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Small Cell Management in Cellular Networks based on User Density Prediction

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Outline

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- Introduction
- User Density Prediction
  - Data Organisation
  - Prediction Scheme
- Evaluation and Discussion
  - Evaluation of the prediction schemes
  - Evaluation of the network performance
- Conclusion and Future work

Challenges of Modern Cellular Networks

- ➢ Anticipated to have 1000 X more data traffic volume
- ➢ At least 10-100 X more number of connected devices
- ➢ 10 X lower latency
- ➢ 10 X longer battery life
- ➢ 100 X energy efficient
- ➢ 5G or 6G systems envision use cases with even higher data demands and stringent latencies. (e.g., VR/XR, telepresence, massive twinning etc.,)
- ➢ Systems are required to be adaptable to dynamic changes in service demands.

eMBB
Enhanced mobile broadband

mMTC
Massive machine Type communication

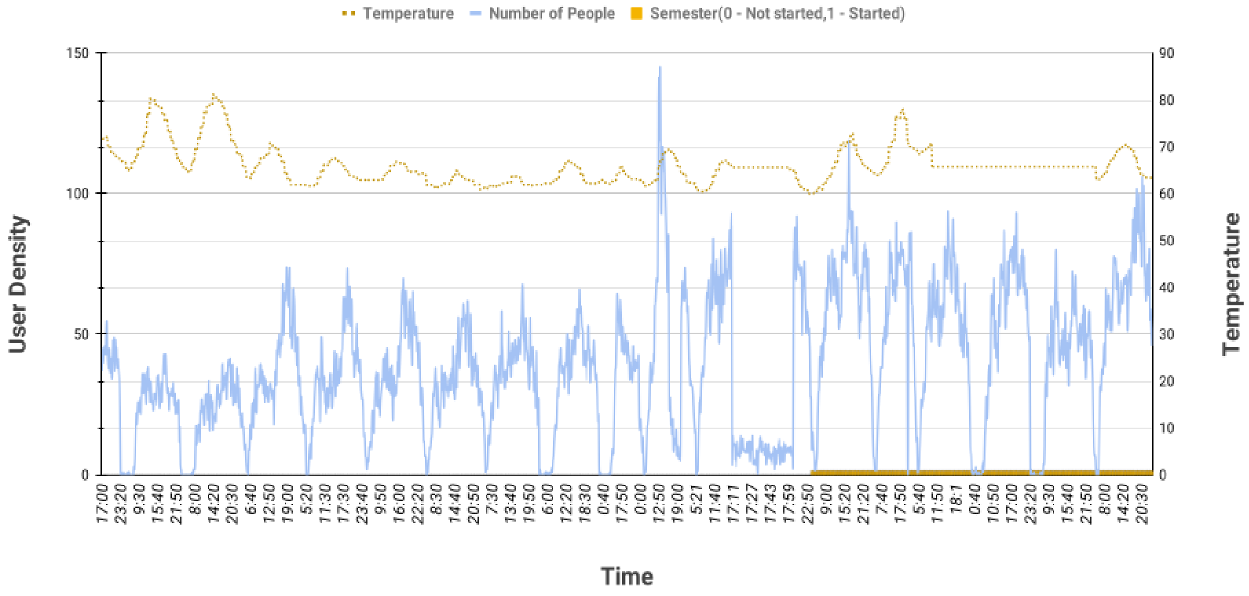
URLLC
Ultra-reliable & Low latency communication

Problem Statement & Solution

- Day-to-day scenarios such as public events, stadiums, shopping malls, etc., a dynamic surge in the user density is expected.
- Designing proactive radio resource management (RRM) schemes → Better QoE
- To combat the high load of a serving base station, schemes such as load balancing, channel borrowing, etc are present.
- These works are based on the worst case scenarios(high arrival, low departure, high bandwidth usage) and are further reactive in nature (cold start problem).
- These schemes are more efficient when there is a **"beforehand knowledge"** of arising crowd formation in a specific cell → proactive triggering of RRM schemes

Data generation

- ➢ An on-campus gym in an university is considered in this work, as the site of frequent crowd formation.
- ➢ Each data point records user density at gym and other features like Date, time, temperature, weather conditions and Semester status when data is recorded
- ➢ The graph represents the number of people in the gym and the temperature, and semester status at that respective point of time.



