

Co-Dimension Two Bifurcations in PWSC Dynamical Systems

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Large Networks of Neurons

- We consider large networks of coupled, two-dimensional, integrate-and-fire networks
- The networks are given by:

$$\begin{aligned} \dot{v}_i &= F(v_i) - w_i + I + g_s(er - v_i) = G(v_i, w_i, s) \\ \dot{w}_i &= \frac{1}{\tau_w}(bv_i - w_i) \\ \dot{s} &= -\frac{s}{\tau_s} + \frac{\lambda_s}{\tau_s N} \sum_{i=1}^N \sum_{t < t_{i,k}} \delta(t - t_{i,k}) \end{aligned}$$

$$v(t^-) = v_{peak}, \rightarrow v(t^+) = v_{reset}, w(t^+) = w(t^-) + \frac{\lambda_w}{\tau_w}$$

where w is the adaptation variable, and v is the voltage.

- In the large network limit, one obtains the first order moment-closure simplified population density equation:

$$\frac{\partial \rho_V(v, t)}{\partial t} = -\frac{\partial}{\partial t}(G(v, \langle w \rangle, s) \rho_V(v, t)) \quad (1)$$

$$s' = -\frac{s}{\tau_s} + \frac{\lambda_s}{\tau_s} J(v_{peak}, t) \quad (2)$$

$$\langle w \rangle' = -\frac{\langle w \rangle}{\tau_w} + \frac{\lambda_w}{\tau_w} J(v_{peak}, t) \quad (3)$$

- The steady state to this system is given by:

$$\begin{aligned} \bar{s} &= \lambda_s \bar{R}, \quad \bar{w} = \lambda_w \bar{R} \\ \bar{R} &= \left(\int_{v_{reset}}^{v_{peak}} \frac{dv'}{G(v, \bar{s}, \bar{w})} \right)^{-1} \end{aligned}$$

- After applying the general approach in [2] to linearize the system of equations, one arrives at the eigenvalue equation:

$$0 = \left(e^{\mu/R} - 1 \right) \left(\mu + \frac{1}{\tau_s} \right) \left(\mu + \frac{1}{\tau_w} \right) \quad (4)$$

$$+ \left(\mu + \frac{1}{\tau_s} \right) \left(\frac{\lambda_w}{\tau_w} \mu \hat{B}(\mu) \right) \quad (5)$$

$$- \left(\mu + \frac{1}{\tau_w} \right) \left(\frac{\lambda_s}{\tau_s} \mu \hat{A}(\mu) \right) \quad (6)$$

where

$$\hat{A}(\mu) = \int_0^1 e^{\mu y/R} \frac{g(er - \eta^{-1}(y'))}{G_1(\eta^{-1}(y') \lambda_s R, \lambda_w R)} dy' \quad (7)$$

$$\hat{B}(\mu) = \int_0^1 e^{\mu y/\langle R \rangle} \frac{-1}{G_1(\eta^{-1}(y') \lambda_s R, \lambda_w R)} dy' \quad (8)$$

and $y = \eta(v)$ is the Abbott-Vreeswijk transform.

- The spectral has a countable solution set μ_i , $i = 1, 2, \dots$ where $\Re(\mu_i) < 0 \forall i$, and for small ϵ in addition to two eigenvalues given by the equation

$$\begin{aligned} 0 &= (\mu_1 + \gamma)(\mu_1 + 1) + \lambda_w(\mu_1 + \gamma) \frac{\partial \langle R_i(t) \rangle}{\partial w} \\ &\quad - \gamma \lambda_s (\mu_1 + 1) \frac{\partial \langle R_i(t) \rangle}{\partial s} \end{aligned} \quad (9)$$

to lowest order in ϵ .

