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Networks and Swarms: The Machine Learning Use Case for Energy Optimisation

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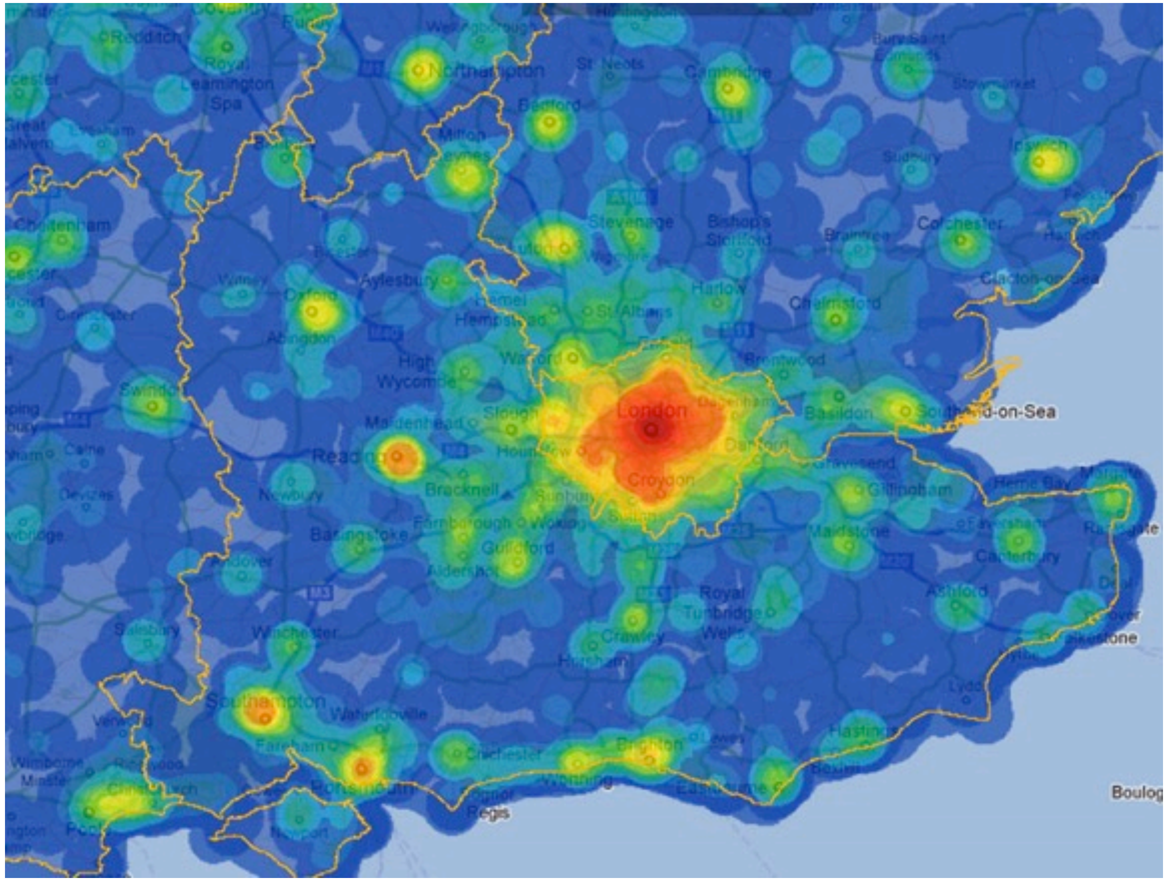
Energy generation and consumption

- Timing of electricity consumption has massive economic and environmental impact.
- The temporal variation in energy generation and consumption can be significant.
- High consumption means generating electricity using expensive & inefficient peaking plants.
- Low consumption leads to over abundance and negative pricing
- Energy grid stability requires a constant balance between generation and consumption.

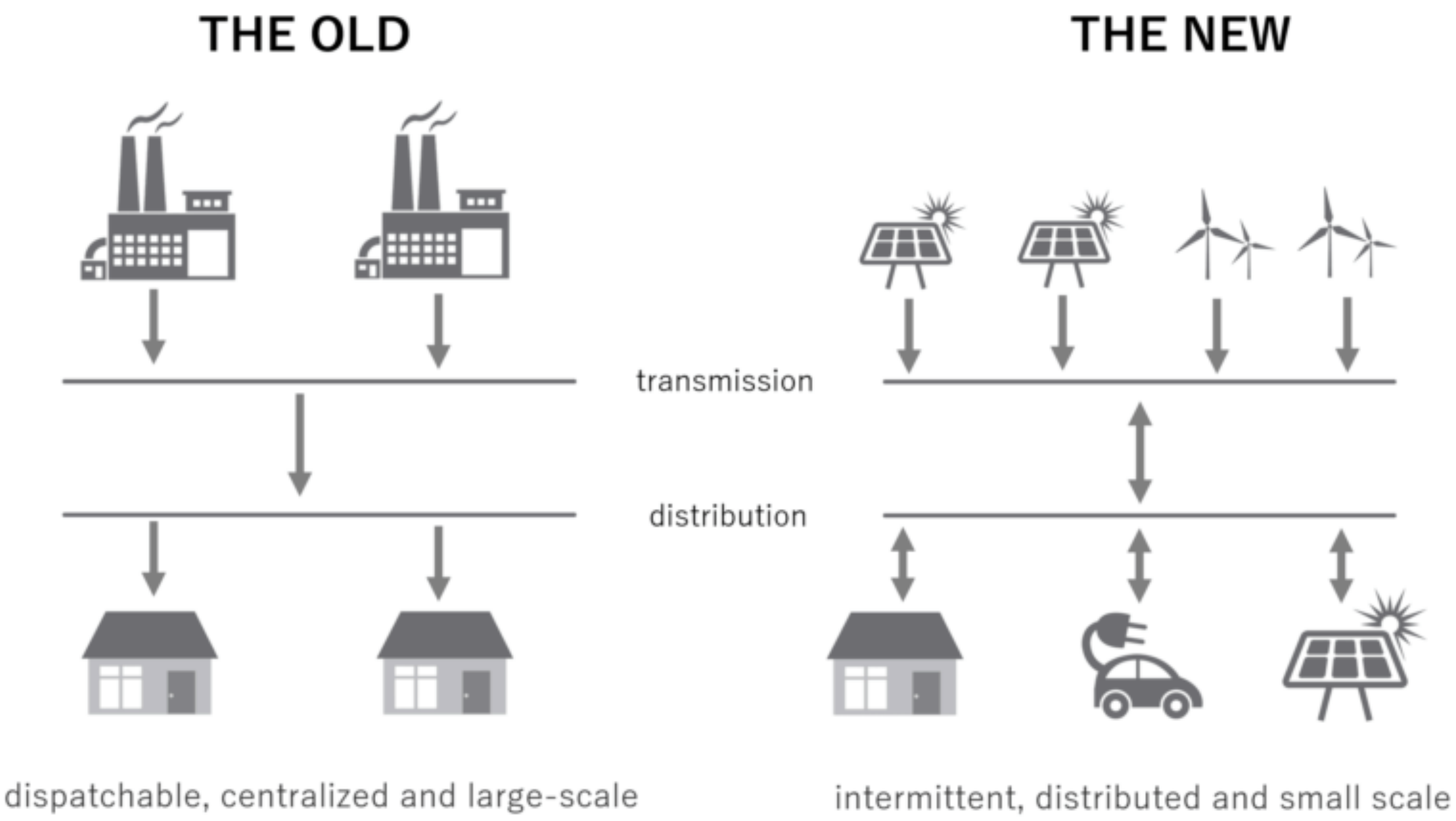
Three challenges: When, where, and how much?

- A demand forecasting and resource allocation optimisation problem:
  - Forecasting demand and supply at point locations
  - Mapping of forecast total demand and supply spatially
  - Optimally allocating energy resources
  - Predicting and optimising pricing
- Having the right amount, in the right place, at the right time!



Complexity of moving to a greener, distributed energy economy

- Intermittent generation is by nature hard to forecast.
- Wind turbine power generation depends on forecasting wind speeds over vast areas.
- Solar power is more predictable but can still see variation as cloud cover changes.
- Greener, distributed energy systems will be harder to model and less predictable



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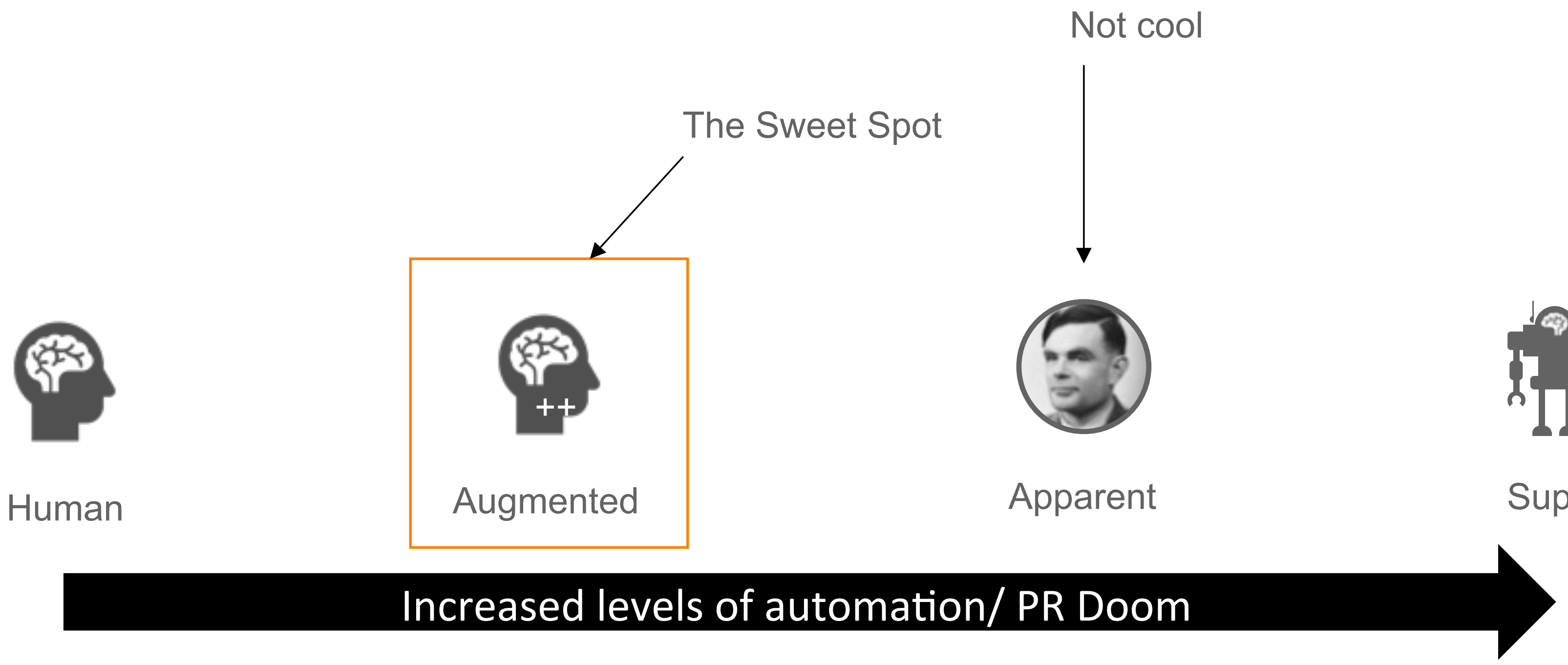
What is the advantage of machine learning in energy systems?

- Accurate models of physical phenomena are complex to formulate
- Can be extremely expensive to solve.
- Deterministic rules cannot guarantee optimality.
- Abstract models are limited by the skill of the modeler

- Assumptions are relaxed and models defined through a data first approach
- Predictions based on 'experience' and training, rather than on explicitly coded rules
- Machine learning models can be retrained quickly
- Machine learning models allow adaptive responses to highly complex inputs in near real time
- Compliment physical models

What about the humans?



The stated goal for applying ML into the energy industry should be to:

“Enable and augment humans in their ability to take accurate decisions in an increasingly dynamic and complex technological society, existing in a complex physical world”

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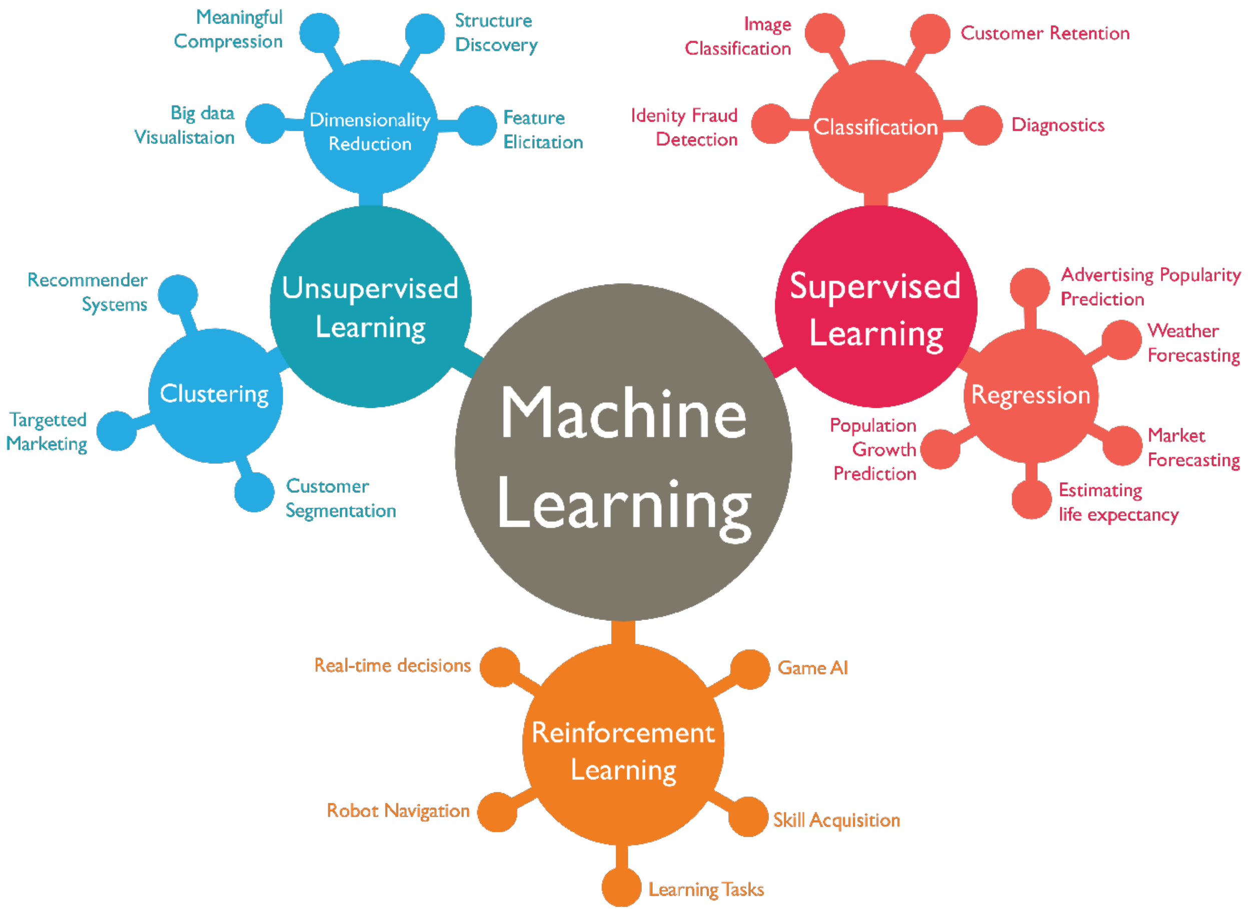
General application of machine learning to energy

- Regression models - forecast energy generation, consumption and price.
- Classification - forecast the probability of a spike in energy prices.
- Reinforcement learning and swarm intelligence - intelligent control of systems and resource allocation



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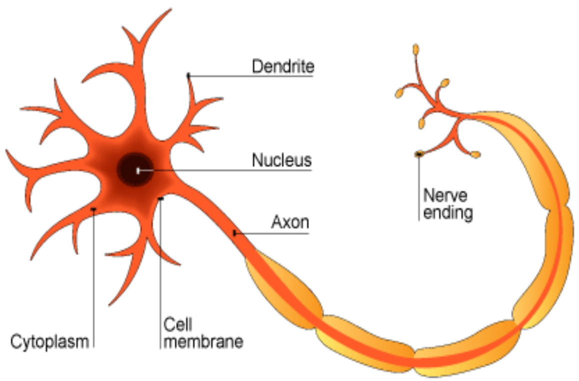
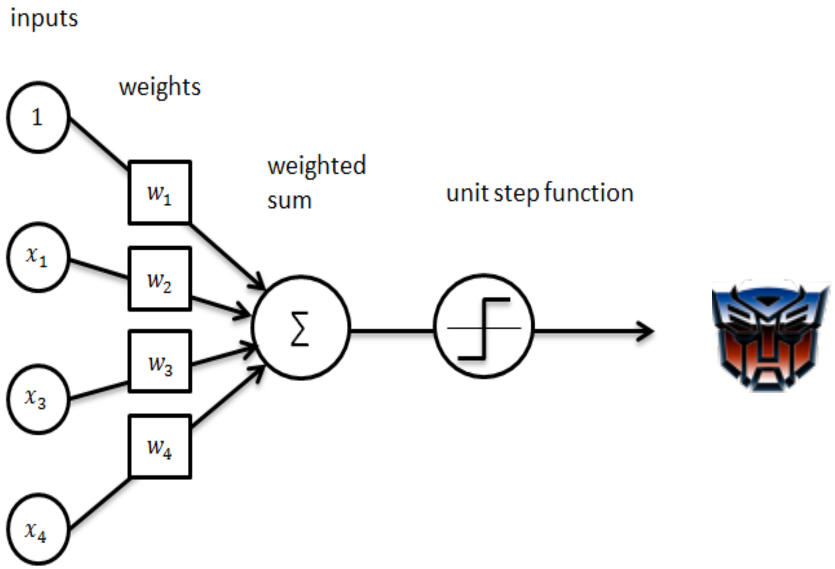
Machine learning inspired from nature: Neural networks

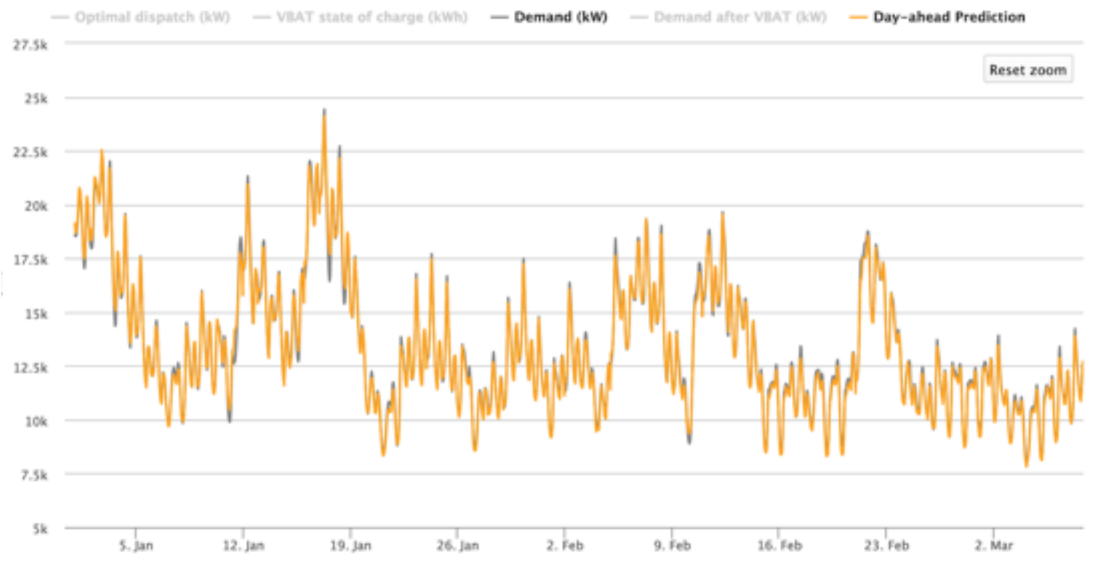
- Many types of network, originally inspired from the structure of neurones
- Developed shortly after breakthroughs in neuroscience
- Earliest was the perceptron… No, not a transformer
- Latest developments: LSTM – Long Short Term Memory

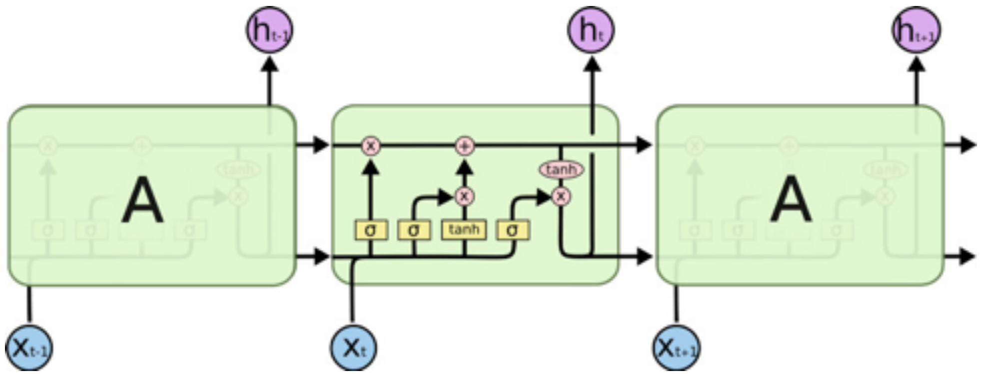




Machine learning inspired from nature: Neural networks

- Complex architecture
- RNN and LSTM very good at time ordered data due to recurrent elements and not being memory-less
- Resolve complex non-linearities well
- Best in class accuracy
- Easily accessible through frameworks such as TensorFlow



