



Model-Based Optimization of Learning Curves: Implications for Business and Government

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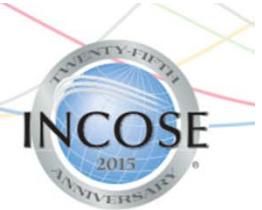
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Outline



- Problem
- Opportunity
- Learning Curves
- Modeling Learning Curves
- Portfolio optimization
- Pilot Study
- Conclusion
- Way Ahead



Problem

- Major corporations spend substantial amounts annually on workforce training and development
- Don't have a way to quantify the Return On Investment (ROI) in terms of impact on learner time-to-proficiency and learning rate
- Also, learner deficiencies are not identified for targeted training
- As a result, companies resort to mass training – exorbitant cost, no guarantee of success

Opportunity



- Learning curves **describe** how:
 - repeated task performance results in decrease in task performance time
 - unit cost decreases as a function of units produced (experience curve)
 - time-to-proficiency decreases with accumulation of knowledge and skills (proficiency curve)
- Observation: learning curves can be **optimized** through optimal **allocation of funds and cohorts** to learning options and courses

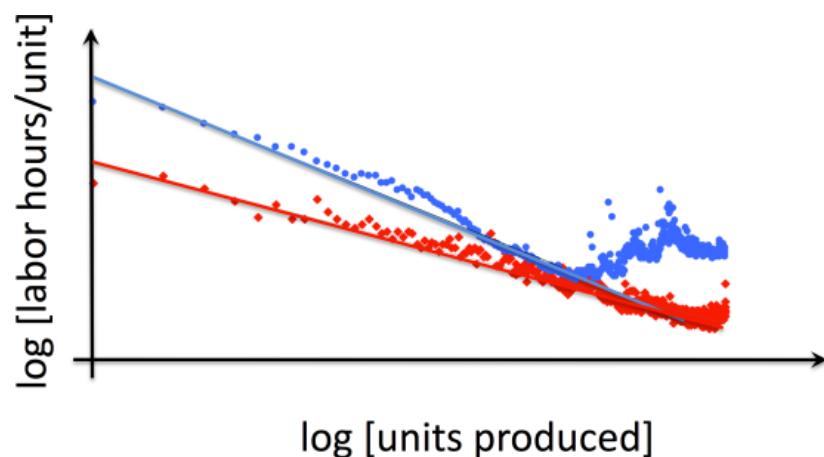


Learning Curves: Origin

- Recognized in the aircraft industry in 1936 (Theodore Paul Wright)
- **Key notion:** accumulating experience leads to improved proficiency and performance
- Boeing discovered that:
 - time to assemble an aircraft declined with increase in number of aircraft assembled
 - cost to assemble a new aircraft was highly predictable
 - rate of improvement (i.e. learning rate) was predictable could be characterized by a math formula
 - this meant that labor hours required for aircraft assembly could also be predicted with reasonable precision
 - phenomenon holds for a variety of manufacturing setups across industries (learning rates varied)
- Generalized by Bruce Henderson of BCG in the form of Power Law in 1968 (“experience curve”)
 - experience curve effects: 10-25% in various industries



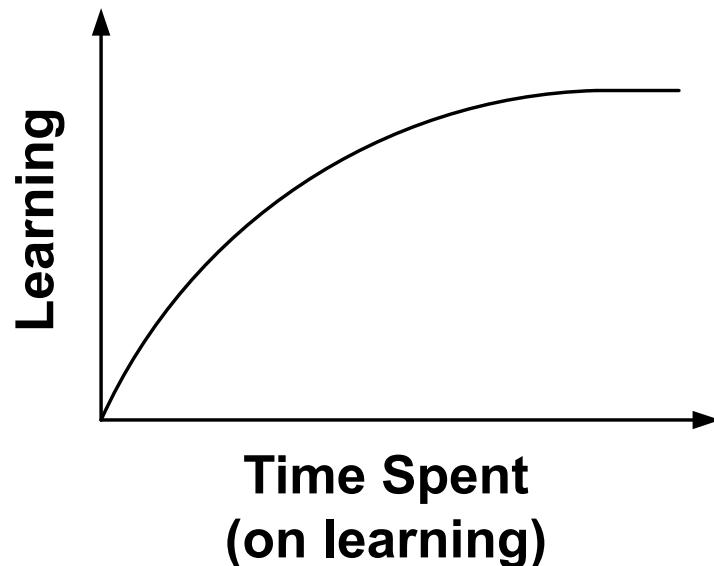
- Increase in experience leads to improved performance
 - time to assemble an aircraft declines with # of aircraft assembled
 - each time a task is performed it takes less time than the time before - task duration decreases over time
 - reduction in time follows a predictable, repeatable pattern
 - cost to assemble new aircraft is predictable - math formula



