# Striking a balance between cost, effectiveness and efficiency of emergency departments in Hong Kong: An integrated approach of data analytics, simulation, and system optimization

(Project No: 14151771)


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# Emergency Department Crowding

# Research on ED Operations

- **Patient waiting time prediction** (Hoot et al., 2009; Sun et al., 2012; Ang et al., 2015)
- **Patient prioritization**
  - Triage category (Wuerz et al, 2000; Fernandes et al., 2005)
  - Patient complexity (Sprivulis, 2004; Ieraci et al., 2008; Saghafian et al. 2014; Ding et al., 2019)
  - Fast track (Hampers et al., 1999; García et al., 1995; Kausha et al., 2015; Kuo et al., 2018)
  - Patient streaming (King et al., 2006; Saghafian et al., 2012)
  - Patient scheduling (He et al., 2019)
- **ED Queuing models** (Green et al., 2006; Huang et al., 2015; Kamali et al., 2018)
- **Simulation modeling of patient flows** (Connelly and Bair, 2004; Hoot et al., 2008; Abo-Hamad and Arisha, 2013; Kuo et al., 2016; Oh et al., 2016; Vanbrabant et al., 2019)
- **Resource planning** (Ahmed and Alkhamis, 2009; Guo et al., 2017)

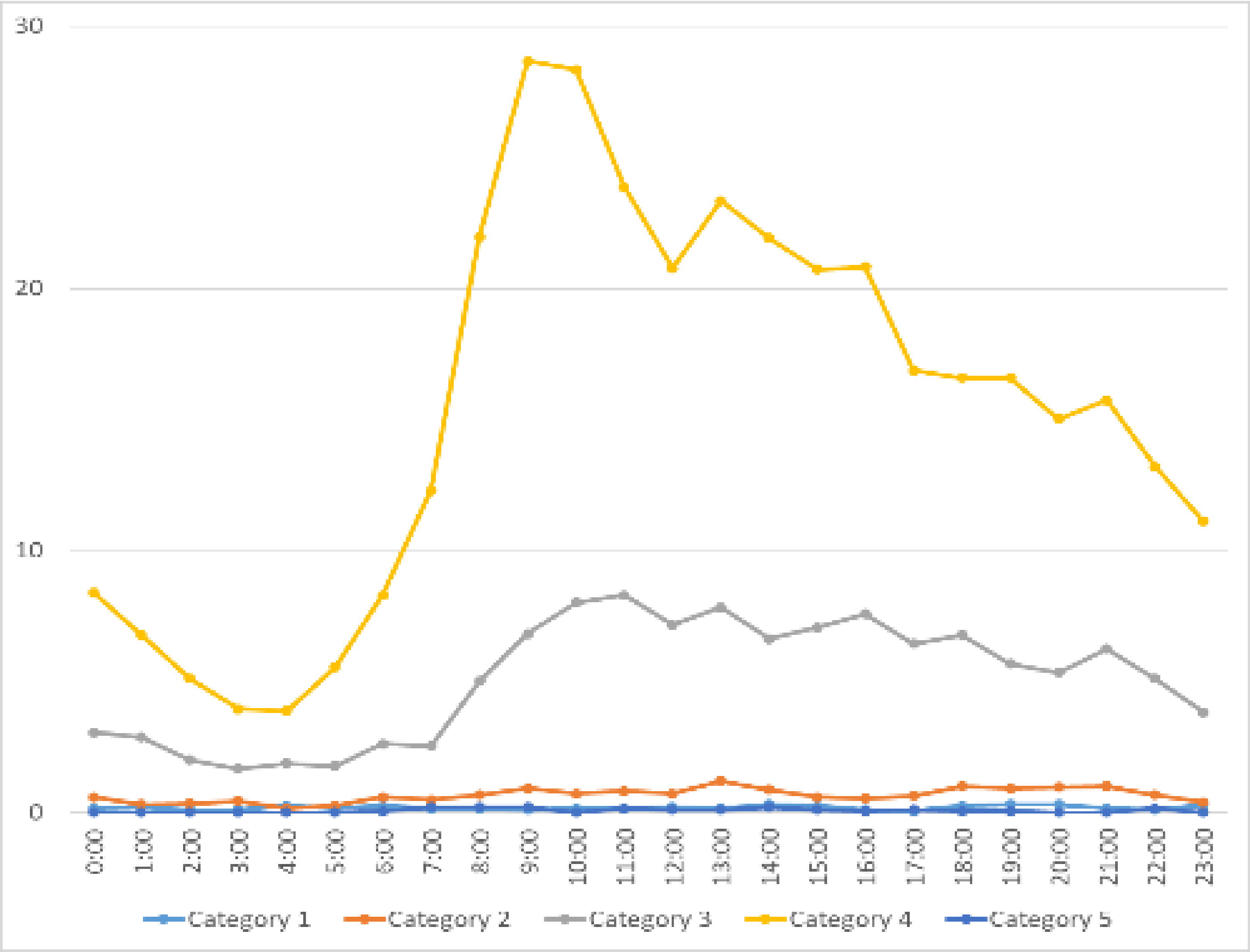
# Aims of the Project

- Measure and analyze patient flow and throughput.
- Develop and apply data-driven techniques for forecasting the ED performance.
- Develop a simulation model to represent the patient flow and processes of the ED.
- Evaluate possible changes in the processes or space-layout that might enhance the system.
- Well utilize resources and improve patient experience.

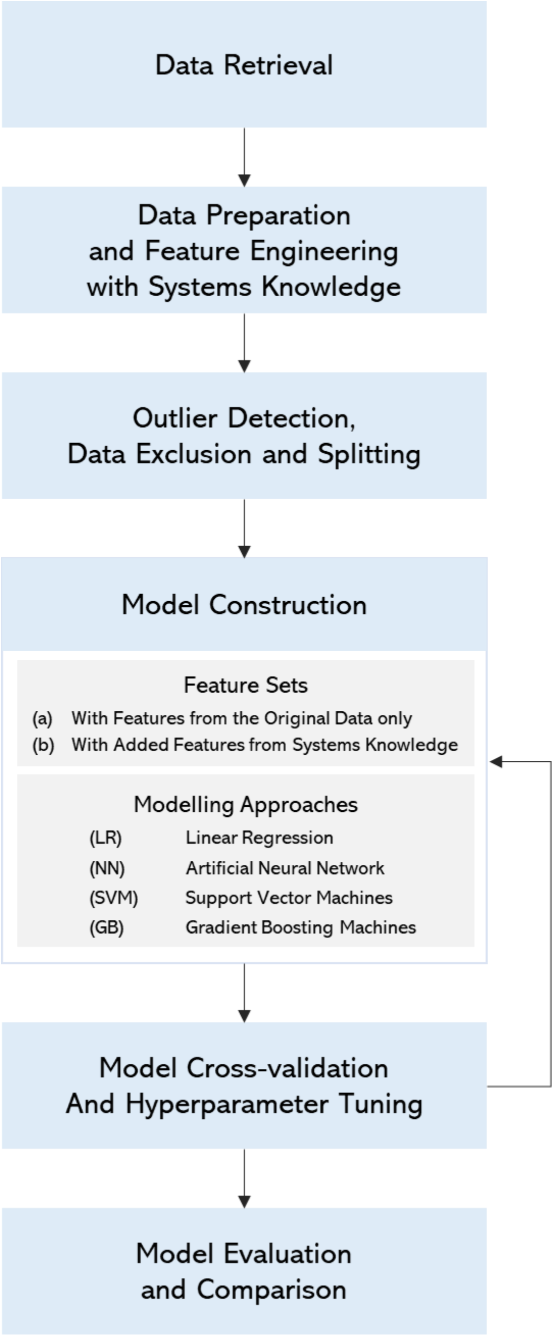
# Waiting time prediction

- **Primary data available**:
  - Time records of events regarding each patient visit:
    - Arrival date
    - Triage category (i.e., level of urgency)
    - Registration start time
    - Triage start time
    - Consultation start time
    - Departure time
  - Staffing level:
    - Number of doctors in the ED in different hours
- **Derived data**:
  - Number of patients in the ED and different queues

# Arrival rates of patients



# Waiting time prediction: Flowchart of the data handling and analysis process





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# Prediction Features

- **Set (a)** contained 11 features:

1. Patient's triage categories (three binary variables where each indicates if the patient is within the corresponding triage category; only urgent, semi-urgent and non-urgent patients are considered in our study);
2. Arrival time; and
3. Numbers of doctors within three hours of the patient's arrival (seven variables in total: three, two, and one hour (s) before the patient's arrival, upon the patient's arrival, and one, two, and three hour(s) after the patient's arrival).