- Equation (9) is the eigenvalue equation for the mean-field system

$$\dot{s} = -\frac{s}{\tau_s} + \frac{\lambda_s}{\tau_s} \langle R_i(t) \rangle$$

$$\dot{w} = -\frac{w}{\tau_w} + \frac{\lambda_w}{\tau_w} \langle R_i(t) \rangle$$

$$\langle R_i(t) \rangle = \begin{cases} \left(\int_{v_{reset}}^{v_{peak}} \frac{dv'}{G(v, s, w)} \right)^{-1} & H(s, w) \geq 0 \\ 0 & H(s, w) < 0 \end{cases}$$

$$H(s, w) = \min_{v \in [v_{reset}, v_{peak}]} G(v, s, w) = G(v^*(s), s, w)$$

Large Networks Continued

- For small $H(s, w)$, one can prove that

$$\langle R_i(t) \rangle \sim \sqrt{\frac{F''(v^*(s)) \sqrt{H(s, w)}}{2 \pi}}$$

- Thus, we consider the system

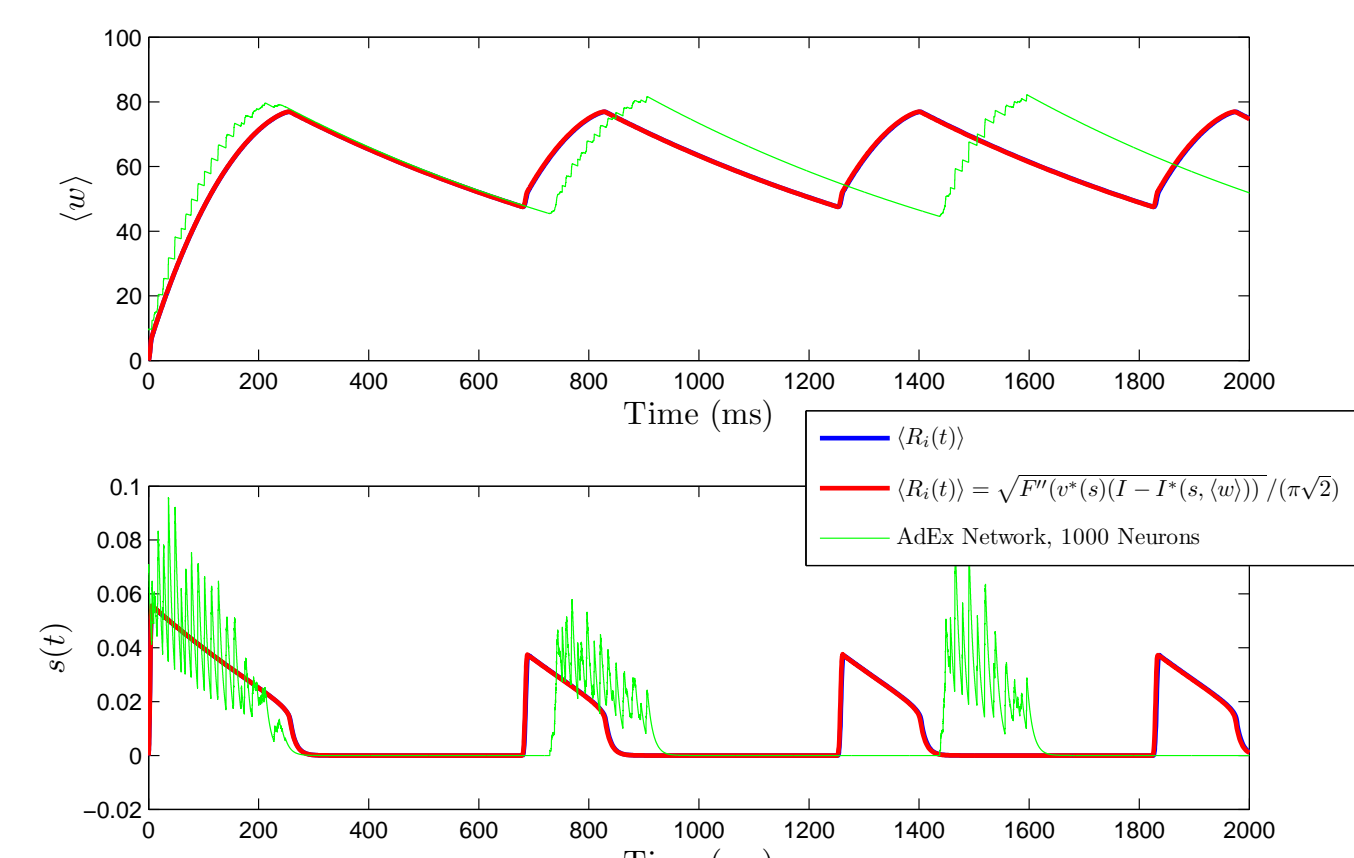
$$\dot{s} = -\frac{s}{\tau_s} + \frac{\lambda_s}{\tau_s} \langle R_i(t) \rangle \quad (10)$$

