The University of Texas at Austin
Cockrell School of Engineering

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# APPLICATION OF ANALYTIC TECHNIQUES TO SUPPORT ORGANIZATIONAL DECISION MAKING

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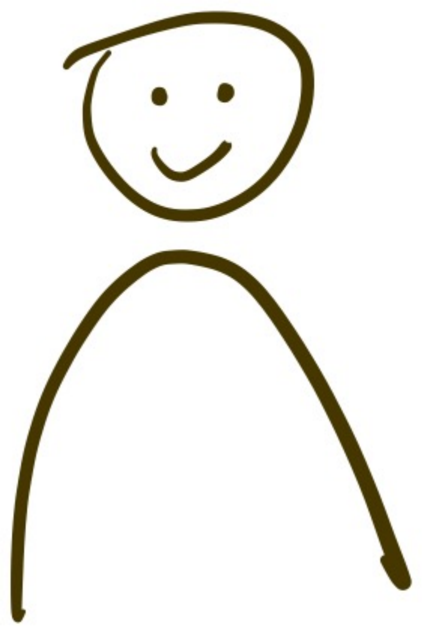
# Outline

- Introduction
- Project 1: Surveillance Testing for Rapid Detection of Outbreak in Long-Term-Care Center
- Project 2: Production Planning for Assembly Systems in the Face of Supply Chain Delays and Labor Shortages
- Summary of Project 3: Workforce Planning for Home Healthcare
- Timeline
- References

# INTRODUCTION

# Operations Research Analytic Techniques



Objectives

✓ Minimize cost

✓ Maximize profit

✓ Best resource configuration

✓ Scheduling

Stakeholders . . .

Fields

Healthcare

Manufacturing

Transportation

. . .

support

implement

Operations Research Anaytic Techniques

# Operations Research Analytic Techniques

**Project 1 – Surveillance Testing**

- **Facility**: Long-term-care center (LTC)
- **Object**: Quickly detect the outbreak of contagious disease in facilities
- **Methodology**: Contact network, discrete-time Markov chain, Monte-Carlo simulation

**Project 2 – Production Planning**

- **Facility**: Semiconductor assembly production line
- **Object** : Configure the production line capacity and bottlenecks
- **Methodology**: Discrete-event simulation, Object-oriented programming, regression

**Project 3 – Workforce Planning**

- **Facility**: Hospital
- **Object** : Schedule nurses' recruitment plan
- **Methodology**: Mixed-integer-linear programming, stochastic optimization

# PROJECT 1

## Surveillance Testing for Rapid Detection of Outbreak in Facilities: A Real-World Case Study in Long-Term-Care Center

# Background

**December 12, 2019**
Covid-19 broke out in Wuhan, China

**January 7, 2020**
CDC established the structure to develop tests

**February 4, 2020**
FDA approved the CDC's diagnostic test kit

**February 29, 2020**
FDA completed the EUA requests allowing more laboratories to create tests

**April 30, 2020**
The Trump Administration funded six promising vaccine candidates

**May 9, 2020**
The unemployment rate in the U.S. is the 14.7%. The hospitality, leisure, and healthcare industries took the greatest hit overall

**May 17, 2020**
Moderna began the first human trials of a vaccine

**June 13, 2020**
CDC released consolidated guidelines for covid-19 testing for facilities such as nursing homes

**July 22, 2020**
The deal of Pfizer BioNetch 100 million does vaccines was reached

**September 2020**
Pfizer and Johnson & Johnson began phase 3 clinical trials of their vaccines

**December 2020**
- A nurse became the first American outside of the clinical trial to receive a vaccine
- Healthcare professionals and people aged 70 years were the priorities to be vaccinated

…

**April 30, 2021**
Lillian got her first shot of the vaccine

# Background

**December 12, 2019**
Covid-19 broke out in Wuhan, China

**January 7, 2020**
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Pfizer and Johnson & Johnson began phase 3 clinical trials of their vaccines

**December 2020**
- A nurse became the first American outside of the clinical trial to receive a vaccine
- Healthcare professionals and people aged 70 years were the priorities to be vaccinated

**January 2021**
More funds were expanded to covid tests and vaccine distribution

- Tests were limited
- No vaccination protection for professionals working in the healthcare industrial
- Healthcare professionals were the most vulnerable group during this time
- Over 200,000 covid deaths (23%) in long-term-care facilities in the US

**The original motivation derives from the need to quickly detect outbreaks of COVID-19 in LTCs in an early stage.**

# Abstract

- **Problem Statement**

  The goal is to detect the outbreak of covid-19 among staff in the LTC when the vaccines are unavailable. We assume residents are one of the possible outside contagious sources of the contact network.

- **Source of Data**

  The staff information of Redstone Greenburg LTC in September 2022.

- **Modeling**

  Construct the agent-based contact network and simulate the disease transmission routes in the network and the susceptible, exposed, and infected (*SEI*) model.

- **Methodology**

  Monte-Carlo simulation.

- **Contribution**

  Provide the optimal testing numbers for facilities like LTC with different thresholds

# Literature Review

- **It is imperative to detect the covid-19 outbreak early**

38%-80% of covid cases are pre-symptomatic or asymptomatic in LTCs (Bernadou et al. 2021, McMichael et al. 2020). Asymptomatic cases cause 56%-95.5% of the covid transmissions (Ferretti et al. 2020, Harada et al. 2020).

- **Existing testing strategies in LTC**

Surveillance testing with contact interventions and health screening (Baek et al. 2020, Garibaldi et al. 2021), daily temperature and oxygen level checks (Danis et al. 2020), serological anti-body checks (Strand et al. 2021), and reverse transcription-polymerase chain reaction (RT-PCR) tests.

- **Existing model**

SEIR/SIR model

- **Research gap**

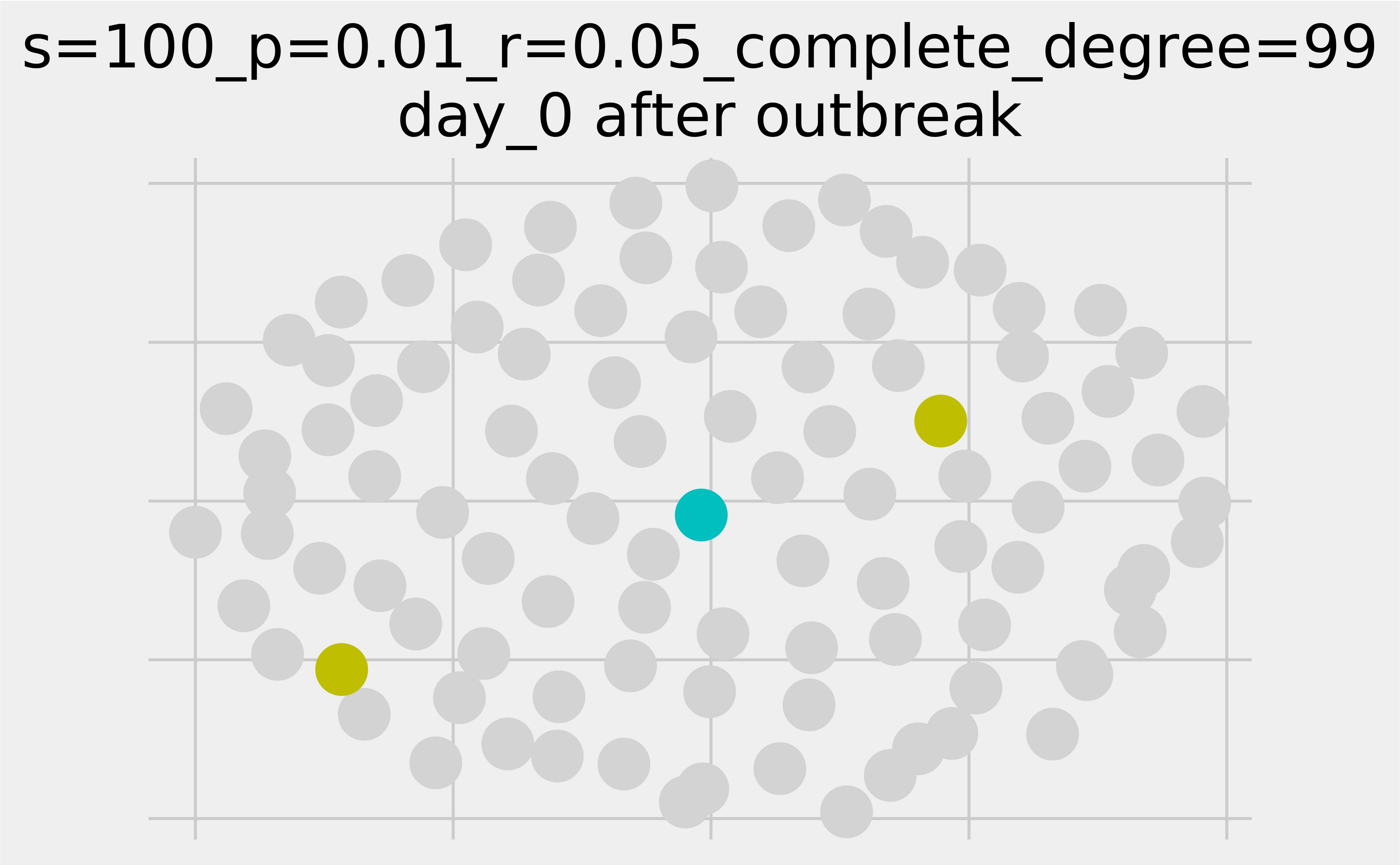
The standard SEIR model might be suitable for predicting outbreak progression in a ***large well-mixed population*** while it might over-simplify dynamics in special networks (Chapman et al. 2021, Chowell et al. 2016). There is no exact guidance on the surveillance testing strategy.