- **Set (b)** contained 18 features:

1. All features from (a);
2. Number of patients in queue for triage upon the patient's arrival;
3. Number of patients in queue for consultation in each category upon the patient's arrival (five categories in total) and
4. Number of patients in queue for departure upon the patient's arrival.

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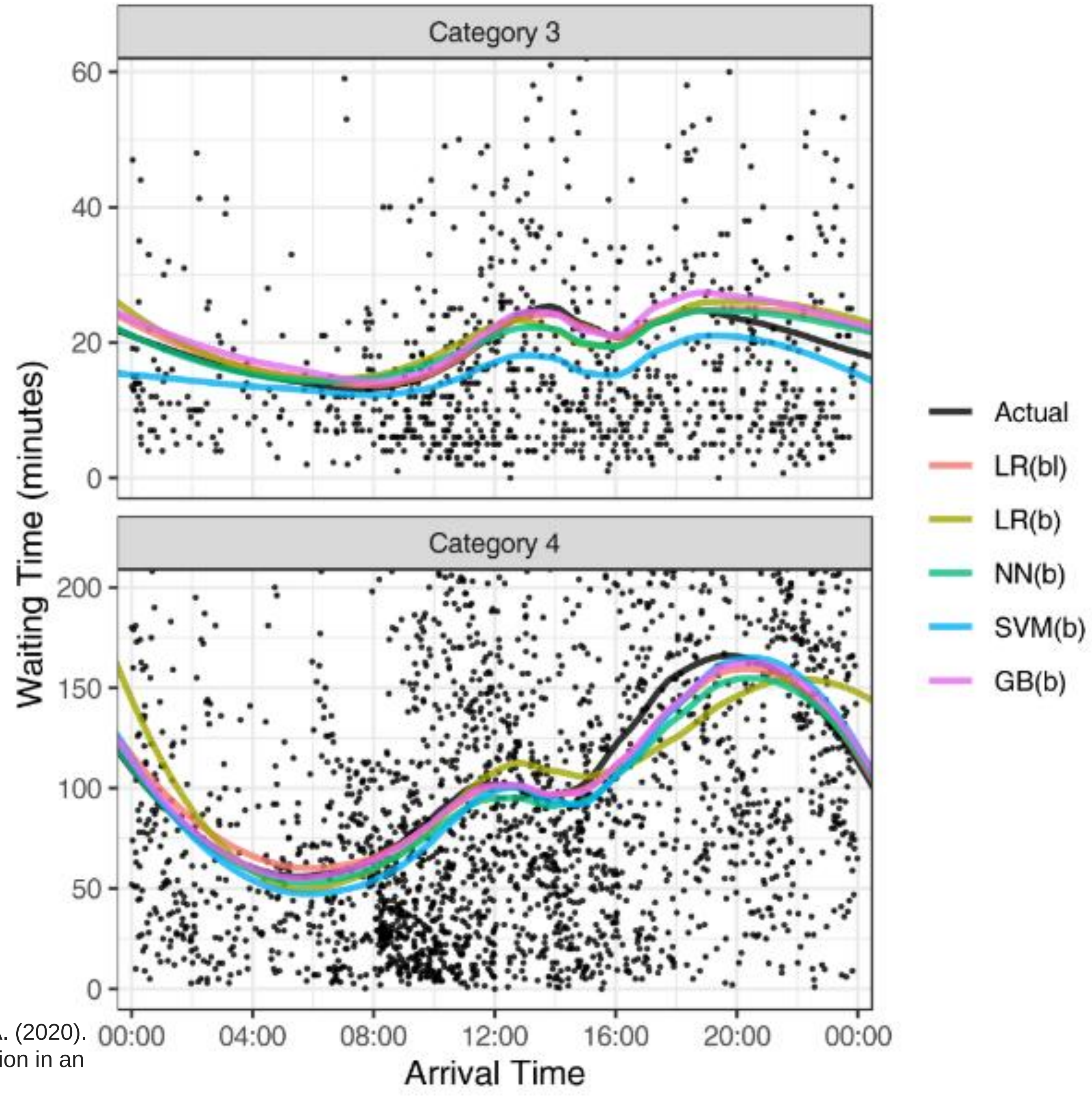
# Actual data & models

- The **baseline model LR(bl)**, which considers only triage category and arrival time, serves as our benchmark for comparison of models.
- The four modelling approaches used in this study were
  - **linear regression (LR)**,
  - **artificial neural networks (NN)**,
  - **support vector machines (SVM)**, and
  - **gradient boosting machines (GB)**.

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| | LR(bl) | LR(a) | NN(a) | SVM(a) | GB(a) | LR(b) | NN(b) | SVM(b) | GB(b) |
|---|---|---|---|---|---|---|---|---|---|
| **Train Set** | | | | | | | | | |
| **R-squared** | 0.377 | 0.352 | 0.388 | 0.360 | 0.400 | 0.528 | 0.599 | 0.568 | 0.699 |
| **MSE** | 3,607 | 3,750 | 3,541 | 3,707 | 3,476 | 2,732 | 2,323 | 2,501 | 1,740 |
| **RMSE** | | | | | | | | | |
| **Category 3** | 22.8 | 23.2 | 22.8 | 23.9 | 22.7 | 22.0 | 21.4 | 22.3 | 18.2 |
| **Category 4** | 69.8 | 71.1 | 69.1 | 70.6 | 68.4 | 60.5 | 55.6 | 57.7 | 48.1 |
| **Category 5** | 44.8 | 45.3 | 49.5 | 50.0 | 49.7 | 20.8 | 22.7 | 19.8 | 31.4 |
| **Test Set** | | | | | | | | | |
| **R-squared** | 0.268 | 0.249 | 0.274 | 0.238 | 0.271 | 0.374 | 0.410 | 0.401 | 0.429 |
| **MSE** | 5,618 | 5,764 | 5,575 | 5,851 | 5,598 | 4,803 | 4,528 | 4,597 | 4,383 |
| **RMSE** | | | | | | | | | |
| **Category 3** | 45.8 | 45.9 | 45.7 | 46.7 | 45.6 | 44.6 | 44.8 | 45.1 | 44.3 |
| **Category 4** | 82.9 | 84.2 | 82.6 | 84.7 | 82.9 | 76.4 | 74.0 | 74.5 | 72.5 |
| **Category 5** | 106.5 | 100.9 | 103.4 | 105.1 | 101.9 | 89.1 | 78.7 | 81.2 | 86.5 |
| **RMSE / SD** | | | | | | | | | |
| **Category 3** | 0.499 | 0.508 | 0.499 | 0.523 | 0.497 | 0.481 | 0.468 | 0.488 | 0.398 |
| **Category 4** | 0.786 | 0.801 | 0.778 | 0.795 | 0.77 | 0.681 | 0.626 | 0.65 | 0.542 |
| **Category 5** | 0.515 | 0.521 | 0.569 | 0.575 | 0.571 | 0.239 | 0.261 | 0.228 | 0.361 |
| **% Difference between (b) and (a)** | | | | | | | | | |
| **Train Set** | | | | | | | | | |
| **R-squared** | NA | NA | NA | NA | NA | 50.00% | 54.38% | 57.78% | 74.75% |
| **MSE** | NA | NA | NA | NA | NA | -27.15% | -34.40% | -32.53% | -49.94% |
| **RMSE** | | | | | | | | | |
| **Category 3** | NA | NA | NA | NA | NA | -5.17% | -6.14% | -6.69% | -19.82% |
| **Category 4** | NA | NA | NA | NA | NA | -14.91% | -19.54% | -18.27% | -29.68% |
| **Category 5** | NA | NA | NA | NA | NA | -54.08% | -54.14% | -60.40% | -36.82% |
| **Test Set** | | | | | | | | | |
| **R-squared** | NA | NA | NA | NA | NA | 50.20% | 49.64% | 68.49% | 58.30% |
| **MSE** | NA | NA | NA | NA | NA | -16.67% | -18.78% | -21.43% | -21.70% |

