in collaboration with

# Towards holistic real-time operation optimization of district cooling systems

*presented by*
**Zhonglin Chiam**
*Ph.D. Student*

*Supervisors*
**Arvind Easwaran**
*Assoc. Professor*

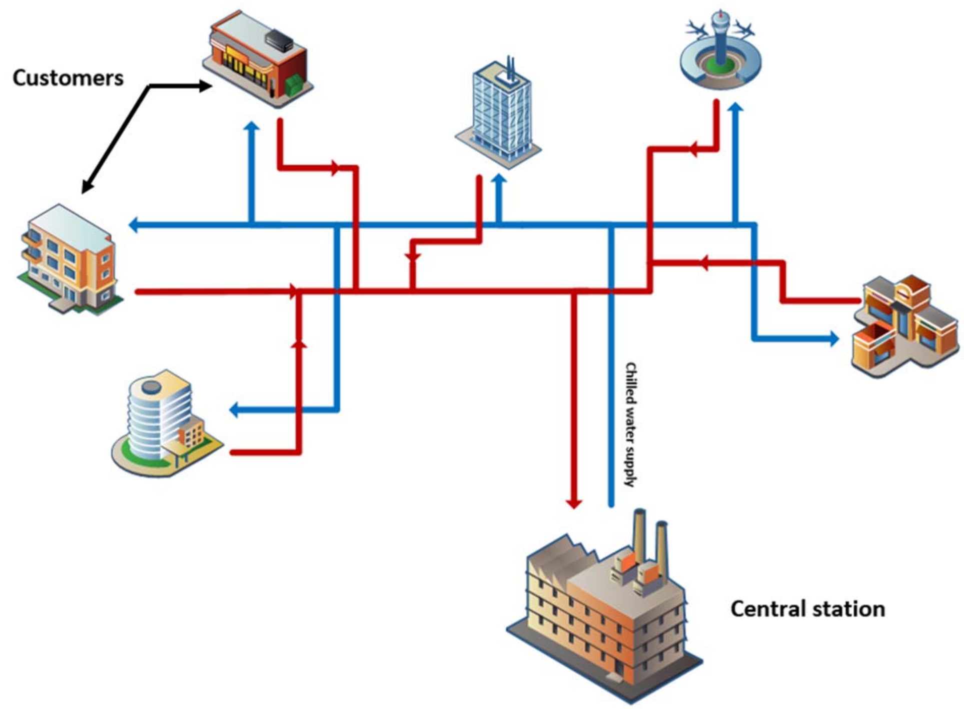
**Claude Guet**
*Professor*

*School of Computer Science & Engineering*
*Nanyang Technological University*

*Friday, 8th November 2019*

# What is a District Cooling System (DCS)?

- Context:
  - Space cooling – 60% of electricity consumption in buildings.
- DCS – centralization of cold energy production.
- Advantages:
  - Higher quality equipment.
  - Distribution infrastructure.
  - Demand aggregation.
  - Consumer savings.