$$\dot{w} = -\frac{w}{\tau_w} + \frac{\lambda_w}{\tau_w} \langle R_i(t) \rangle \quad (11)$$

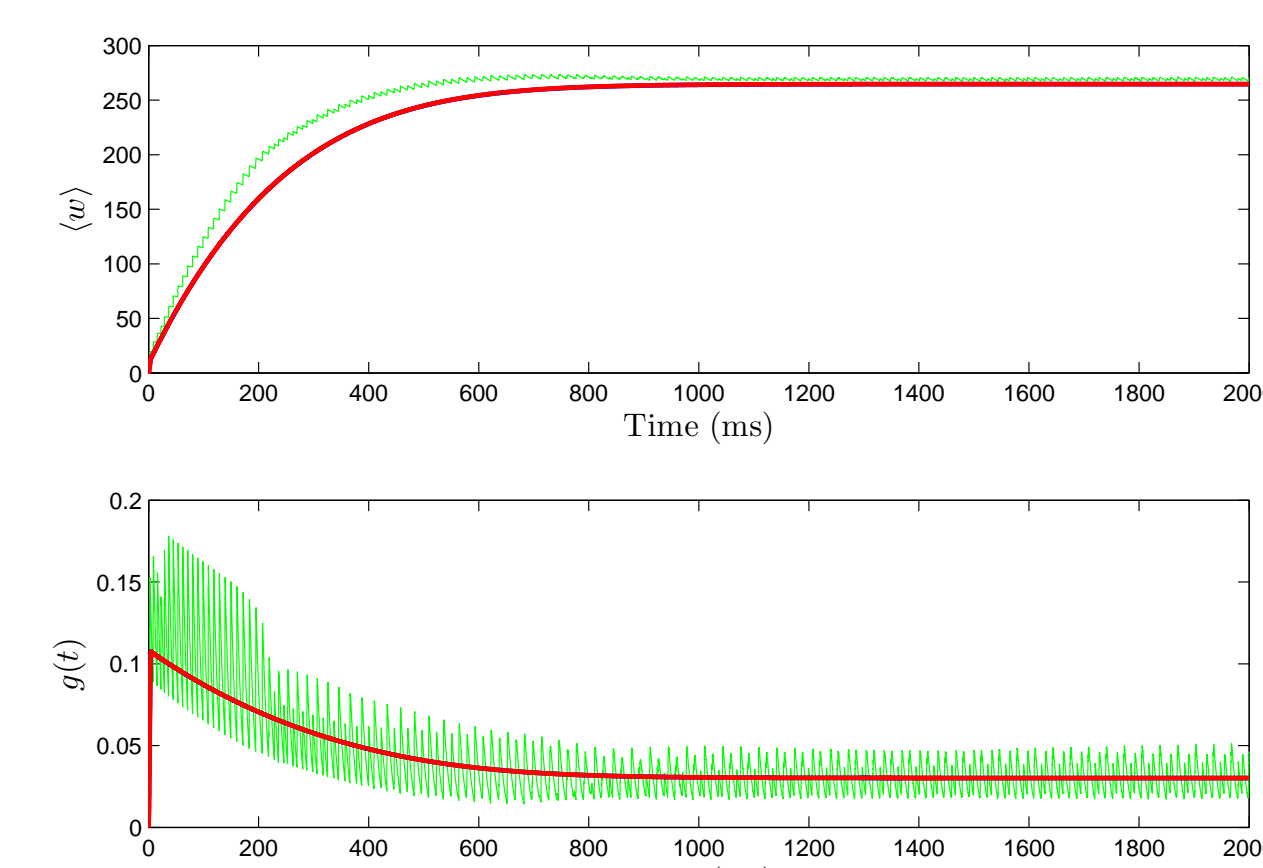
$$\langle R_i(t) \rangle = \begin{cases} \sqrt{\frac{F''(v^*(s)) \sqrt{H(s, w)}}{2 \pi}} & H(s, w) \geq 0 \\ 0 & H(s, w) < 0 \end{cases} \quad (12)$$

for analysis.