# Model Description - Parameters

The first component of our model is a contact graph $G = (V, E)$ on a set $V$ of nodes and a set $E$ of undirected edges. We call two nodes neighbors if an edge connects them.

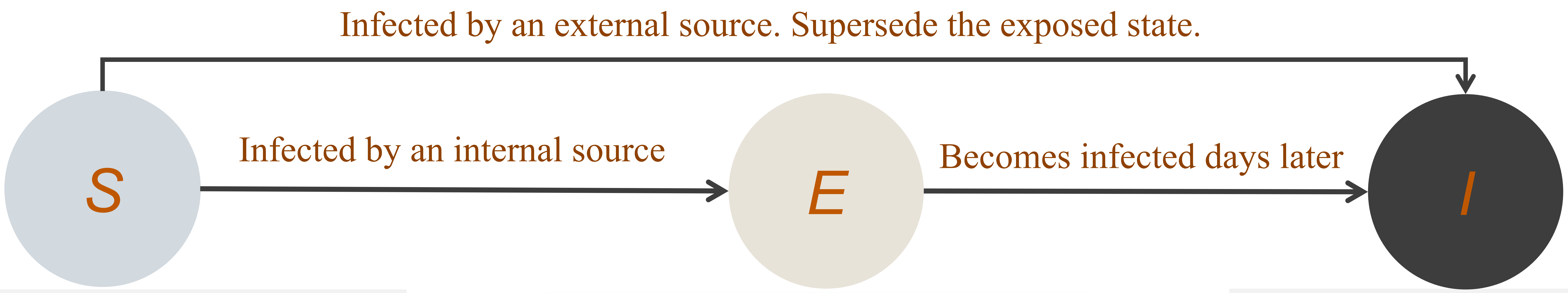
| | |
|---|---|
| $S$ | $\lvert V \rvert$, the number of staff in the facility |
| $p$ | Daily probability of external infection |
| $l$ | Latency, the number of days to move from the exposed state to the infected state |
| $d$ | Degree of each node in the symmetric case, indicating the density of contact graph |
| $r$ | Daily probability of infection between neighbors, a representation of the force of infection |
| $f$ | False negative rate for a disease test, after a node is infectious |
| $t$ | Outbreak threshold tolerance, in days. |

# An example Outbreak of covid in a 100 staff facility



# Model Description – *SEI* States

Define "outbreak" as when there is more than one staff in the network in the $I$ state.
Internal and external transmission routes are mutually independent.




- With $p$ probability becoming direct infected
- With $r$ probability of becoming exposed by a given infected neighbor

- $l = 3$ days "incubation" period
- The individual is infected, asymptomatic, non-infectious, can not be detected

- Become infectious and detectable with $f$=21%
- Will be treated or guaranteed if detected.

**Figure 1. Descriptions of *SEI* model**

We assume this direct move of external infection because an exposed node cannot be detected by a test, and cannot infect other nodes, until it is in the "infected" state.

# Heterogeneous Graphs and Real-World Test Case

Table 1. Staff data for the LTC case study

| Job Title | Staff no. | No. of daily contact with residents 22 | No. of daily contact with staff | Avg. contact distance (ft) | Avg. contact duration (min) |
|---|---|---|---|---|---|
| Nurse and nurse aid | 69 | 30 | 20 | < 6 | > 15 |
| House keeping | 16 | 10 | 10 | > 6 | < 15 |
| Rehabilitation | 4 | 10 | 10 | < 6 | > 15 |
| Mission and activity lifestyle | 12 | 20 | 10 | < 6 | 15 |
| Salon | 2 | 10 | 10 | < 6 | 15 |
| Maintenance | 12 | 10 | 10 | < 6 | < 15 |
| Reception | 6 | 10 | 40 | < 6 | > 15 |
| Dining | 6 | 30 | 20 | < 6 | < 15 |
| Social | 5 | 10 | 10 | < 6 | < 15 |
| Administration and finance | 14 | 0 | 10 | < 6 | > 15 |
| Logistics | 3 | 0 | 20 | < 6 | < 15 |
| Driver | 4 | 20 | 10 | < 6 | > 15 |

An LTC with 152 staff and 12 categories of worker

The staff categories are given by the $C = \{1, 2, ..., c\}$

# Heterogeneous Graph Information

**Table 2. Estimated daily contacts between staff of different categories (rounded to two decimal places)**

| Job Title | NR | HK | RH | MS | SL | MT | RC | DN | SC | AD | LG | DR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **NR** | 15 | 1.5 | 0.2 | 1 | 0.1 | 0.1 | 2 | 0.5 | 1 | 1 | 0.5 | 0.22 |
| **HK** | - | 4 | 0.5 | 0.5 | 0.1 | 1 | 1 | 0.2 | 0.2 | 1 | 0.1 | 0.25 |
| **RH** | - | - | 1.5 | 2 | 0.1 | 0.1 | 0.5 | 0.2 | 0.2 | 1 | 0.5 | 0.2 |
| **MS** | - | - | - | 3 | 0.1 | 0.1 | 0.5 | 0.2 | 0.2 | 1 | 0.5 | 0.2 |
| **SL** | - | - | - | - | 1 | 0.1 | 0.5 | 0.1 | 0.1 | 1.2 | 0.5 | 0.2 |
| **MT** | - | - | - | - | - | 4 | 0.5 | 0.1 | 0.1 | 1.2 | 0.5 | 0.3 |
| **RC** | - | - | - | - | - | - | 2 | 0.1 | 0.1 | 3 | 1 | 0.4 |
| **DN** | - | - | - | - | - | - | - | 4 | 1 | 1 | 0.1 | 0.1 |
| **SC** | - | - | - | - | - | - | - | - | 3 | 1 | 0.5 | 0.2 |
| **AD** | - | - | - | - | - | - | - | - | - | 5 | 1 | 0.5 |
| **LG** | - | - | - | - | - | - | - | - | - | - | 1.5 | 0.4 |
| **DR** | - | - | - | - | - | - | - | - | - | - | - | 0.5 |

Abbreviations: NR, nurse and nurse aid; HK, housekeeping; RH, rehabilitation; MS, mission (activity and lifestyle); SL, salon; MT, maintenance; RC, reception; DN, dining; SC, social; AD, administration (finance); LG, logistics; DR, driver.