1. *Model A (blue) shows initial faster learning 0.67 (solid blue line), while model B (red) has 0.39 (solid red line).*
2. *Late in the history of model A's production labor hours/unit increased sharply due to the reconfiguration of the original subsystem*

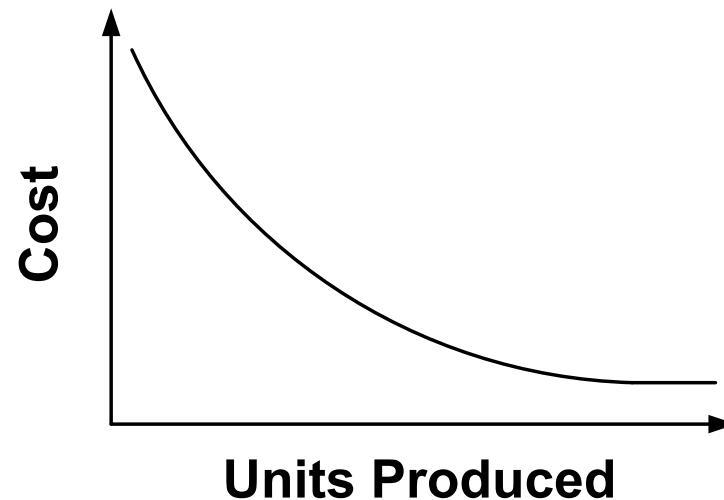


Proficiency Curve



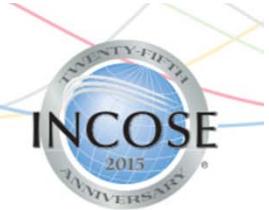
Training Environment

Experience Curve



Production Environment

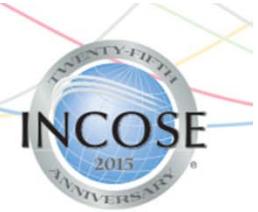
Learning Curve: Implications



- Finding ways to accelerate learning can produce competitive advantage (e.g., starting production sooner than competitors)
- Strategies to improve learning rate invariably require **investment**
- Tradeoff between **investment (cost)** and **savings (benefit)** realized through increase in learning rate



Modeling and Analysis Framework



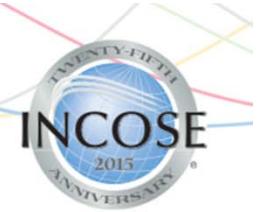
- Inputs and outputs
 - **Inputs:** budget, courses, learning options, learner pool (fixed)
 - **Output:** allocation of budget and cohorts to various learning options
- Types of **modeling and analyses**
 - **Investment optimization** - what-if budget allocation and learner allocation to learning strategies
 - **Sensitivity Analysis** - sensitivity of learning curves to changes in budget and learner allocation to learning options
 - **Comparative analysis** - compare different \$ and cohort allocations in terms of time-to-proficiency, organizational metrics

Modeling Approaches



- Systems dynamics modeling
 - model systems at aggregate level using rates of changes and state variables
 - **strengths:** results easy to interpret; can be rapidly simulated
- Agent-based modeling
 - model individuals with their unique properties and interactions between individuals
 - **strengths:** easy to relate to results; useful for communication; can model systems in great detail
- The combination provides both structure and behavior