- This system is the slow system of (1)-(3) when $\tau_s, \tau_w \gg 1$ and $0 \leq H(s, w) \ll 1$. The stability and existence of the asynchronous state(s) of (1)-(3) is determined by the stability of the steady state(s) of (10)-(12)



a: Bursting AdEx Network



b: Tonic Firing AdEx Network

Figure 2: Shown above is a network of 1000 AdEx neurons (green) in comparison to the mean-field system with $\langle \langle R \rangle \rangle = \left(\int_{v_{reset}}^{v_{peak}} \frac{dv'}{G(v, s, w)} \right)^{-1}$ (blue) and the system with $\langle R \rangle$ from equation (12)(red)

Existence and Steady States

- By expanding in small s (which based on the steady state conditions of (10)-(12) is equivalent to $0 \leq H(s, w) \ll 1$, one can show that there are up to two equilibria, $e_{\pm} = (s_{\pm}, w_{\pm})$:

$$\begin{aligned} s_{\pm} &= M(g)(g - g^*) \pm \sqrt{M(g)^2(g - g^*)^2 \pm \tilde{I}} \\ w_{\pm} &= \frac{\tau_w w_{jump}}{\tau_s s_{jump}} s_{\pm} = \eta s_{\pm} \end{aligned}$$

- A third solution is the non-firing solution, $s = \langle w \rangle = 0$
- The equilibria $(s_{\pm}, \eta s_{\pm})$ undergo a **saddle-node bifurcation** when

$$\tilde{I} = -M(g)(g - g^*)^2 + O((g - g^*)^3)$$

Non-Smooth Bifurcations

- The saddle-node bifurcation is generic for $g > g^*$
- $(s_+, \eta s_+)$ undergoes a **Hopf bifurcation** when $\tilde{I} = -2M(g)N(g)(g - g^*)(g - \bar{g}) + O((g - \bar{g})^2)$
- The Hopf bifurcation is generic for $g > \bar{g}$ with first Lyapunov coefficient given by:

$$l_1(0) = \frac{3}{82} \frac{\lambda_w^2}{(e_r - v^*(0))^6 \lambda_s^2 (g - \bar{g})^2} \epsilon^3 + O(\epsilon^2)$$

- as $l_1(0) > 0$ for $g > \bar{g}$, $\tau_w, \tau_s \gg 1$, the Hopf bifurcation is subcritical

- Bifurcation curves are valid for $g > g^*$ (saddle-node) and $g > \bar{g}$ (Hopf). The points (I_{rh}, g^*) and (I_{rh}, \bar{g}) are cp-dimension 2 non-smooth bifurcation points.

