Engineering and the Design and Operation of Manufacturing Systems

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    - ▶ When aerospace systems fail, people die; when factories fail, people lose jobs or money.

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- Common sense and relatively simple methods were sufficient for factory design and operation, even as manufacturing technology advanced. Sophisticated theory was not needed.

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- That theory is being developed, but it many important problems have not been solved ...
- ... and some important problems have been solved, but their solutions are not widely used.

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- Every factory has special features that do not fit into generic software or research models.
- Design and operation of manufacturing systems must take place in the presence of *variability, uncertainty, and randomness.*

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  - ***To design and operate manufacturing systems that deliver the best possible performance, we must use scientific tools for understanding variability, uncertainty, and randomness.***
- For the foreseeable future, factories cannot be designed or operated without people.

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  - ⋆ ... and because the scientific community has not consistently been guided by the needs of manufacturers to develop more and better tools.

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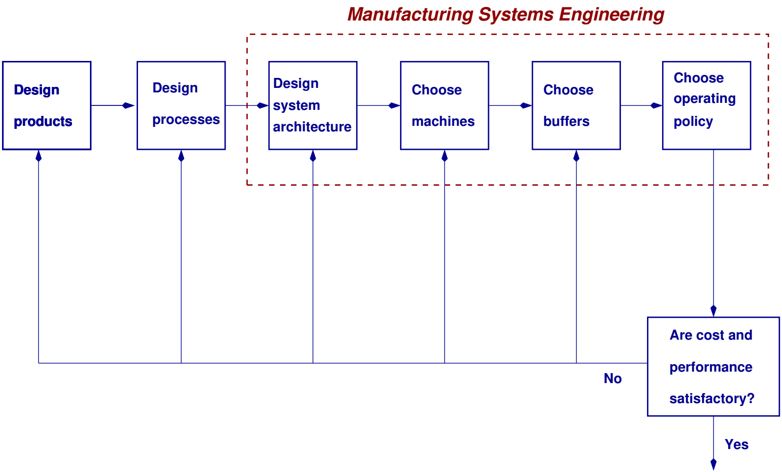
- reduce the ***propagation*** of variability, uncertainty, and randomness in systems.

Manufacturing Systems Engineering

Product/Process/Factory Design



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- ***Be robust.***
  - ***Be insensitive to disruptions.***
  - ***Respond gracefully to disruptions.***
  - ***Respond gracefully to demand changes, engineering changes, etc.***

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The modelers must work closely with those with practical experience, and they must become familiar with factory floors.

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- To do manufacturing systems research, and
- To document their work in order to educate manufacturing systems engineers. This will include education in the
  - ⋆ theory,
  - ⋆ analysis, design, and operation techniques, and
  - ⋆ ***intuition***

  of manufacturing systems.

Team Deliverables

- Industry-supported projects for specific manufacturing systems, such as:
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- Research that will lead to practical tools for design and operation of manufacturing systems.
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The research and educational materials will be motivated by experience gained in projects.

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  - ⋆ Good intuition provides a good starting point for design. It can then be refined by computational tools.
- Intuition is needed to create strategies for solving new problems.

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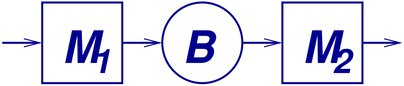
- ***Manufacturing systems intuition must include intuition about variability, uncertainty, and randomness.***

Engineering Intuition

Two-Machine Line Behavior



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Engineering Intuition

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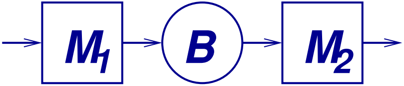

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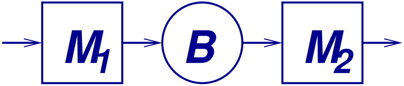

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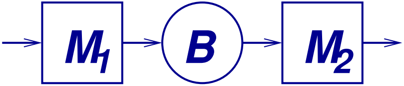

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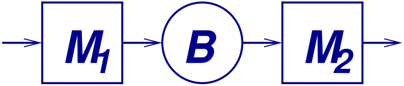

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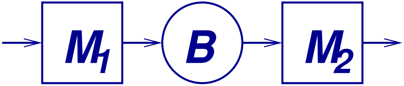

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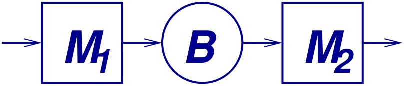

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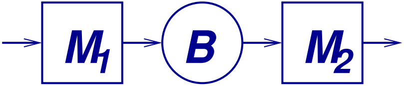

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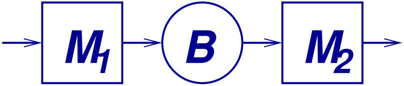

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In the next slide, $p_1 = p_2 = .01; r_2 = .1$. N and r_1 vary.