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| | LR(bl) | LR(a) | NN(a) | SVM(a) | GB(a) | LR(b) | NN(b) | SVM(b) | GB(b) |
|---|---|---|---|---|---|---|---|---|---|
| **Train Set** | | | | | | | | | |
| **R-squared** | 0.377 | 0.352 | 0.388 | 0.360 | 0.400 | 0.528 | 0.599 | 0.568 | 0.699 |
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| **Category 3** | 45.8 | 45.9 | 45.7 | 46.7 | 45.6 | 44.6 | 44.8 | 45.1 | 44.3 |
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| **RMSE / SD** | | | | | | | | | |
| **Category 3** | 0.499 | 0.508 | 0.499 | 0.523 | 0.497 | 0.481 | 0.468 | 0.488 | 0.398 |
| **Category 4** | 0.786 | 0.801 | 0.778 | 0.795 | 0.77 | 0.681 | 0.626 | 0.65 | 0.542 |
| **Category 5** | 0.515 | 0.521 | 0.569 | 0.575 | 0.571 | 0.239 | 0.261 | 0.228 | 0.361 |
| **% Difference between the Model and LR(bl)** | | | | | | | | | |
| **Train Set** | | | | | | | | | |
| **R-squared** | NA | -6.63% | 2.92% | -4.51% | 6.10% | 40.05% | 58.89% | 50.66% | 85.41% |
| **MSE** | NA | 3.96% | -1.83% | 2.77% | -3.63% | -24.26% | -35.60% | -30.66% | -51.76% |
| **RMSE** | | | | | | | | | |
| **Category 3** | NA | 1.75% | 0.00% | 4.82% | -0.44% | -3.51% | -6.14% | -2.19% | -20.18% |
| **Category 4** | NA | 1.86% | -1.00% | 1.15% | -2.01% | -13.32% | -20.34% | -17.34% | -31.09% |
| **Category 5** | NA | 1.12% | 10.49% | 11.61% | 10.94% | -53.57% | -49.33% | -55.80% | -29.91% |
| **Test Set** | | | | | | | | | |
| **R-squared** | NA | -7.09% | 2.24% | -11.19% | 1.12% | 39.55% | 52.99% | 49.63% | 60.07% |

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# Key Insights

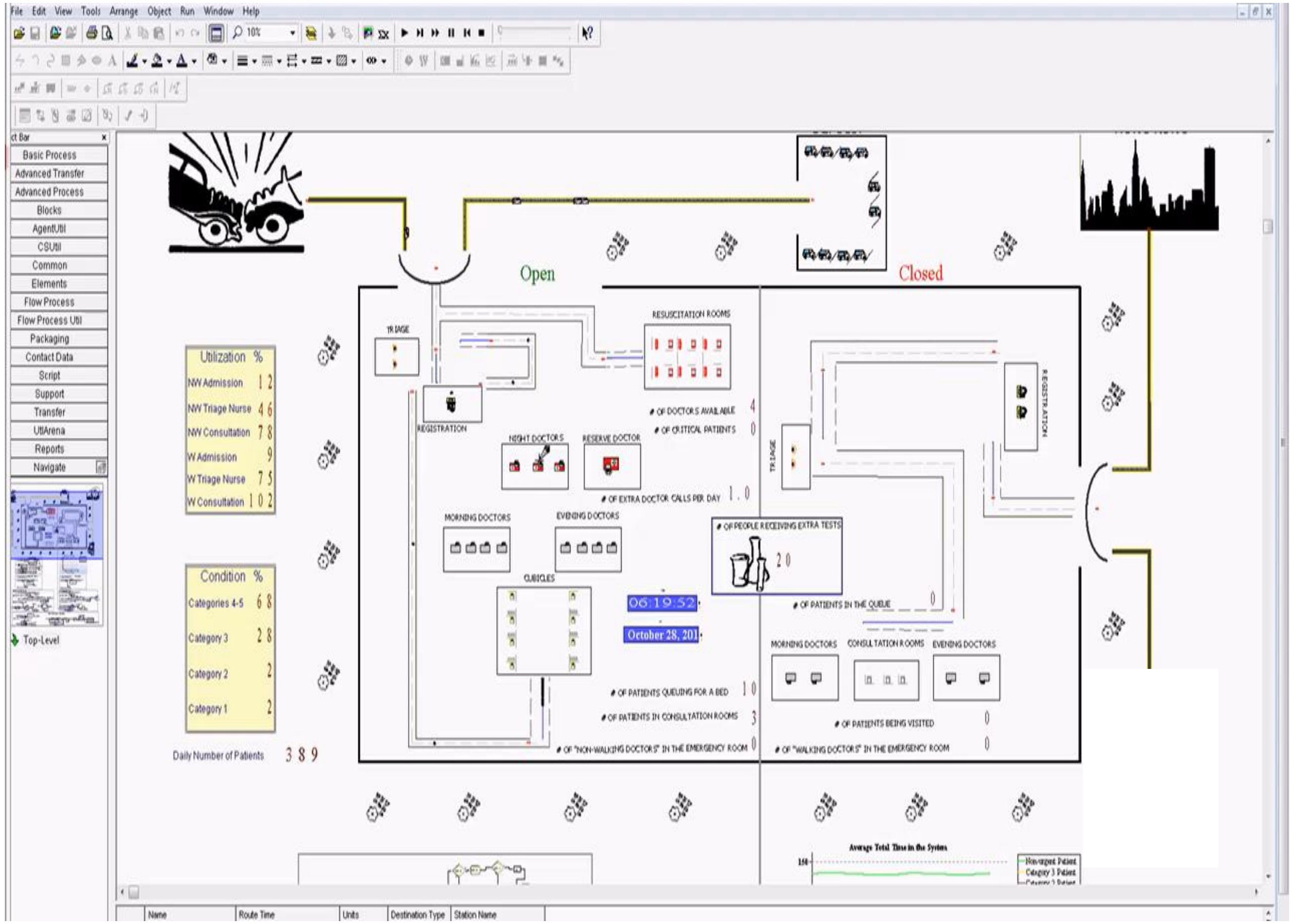
- The stepwise multiple linear regression **reduced the mean-square error by almost 15%**.
- The other three algorithms had similar performances, **reducing the mean-square error by approximately 20%**.
- **Reductions of 17 –22%** in mean-square error due to the **utilization of systems knowledge** were observed.
- Artificial intelligence may help improve prediction accuracy, but the knowledge of the ED system seems to be more important.