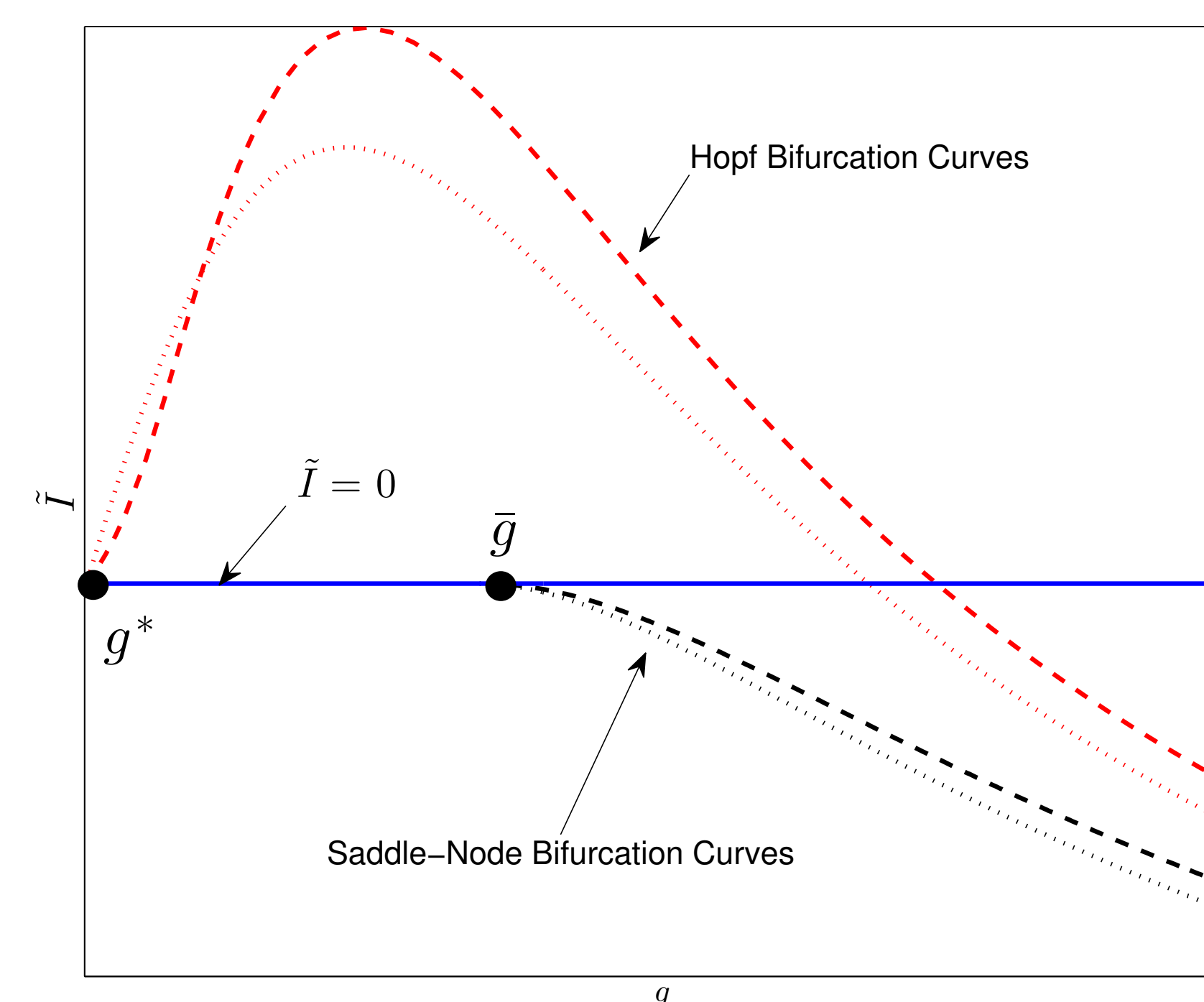