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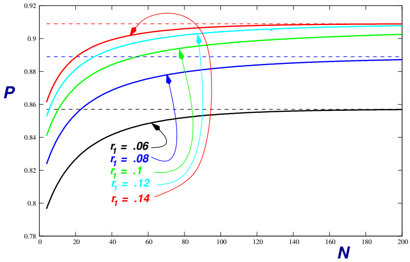

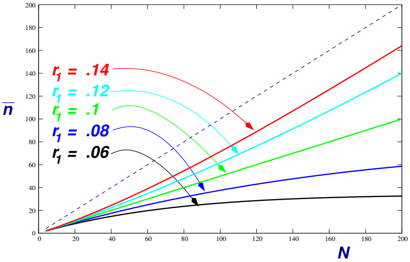

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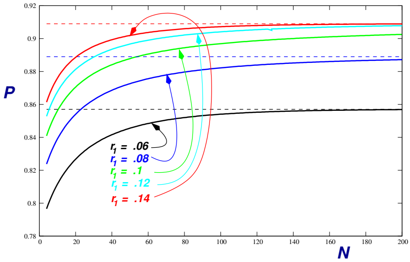

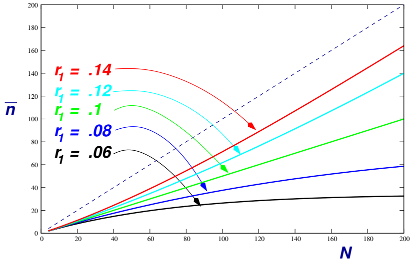

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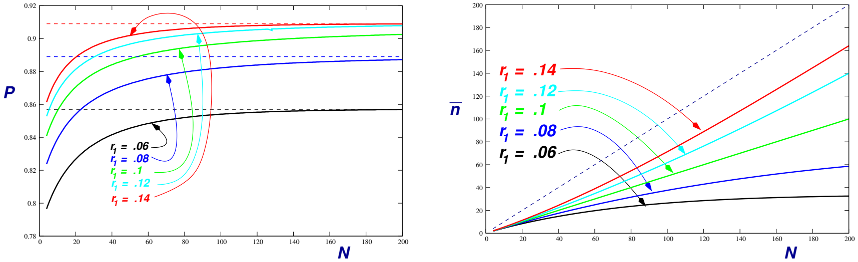

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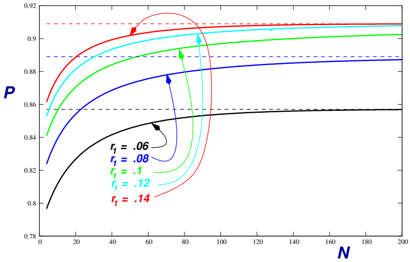

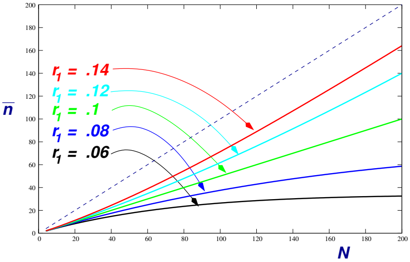

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- If the second machine is a bottleneck, $N - \bar{n}$ approaches an upper limit.

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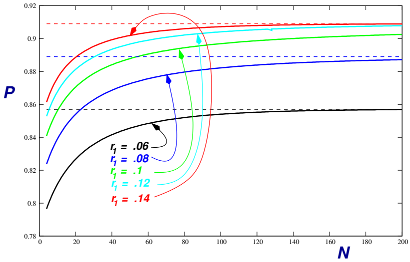

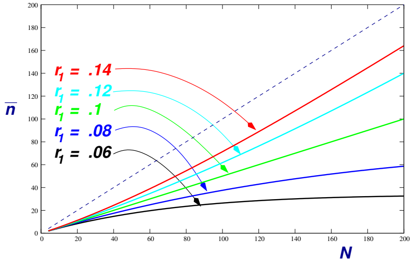

As $N \to \infty$,

- Production rate approaches an upper limit monotonically.
- If the first machine is a bottleneck, average inventory $\bar{n}$ approaches an upper limit.
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- If the machines are identical, $\bar{n} = N/2$.

Engineering Intuition

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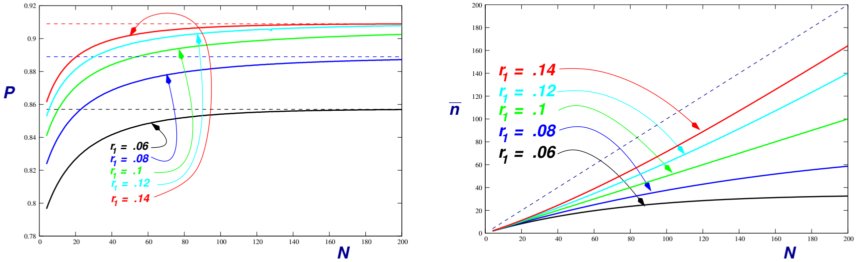

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$\bar{n}$ increases as the first machine becomes faster (i.e., more productive).