# Analysis of Emergency Room Operations

- **Simulation**
  - Represent the ED system (operations & patient flows)
  - Trained by actual data
- **Analysis and optimization**
  - Examine different “what-if” scenarios and potential changes in the system
  - Forecast ED performance metrics (e.g., patient waiting time, total length of stay, number of patients in the ED, resource utilization)
  - Optimize decisions

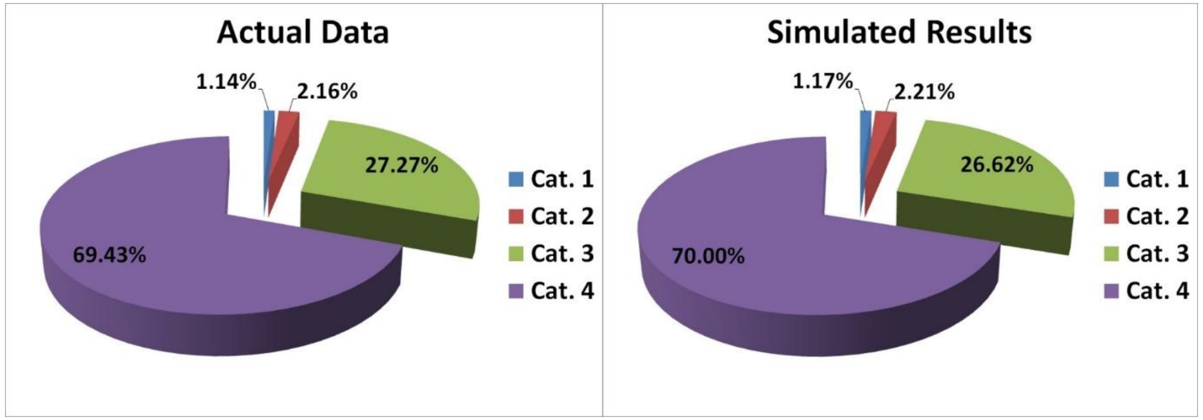
# Simulation Tool

- We captured all relevant treatment processes
  - Triage
  - Consultation
  - Lab tests
- The standard **input parameters** are
  - Time-varying patient arrival rates
  - Service-duration probability distributions
  - Available resources
- The **outputs** are **key performance indicators**
  - Patient waiting time
  - Queue lengths
  - Doctor utilization

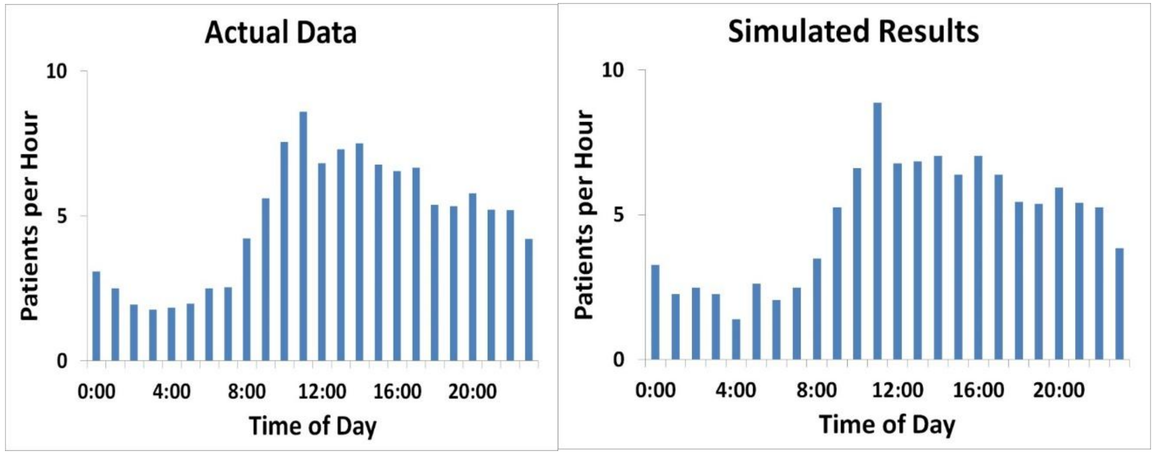


# Model Validation

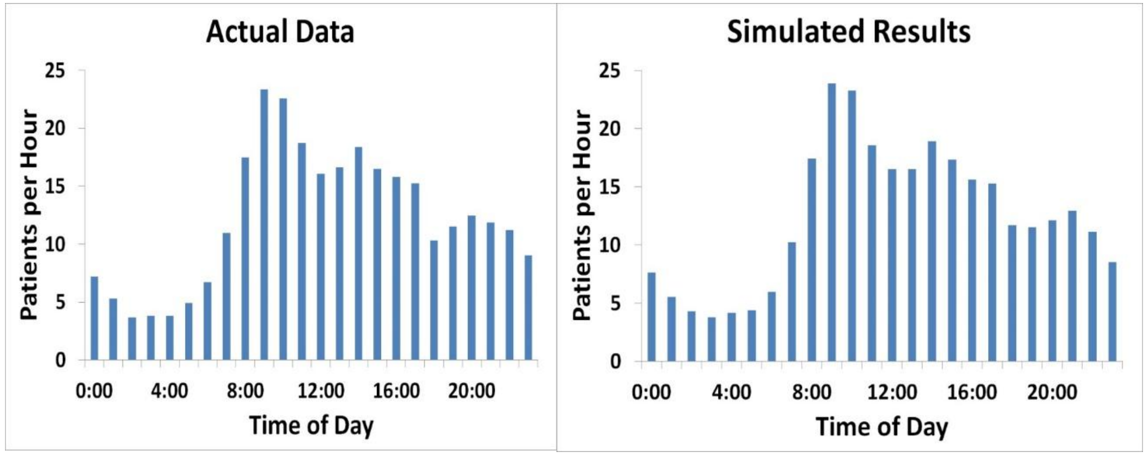
**Proportion of patients in each category**