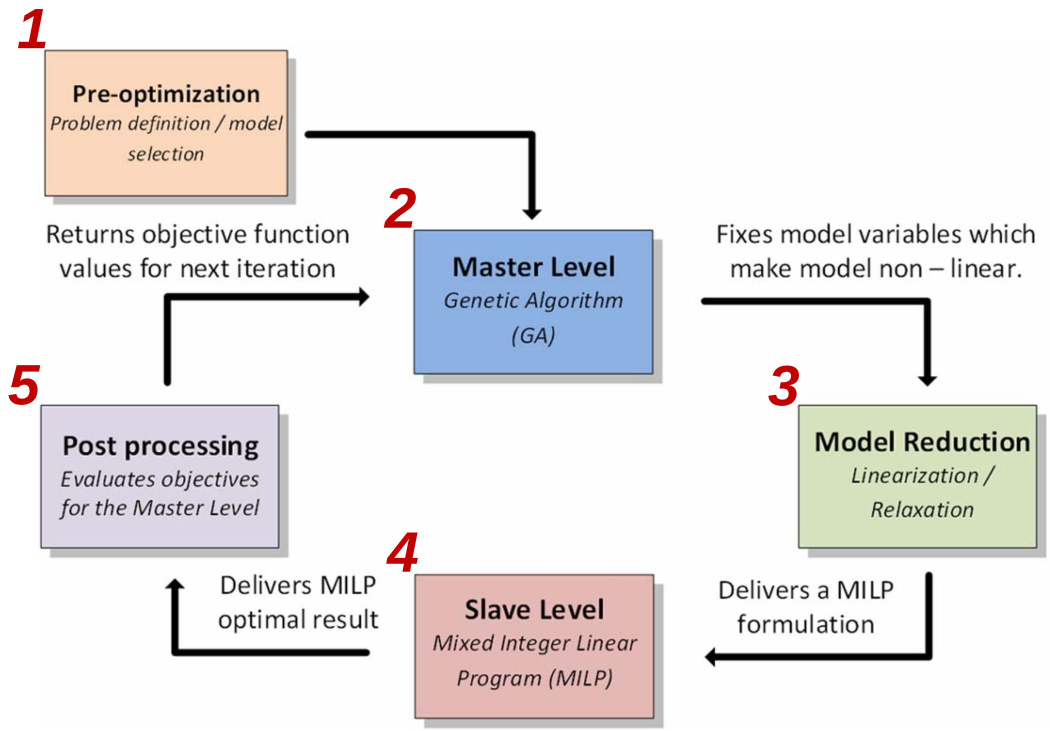

NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

# Research Motivation

- Issue:
  - Inefficiency caused by incongruency between design and operating conditions.
  - Compounded by rigid operating practices.
- Solution:
  - Optimization framework for DCS.
  - Steps:
    - Building component models.
    - Choosing optimization algorithms.
    - Model abstraction.

# DCS Optimization Framework

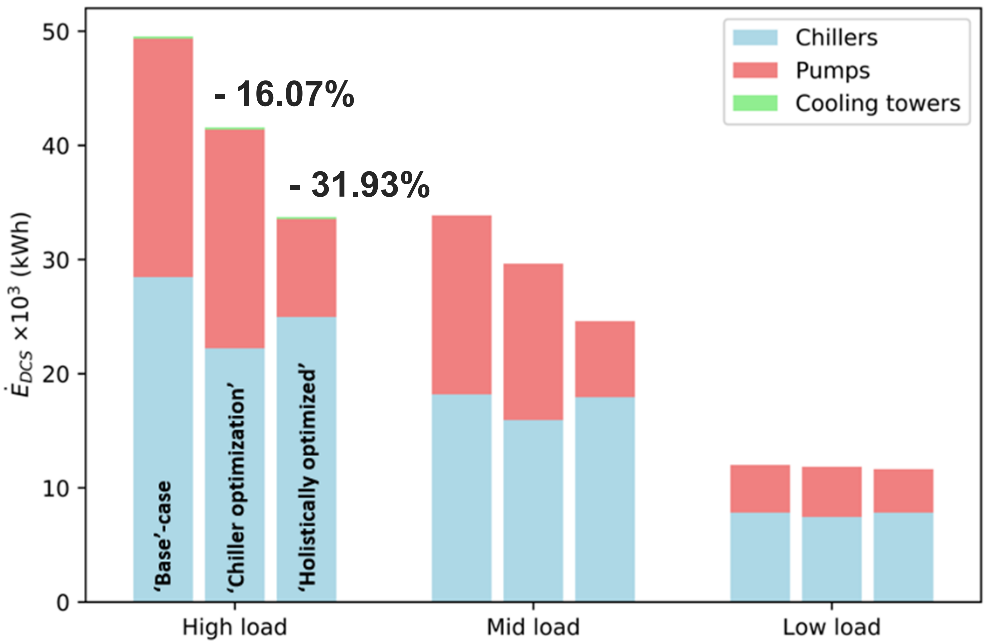
- Bi-level optimization approach (GA - MILP).
  - Complex problem.
  - Greater scalability.
  - Improved performance over pure usage of metaheuristics.




NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

# Importance of Holistic Optimization

- Not all components experienced a decrease in electricity consumed.
  - Pump savings were most significant.
  - Improved pressure regulation.
  - Overall lower flowrates.
- Component-level optimization is insufficient.