Regression based User Density Prediction

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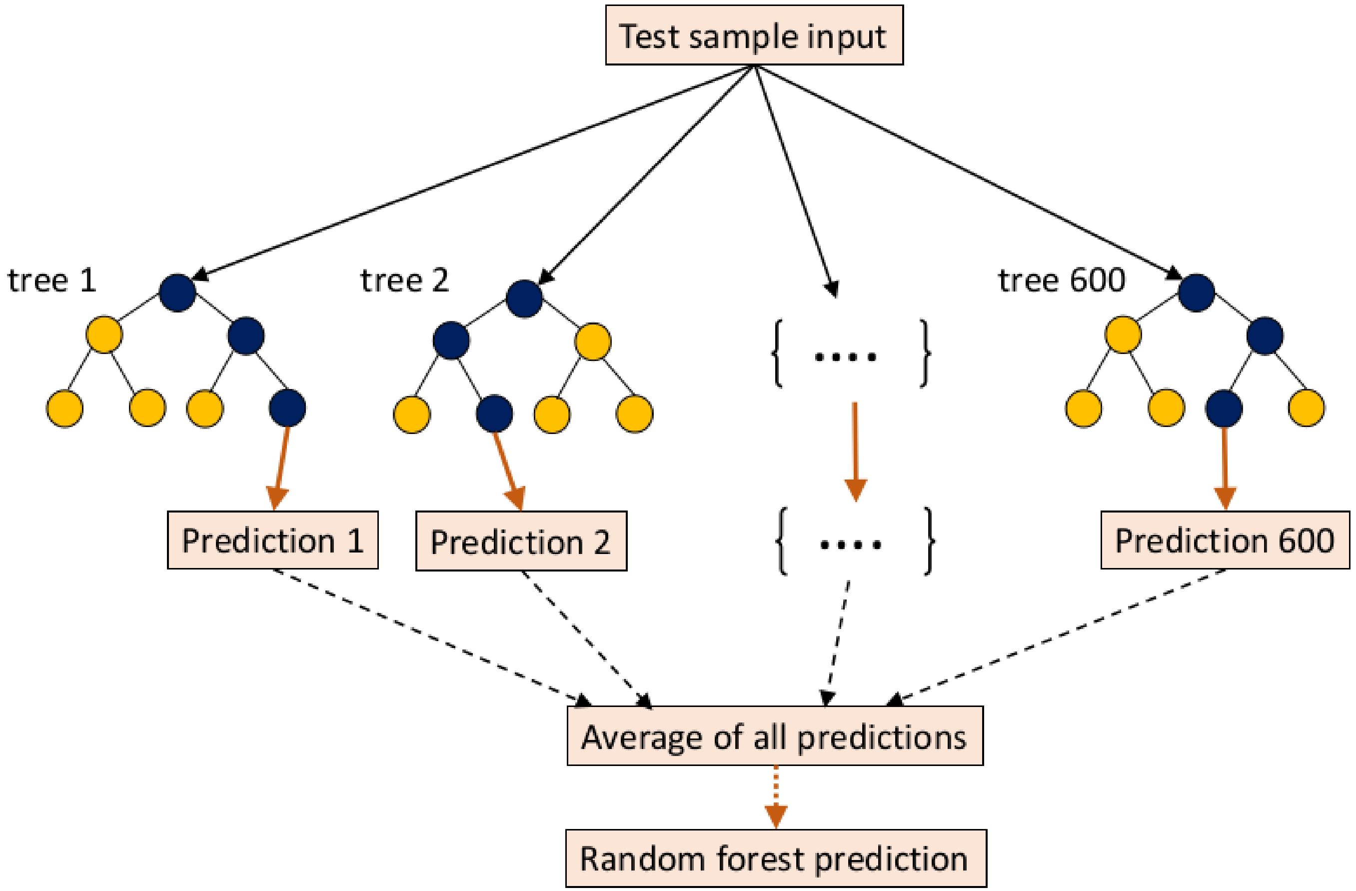
Random Forest



Random Forest Algorithm

Steps to implement Random Forest Algorithm:

- First, a sample from the training data set is taken randomly with replacements.
- A subset of all features is selected randomly and whichever feature gives the best split is used to split the node iteratively.
- The tree is grown to the largest.
- The above steps are repeated and the predictions are given based on the aggregation of prediction from n number of trees