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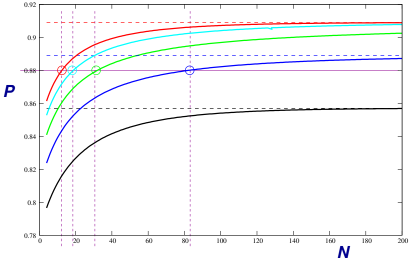

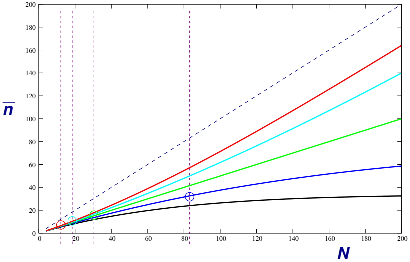

Problem: Select M_1 and N so that $P = .88$.

Solution:

r_1	N	$\bar{n}$
.14	13	7.0819
.12	19	10.1153
.10	32	16.0000
.08	82	32.2112

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Manufacturing systems intuition and research are needed for the last two items.

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In practice, the distinction may not always be clear-cut.

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Static and dynamic data are used differently.

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- Factory design: Given a set of machines, how large do buffers have to be in order for the factory to meet a production rate target?
- Given a set of machines and buffers, what is the maximum number of parts to allow in a production line?

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    - ▶ When the measured wear on the machine has reached a specified threshold?

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  - ⋆ *We also need to know when the machines are idle* (when they are prevented from working by starvation, blockage, or other reason).

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- Also, they should test the tool and decide if the results make intuitive sense.

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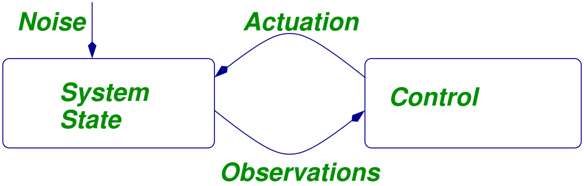

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- In reality, some (most?) factories are managed by real-time human improvisation.

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These problems can lead to reduced effective capacity and difficulties in predicting delivery dates.

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- ***Advantages:*** This would be the best possible way to run the factory.

Feedback Control

The ideal approach:

- Formulate an optimal control problem.
  - ⋆ It includes a detailed model of the factory dynamics, including material movement, random events, setup times and costs, demand as a stochastic function of time, inspection, rework, batching, maintenance, etc.
  - ⋆ The objective would be to maximize expected profit, minimize expected cost, maximize service rate or to optimize another performance measure.
- Solve the problem to obtain an optimal feedback policy.
- Implement.
- ***Advantages:*** This would be the best possible way to run the factory.
- ***Disadvantages:*** The optimal control problem cannot be solved.

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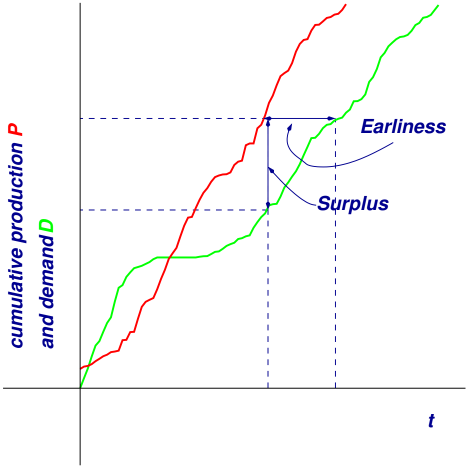
- Difficulty: Demand and machine reliability are both stochastic.



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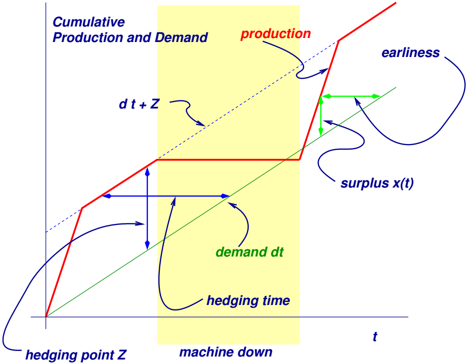

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    - ▶ How much does production rate increase with an optimal allocation of the current buffer capacity? 7.32%.
    - ▶ How much does production rate increase with a better allocation of the current number of operators? 2.7%.

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- This is possible only if manufacturing systems engineers have a fundamental understanding of the behavior of manufacturing systems, and of how variability, uncertainty, and randomness affect them.
- Such an understanding can be developed by teams consisting of people with manufacturing knowledge and understanding, researchers skilled in mathematical modeling and analysis, and IT professionals.

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- Will human intuition still be important?

Thank you.

References

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From Patchong et al. (2003):

- People used to think that the capacity of buffers that are always full must be increased so that there would be enough place to store more material for the good of the production. We proved that one must focus on half-full buffers and then, whenever possible, ***reduce*** the capacity of buffers that are full all of the time to increase the capacity of half-full buffers.

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