

Can System Dynamics Models Learn?

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Can System Dynamics Models Learn and Adapt?

- ◆ Of course not! Models don't learn; people do.
- ◆ Learning and adaptation require internal changes,
- ◆ And system dynamics models have fixed structure (equations),
- ◆ So system dynamics models can't learn.
- ◆ But how close can they come?

Can System Dynamics Models Learn and Adapt?

- ◆ System dynamics models can change dominant structure:
 - ◆ Nonlinearities are our source of endogenous system change
- ◆ So the question becomes
 - ◆ How close can endogenous shifts in loop dominance, generated by nonlinearities, come to resemble learning?
- ◆ And the answer is: Pretty close!

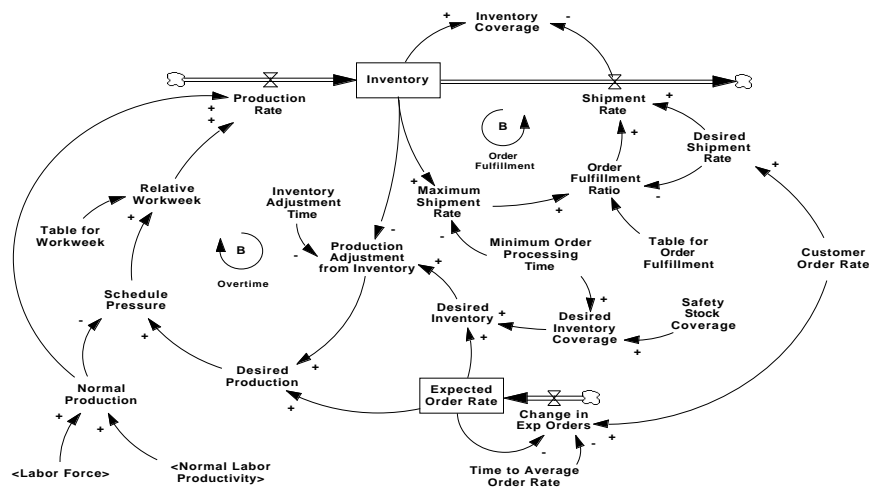
What is Required?

- ◆ Model structure for the *self-perception of model behavior*
- ◆ Model structure for *adaptation and 'learning'*
- ◆ And perhaps, model structure for endogenously generated *experimentation leading to 'learning'*

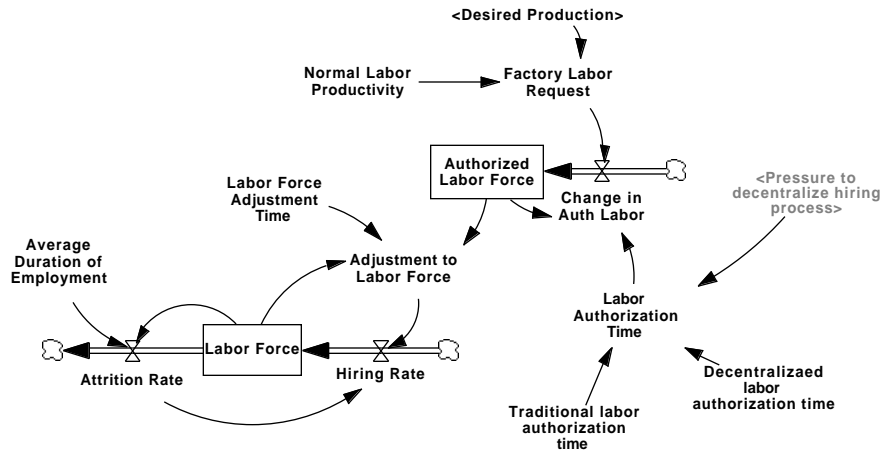
An example: Inventory / Workforce Instabilities

- ◆ Classic structure of Inventory / Workforce oscillations in response to randomness in customer orders
- ◆ Oscillations stem from delays in adjusting the workforce to changes in the desired production schedule
- ◆ Two policies dampen the oscillations:
undertime/overtime and re-engineering hiring