**Category 3 patient arrivals per hour by time of day**

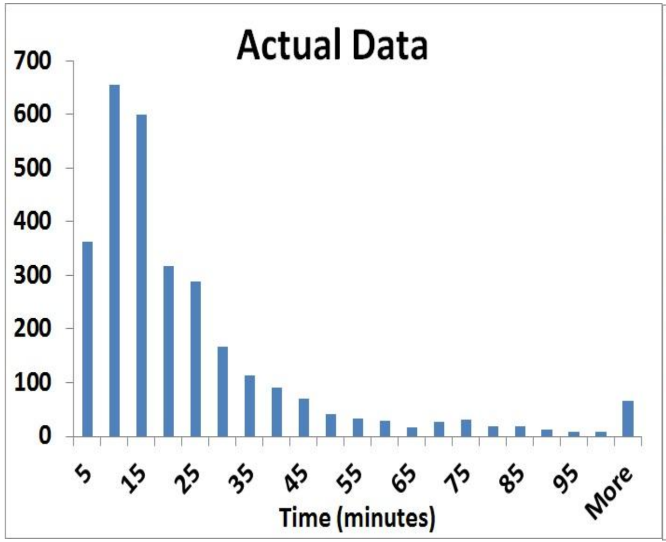


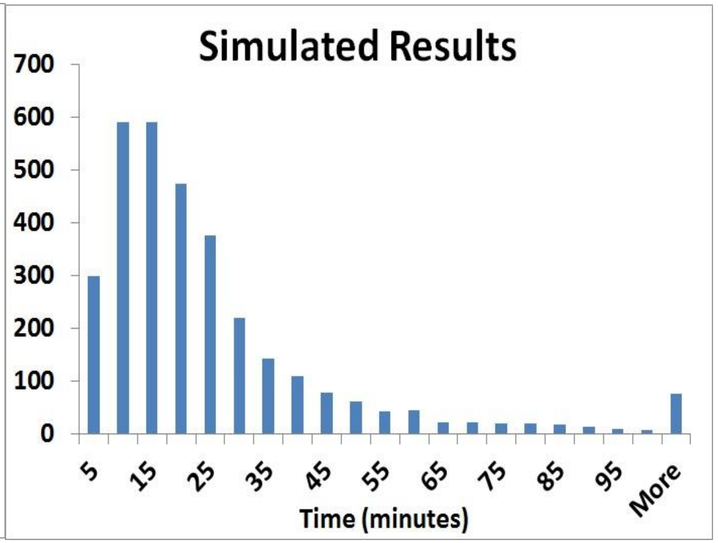

**Category 4 patient arrivals per hour by time of day**



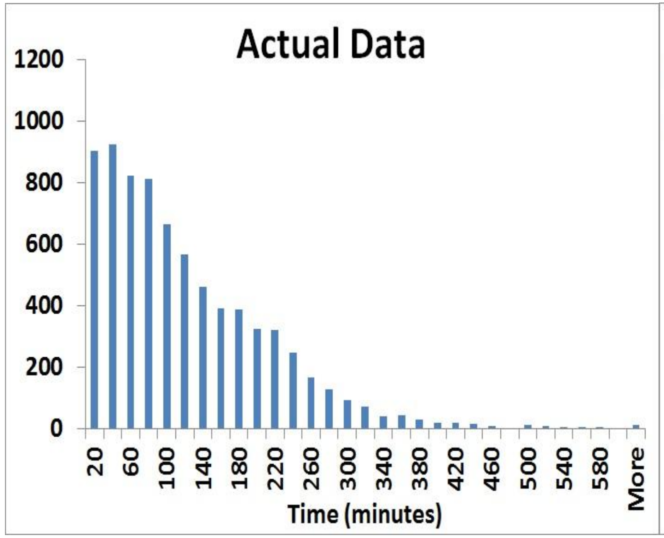
# Model Validation

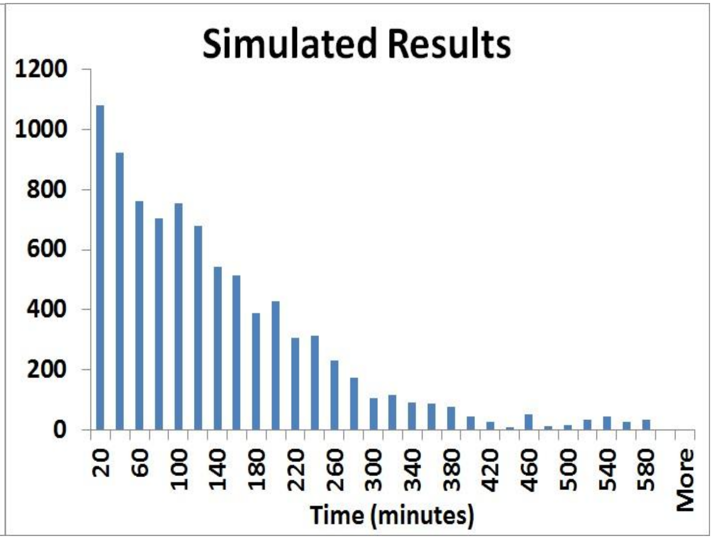
**Category 3 patient net time from triage to consultation**



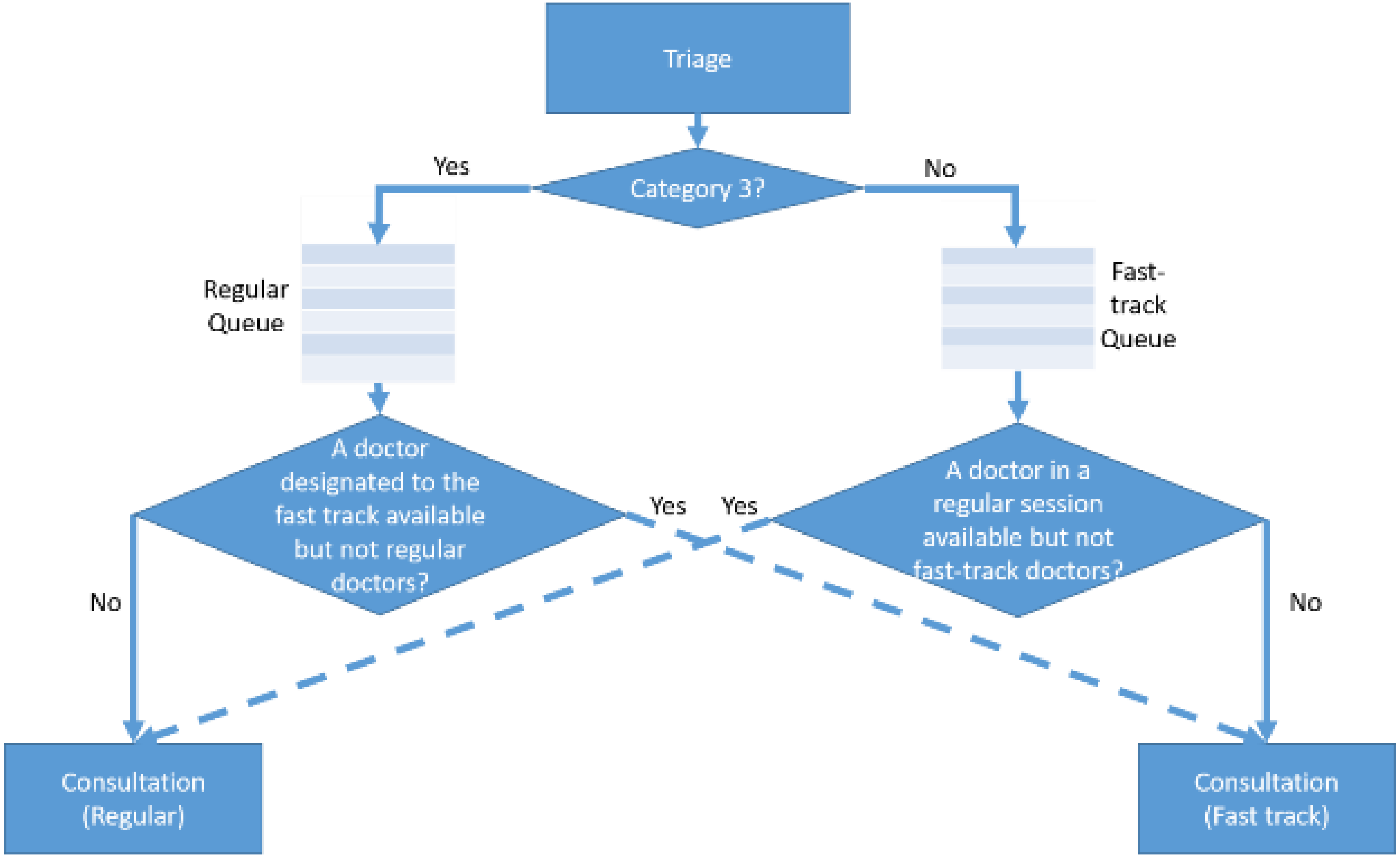




**Category 4 patient net time from triage to consultation**



# Evaluation of a Fast-Track System

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# Scenarios in the Simulation Study

| Scenario | Description |
|---|---|
| S0 | The simulation model adopts the original settings. |
| S1 | The proportions of category 3 and category 4 patients are 20% and 80% respectively (assuming the numbers of category 1 and 2 patients are negligible). |
| S2 | The proportions of category 3 and category 4 patients are 40% and 60% respectively (assuming the numbers of category 1 and 2 patients are negligible). |
| S3 | All the patient arrival rates decrease by 5%. |
| S4 | All the patient arrival rates increase by 5%. |
| S5 | The average of the consultation time for category 3 patients decreases by 5%. |
| S6 | The average of the consultation time for category 3 patients increases by 5%. |
| S7 | The average of the consultation time for category 4 patients decreases by 5% |
| S8 | The average of the consultation time for category 4 patients increases by 5% |