Gini Importance

Random Forest calculates node importance using Gini Importance, assuming only two child nodes (binary tree) as shown in Equation 1.

$$ni_j = w_j C_j - w_{\text{left }(j)} C_{\text{left }(j)} - w_{\text{right }(j)} C_{\text{right }(j)} \qquad (1)$$

The importance for each feature on a decision tree is then calculated as shown in Equation 2.

$$fi_i = \frac{\sum_{j:node j \text{ splits on feature } i} ni_j}{\sum_{k \in \text{ all nodes}} ni_k} \qquad (2)$$

Gini Importance

Features can then be normalized to a value between 0 and 1 by dividing by the sum of all feature importance values as shown in Equation 3.

$$\text{norm } fi_i = \frac{fi_i}{\sum_{j \in \text{ all features}} fi_j} \tag{3}$$

The final feature importance at the Random Forest level is the average of all the trees. The sum of the features importance value on each trees is calculated and divided by the total number of trees as shown in Equation 4.

$$RF fi_i = \frac{\sum_{j \in \text{ all trees}} \text{normfi}_{ij}}{T} \tag{4}$$

Modeling and Evaluation

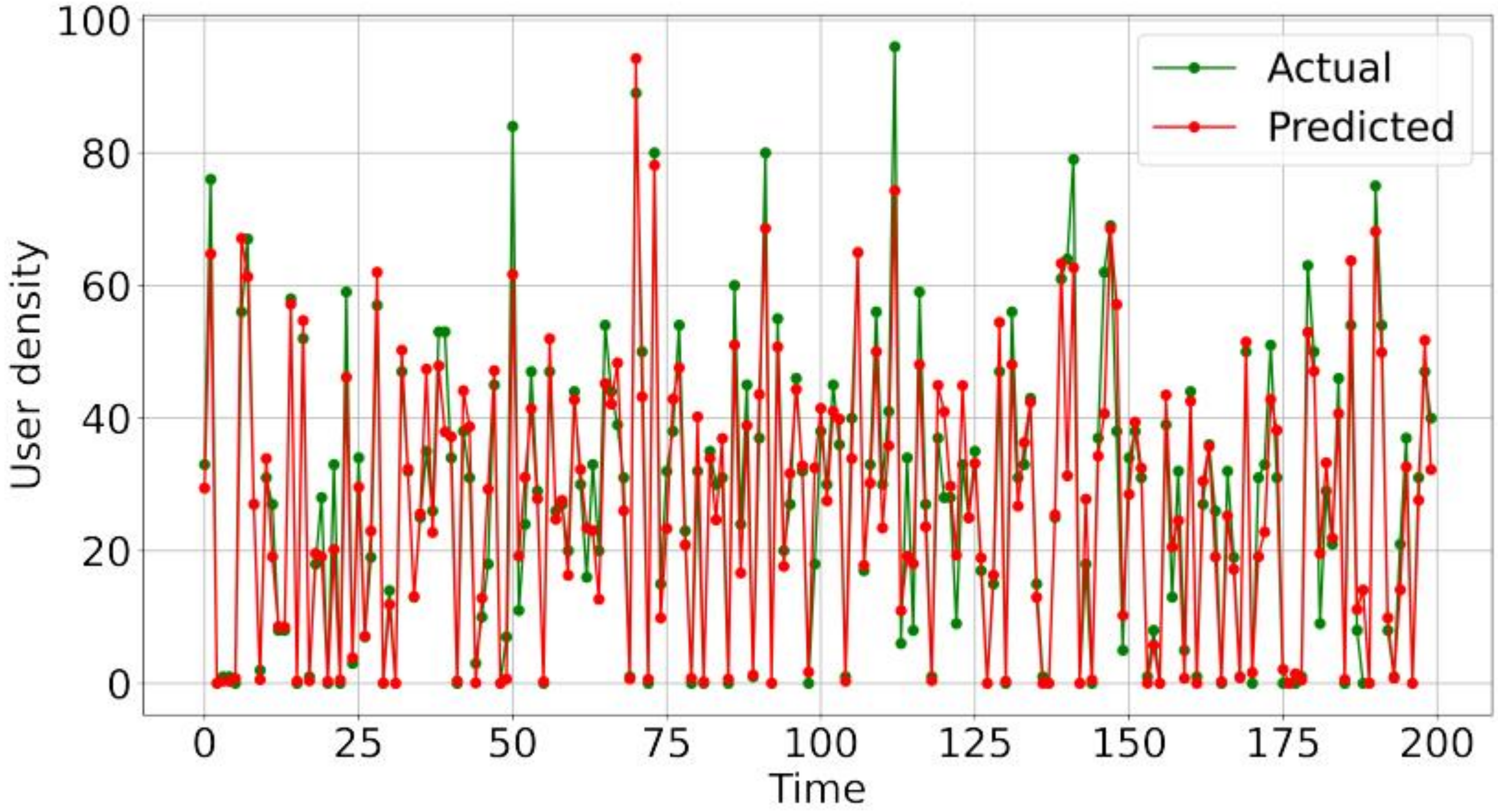
Evaluation Metric: Root-mean-square deviation(RMSE) is used as an evaluation metric to measure the performance of the Random Forest model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2}{N}}$$