Inventory, Production, & Shipments



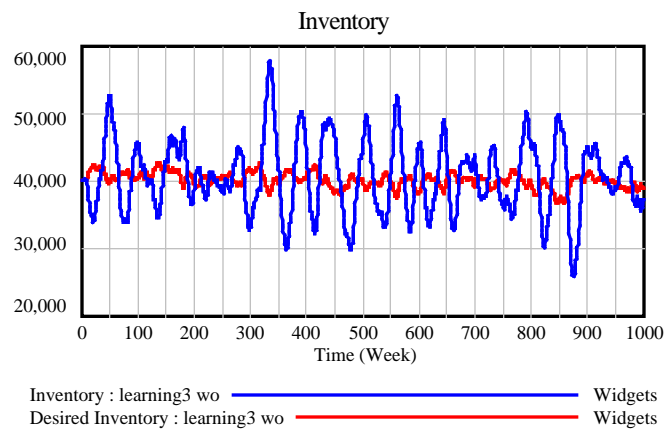
Hiring Delays



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Persistent oscillations in Inventories



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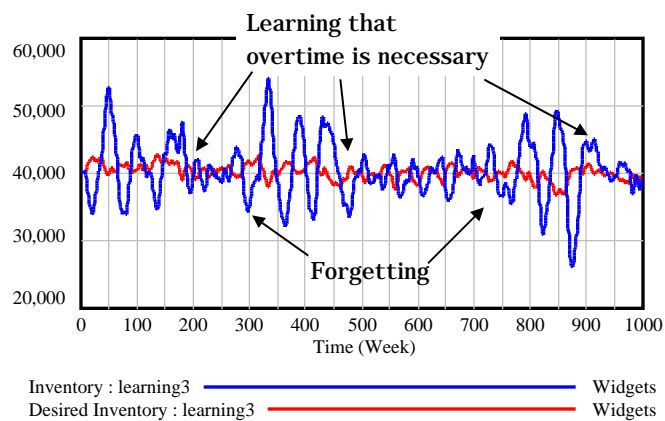
...and the Laborforce



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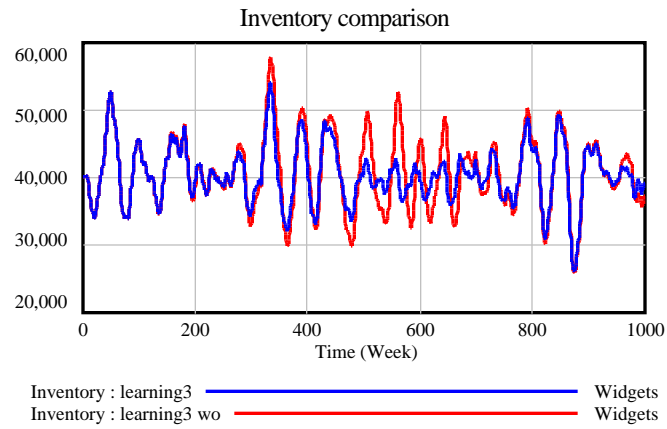
Learning and forgetting



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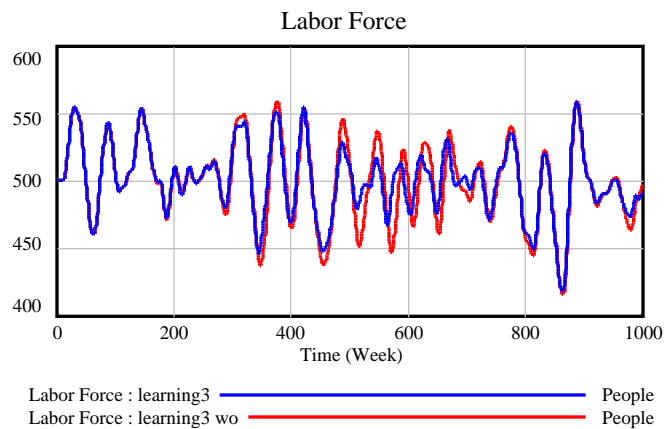
Inventory, with and without learning



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Labor, with and without learning



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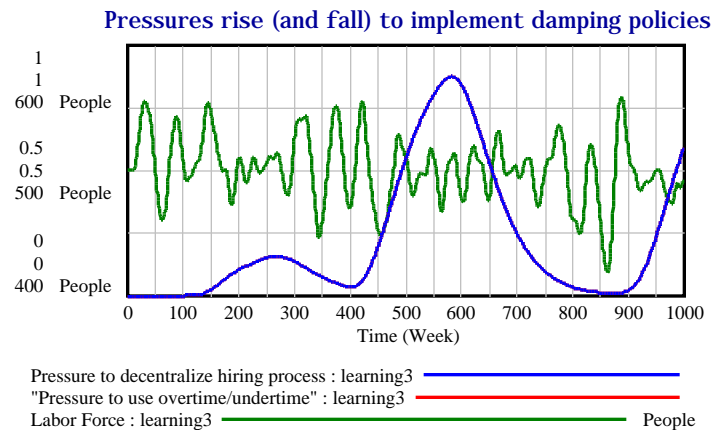
How does the model 'learn'?