Acquiring data and modeling Learning Curves

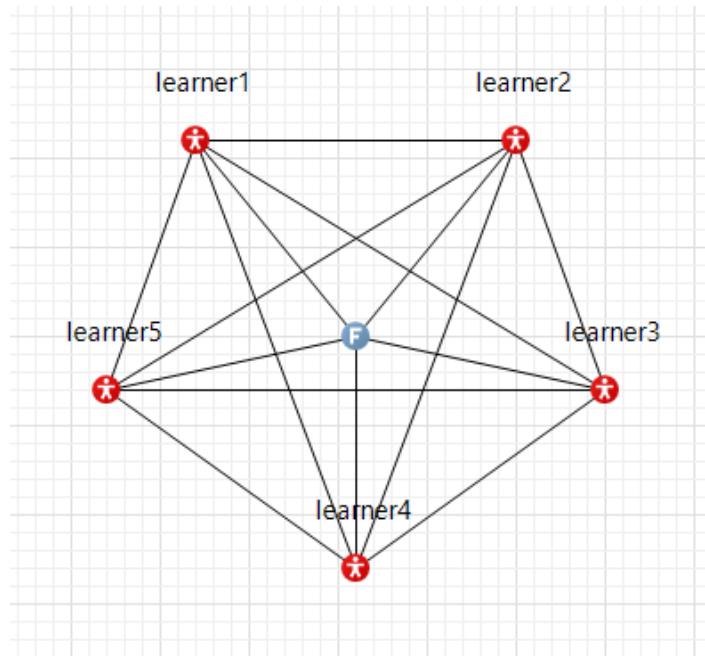


- Statistical curve fitting
 - fit pre- and post-assessment data collected for various learning options to generate learning curves
- System Dynamics modeling
 - Optimize learning curve by performing sensitivity analysis
 - model individual student's learning and forgetting behavior
- Given data and an optimization metric, two approaches can be cross-verified and then used as an input to portfolio optimization

Generating and Analyzing Learning Curves

■ Agent-based modeling

- represent and track progress of learners/cohorts as they take courses using different learning options
- Represent agents and their learning state



Statistical Curve Fitting

- Standard power function fit to learning curve data

$$y = ax^b + c$$

- **y** is proficiency
- **x** is customer's resource variable (\$, time)
- **a and b** control the shape of the curve
 - **a** controls height of curve
 - **0 < b < 1** (steep beginning, later flattening)
- **c**: initial proficiency (when resource allocation is zero)

$$y_{\text{online}} = a_1 * t^{b_1}$$

$$y_{\text{inperson}} = a_2 * t^{b_2}$$

(with initial proficiency = 0)

- Assumes learner takes a single course over n days
- Course taught using one or more learning options
- Learning options employed in preferred proportion for entire course
- Student learns course material for a specified time (e.g., 6 hrs) each day
- Student forgets a fraction of the material during non-learning period

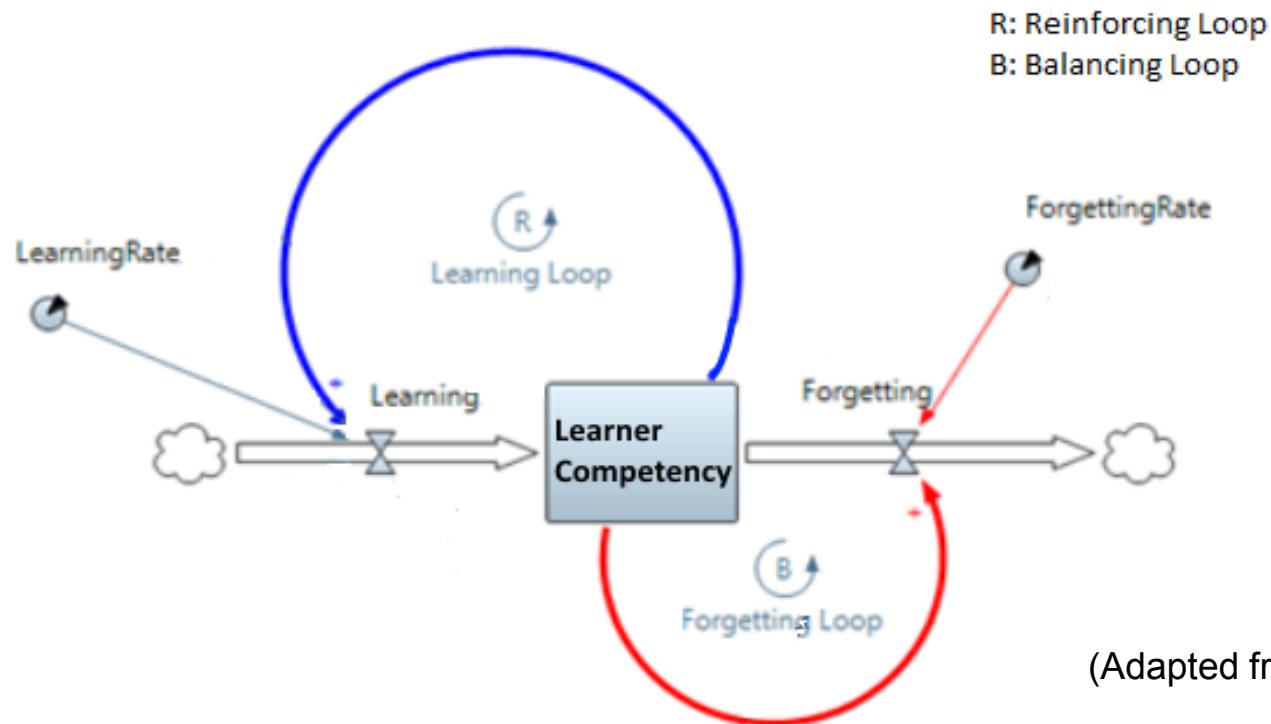
■ Mathematical model:

$$LC_t = LC_0 + \sum_{t=1}^n (L_t - F_t)$$

- LC_t is learner competency (or competencies) at day t of course
- LC_0 is learner competency before course
- L_t is learning (knowledge and skill) gained during day t
- F_t is forgetting (knowledge lost) during day t
 - Note that $F_t = (LC_{t-1} * LF) * (1 - c)$
 - F_t is forgetting knowledge and skills during day t
 - LF is learner's forgetting rate per learning option

- Assumes course taken over a specified period
- Learner spends a fraction of time per day on the course (e.g. 6 hours, or 25% of the day)
- Learner forgets some portion of material learned when not engaged in course
- Learner attributes
 - current competency level in course
 - pre-course competency level
 - learning rate (varies by learner and learning option)
 - forgetting rate
- Learner's competency re-evaluated daily

Systems Dynamic Model



Model Shows Learning and Forgetting Behavior

Optimizing Learning Curves

- Optimal allocation of funds and cohorts to learning options and courses
 - accelerate workforce development
 - accelerate time-to-proficiency for learner/job performer
- Can be formulated as a **portfolio optimization** problem
 - allocate a fixed resource (e.g. time, money) over several learning options to maximize overall proficiency/time to proficiency ratio
 - allocate some fraction (α_i) of available resource to each learning option, X_1 to X_n :

$$\max_{\alpha} \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_n X_n \quad s.t. \sum_{i=1}^n \alpha_i = 1$$

- for example, if $\alpha_1 = 0.5$, then 50% of resources allocated to option 1

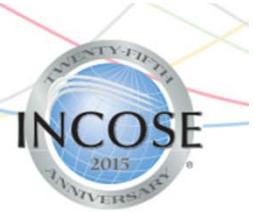
Portfolio Optimization



- A well-studied problem in management sciences
- Statistical methods can be extended to portfolio optimization
- Involves weighting each individual learning option (e.g., F2F, online) to achieve optimal allocation of fixed resources (\$,time)
 - weights can be thought of as fraction of total \$ or time allocated to each curve
- Assume proficiency is additive
 - Learning curves are distinct with no overlap (in proficiency gains)
- Proficiency function:

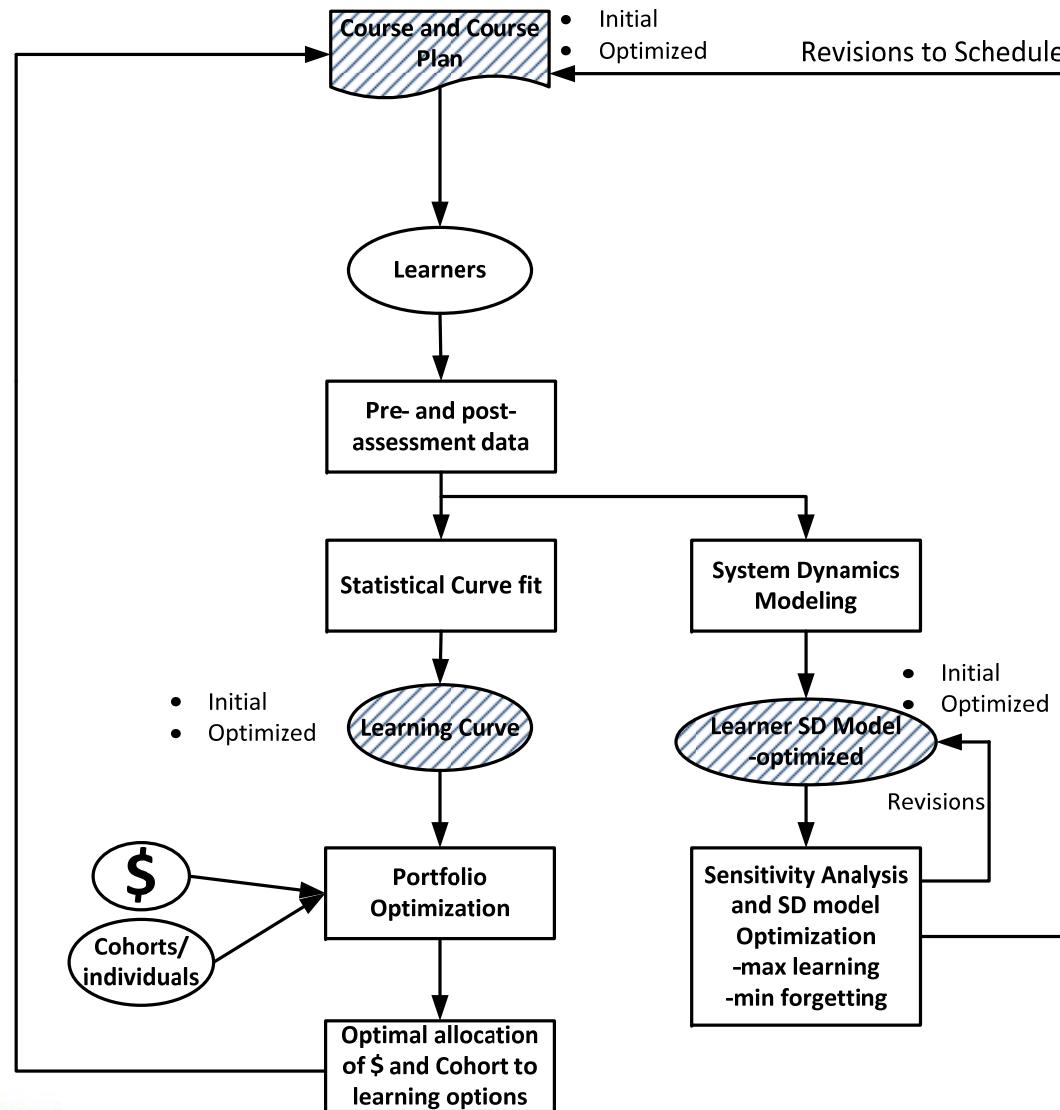
$$y = \sum_{i=1}^n a_i * t_i^{b_i} + c_i , \quad i = \text{separate learning option/cohort combination}$$

Applying Portfolio Optimization



- Generally, the portfolio optimization problem is formulated to maximize some specific portfolio measure defined by the investor
 - e.g., portfolio return
- In our problem, initially we are less concerned with maximizing returns and more concerned with building a model in which investment options weights can be treated as “tuning” parameters
 - e.g., what happens if we increase/decrease w_1 ? How will the model change?
- After answering such questions, optimization can be performed for a variety of output variables

Methodology: Initial Experience



Preliminary Data Collection



- Purpose: to formulate and structure the problem to collect insights
- Conducted by Boeing overseas
- Learners participated in two 12 hours long composite course
 - first course offered through WebEx in one location
 - second course delivered in person in a different location
- Learning format for first course
 - distributed model, prior reading and preparation, formal lectures online via the internet
- Learning format for second course
 - in-person, instructor-led, with prior preparation and formal lectures
- Same pre- and post-assessment for both formats
- Data collected from this study was used to calibrate learning curves and make an initial run of portfolio optimization algorithms
- Models fitted to data used to perform sensitivity analysis



- Each learning option has its own learning curve:

$$y_{online} = a_1 * t^{b_1}$$
$$y_{inperson} = a_2 * t^{b_2}$$

- Combined learning curve (total proficiency)