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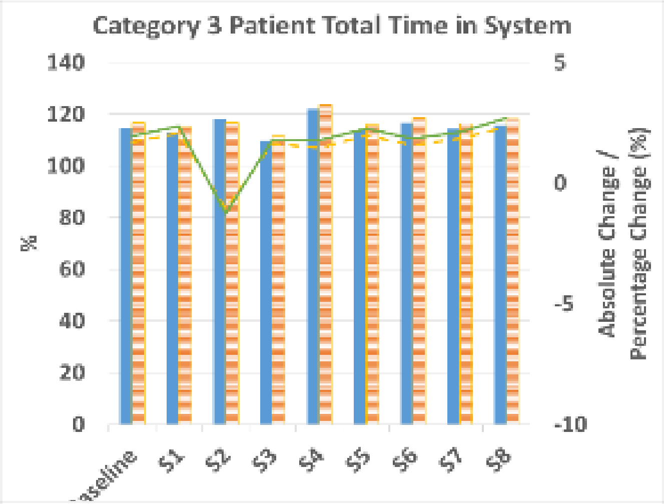
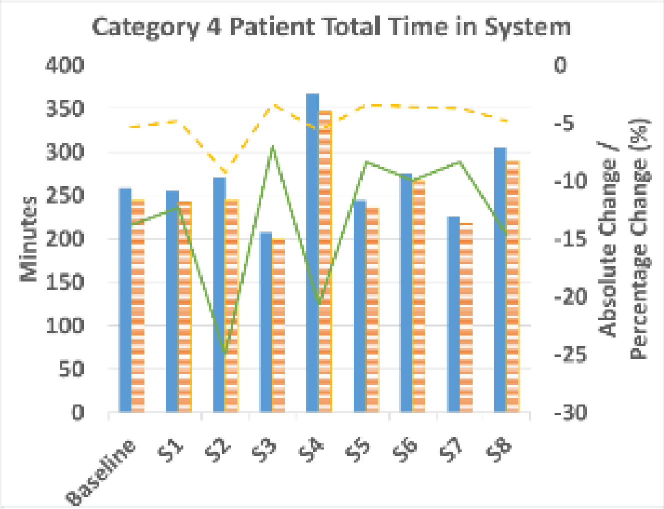
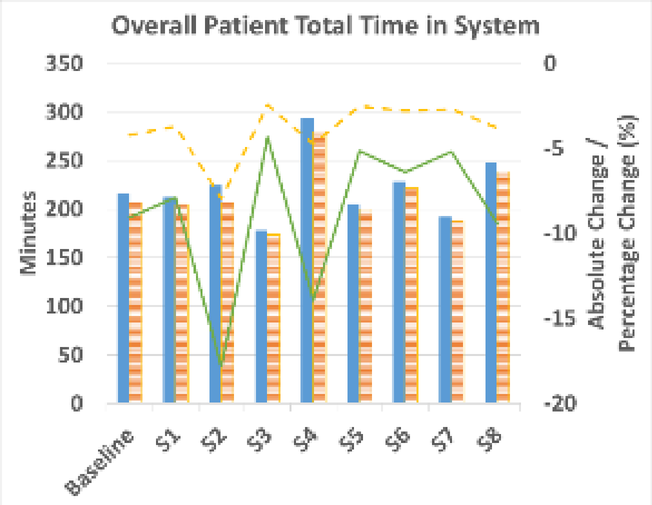
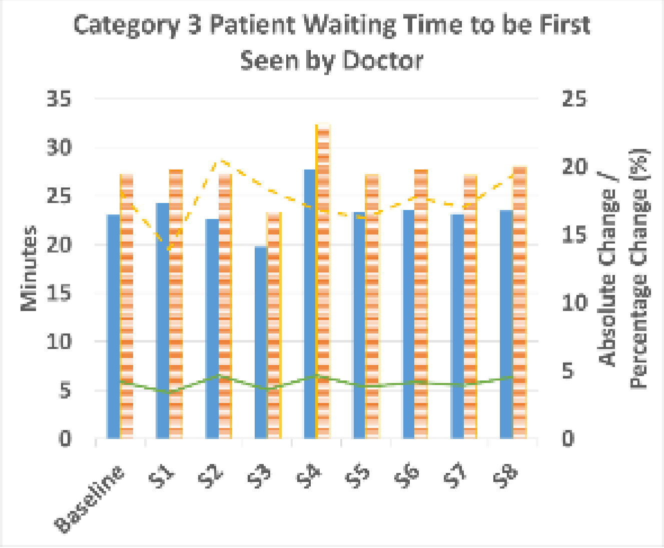
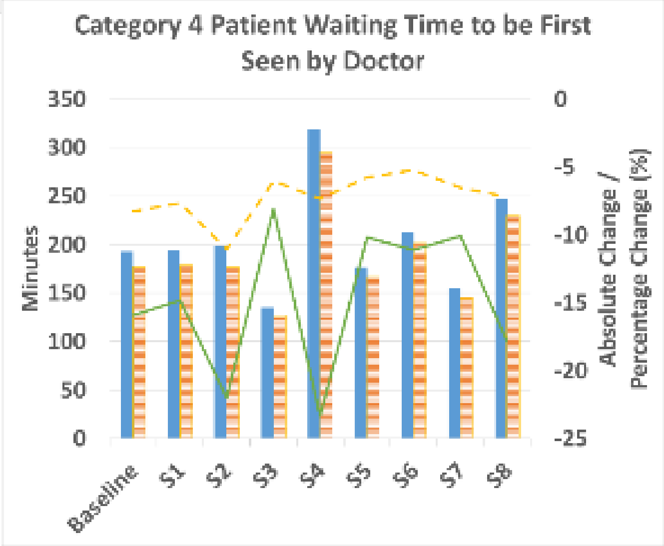
# Patient Times in System