# Heterogeneous Graph – a simplified example

Suppose we have 6 RN, 5 HK, and 2 RH

Will not traverse node 1 in this step

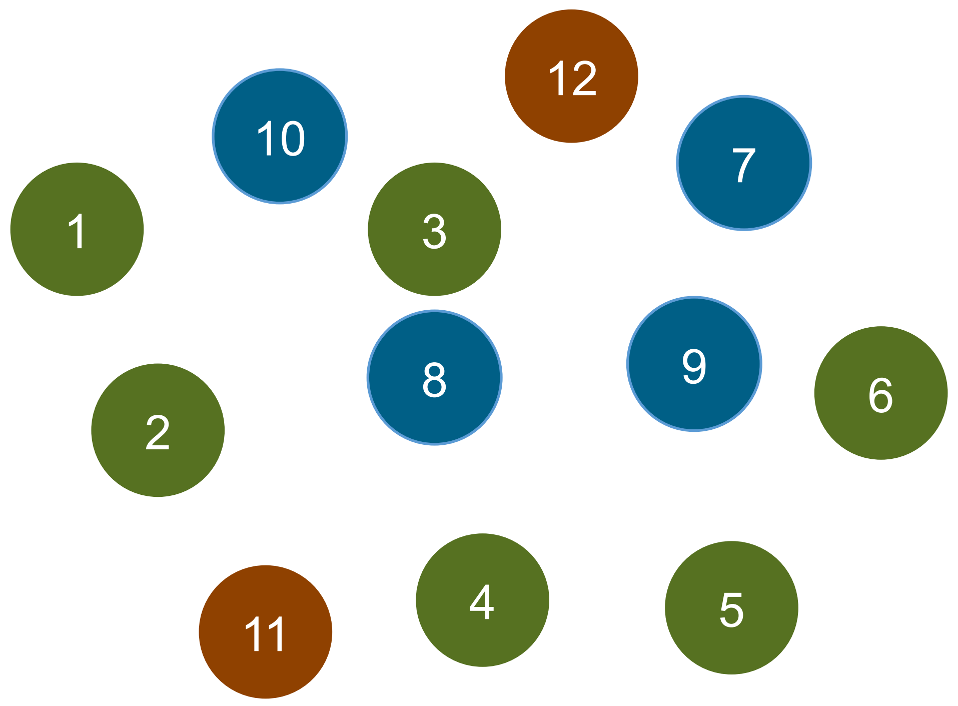



Figure 2.1 Un-edged graph

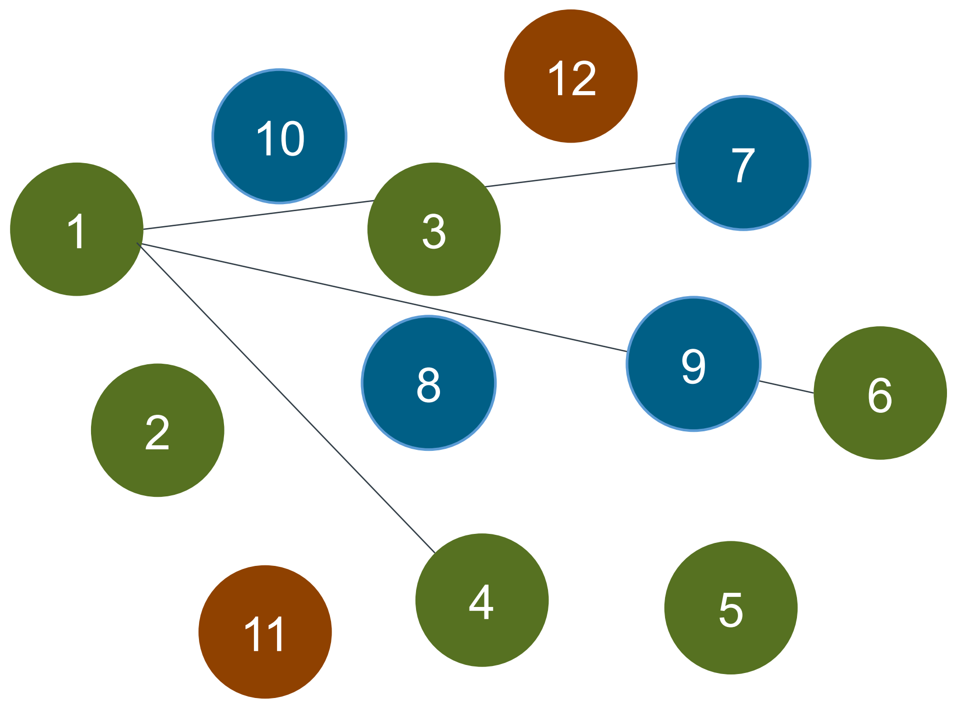



Figure 2.2 Generate the edges for node 1

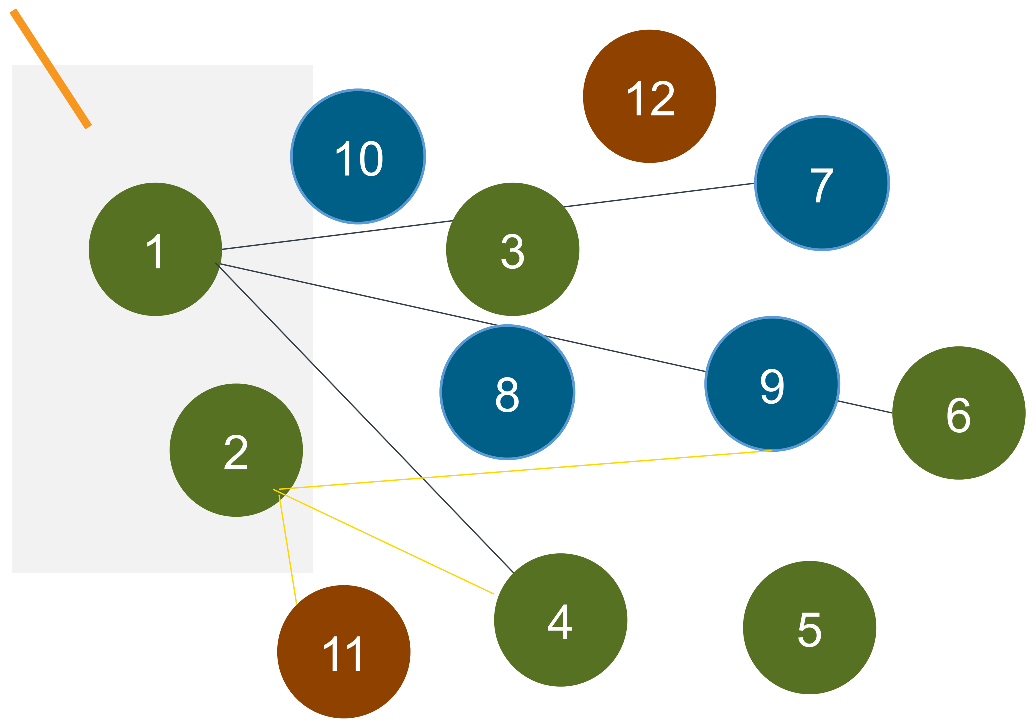



Figure 2.3 Generate the edges for node 2

| Job Title | NR | HK | RH |
|---|---|---|---|
| NR | 2 | 1 | 0.3 |
| HK | - | 2 | 0.3 |
| RH | - | - | 1 |

- P(an edge between NR and NR) = 2/(6-1) = 0.4
- P(an edge between NR and RH) = 0.3/2= 0.15

**Observations**

- The table is not symmetric.
- But only the upper diagonal or lower diagonal information should be enough to generate the contact graph

**Algorithm of graph edge generation**

- Traverse each worker category
- Traverse each worker, generate an edge for the workers who are not traversed

# Heterogeneous Graph – a real-world example

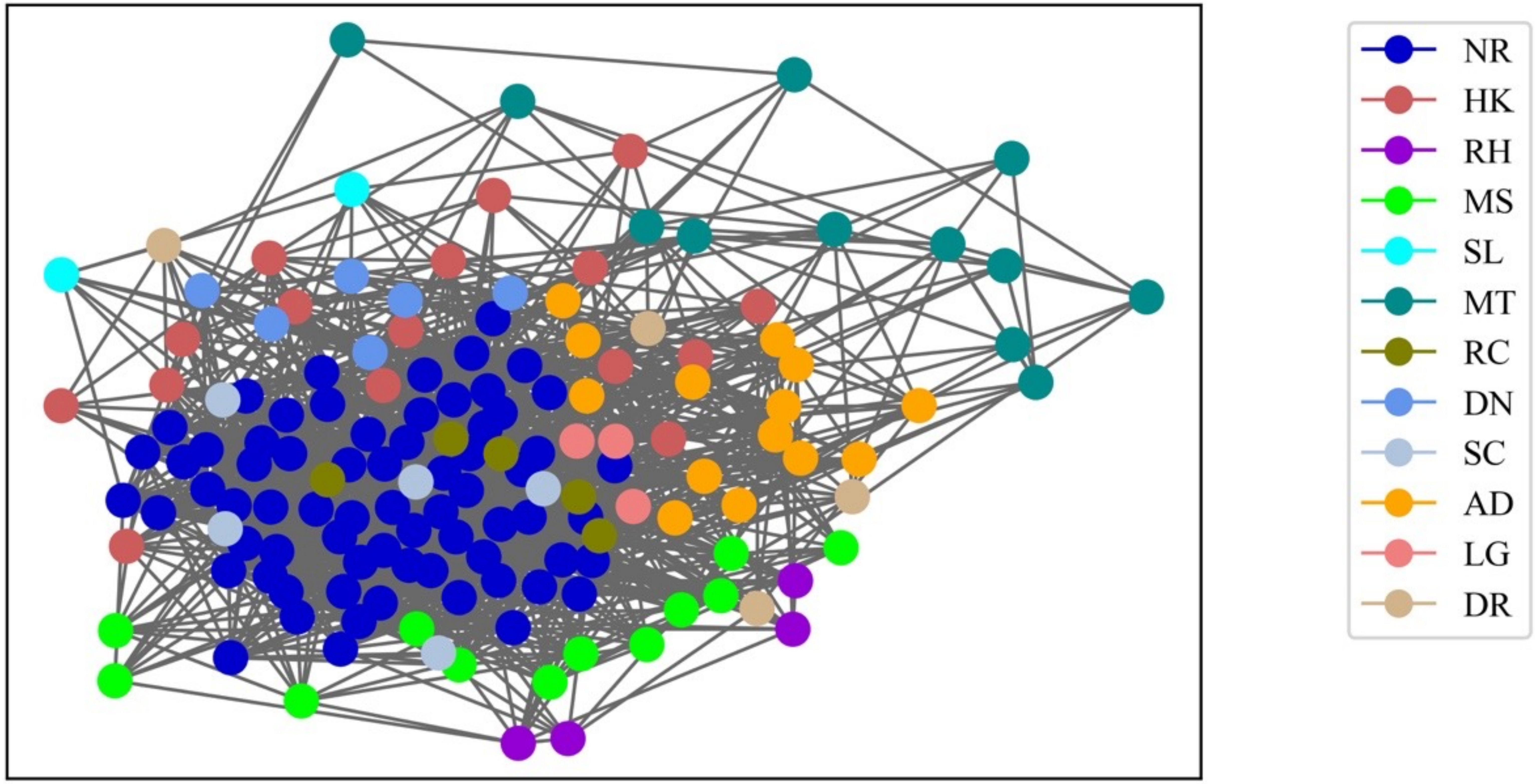



Figure 3. Redstone Greenburg LTC network with $s = 152$, $c = 12$

# Heterogeneous Graph Information

**Table 3. Estimated probability of internal infection among staff in different categories**

| Job Title | NR | HK | RH | MS | SL | MT | RC | DN | SC | AD | LG | DR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **NR** | 0.08 | 0.01 | 0.06 | 0.015 | 0.01 | 0.01 | 0.04 | 0.02 | 0.02 | 0.01 | 0.01 | 0.08 |
| **HK** | - | 0.08 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.01 | 0.01 | 0.04 |
| **RH** | - | - | 0.08 | 0.015 | 0.01 | 0.01 | 0.04 | 0.02 | 0.02 | 0.01 | 0.01 | 0.08 |
| **MS** | - | - | - | 0.08 | 0.01 | 0.01 | 0.04 | 0.02 | 0.02 | 0.01 | 0.01 | 0.08 |
| **SL** | - | - | - | - | 0.08 | 0.01 | 0.01 | 0.02 | 0.02 | 0.01 | 0.01 | 0.08 |
| **MT** | - | - | - | - | - | 0.08 | 0.01 | 0.02 | 0.02 | 0.01 | 0.01 | 0.04 |
| **RC** | - | - | - | - | - | - | 0.08 | 0.02 | 0.02 | 0.01 | 0.02 | 0.08 |
| **DN** | - | - | - | - | - | - | - | 0.02 | 0.04 | 0.02 | 0.01 | 0.08 |
| **SC** | - | - | - | - | - | - | - | - | 0.02 | 0.03 | 0.02 | 0.08 |
| **AD** | - | - | - | - | - | - | - | - | - | 0.08 | 0.03 | 0.08 |
| **LG** | - | - | - | - | - | - | - | - | - | - | 0.08 | 0.08 |
| **DR** | - | - | - | - | - | - | - | - | - | - | - | 0.08 |

$r = p_0 \times d_0 \times n_0$ (Smith et al. 2020)

$p_0$ The probability of infection per minute between two individuals

$d_0$ the average contact duration (in minutes)

$n_0$ the average contact frequency

# Computational Experiments

- We perform Monte-Carlo simulations of disease spread.
- Given a particular network and testing protocol we typically simulate 50,000 outbreaks in a facility.
- Outbreak is initiated by at least one node becoming infectious at time 0.
- Stopping criteria – outbreak is tested or hit the breakout threshold $t$
- Produce point estimates and confidence intervals on the true detection probability for a particular testing protocol.

