

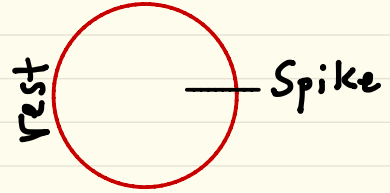
# Synaptic Plasticity and Synchronization

Morteza Fotouhi  
Sharif Univ.

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IASBS, August 2014

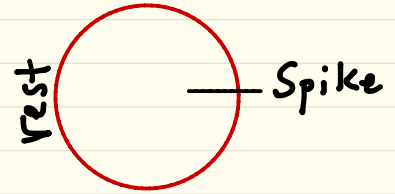
Kuramoto model: (Neuron as oscillator)



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$K_{ij}$ : Connection weight,  $K_{ij} \geq 0$

$\omega_i$ : natural frequency of neuron  $i$

# Synchronization Parameter

$$P = \frac{1}{N} \left| \sum_{j=1}^N e^{i\theta_j} \right|$$

$$0 \leq P \leq 1$$

# Synaptic Plasticity

rule I: locality

rule II: type invariant

rule III: boundedness

rule IV: option of decreasing

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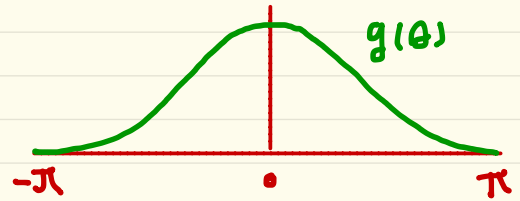
# Synaptic Plasticity

rule I: locality

rule II: type invariant

rule III: bandedness

rule IV: option of decreasing



$$g(\theta) = \frac{1 + \cos \theta}{2}$$

$$\frac{dK_{ij}}{dt} = \varepsilon(-K_{ij} + \mu g(\theta_i - \theta_j))$$

# Excitatory Network

$$\begin{cases} \dot{\theta}_i = \omega_i + \sum_j K_{ij} \sin(\theta_j - \theta_i) \\ \dot{K}_{ij} = \varepsilon (-K_{ij} + \mu f(\theta_i - \theta_j)) \end{cases}$$



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Identical Network:  $\omega_1 = \omega_2 = \dots = \omega_N$

$$\varphi_i = \theta_i - \omega_i \Rightarrow \dot{\varphi}_i = \sum_j K_{ij} \sin(\varphi_j - \varphi_i)$$

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Gradient System  $V = \sum_{i < j} \frac{1}{2} K_{ij}^2 - \mu K_{ij} g(\varphi_i - \varphi_j)$

$$\frac{dV}{dt} \leq 0$$

$V$  is bounded from below, then all trajectories converge to the local minimum of  $V$ .

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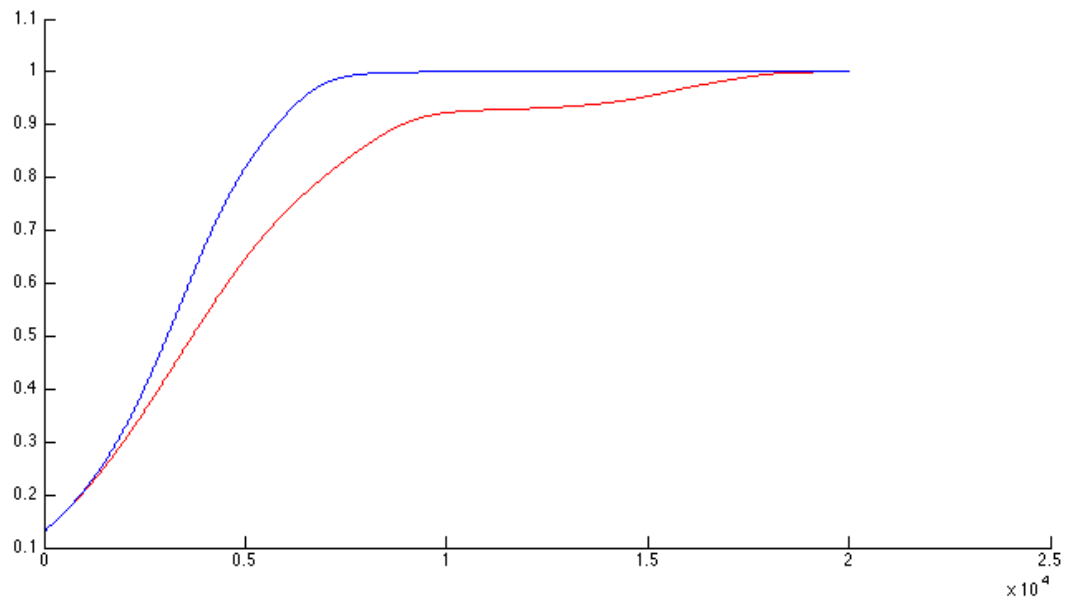
Guess: ' $\varphi_1 = \varphi_2 = \dots = \varphi_N$ ' is the only minimum points.