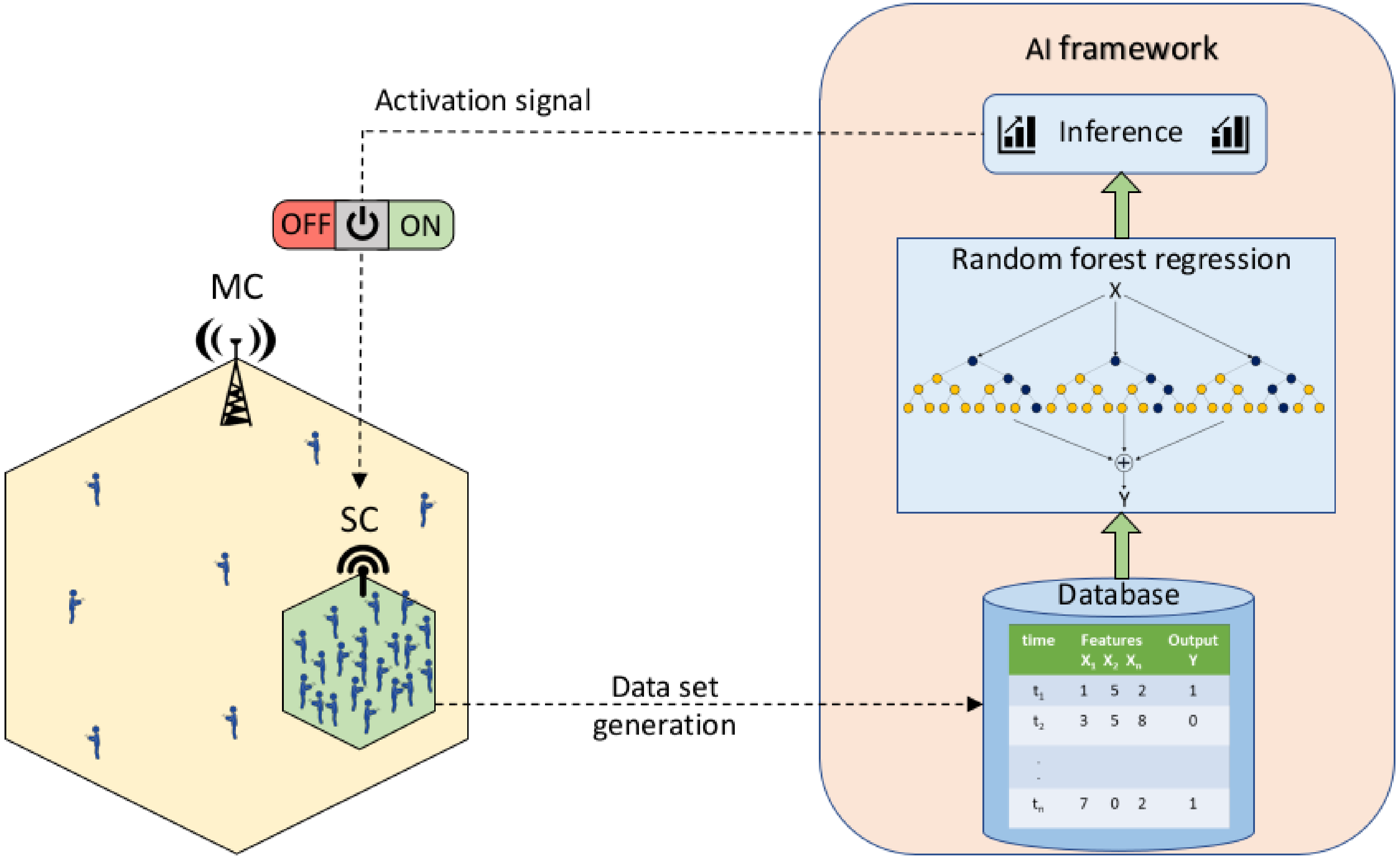
Hyperparameter Tuning: Grid search is used for performing hyperparameter tuning in order to determine the optimal values for given model.