# Computational Experiments

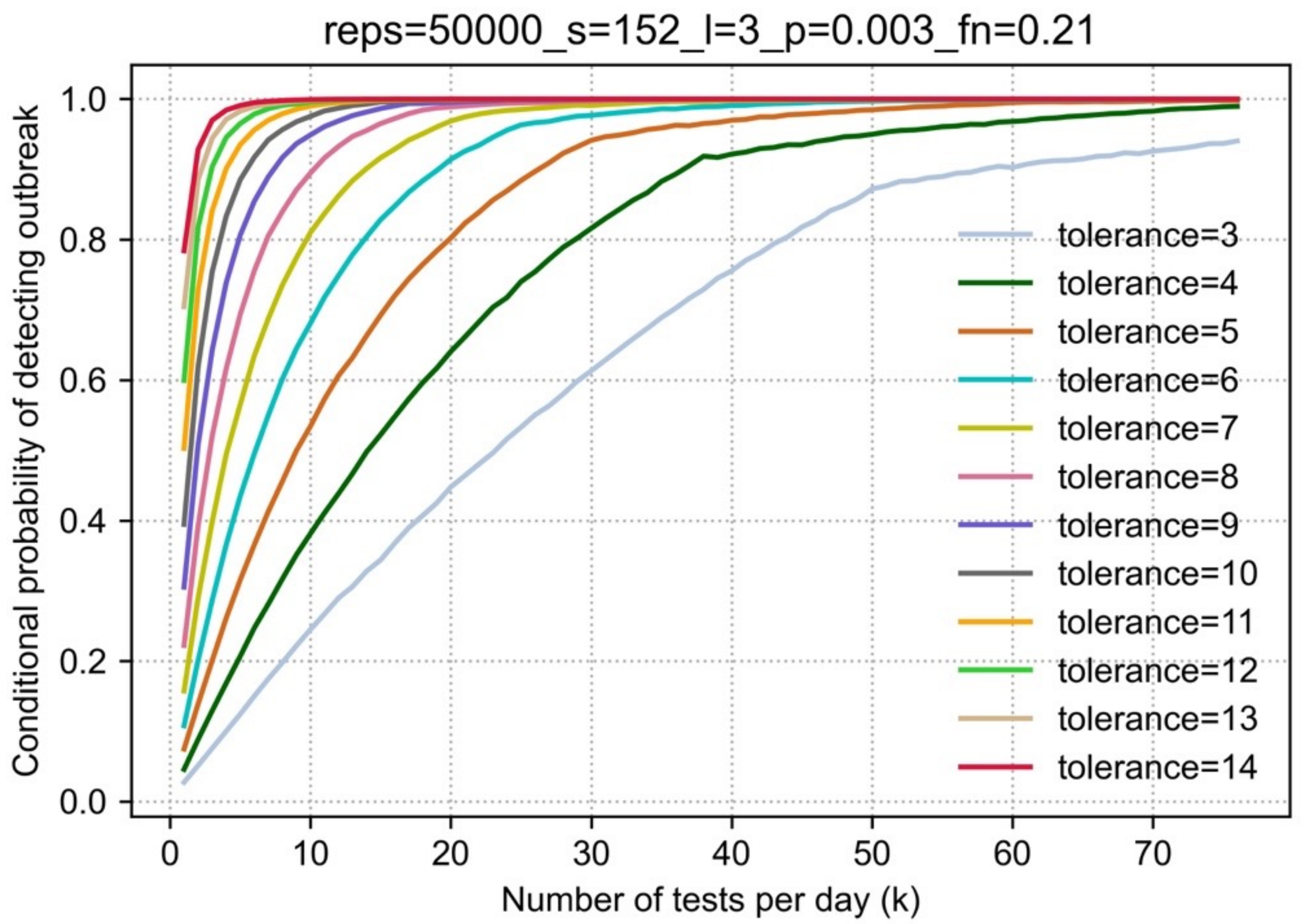



**Figure 4. Estimated probabilities of outbreak detection for $K$ = 152, $c$ = 12, and $p$ = 003 for various values of $t$**