- ◆ It 'perceives' that it, itself, is oscillating,
 - ◆ In particular, that the Laborforce is oscillating.
- ◆ It 'perceives' the period and amplitude of its own oscillations, much as a person would.
- ◆ It comes to perceive that the amplitude of its oscillations is above its tolerance,
- ◆ So 'pressures' mount to phase in undertime & overtime and decentralize hiring

How does the model 'forget'?

- ◆ The model 'perceives' that its Laborforce variations are within its acceptable tolerance,
- ◆ So the pressures for undertime & overtime and removing hiring delays subside,
- ◆ And the damping policies are phased out -- the model 'forgets' that it ever had a problem.

The dynamics of pressures to adjust



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Modeling pressures to adjust

- ◆ Perceive peaks and valleys of the oscillations
- ◆ Estimate period and amplitude
- ◆ Pressure to adjust = $f(\text{Amplitude}/\text{Tolerance})$
- ◆ Pressures to adjust are then applied to hiring delays and the undertime/overtime policy
- ◆ Relative workweek =

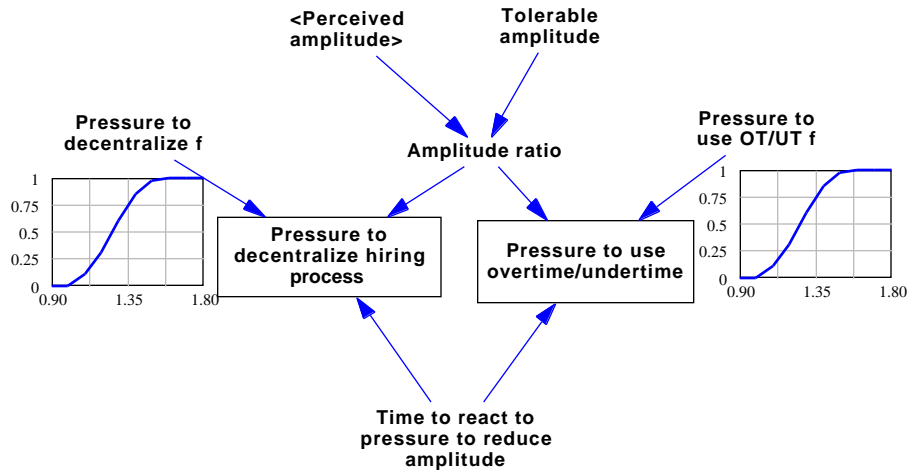
$$\text{Pressure to use overtime/undertime} * \text{Table for Workweek}(\text{Schedule Pressure}) + (1 - \text{Pressure to use overtime/undertime}) * 1$$
- ◆ Labor authorization time =

$$\text{Pressure to decentralize hiring process} * \text{Decentralized labor authorization time} + (1 - \text{Pressure to decentralize hiring process}) * \text{Traditional labor authorization time}$$

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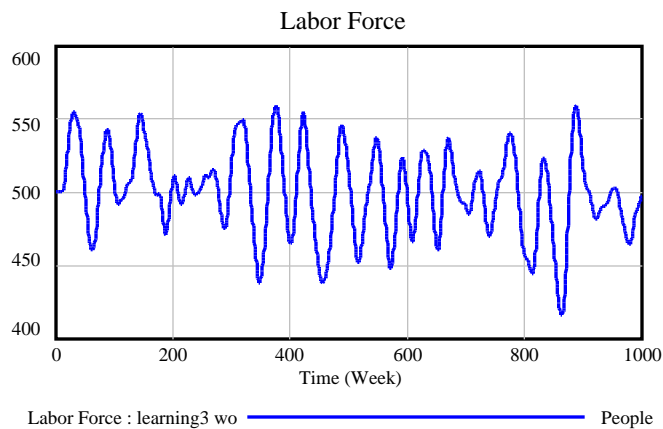
Modeling pressures to adjust