Hyperparameters	**Value**
bootstrap	True
max_depth	70
max_features	auto
min_samples_split	10
n_estimators	200

Predictions from Random Forest

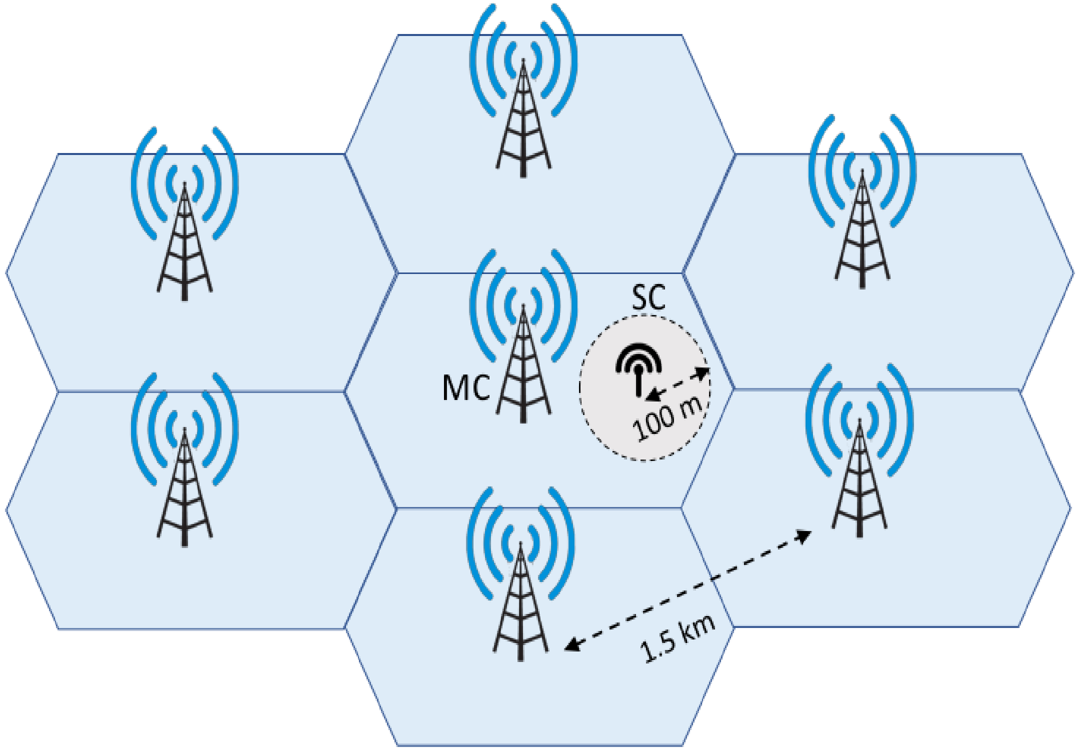


Model Architecture

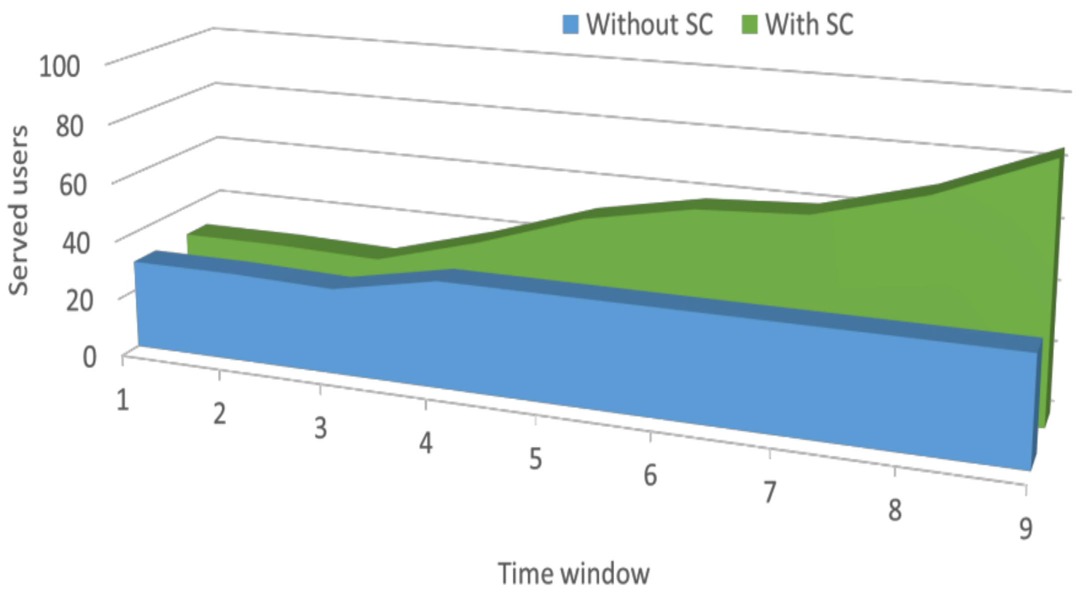


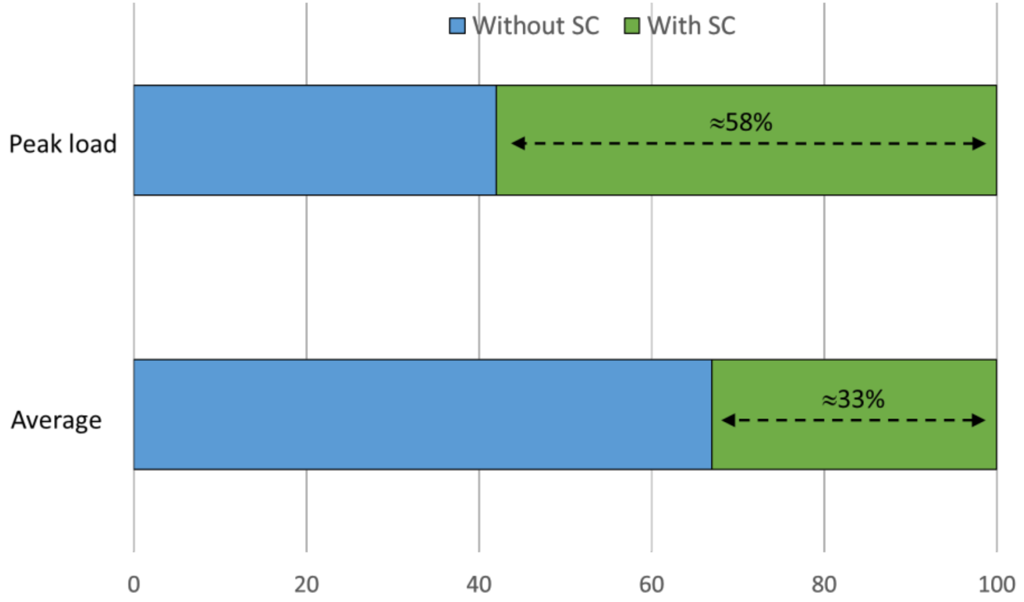
Simulation Setup

- Figure depicts the cellular setup considered in our simulations.
- A two-tier macro cellular layout is considered, and the cell in the centre (in blue) is the site of interest (Gym)
- Management of the small cell is controlled by Machine learning framework
- Simulation is carried out for time period of one day
- Small Cell(SC) is activated once the crowd density prediction value reaches threshold, activation of SC assists Main Cell in serving the excess users.



Results


Without SC
With SC
100
80
60
40
20
0
Served users
1
2
3
4
5
6
7
8
9
Time window


Without SC
With SC
Peak load
≈58%
Average
≈33%
0
20
40
60
80
100

Summary and future work

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➢Knowledge of upcoming crowd in a cell will be beneficial in designing smart RRM (in this work, smart activation of small cell)

➢Random Forest algorithm is investigated for their suitability in forecasting crowd density that a cell will experience in its near future

→ from a cellular network perspective

➢Simulation results shows 58 % improvement when small cell is switched on proactively.

Future work:

➢To look into similar user density data with continuous time stamps and associated user mobility information , which helps in predicting more dynamic variations in data traffic demand

Thank you for your attention.

Questions?