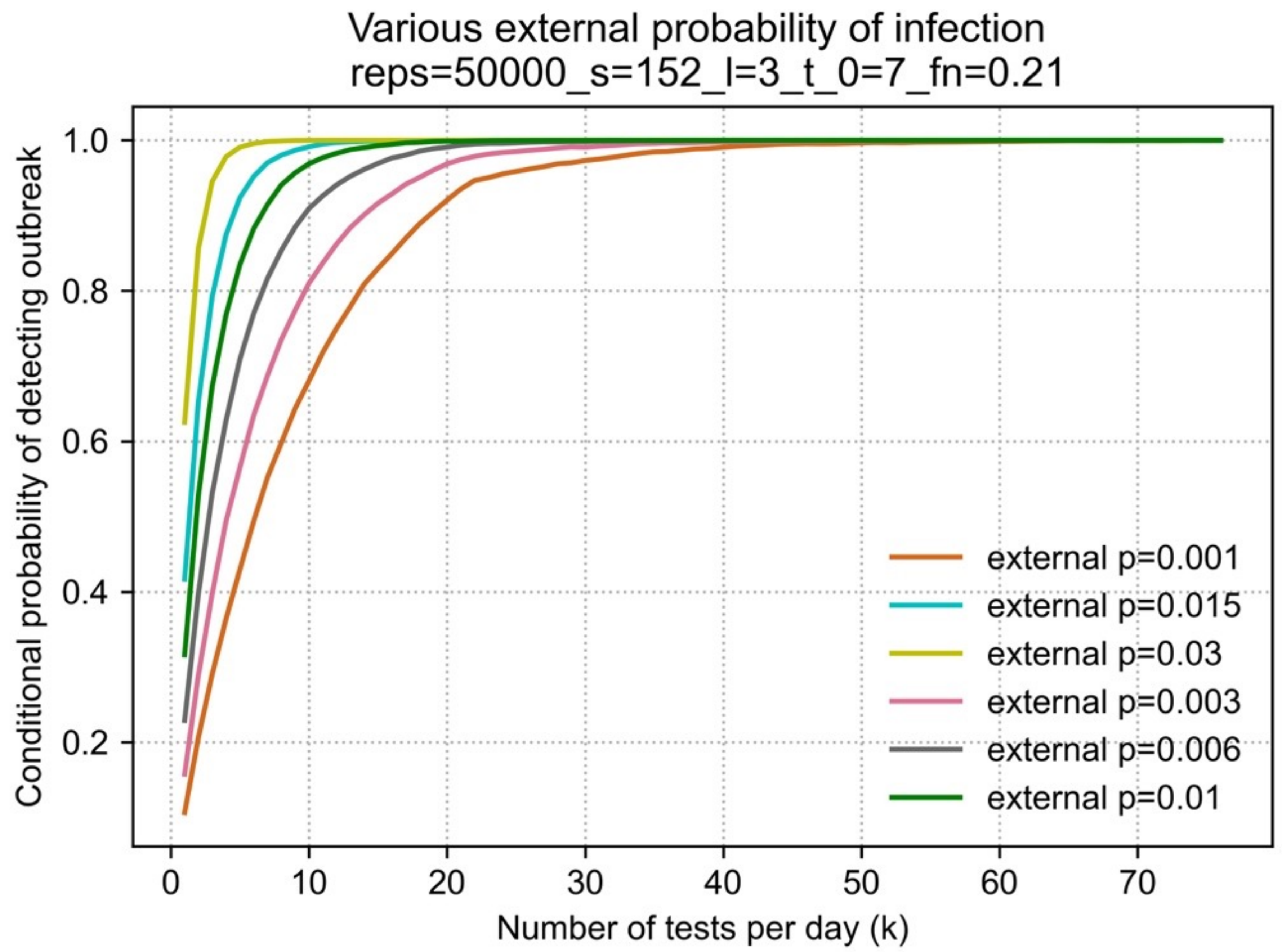



**Figure 5. Estimated probabilities of outbreak detection for $K$ = 152, $c$ = 12, $t$ = 7 and varying values of $p$**

# Computational Experiments

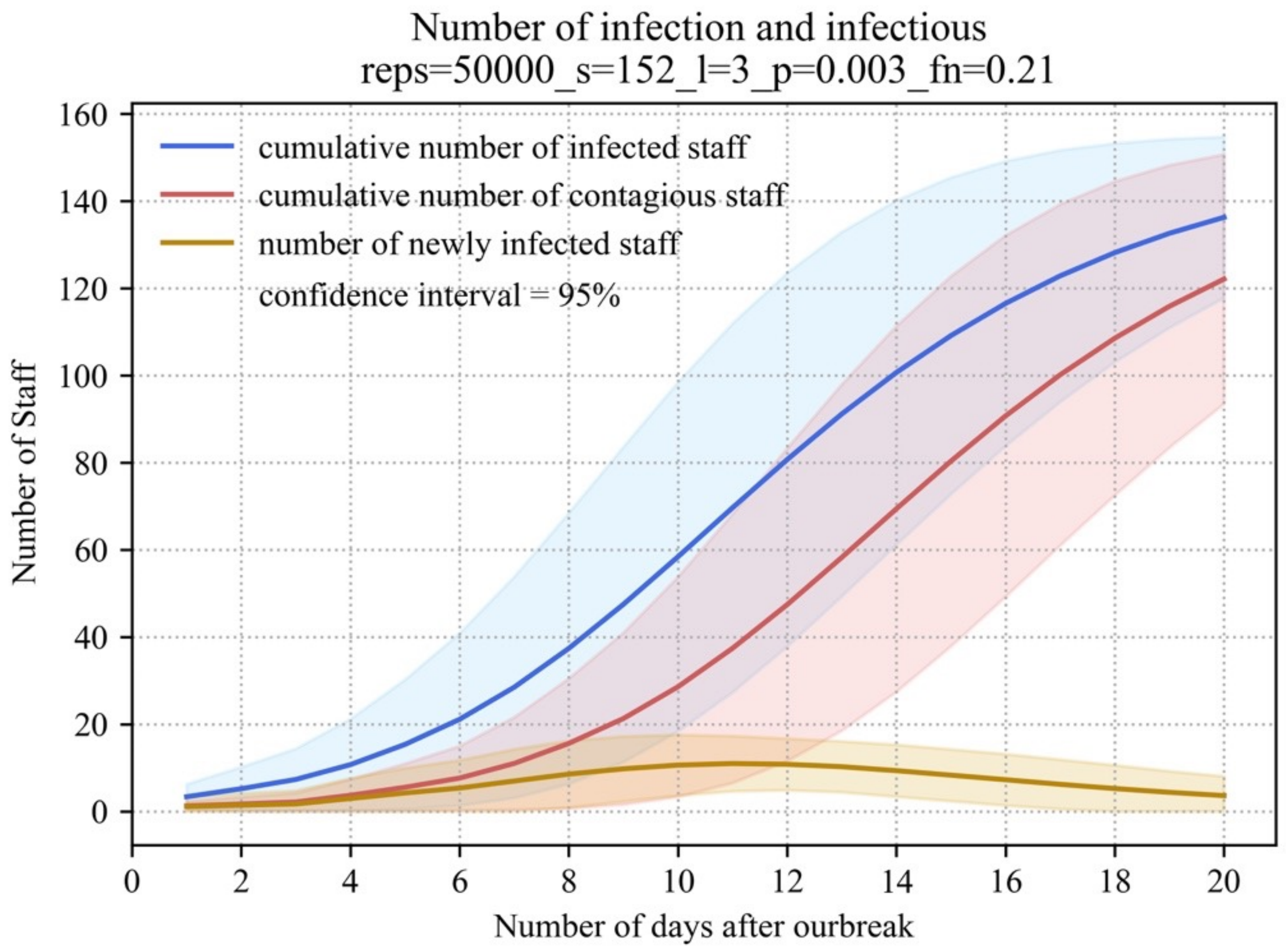



**Figure 6. Infection statistics in a real-world LTC network model with $K$ = 152, $c$ = 124, $p$ = 0.003, $l$ = 3, and $f$ = 0.21**

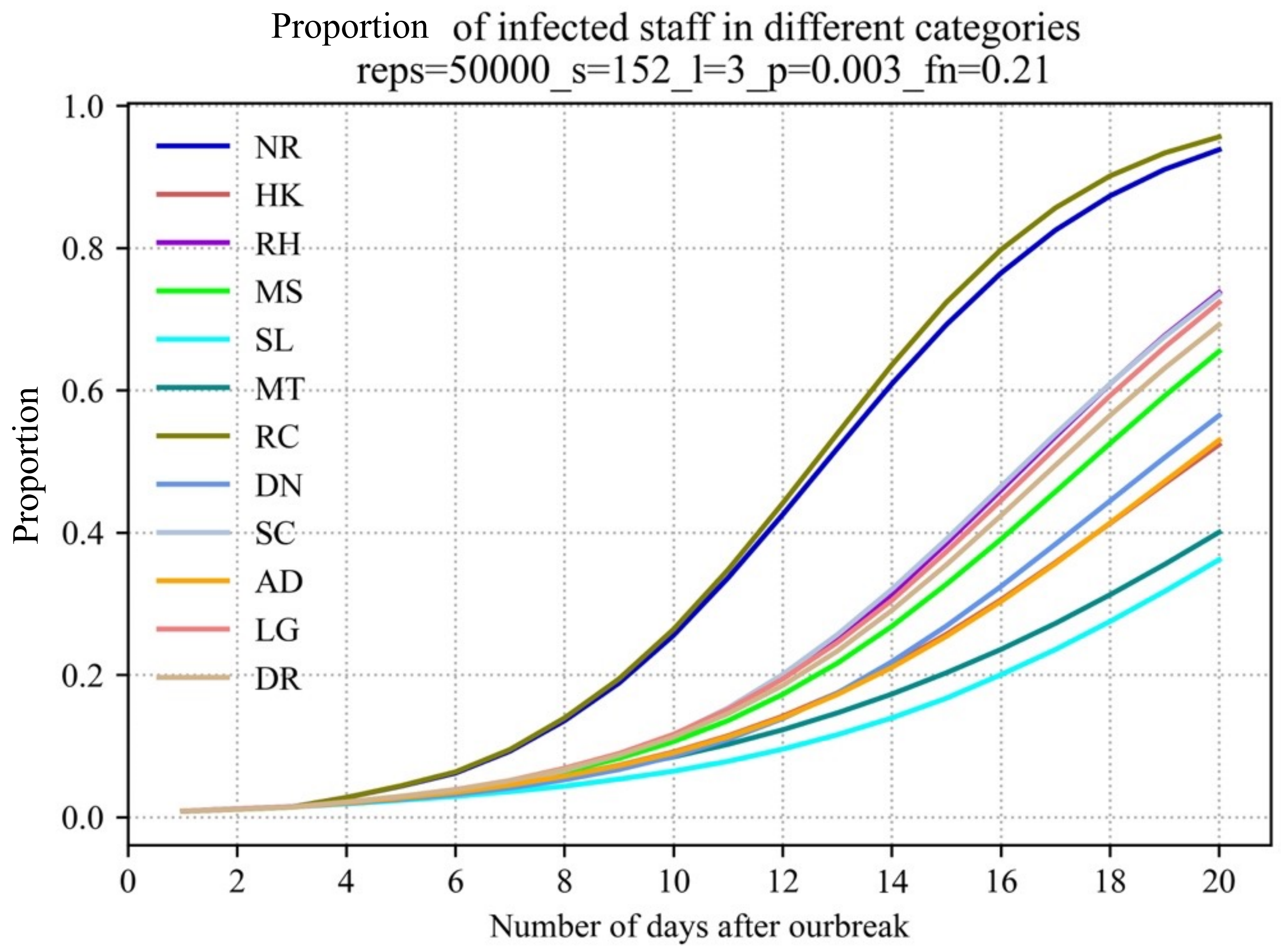



**Figure 7. Proportion of infected staff in different job categories with $s$ = 152, $c$ = 12, $p$ = 0.003, $l$ = 3, and $f$ = 0.21**

# Contribution

Table 3. CDC surveillance testing guidance for LTCs (August 2020)

| Time all the staff should be tested | County positive rate past week | Positivity estimation |
|---|---|---|
| once a month | <5% | low |
| once a week | 5% - 10% | median |
| twice a week | >10% | high |

- Compared with CDC surveillance guidance, our guidance is more detailed and insightful for stakeholders with different needs.
- Our agent-based model is more suitable for small or medium size facilities like LTCs
- Provides insights on the surveillance testing guidance for the possible contagious disease breakout in the future

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# PROJECT 2

## Production Planning for Assembly Systems in the Face of Supply Chain Delays and Labor Shortages

# Introduction of the Manufacturing Environment

- Persistent material delays from upstream suppliers.
- Difficulties in hiring and training technicians in a tight labor environment.
- Uncertain processing times associated with the advanced product line.
- The heavy workload for those charged with day-to-day planning.
- Persistent job completion delays with many jobs being pushed downstream by weeks or months - roughly 50% of the jobs failed to finish before their planned EOP in the past five quarters of the pandemic.
- Despite all those hurdles, they are still planning to increase the capacity to satisfy the demand.

# Abstract

- **Problem Statement**

  The ultimate goal is to develop a methodology for guiding shop floor personnel when reallocating resources to recover from the types of disruptions manufacturers experienced during the corona pandemic.

- **Source of Data**

  A production line in a leading North American semiconductor equipment company

- **Modeling**

  Two-stage job flowshop with machine and labor constraints

- **Methodology**

  Discrete-event simulation, simulation and regression metamodeling, object-oriented programming

- **Contribution**

  Novel method in modeling the labor constraint

  Provide insights on how the throughput will be affected by the material and labor shortages

# Literature Review

- **Flowshop problem**

The classical flowshop problem in which jobs are processed unidirectionally through stages was first introduced by Johnson (1954).