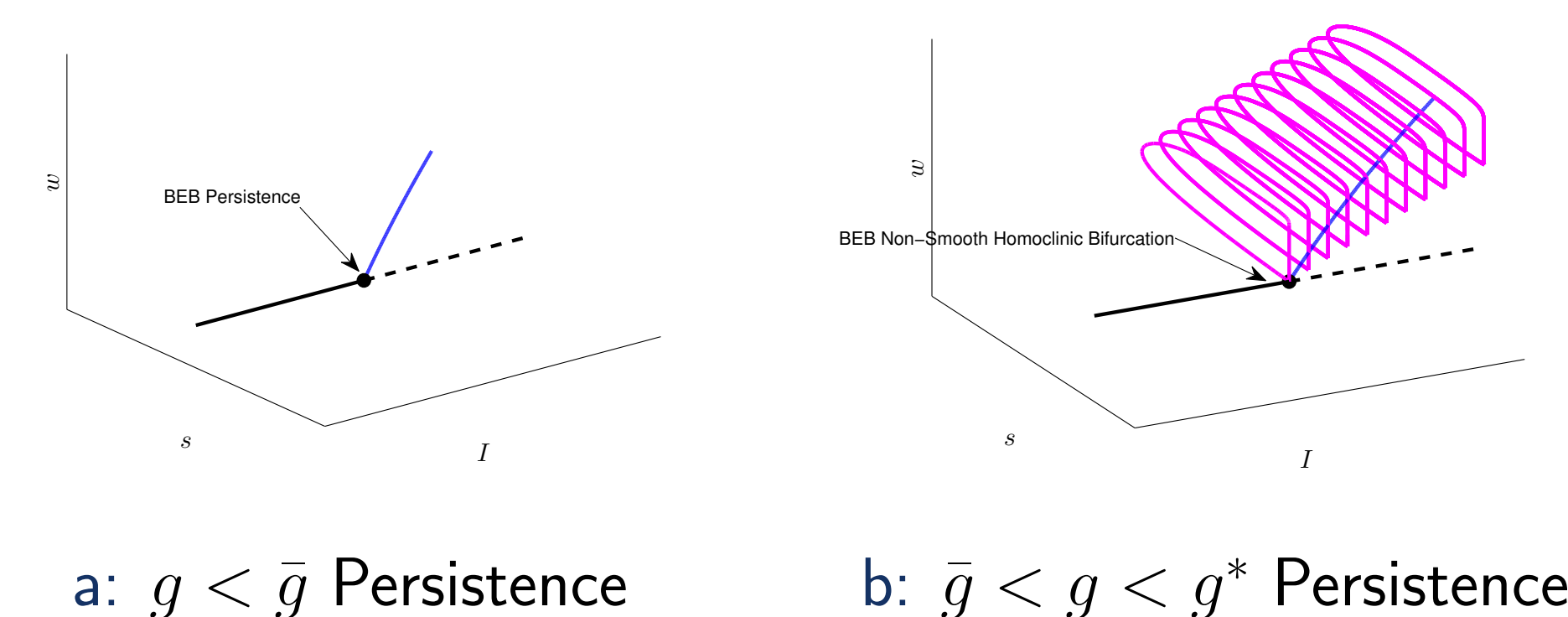