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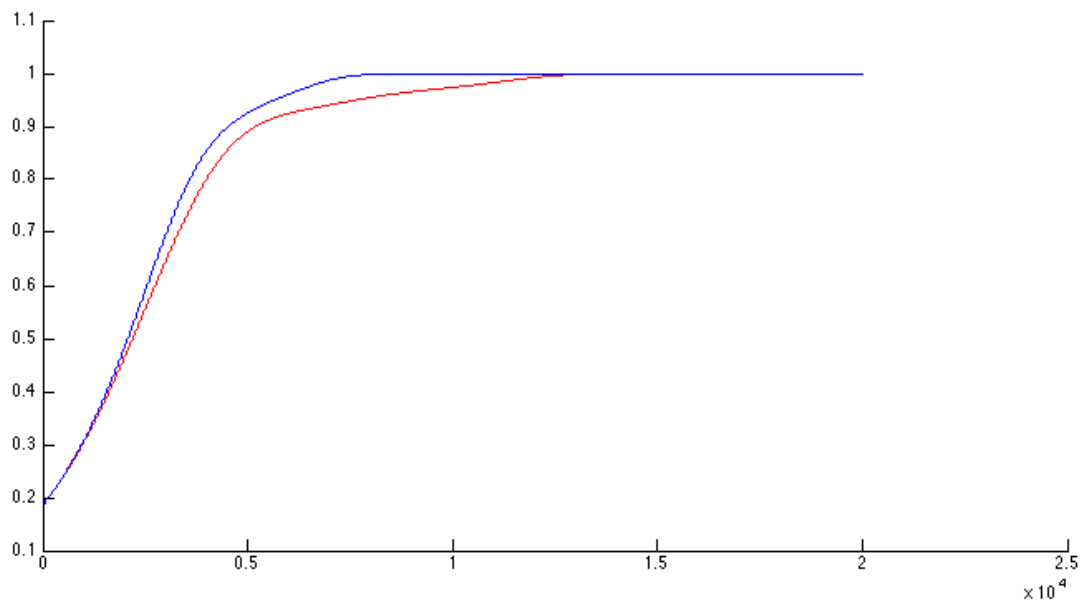
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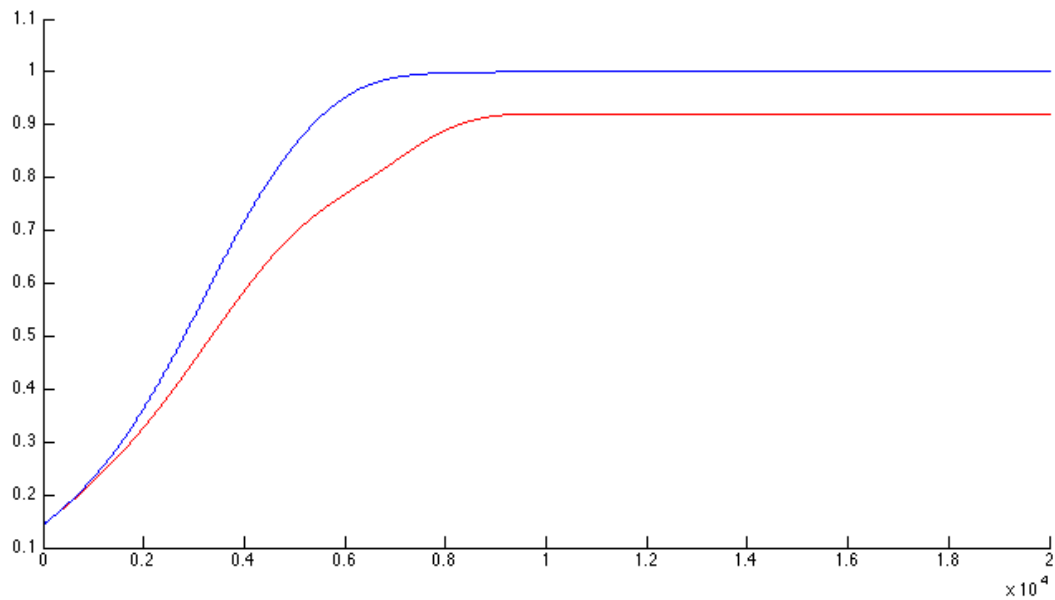
observe: network without plasticity gets synchronized faster.