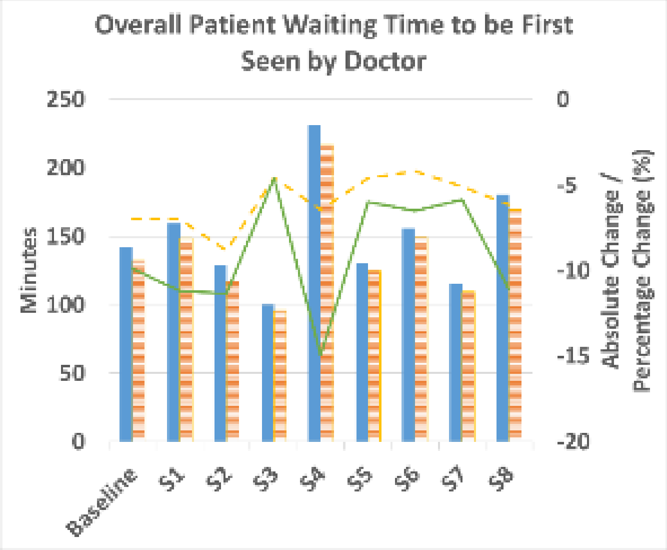
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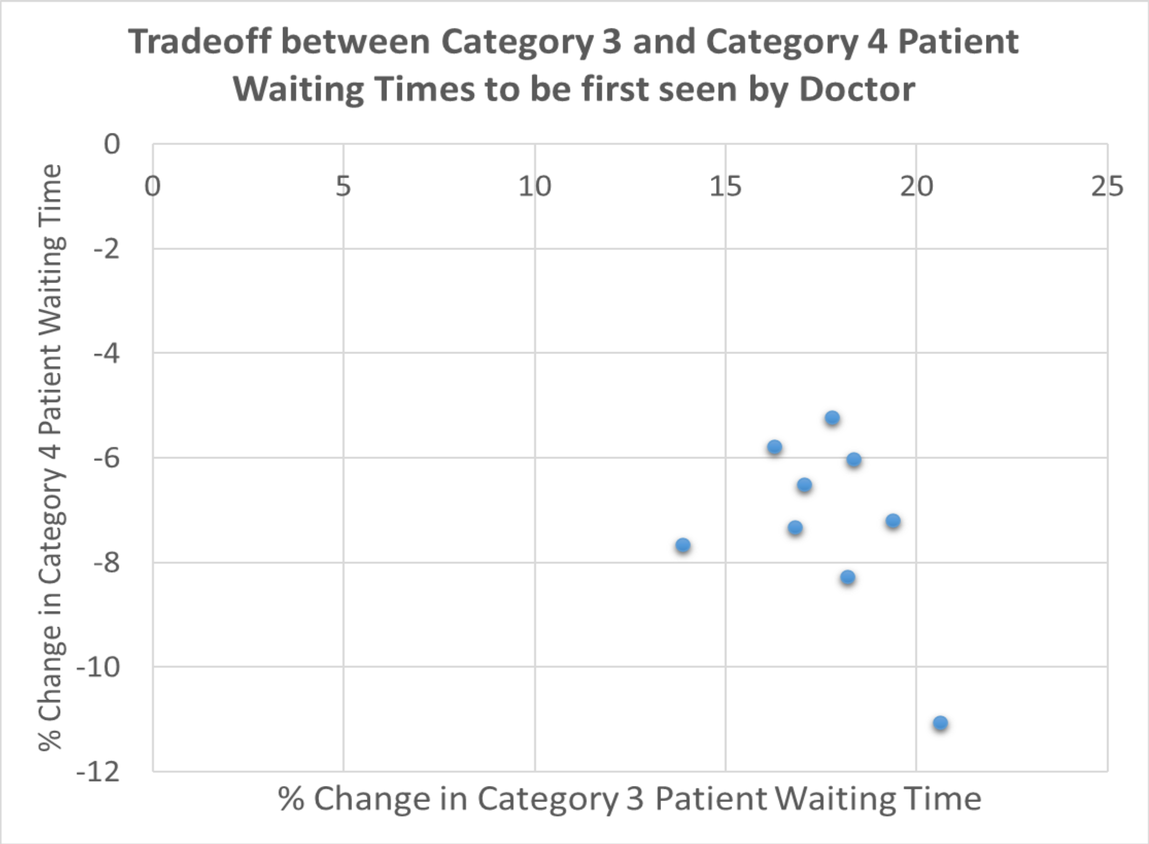
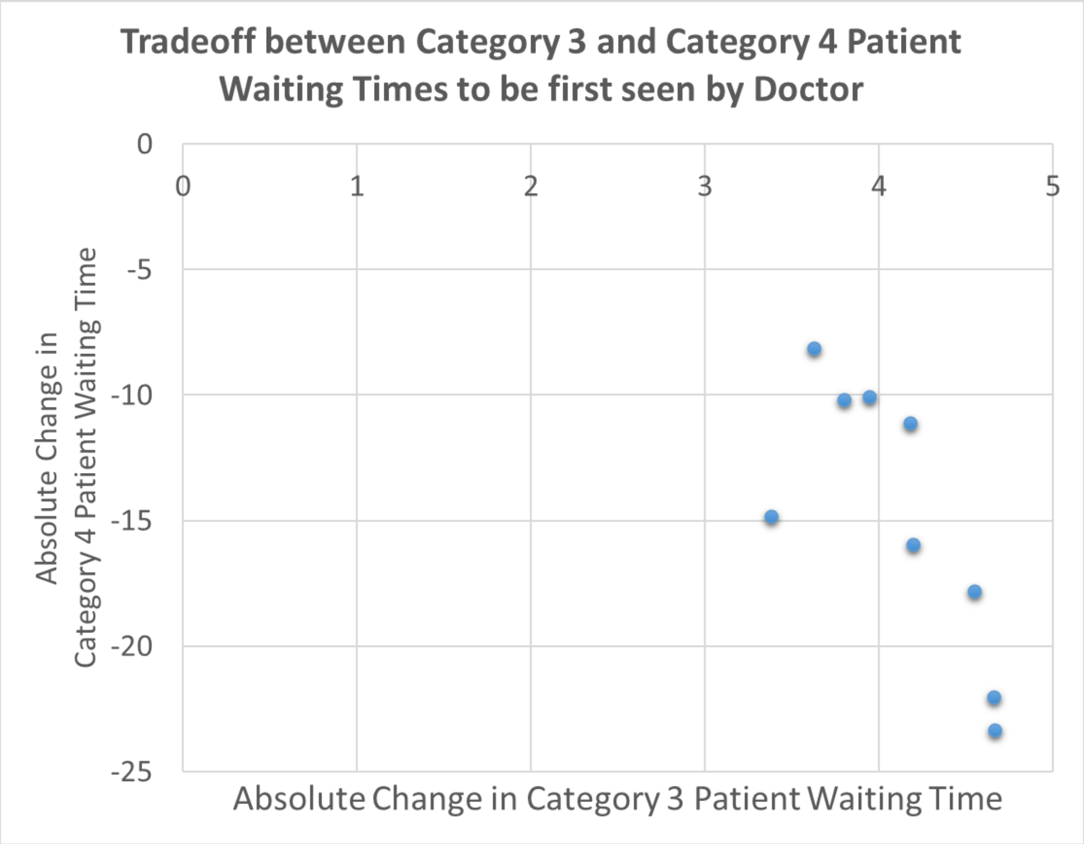
# Tradeoff between Cat 3 & 4 Patient Waiting Time

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# Physician Scheduling

- Challenge: highly stochastic environment (patient arrivals, patient types, required treatments, service times, etc.)
  - Solution: the simulation tool can provide a way to evaluate the system performance.
- However, exploration of all possibilities is practically impossible.
  - For instance, in the ED of PWH, there are 15 physicians on duty each day, which results in $48^{15} \approx 1.65 \times 10^{25}$ feasible physician work schedules.
- Our proposed approach: **Workforce optimization model**

$$min \sum_{k \in K} \sum_{c \in C} V_k^{c,min} - \sum_{m=1}^{P} \beta_{km}^{c} Y_{km}$$

$$\sum_{j \in J} a_{kj} X_j - \sum_{m=1}^{P} Y_{km} \geq Sr_k^{min} \qquad \forall k \in K$$