Figure 3: The saddle-node (black) and Hopf bifurcation curves (red) for the full mean-field system (dashed) and the reduced mean-field system (dotted) for a network of Izhikevich neurons. The full mean field system's bifurcation curves are determined via continuation in MATCONT. The points \bar{g} and g^* at $\tilde{I} = 0$ correspond to non-smooth co-dimension 2 bifurcation points.



a: $g < \bar{g}$ Persistence
b: $\bar{g} < g < g^*$ Persistence
c: $g > g^*$ Non-Smooth Fold
d: $g > g^*$ Non-Smooth

Figure 5: Shown above are the four branches of boundary equilibrium bifurcations. In all figures, the equilibria are $(0, 0)$ (in black), $(s_+, \eta s_+)$ (blue) and $(s_-, \eta s_-)$ (green). The limit cycle is shown in magenta and is determined through direct integration of the reduced mean-field system.

- These co-dimension 2 non-smooth bifurcations appear to be non-generic versions of those that appear for regular PWSC systems [3].

Non-Smooth Continued

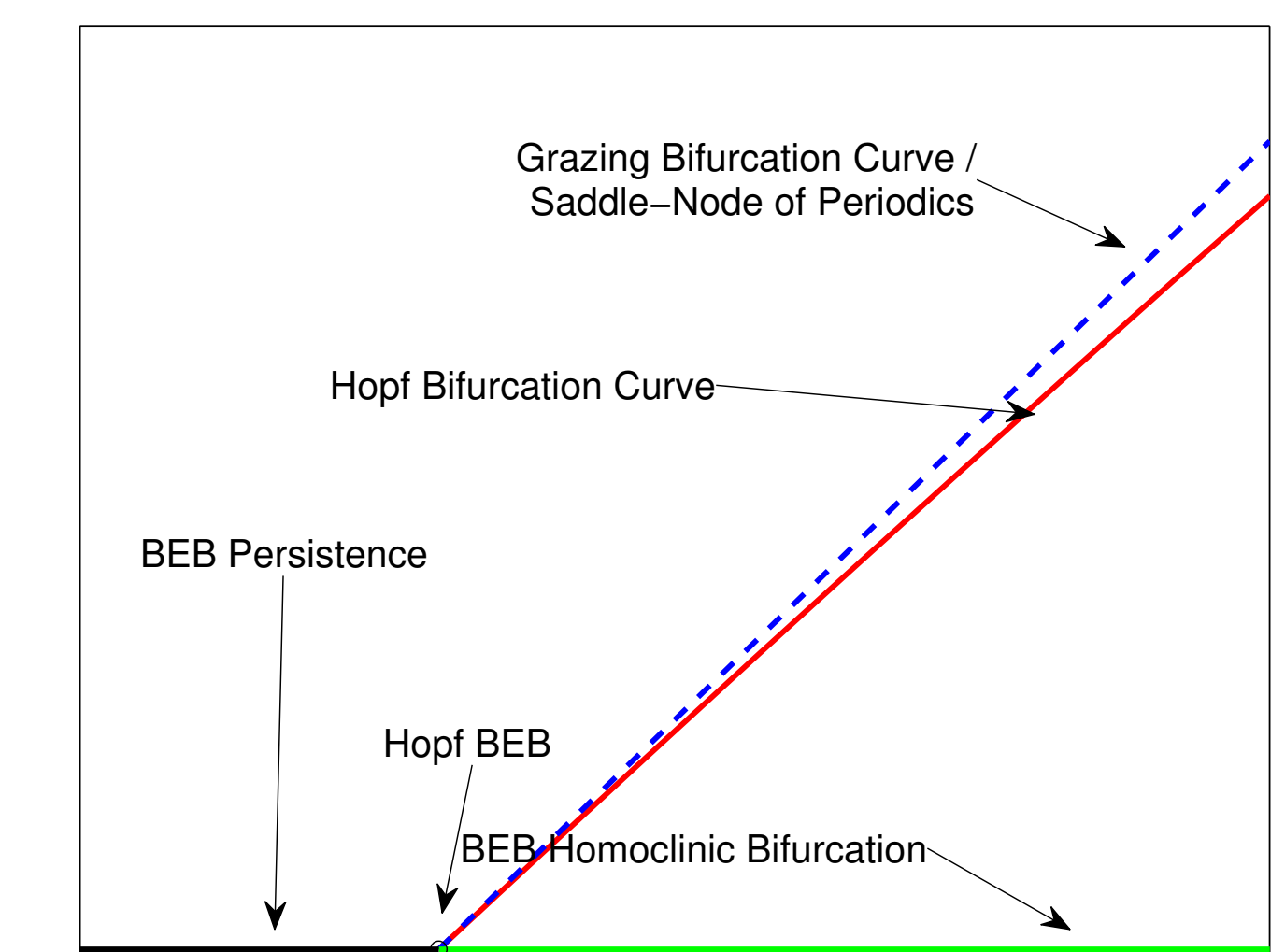


Figure 6: Hopf-BEB Point

Figure 7: Shown above is the collision of the Hopf bifurcation curve with the the non-smooth bifurcation branches.

Conclusions

- A system of PWSC ODE's is derived in the limit that $\tau_s, \tau_w \gg 1$, $H(s, w) \ll 1$ from the moment closure reduced population density equation for a network of Type-I neurons.
- The system of ODE's has saddle-node and hopf bifurcation branches, and two non-smooth co-dimension 2 bifurcation points. The bursting behavior of a full network fo neurons is organized by these points.

References

- W. Nicola, and S.A. Campbell. Bifurcations of large networks of two-dimensional integrate and fire neurons *Journal of Computational Neuroscience*, 35: 87–108, 2013.
- L.F. Abbott and C. van Vreeswijk. Asynchronous states in networks of pulse-coupled oscillators *Phys. Rev. E.*, 48: 1483–1490, 1993.
- D.J.W. Simpson. Bifurcations in piece-wise smooth continuous systems World Scientific. 2010.

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