$N=50$ ,  $\epsilon=0.5$



N=50, epsilon=0.2

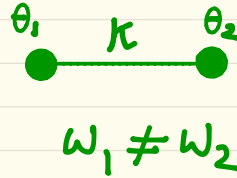


N=50, epsilon=2



# Inhomogeneous Network

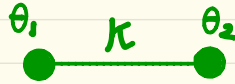
Two Neurons



$$\begin{cases} \dot{\theta}_1 = \omega_1 + K \sin(\theta_2 - \theta_1) \\ \dot{\theta}_2 = \omega_2 + K \sin(\theta_1 - \theta_2) \\ \dot{K} = \varepsilon(-K + \mu g(\theta_1 - \theta_2)) \end{cases}$$

# Inhomogeneous Network

Two Neurons



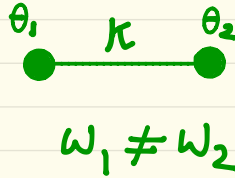
$$\omega_1 \neq \omega_2$$

$$\begin{cases} \dot{\theta}_1 = \omega_1 + \kappa \sin(\theta_2 - \theta_1) \\ \dot{\theta}_2 = \omega_2 + \kappa \sin(\theta_1 - \theta_2) \\ \dot{\kappa} = \epsilon(-\kappa + \mu f(\theta_1 - \theta_2)) \end{cases}$$

$$\varphi = \theta_1 - \theta_2 \longrightarrow \begin{cases} \dot{\varphi} = \Delta\omega - 2\kappa \sin\varphi \\ \dot{\kappa} = \epsilon(-\kappa + \mu f(\varphi)) \end{cases}$$

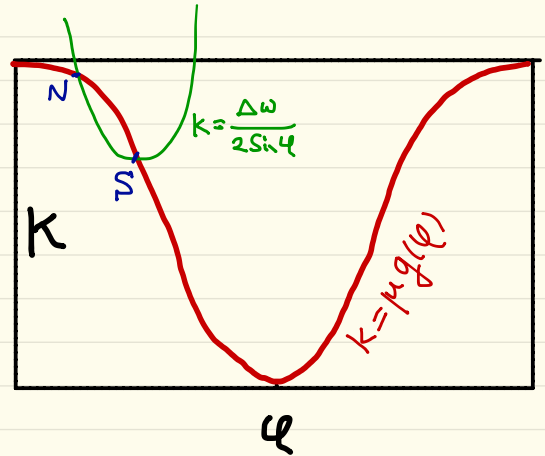
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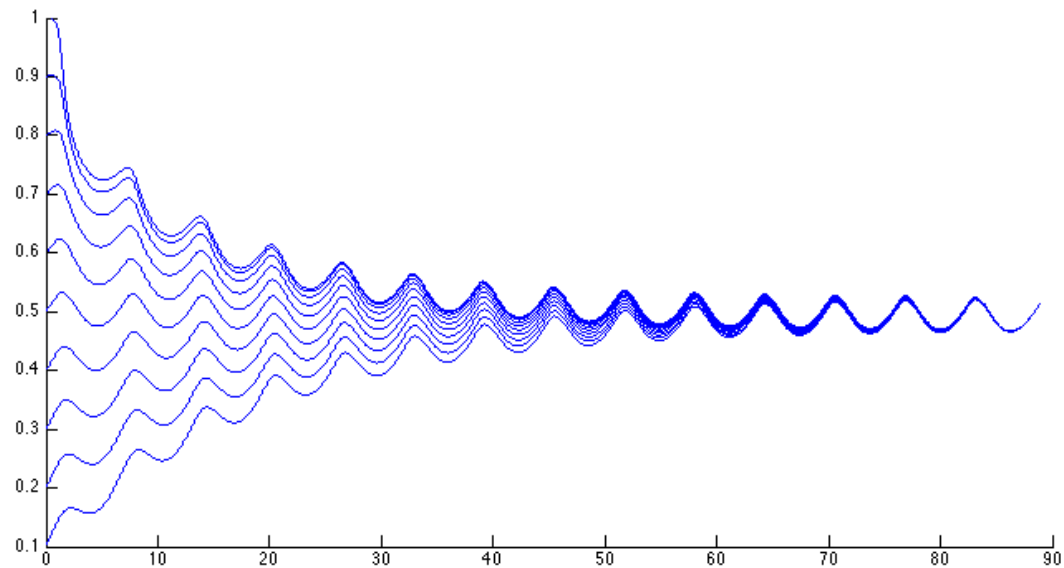
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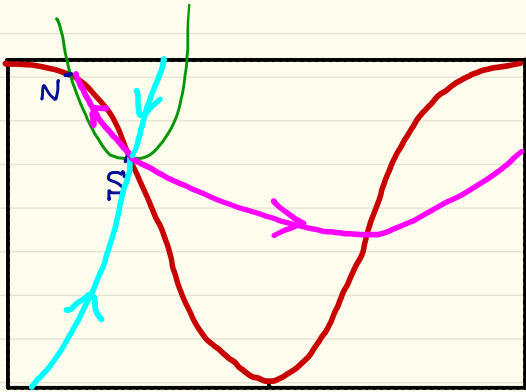
Result 1: If  $|\Delta\omega| > M = \max \mu \sin\varphi (1 + \cos\varphi)$ , then  
there is a periodic global asymptotic solution.