$$\sum_{j \in J} X_j \leq P$$

$$X_j \in \mathbb{Z}^+ \cup \{0\} \qquad \forall j \in J$$

$$Y_{km} \in \{0,1\} \quad \forall k \in K, m = 1, \dots., P$$

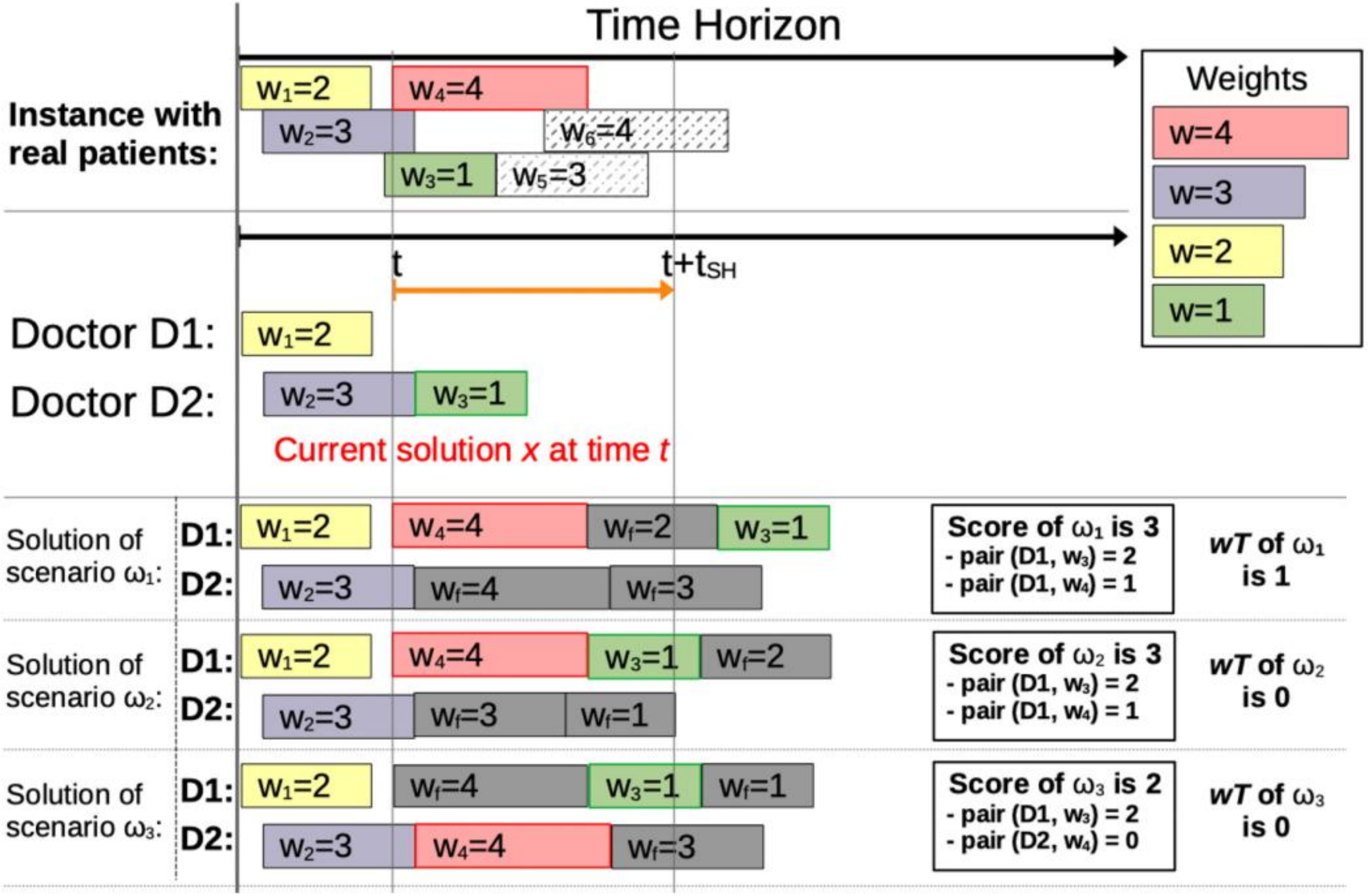
# Patterns of Optimal Staffing Level


**Managerial Insights**:

- The profile of the best staffing level shifts **1.5–2 hours behind the arrival pattern**.
  - ➢ Patients have to go through other procedures (registration and triage) before consultation.
  - ➢ In order to best-utilize the physicians, it is better to schedule them to the periods which the queues are reasonably long (so that most of the time they would not be idle).

- The staffing level changes very frequently over time.
  - ➢ The use of **staggered shifts** can better-match physicians with patient demand.

# Dynamic Scheduling of Patients




**Algorithm 2** General VNS for the problem.

Let $x$ be an initial solution
**while** number of consecutive iterations without improvement $\leq NO_{imp}$ **do**
    $k \leftarrow 1$
    **while** $k \leq K$ **do**
        $x' \leftarrow$ neighbor solution from $N_k(x)$
        $x'' \leftarrow$ VND($x'$)
        **if** $wT(x'') < wT(x)$ **then** $x \leftarrow x''$; $k \leftarrow 1$
        **else** $k \leftarrow k + 1$
**return** $x$

**Algorithm 5** SBPA-VNS - scenario-based planning approach with VNS.

Let $\Omega$ be the set of scenarios with fictive patients
**while** there is an event **do**
    $t \leftarrow$ time at which the event happens
    $x \leftarrow$ add the newly revealed patients that are ready
    **for all** scenarios $\omega \in \Omega$ **do**
        $x_\omega \leftarrow x \cup$ {fictive patients $j$ of scenario $\omega$ having $r_j \in [t, t + t_{SH}]$
        Optimize $x_\omega$ with the VNS
        Update $x_\omega$ by substituting each fictive patient by an idle time $t_{wait}$
    $x_{best(\omega)} \leftarrow$ the solution $x_\omega$ with the highest consensus function score
    Update $x$ with the decisions in $x_{best(\omega)}$

de Queiroz, T. A., Iori, M., Kramer, A., & Kuo, Y. H. (2023). Dynamic scheduling of patients in emergency departments. *European Journal of Operational Research*, *310*(1), 100-116.

# Impact of the Number of Doctors in the ED

| Method | 2 doctors | | 3 doctors | | 4 doctors | | 5 doctors | | 6 doctors | |
|---|---|---|---|---|---|---|---|---|---|---|
| | time | *wT* | time | *wT* | time | *wT* | time | *wT* | time | *wT* |
| ARC-FLOW | 34.66 | 858.87 | 23.20 | 49.60 | 0.09 | 0.11 | 0.04 | 0.00 | 0.01 | 0.00 |
| VNS | 2.95 | 871.88 | 1.13 | 50.93 | 0.42 | 0.21 | 0.29 | 0.00 | 0.23 | 0.00 |
| REO-QUEUE | < 0.01 | 1417.91 | < 0.01 | 111.21 | < 0.01 | 4.94 | < 0.01 | 1.36 | < 0.01 | 0.65 |
| REO-VNS | 2.33 | 1191.42 | 0.76 | 87.84 | 0.10 | 3.17 | 0.07 | 1.31 | 0.07 | 0.56 |
| SBPA-VNS | 592.12 | 1175.55 | 478.11 | 81.19 | 238.41 | 3.17 | 235.32 | 1.23 | 231.36 | 0.56 |
| Red. SBPA-VNS 2 doctors (%) | - | - | 19.25 | 93.09 | 59.74 | 99.73 | 60.26 | 99.90 | 60.93 | 99.95 |
| Red. SBPA-VNS 3 doctors (%) | - | - | - | - | 50.13 | 96.10 | 50.78 | 98.49 | 51.61 | 99.31 |
| Red. SBPA-VNS 4 doctors (%) | - | - | - | - | - | - | 1.30 | 61.20 | 2.96 | 82.33 |
| Red. SBPA-VNS 5 doctors (%) | - | - | - | - | - | - | - | - | 1.68 | 54.47 |

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# Key Takeaways

- An integrated approach powered by **data analytics**, **simulation**, and **system optimization** is effective to evaluate solutions to improve emergency department operations.
- **Operational data** at ED are leveraged to train **machine learning** and **simulation models**.
- **System knowledge** is important for improving the performance of machine learning models.
- Simulation provides hospital administrators with a tool to examine potential solutions for improving patient flows.
- Optimization procedures can be applied to identify good **physician rosters** and **patient schedules**.
- The integrated approach can be used not only for emergency department operations but also for other healthcare systems.

# Thank you!
# Any questions?

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Key publications:

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