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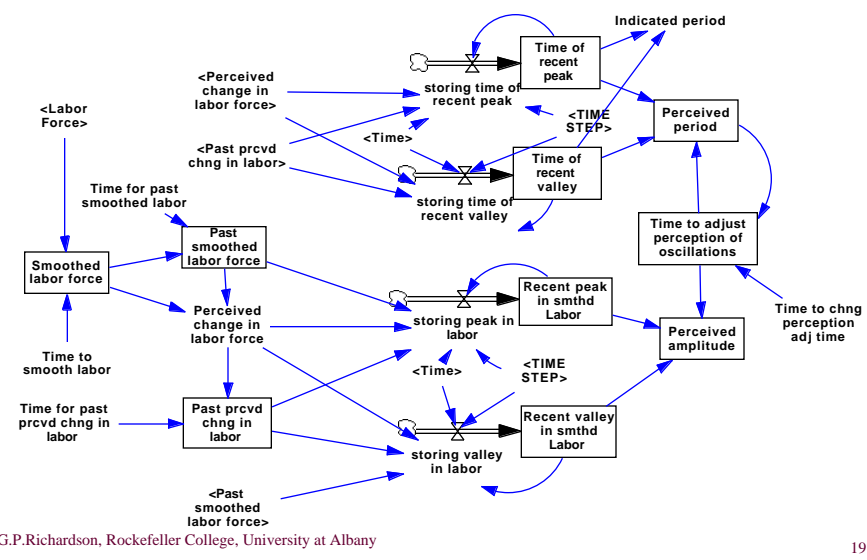
Perceiving peaks, valleys, period, and amplitude



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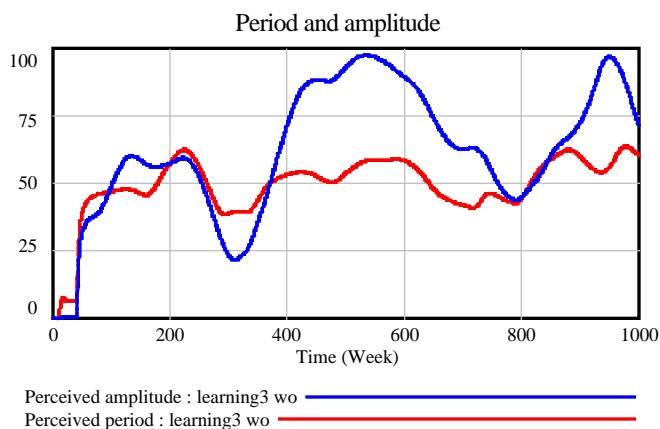
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The hard part is modeling the perception of peaks and valleys...



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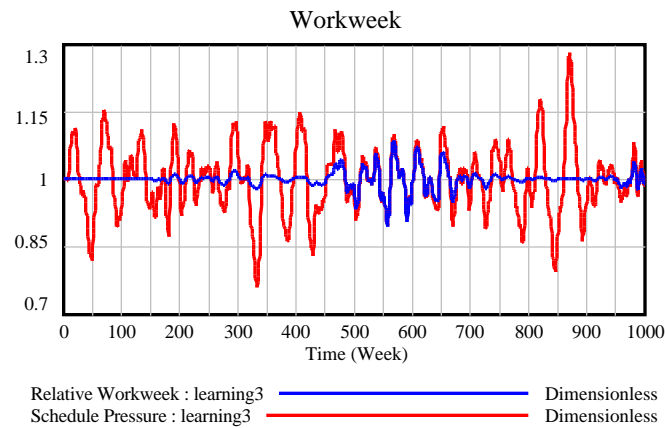
Perception of period and amplitude



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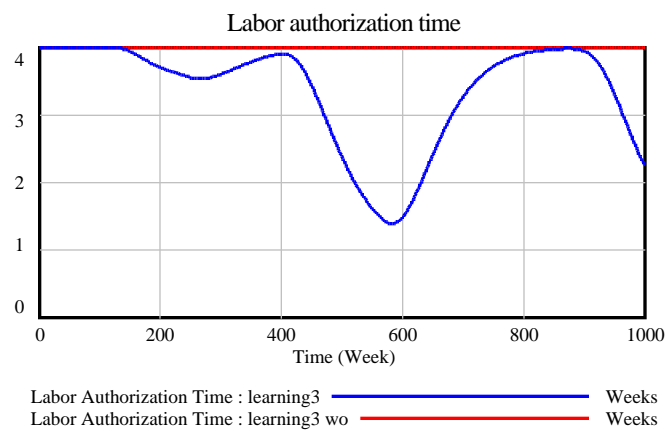
Learning to adjust the workweek policy



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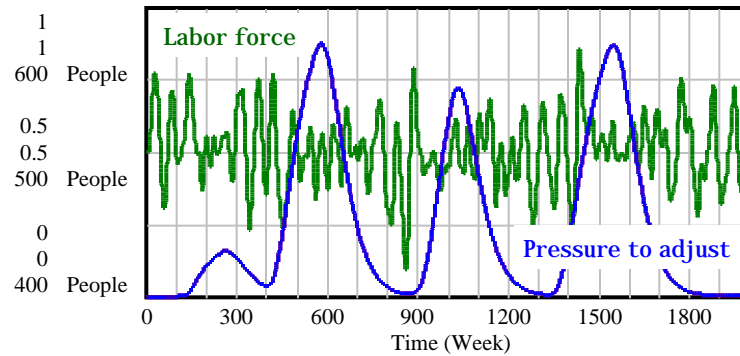
Learning to re-engineer the hiring policy



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Long run dynamics



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What have we learned?