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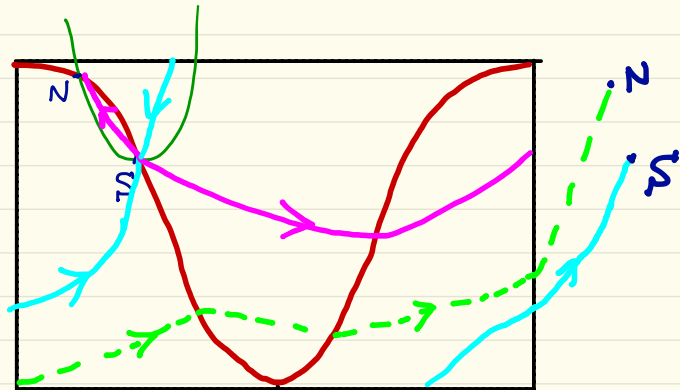
$\Delta=2, \epsilon=0.2, \mu=1$

$$\Delta\omega < M ?$$

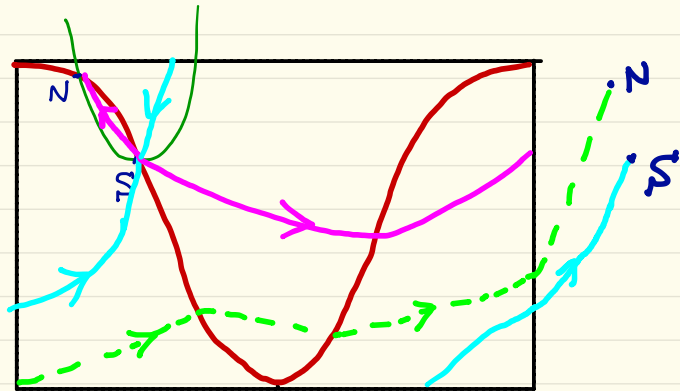


lucky case

all solutions, except the stable curves, will converge to the stable nodes "N".