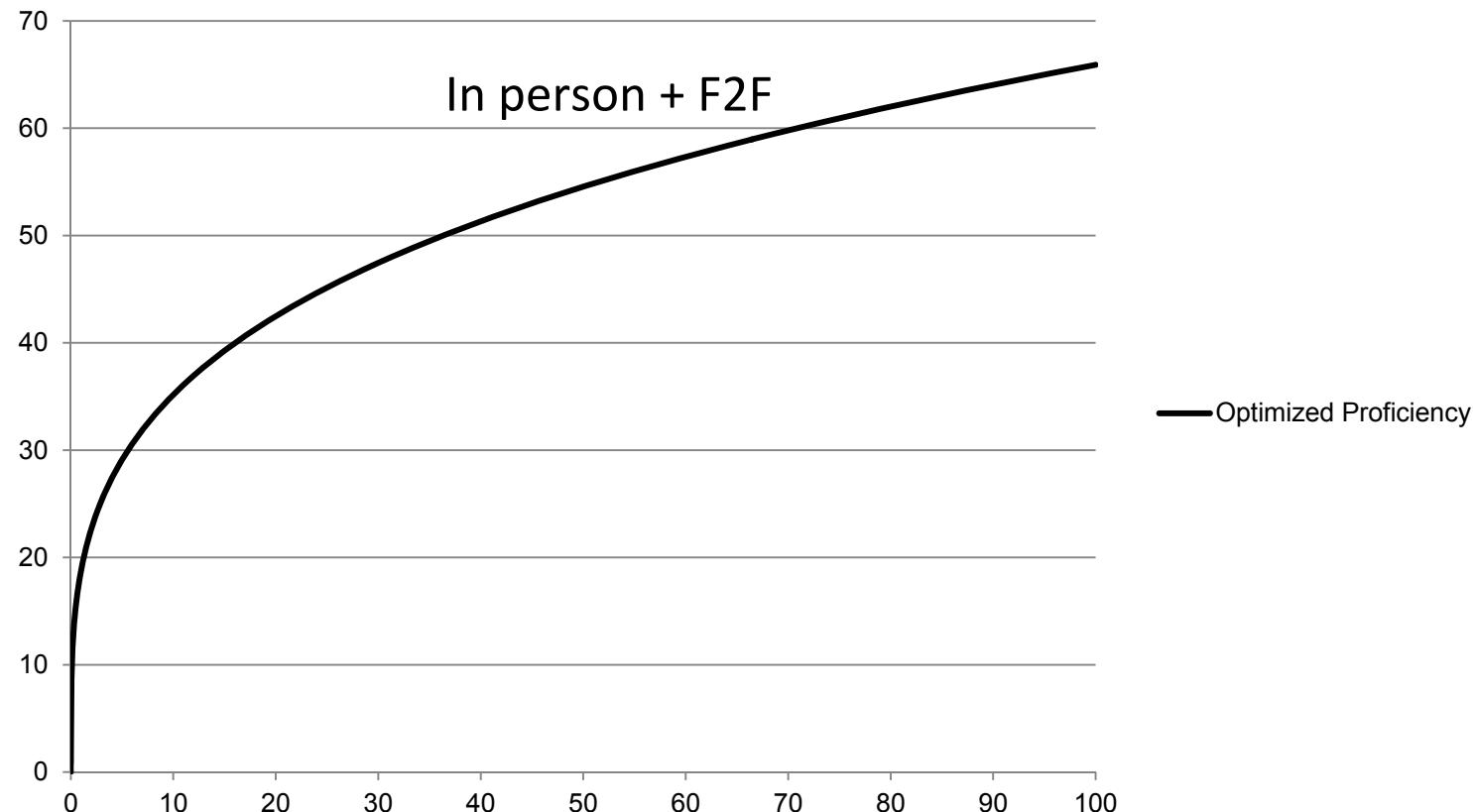
$$y_{total} = a_1 * t_{online}^{b_1} + a_2 * t_{inperson}^{b_2}$$

- Sample results*:

- approximately 74% tested proficient overall

**Boeing study: small sample sizes and different testing procedures*

Preliminary Data Collection: Combined learning curve



Optimized learning curve combining the two learning strategies:
 $a = 5.3375$, $b = 0.2729$, $c = 0$



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25th anniversary
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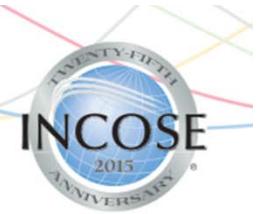
Conclusion



- Learning curves graphically depict increase in learning with experience
- Learning curves have been used to **describe** learning that occurs in a production environment and in physical or virtual classrooms
- Learning curve concept is used in two ways
 - learning that occurs when same task is performed repeatedly over time
 - learning that occurs when a body of knowledge is accumulated over time
- We used learning curves as a **function to optimize** to accelerate learning
- Our approach combines statistical curve fitting, system dynamics modeling, portfolio optimization, and agent based modeling to create this capability
- Approach is being applied in a Boeing-sponsored research activity
 - Components of the approach were successfully applied in a Boeing pilot study conducted overseas



Way Ahead



- Expand data collection to include:
 - Pre-assessment
 - Mid-assessment
 - Post-assessment
- Incorporate clickers to collect data on each module
- Apply approach to two courses offered within Boeing
 - Process Design and Management
 - Systems Thinking and Complexity Management



Thank You



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