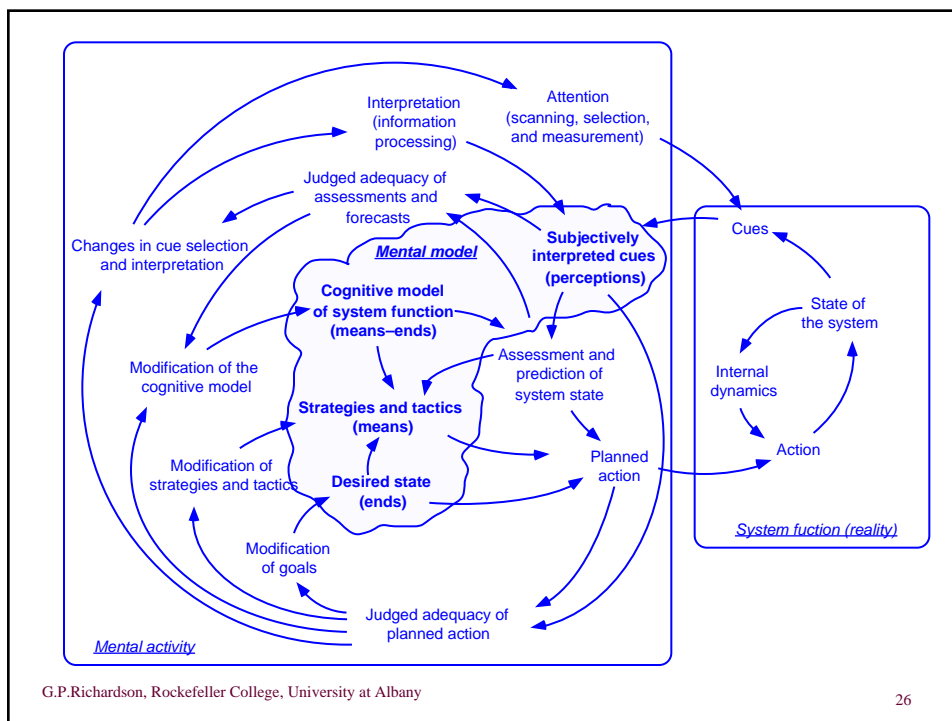
- ◆ If the model didn't forget, the problem would be solved.
- ◆ Nonlinearities enable continuous models to adapt and change over time.
- ◆ Modeling the model's perception of its own dynamics is tricky.
- ◆ We are thinking of 'learning' as *purposeful adaptation in response to system behavior to come closer to goals*.
- ◆ So far, the model can 'learn' and 'forget' only what we tell it to.

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Can a model *explore* multiple policies and *select* on its own the most advantageous?

- ◆ Why not?
- ◆ In addition to what we've seen, the model would require:
 - ◆ an *Exploration* sector that sets out the structure for explorations;
 - ◆ A *Selection* sector that contains criteria for evaluation of the model's own dynamic behavior.
- ◆ None of that seems impossible, but it could be daunting...



Why build models that learn?

- ◆ To achieve real-time adaptive control at the policy level
- ◆ To compress human learning time
 - ◆ Ask models to show us what we can't learn without them
- ◆ To prove that we can do it
- ◆ Because we've solved all the easier dynamic problems
 - ◆ Not bloody likely!
- ◆ Because it's New Year's Eve and we're looking for something to do...

Further reading

- ◆ Self-learning policies in Urban Dynamics, *Readings in Urban Dynamics II* (1975).
- ◆ DeJong, Learning to plan in continuous domains. *Artificial Intelligence* 65 (1994).
- ◆ Ram & Santamaria, Continuous case-based reasoning. *Artificial Intelligence* 90 (1997)
- ◆ Richardson, Andersen, Maxwell & Stewart, Foundations of Mental Model Research (1994)
- ◆ Powers, *Behavior, the Control of Perception* (1973)