- **Solutions to flowshop problem**

Flowshop problems are typically formulated as mixed-integer linear programs (MILP) that often require over-simplified and unsuitable assumptions for complex assembly systems with dynamic variations and multiple resource constraints (Deng et al. 2010, Ruiz and Vázquez-Rodríguez 2010). Few of the researchers has taken into account of labor constraints and outsourcing scenarios.

- **Research gap**
  - Lack of stochastic features
  - Labor constraints and utilization analysis
  - Considerations on the learning effect and outsourcing

# Production Line Process Flow

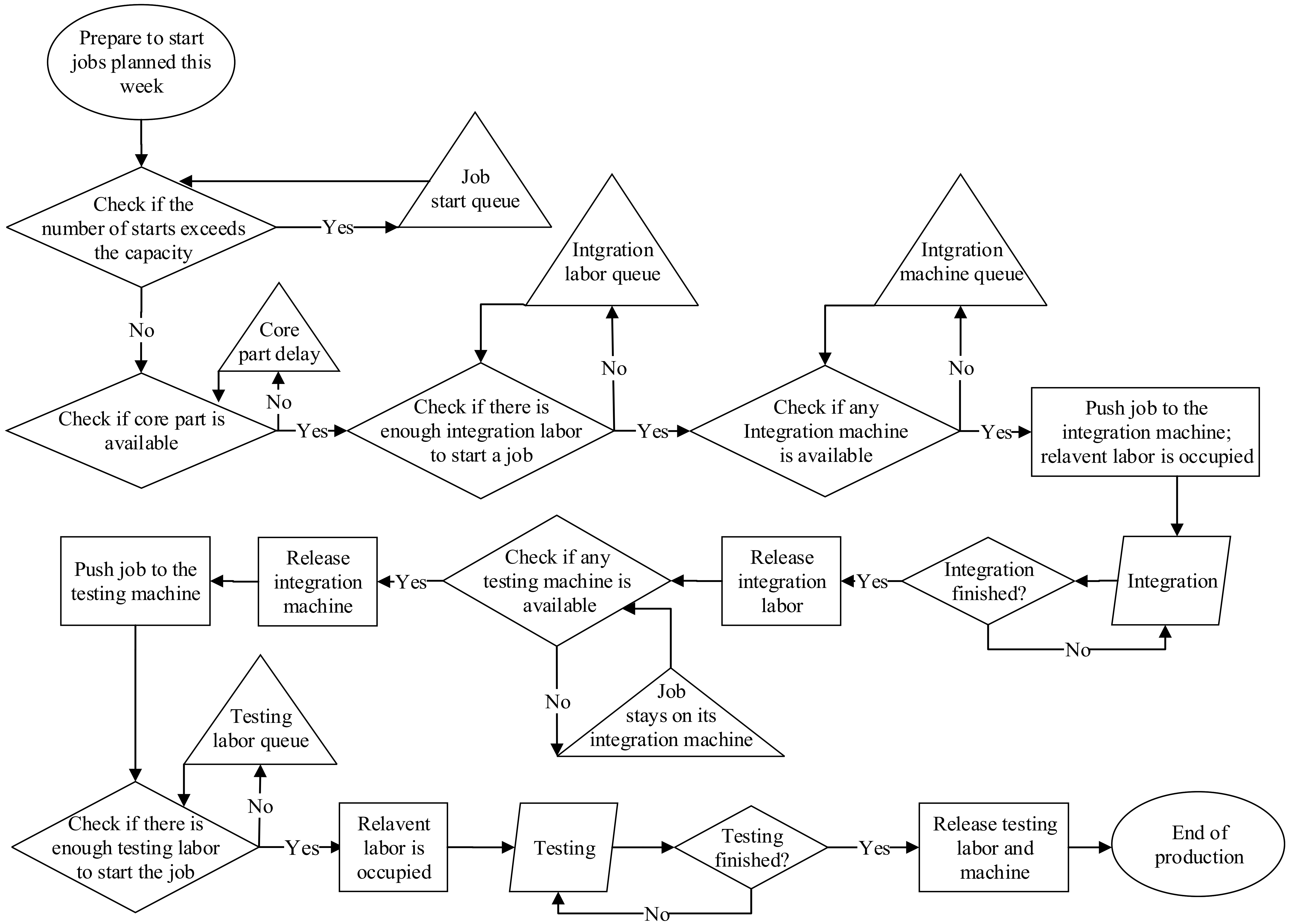


**Figure 8. Manufacturing production line flow diagram**

# Two-stage flowshop Model

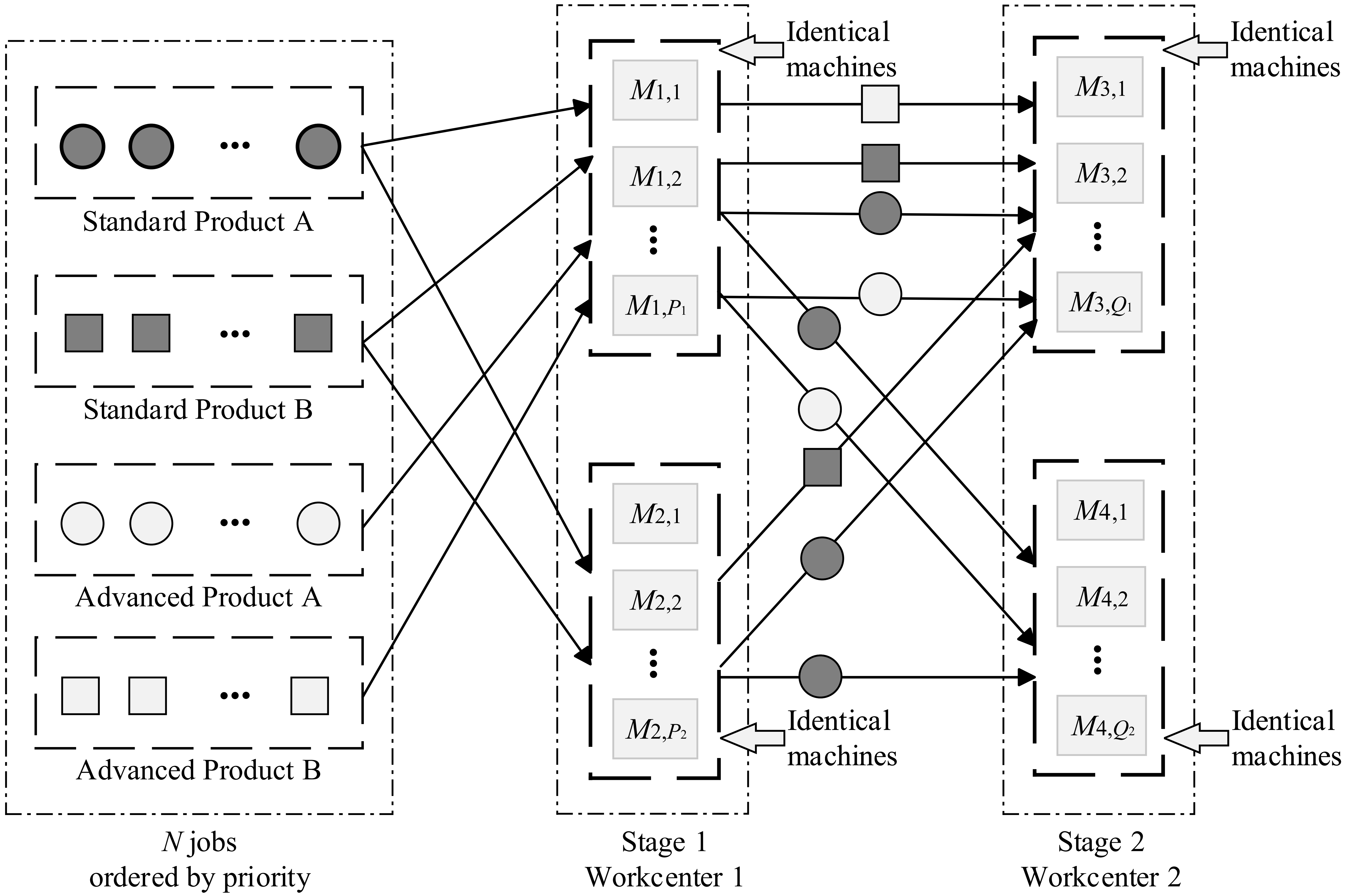


**Figure 9. System configuration with various categories of jobs and types of machines**

- M1 machines are more advanced. They can process both Standard and Advanced products.
- M3 machines are more advanced, they can process both Product A and Product B.

# Model Assumption

- **Assumption 1.** Machine breakdowns and disturbances are ignored.
- **Assumption 2.** Machine setup and cleaning times are negligible.
- **Assumption 3.** Simulation is in one-day unit.
- **Assumption 4.** Labor constraints are only considered for Standard Product A.
- **Assumption 5.** In practice, technicians with different levels of experience and training have different productivity rates (Ruf et al. 2022). But we assume workers are homogeneous within each category.

**Table 4. Characterization of the workforce**

| Technician type | Work experience | Proportion | Productivity |
|---|---|---|---|
| **Level 1** | 0-3 months | 20% | 0.5 |
| **Level 2** | 3-6 months | 30% | 0.8 |
| **Level 3** | more than 6 months | 50% | 1.0 |

**Labor Inefficiency Factor (LIF) = $0.5 \times 20\% + 0.80 \times 30\% + 1.0 \times 50\% \approx 0.85$**

# Model Assumption

- **Assumption 6.** Discounting the contribution of labor hours (CLHs) for additional technicians.