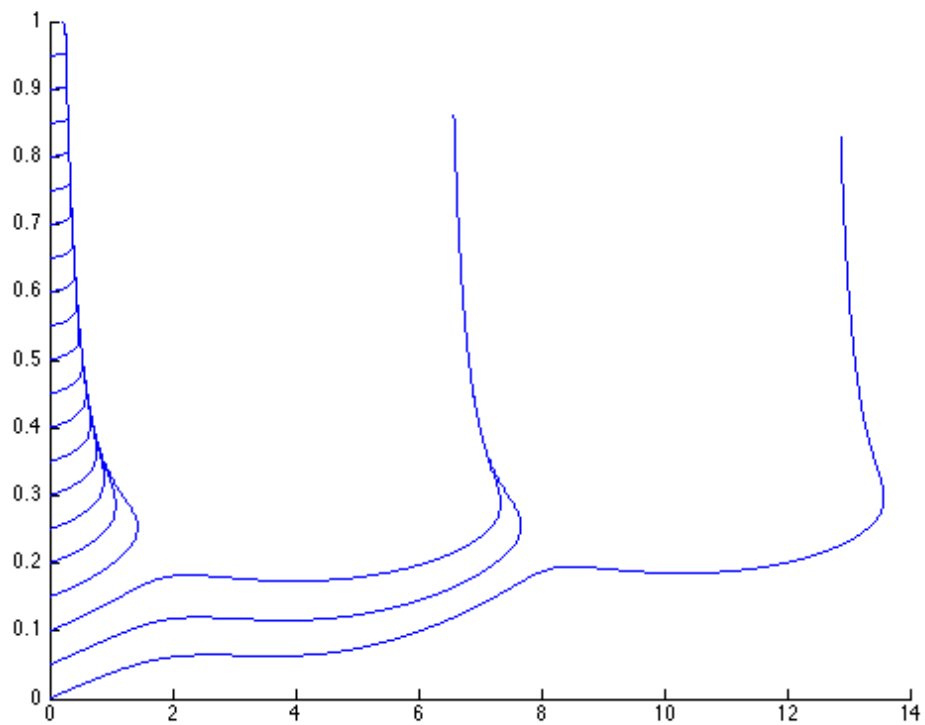
lucky case



lucky case

Result 2 : For  $\Delta w < \mu$ , we will have  
the lucky case.