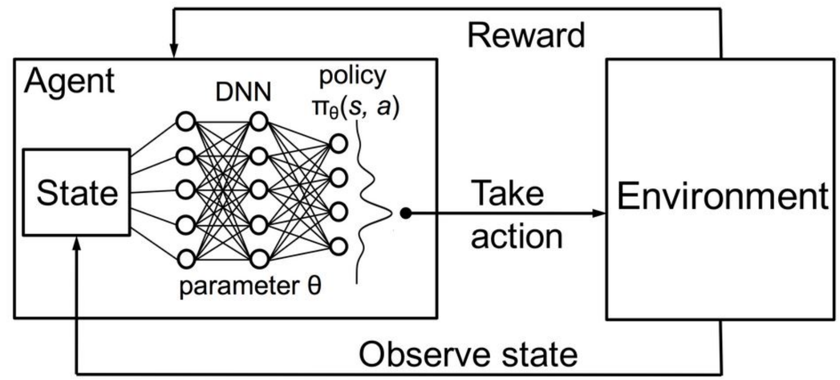

NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

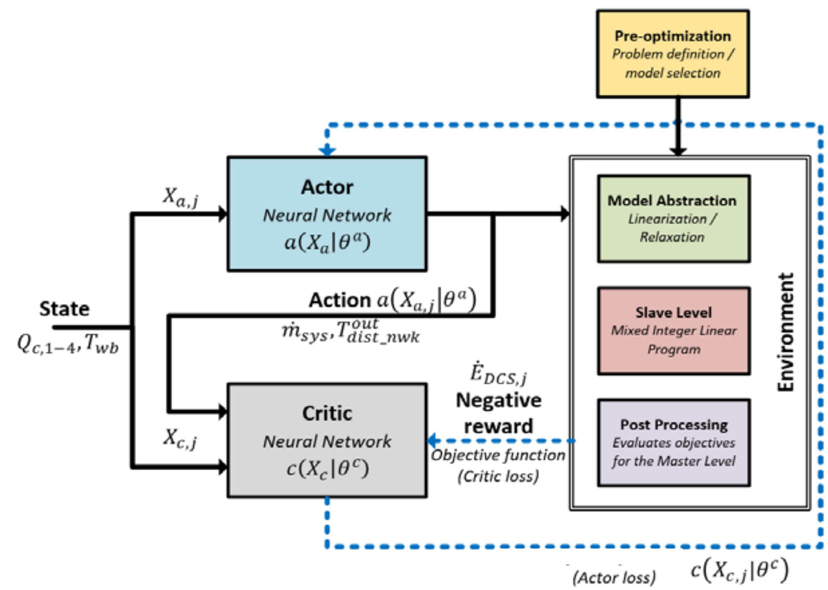
# Towards real-time optimization

- GA-MILP approach is slow.
  - Population-based metaheuristic.
  - Not suitable for real-time use.
- Replace GA with a reinforcement learner (RL).
  - Training takes place ‘offline’.
  - Only 1 iteration of the MILP is needed when the model is trained.

# Reinforcement learning

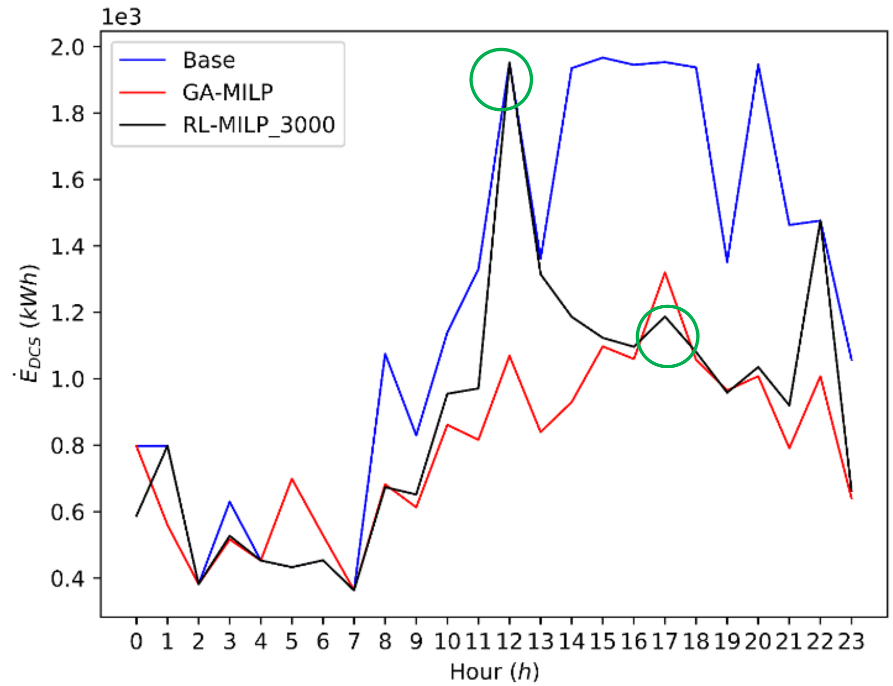
- Generic machine learning framework
  - Agent takes actions
  - Environment gives out rewards
  - Agents update themselves to achieve better rewards.
- Successful deployment for games (Atari, Go, etc.) and image recognition.



# RL-MILP results

- RL-MILP achieved 84% of the savings by the GA-MILP approach.
- At times it performs…
  - Better (local search)
  - Worst (local trap)
- Resolution time improvement:
  - 1 vs 15000 iterations.




| *Episodes* | *Percentage difference (Base)* | *Percentage difference (GA-MILP)* |
|---|---|---|
| 1000 | -3.92 | 46.38 |
| 2000 | -23.68 | 16.27 |
| 3000 | -26.84 | 11.45 |
| 4000 | -22.55 | 18.00 |

*Table 2: Comparison of difference in $\dot{E}_{DCS}$ $(kWh)$ between the base-case and MILP-GA approach over*



NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

# Conclusion

- RL-MILP approach for holistic real-time optimization of DCS operation
  - Shifts heavy computation offline.
  - Close to optimum results available almost instantly.
  - Sacrifice only 26% of savings for huge improvement in resolution speed.
  - Able to update it self using new data traces.

# Future work

- Improve training results
  - Ensemble learning
- Scalability of the framework
  - More features, storage, etc.
- Accounting for stochasticity in demand.

# Thank you for your kind attention!




NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE