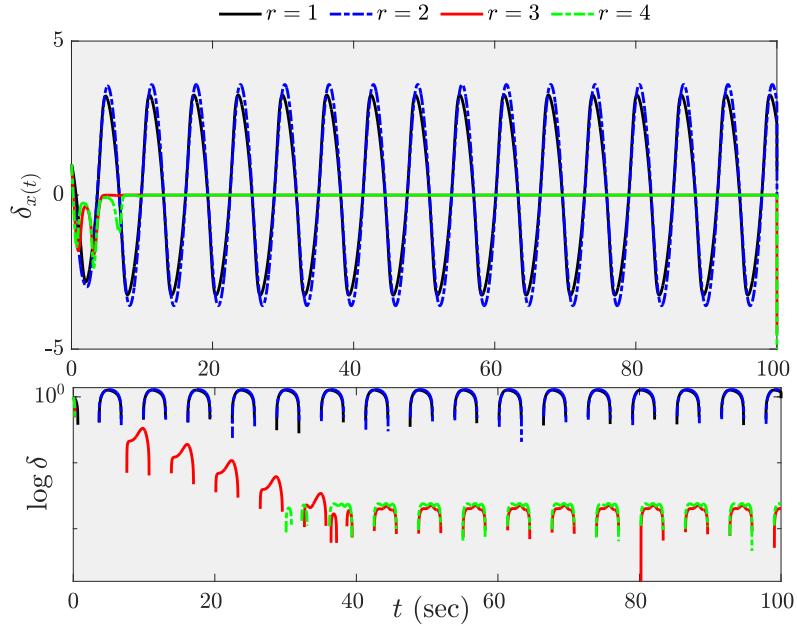


**Figure 10.** The CPU computation time for the four different desired trajectories.

138 by nonlinear feed-forward control for the van der Pol dynamics in Table 1. The table  
 139 quantitatively showed that the forced feed-forward control does display smaller errors.

#### 140 4.2. Stability of feed-forward control

141 As the desired trajectory changes, the stability of the controlled scheme may also  
 142 change. Figure 9 shows how changing of radius may change the convergence of con-  
 143 trolled signals: when radius are at 3 to 4, the controlled signal converge to the desired  
 144 trajectories (subfigures **C** and **D** in Figure 9), similar with what has been observed when  
 145  $r = 5$ , as in Figure 3. However, when the radius is approximately 1 to 2, it has been ob-  
 146 served that the signal did not converge to the desired trajectories so well as in subfigures  
 147 **A** and **B** in Figure 9. Also, based on the color bar one can deduce the signal tend to be  
 148 strong at points neighboring the trajectory of inherent unforced van der Pol dynamics.  
 149 Further, we proposed an explanation for subfigure **A** as the trajectory does not follow the  
 150 implemented signal: the desired trajectory's radius was way smaller than the original  
 151 shape of the van der Pol dynamics, which makes the controller exhibit the unforced  
 152 state. As it is only roughly discussed for the relation between the desired trajectory and  
 153 controlled state, further investigation including detailed quantitative analysis on how  
 154 radius variate final state is to be carried out.



**Figure 11.** The errors of the four different desired trajectories with plotted in both linear (top) and log scale (down).

155 Besides, estimation on the different trajectory's effect on computation time are also  
 156 carried out, as shown in Figure 10. It can be observed that with larger value of radius of  
 157 desired trajectory, the CPU time increases at a mild rate.

158 Targeting Figure 9, it remains an open problem on how the errors variate between  
 159 desired and actual trajectory. From Figure 11 it can be evidently observed that as time  
 160 increasing, the  $r = 3$  and  $r = 4$  trajectories converge to the desired trajectory yet the  
 161  $r = 1$  and  $r = 2$  trajectories displays strong periodic fluctuation errors. Plotting the  
 162 errors in log scale as in the bottom subfigure one can discern that even for  $r = 3$  and  
 163 4 the errors still displays a periodic fluctuating form, which is of interest for further  
 164 investigations.

## 165 5. Conclusion and outlook

166 The robust nonlinearity of the van der Pol oscillator has been a strenuous task to  
 167 control, yet possesses wide applications background from microelectronics to biological  
 168 systems. Here, taking Cooper *et al.*'s approach [5], we investigate the behavior of forced  
 169 van der Pol equation with implemented deterministic control algorithm of feedback,  
 170 feed-forward, and feedback feed-forward combined control approach in comparison  
 171 with the benchmark problems of two different radii with no control. Simulation results  
 172 indicate the idealized nonlinear feed-forward control signal displays the best control  
 173 accuracy, same as proposed by Cooper *et al.* [5]. Further investigation it can be deduced  
 174 that for linearized feedback control and the combined approach the signal fitting for  
 175 position  $x(t)$  still displays good accuracy, yet the rate and positions display evident  
 176 errors. What's more, it is found that the changing of the radius can variate the stability  
 177 of the controlled signal. Targeting this issue, an investigation on the different desired  
 178 trajectory of radius  $r = 1, 2, 3, 4$  was carried out and it has been found that for  $r = 3$  and  
 179 4 and controlled state still converge to the desired signals, yet for  $r = 1$  and 2, a strong  
 180 trajectory fluctuation occurred. The CPU computation time indicates that as the radius  
 181 of the desired trajectory increases the computation time increases. The log scaled error  
 182 plot showed that even for  $r = 1$  and 2, which seems to converge to the desired trajectory,  
 183 there are still periodic fluctuating errors that occur along with time.

**184 Acknowledgement**

**185** The author greatly acknowledge the guidance and valuable discussions with Pro-  
**186** fessor Timothy Sands.

**References**

1. Chen, G. and Ueta, T., 2002. Chaos in Circuits and Systems, World Scientific Publishing Co., Singapore, ISBN 981-02-4933-00.
2. Gierer A., and Meinhardt H. 1972. A theory of biological pattern. *Kybernetik*. 12:30–39.
3. Lorenz, E. 1963. Deterministic Non periodic flow, *Journal of Atmospheric Sciences*
4. van der Pol, B.; van der Mark, J. Frequency de-multiplication. *Nature* 1927, 120, 363–364.
5. Cooper, M.; Heidlauf, P.; Sands, T. Controlling Chaos—Forced van der Pol Equation. *Mathematics* 2017, 5, 70.
6. John Guckenheimer, Kathleen Hoffman, and Warren Weckesser. The Forced van der Pol Equation I: The Slow Flow and Its Bifurcations. *SIAM J. Appl. Dyn. Syst.*, 2(1), 1–35.
7. Matthew M. Peet. Systems Analysis and Control. URL: <http://control.asu.edu/Classes/MMAE443/443Lecture03.pdf>.
8. Alvarez-Gallegos, J., Nonlinear Regulation of a Lorenz System by Feedback Linearization Technique, *J. Dynam. Control*, 1994, no. 4, pp. 277–298.
9. Chen, L.Q. and Liu, Y.Z., A Modified Exact Linearization Control for Chaotic Oscillators, *Nonlin. Dynam.*, 1999, vol. 20, pp. 309–317.
10. Fradkov, A., Guzenko, P., and Pavlov, A., Adaptive Control of Recurrent Trajectories Based on Linearization of Poincaré Map, *Int. J. Bifurcat. Chaos*, 2000, vol. 10, pp. 621–637.
11. Slotine, J. Applied Nonlinear Control; Prantice-Hall: Englewood Cliffs, NJ, USA, 1991; Chapter 9.
12. Sands, T. Physics-Based Control Methods. In Advances in Spacecraft Systems and Orbit Determination; Rushi, G., Ed.; In-Tech Publishers: Rijeka, Croatia, 2012; pp. 29–54.