**Table 5. CLHs for Standard Product A for each production stage**

| No. of technicians per day | Stage | Daily CLHs |
|---|---|---|
| **4** | Integration | 32 |
| **5** | Integration | 37.6 |
| **6** | Integration | 43.2 |
| **2** | Testing | 16 |
| **3** | Testing | 21.6 |
| **4** | Testing | 27.2 |

**Example1.** Four technicians working each day, the CLHs = 2 (no. of technicians per shift) × 2 (no. of shifts per day) × 8 (working hours each shift) = 32.
**Example 2.** When a third technician works on either the day shift or the night shift, CLHs = 32 (CLHs of standard configuration) + 1 (no. of the additional technicians) × 8 (working hour each shift) × 70% (discount of one additional technician per shift) = 37.6.

# Model Assumption

- **Assumption 7.** Technicians can leave a job and work on another product when back-end materials are not available for their current job
- **Assumption 8**. If the available number of technicians on a particular day is less than the minimum number required, no job will be started.
- **Assumption 9**. Outsourcing and learning as output increases affect the cycle time (CT) at all stages of production.

# Simulation Description

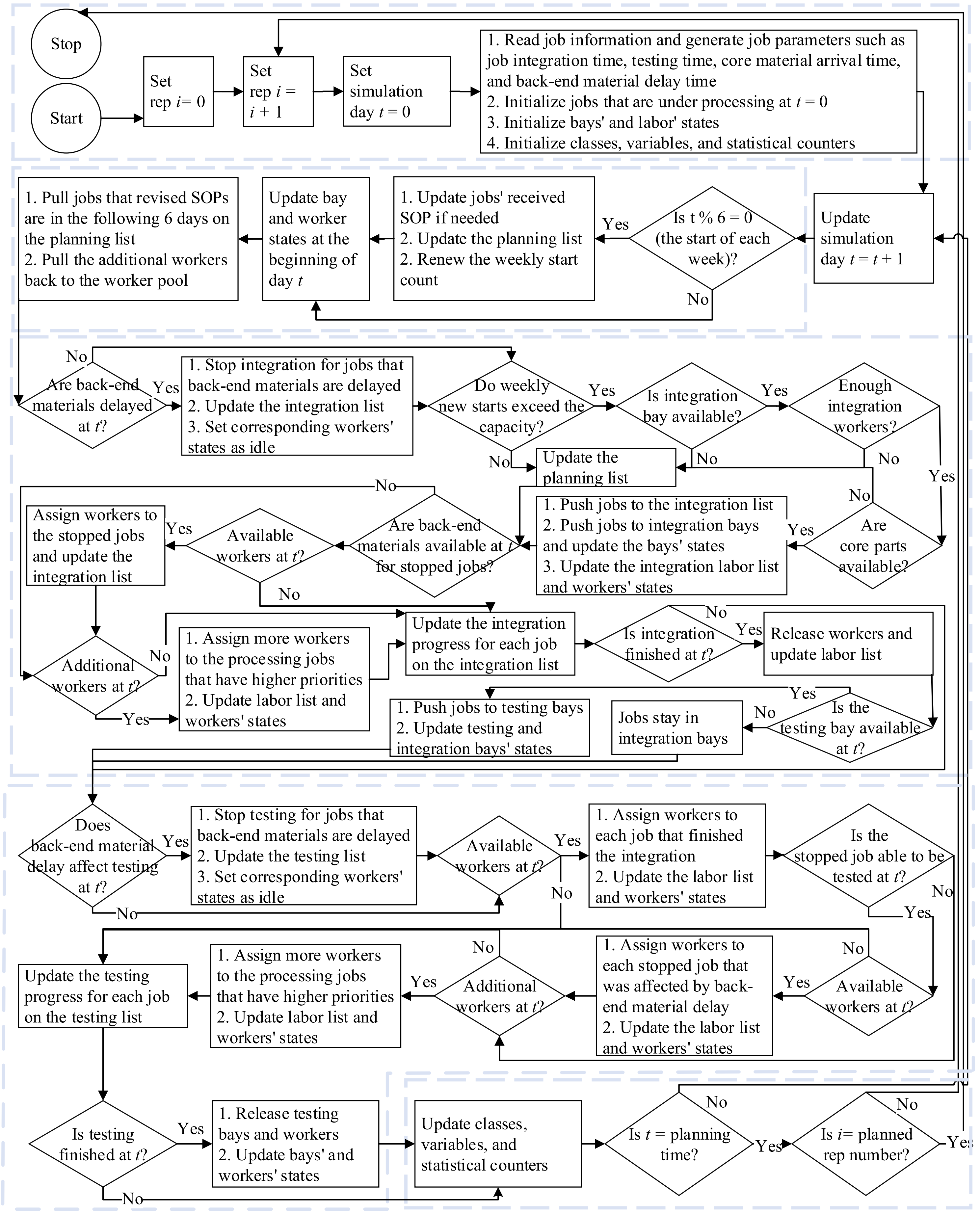


**Figure 10. Detailed Simulation Diagram**

- **Step 1.** Start and Initialization
- **Step 2**. Replanning function. Replan the job release order every 6 days
- **Step 3**. Integration.
- **Step 4**. Testing.
- **Step 5.** Wrap up the simulation information.

- **Simulation Platform.** Python 3.7
- **Benefits**. More flexible parameter settings and more complex model logic than the existing simulation software.

# Simulation Validation

**Regular-supply:** Before 2021 when materials are not in shortage.
**Shortage-supply:** After the beginning of 2021 when materials are in shortage.

In the production line under investigation, most parameter values were estimated from the historical data recorded from November 2019 to February 2022. Only the percentages of standard labor hours (SLHs) for Standard Product A and LIF were estimated from expert experience.

**Table 6. No. of jobs that fail to finish before the planned EOP**

| Data source | 2021 Q1 | 2021 Q2 | 2021 Q3 | 2021 Q4 | 2022 Q1 |
|---|---|---|---|---|---|
| Historical record | 21 | 22 | 49 | 57 | 48 |
| CI from simulation | [23.6, 31.2] | [19.5, 28.4] | [24.8, 44.9] | [48.1, 58.2] | [44.9, 51.8] |

**Table 7. Comparison of historical and simulation results for Standard Product A's CT**

| Data source | Int CT regular-supply | | Test CT regular-supply | | Int CT shortage-supply | | Test CT shortage-supply | |
|---|---|---|---|---|---|---|---|---|
| | Mean | CI | Mean | CI | Mean | CI | Mean | CI |
| Historical records | 9.7 | [0.7, 18.7] | 8.7 | [0.0, 18.0] | 12.4 | [4.7, 20.2] | 10.7 | [0.0, 21.3] |
| Simulation results | 10.5 | [6.6, 14.3] | 8.0 | [5.6, 10.3] | 12.5 | [9.1, 15.9] | 10.0 | [5.4, 14.5] |

# Simulation Experiment

**Table 8. Simulation features**

| Feature | Scenario | Count |
|---|---|---|
| Core supply | Cores arrive on time | 2 |
| | Cores delayed | |
| Back-end material supply | Processing time under normal back-end material supply (no shortage) | 2 |
| | Processing time are delayed due to back-end material shortage | |
| Labor supply | Current (labor capacity < machine capacity) | 2 |
| | Planned (labor capacity = (19, 15) machine capacity) | |
| Machine combinations | (19, 15), (19, 16), (19, 17), (20, 16), (20, 15), (18, 16), (20, 17) | 7 |
| Number of new starts per week | 6 | 3 |
| | 8 | |
| | 10 | |

- We simulate the 168 scenarios and run 100 replications for each scenario.
- Transforming the features into dummy variables and regressing throughput on them using ordinary least squares (OLS).
- Main effect: one feature
- Interaction effect: a combination of two features

# Regression Analysis

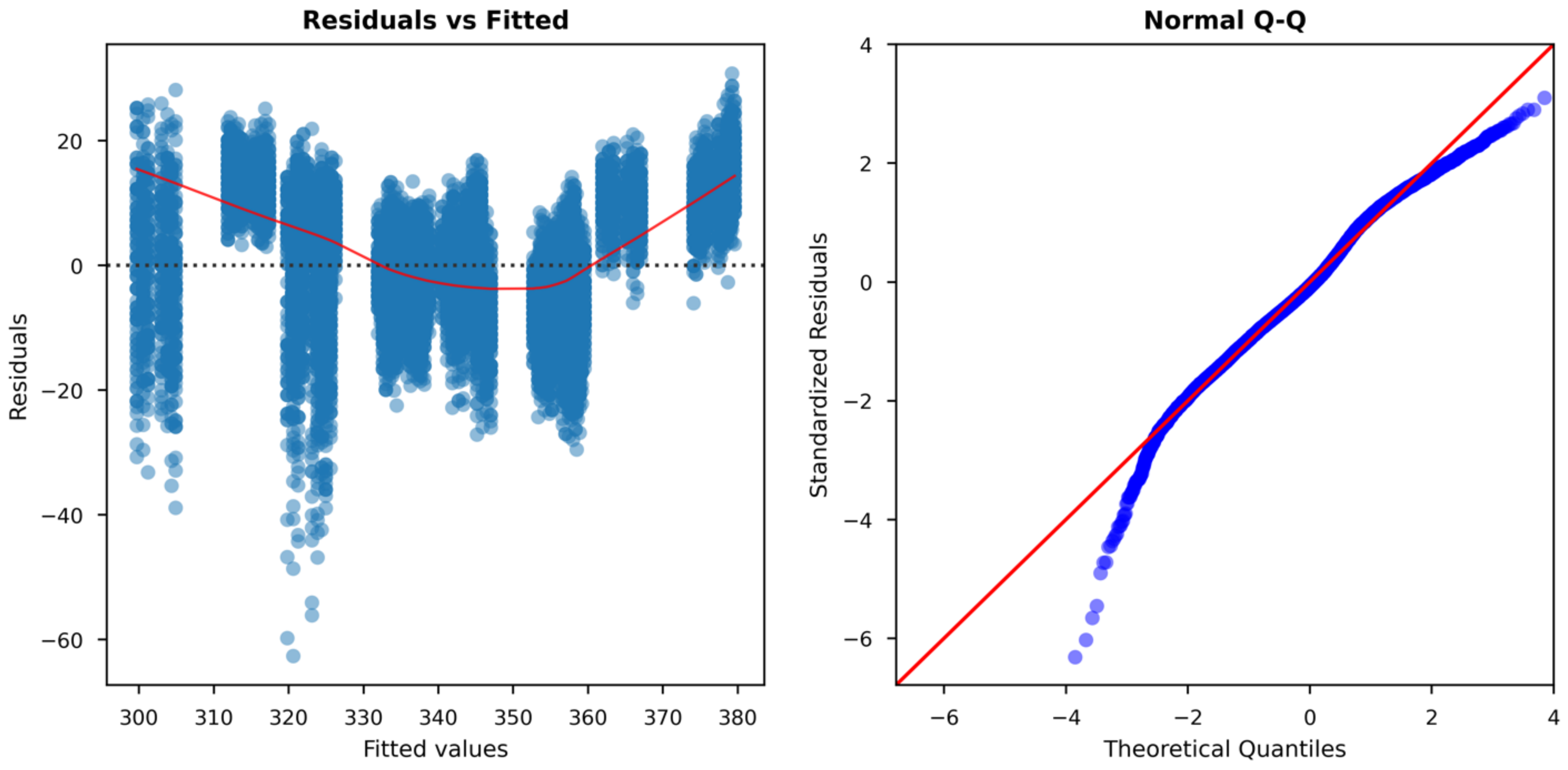


**Figure 11. Homogeneity and normal tests for OLS**

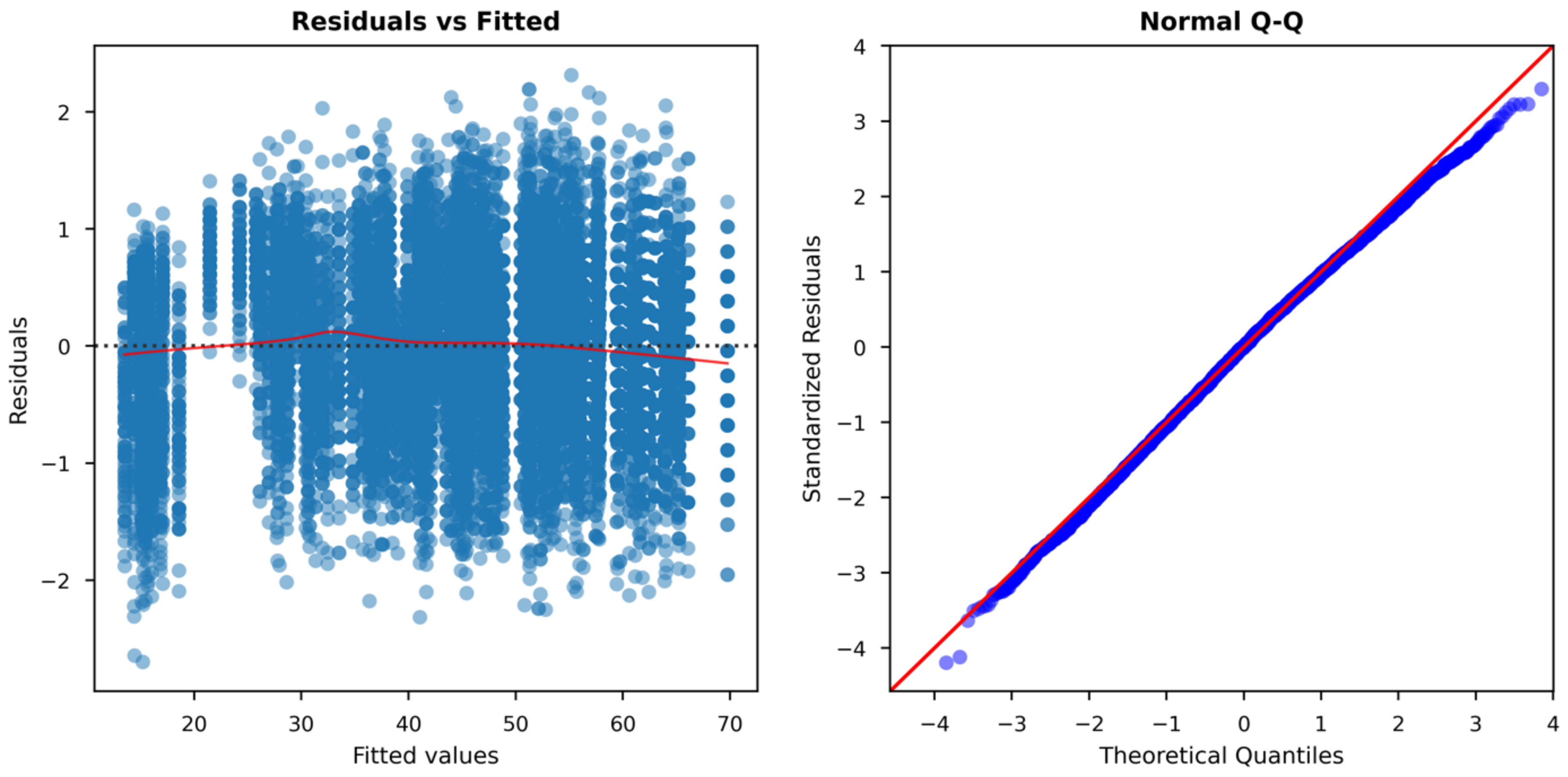


**Figure 12. Homogeneity and normality tests for WLS**

- OLS can not pass the homogeneity and normality tests

- Conduct weighted least squares (WLS) regression. The weights were estimated from the standard errors of the 100 replications at each of the 168 points in the experimental design (Judge 1988).

# Regression Insight

**Table 14. WLS regression summary of simulation results of main effects + the most significant interaction effect**

| | Model | |
|---|---|---|
| | Adjusted-$R^2$ = 0.9997 | |
| Regression Model Term | Coefficient | p-value |
| Constant | 317.65 | <0.001 |
| Core = No delay | -4.32 | <0.001 |
| Labor = Planned labor | 3.04 | <0.001 |
| Back-end = No delay | 10.51 | <0.001 |
| NewStart = 10 | 9.53 | <0.001 |
| NewStart = 8 | 9.13 | <0.001 |
| BayPair = (18, 16) | 0.73 | 0.104 |
| BayPair = (19, 16) | 0.10 | 0.830 |
| BayPair = (19, 17) | -0.41 | 0.382 |
| BayPair = (20, 15) | -1.00 | 0.022 |
| BayPair = (20, 16) | -1.29 | 0.004 |
| BayPair = (20, 17) | -2.17 | <0.001 |
| Interaction(Core = No delay,Labor = Planned labor) | 24.53 | <0.001 |

**Insight 1**. Eliminating back-end material delay by itself offers the greatest improvement to throughput among the main effects.
**Insight 2.** Increasing new starts also yields significant throughput improvement of close to 3% through the main effects
**Insight 3.** Eliminating core delay by itself is not beneficial.
**Insight 4.** Eliminating core and back-end material delays together provides a similar benefit as evidenced by a 7% increase in throughput.
**Insight 5.** Achieving planned staffing targets with no back-end material delay yields a benefit of 6% increase in throughput.
**Insight 6**. Adjusting the machine configuration can provide incremental increases in throughput, but for the most part they are only modest.
**Insight 7**. The effects of most features are synergistic. Under the best scenario, the throughput can increase by 20%.

# Contribution

- Model insights provided immediate benefits to the semiconductor company.  The managers in the other production line also confirmed our insights.  The manager in the studied production line plan to have 8 starts per week.
- Modeling analysis have relevance to a wide range of equipment and component manufacturers.
- Our assumptions on the labor productivity rate, learning rate, and labor reallocation when the back-end materials are consistently delayed can be easily adapted to the other labor-intensive manufacturing systems.
- Modeling logic can be easily extended to more complex flowshop problems.

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# PROJECT 3

## Workforce Planning for Home Healthcare

# Abstract

- **Problem Statement**

  The nurse's resignation rate is high. We provide clues to nurse managers what size of nurses, with a certain type of skill and experience, should be hired for each time period over the planning horizon and how many higher-level nurses should be downgraded in a certain period. We assume the workforce structure is highly hierarchical and downgrading is not expected.

- **Source of Data**

  One of the hospitals in Texas

- **Modeling**

  Mixed-Integer-Linear Programming

- **Methodology**

  Column generation and stochastic optimization

# Dissertation Completion Timeline

| Project | Task | Planned start time | Planned finish time |
|---|---|---|---|
| **Surveillance testing** | Modify the parameters and contact graph and re-run the simulation | 5/4/23 | 5/14/23 |
| **Home healthcare** | Work on deterministic model solving algorithms | 5/15/23 | 6/30/23 |
| | Build stochastic model | 7/1/23 | 7/31/23 |
| | Work on stochastic model solving algorithm | 8/1/23 | 8/15/23 |
| | Finish the paper draft | 6/1/23 | 8/15/23 |
| **Dissertation** | Finish the dissertation draft | 8/15/23 | 8/31/23 |

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