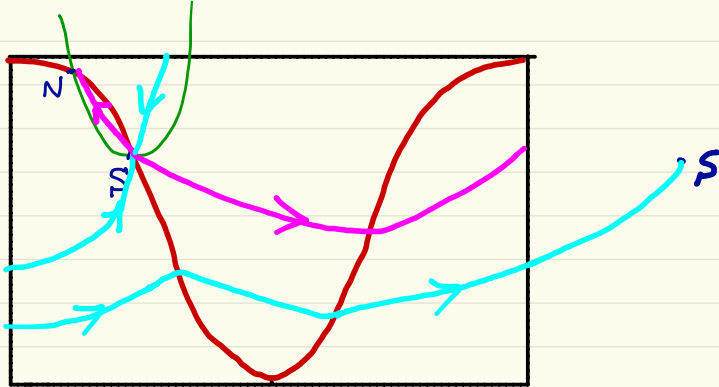




Delta=0.5, epsilon=0.2, mu=1

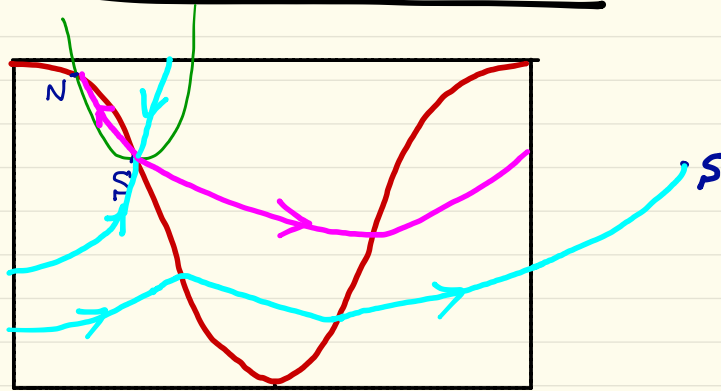
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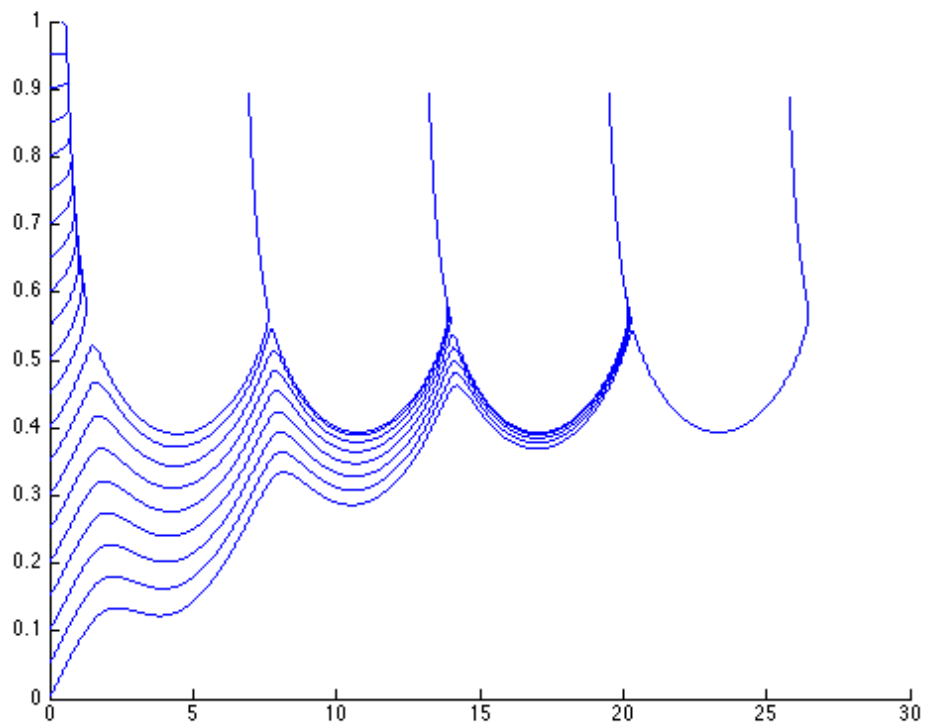
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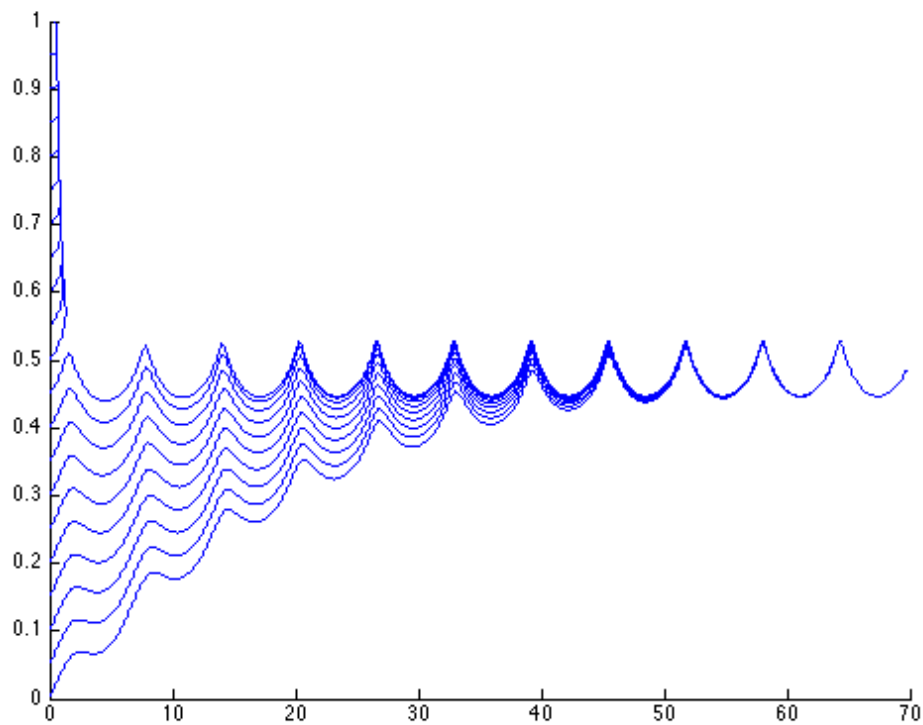


Result 3: There is  $\varepsilon_0 > 0$ , sth for  $\varepsilon > \varepsilon_0$  the lucky case will be happened.

For  $\varepsilon < \varepsilon_0$ , there exists a periodic attractor solution



Delta=1.1, epsilon=0.1, mu=1



Delta=1.1, epsilon=0.05, mu=1

# Without plasticity

$$\varphi = \theta_1 - \theta_2 \implies \dot{\varphi} = \Delta\omega - 2K \sin\varphi \quad \text{where 'K' is a constant.}$$

$$\exists \text{ stable node } \bullet \varphi_* < \pi/2, \quad \sin\varphi_* = \frac{\Delta\omega}{K}$$

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Question: Plasticity  $\longrightarrow$  Synchrony?