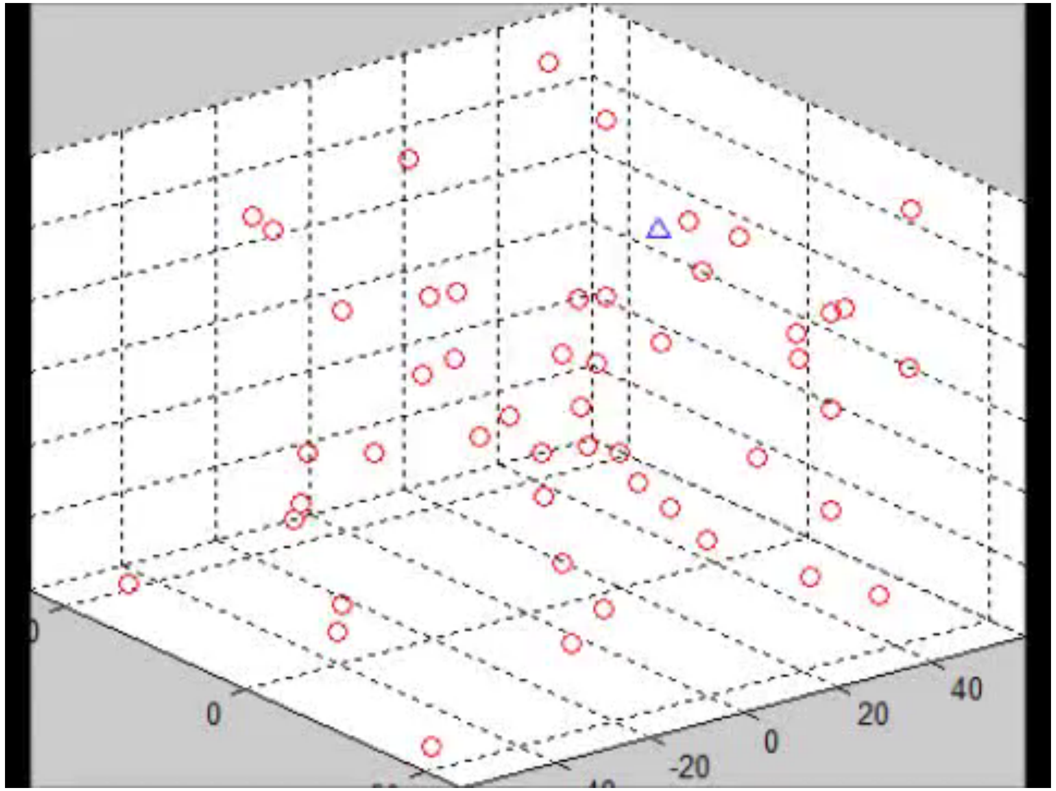


Machine learning inspired from nature: Swarm optimisation

- Particle, Bee, Ant
- Inspired by study of collective intelligence in animal swarms
- Swarm intelligence – collective memory of the group
- Mathematically defined particles locate global maxima or minima of a function
- Can be used to optimise resource allocation and scheduling problems

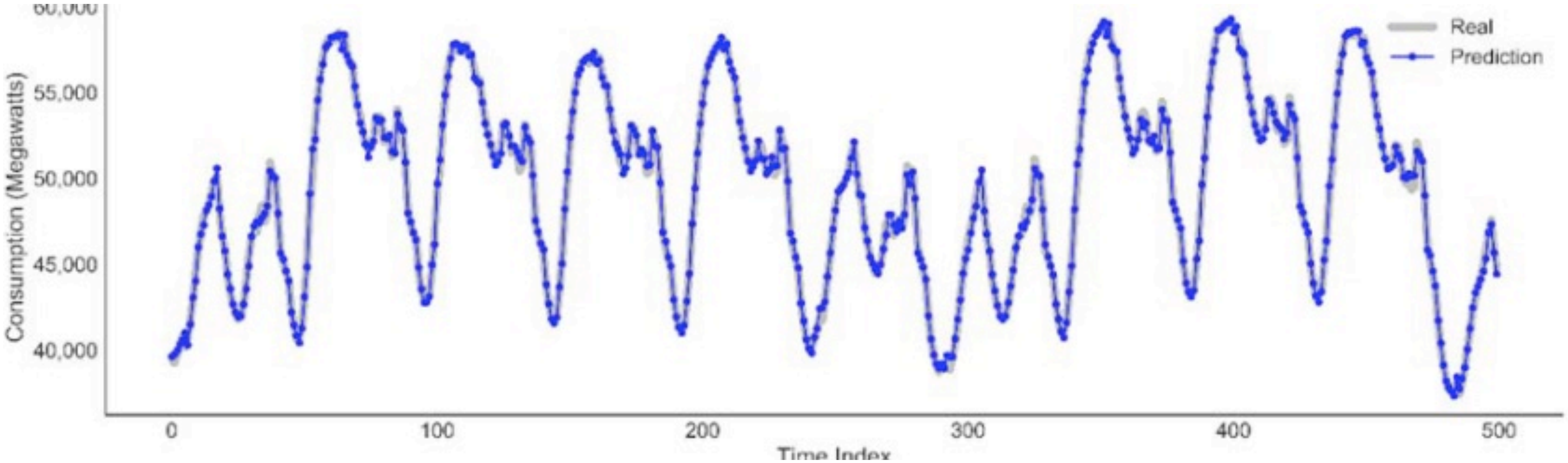
Swarms adapt to changing conditions and find new optima

- As in nature, as conditions change, swarms adapt to new optima through collective intelligence
- As forecasts of supply and demand change, swarm intelligence allows us to intelligently and dynamically allocate resources optimally across an energy network



Case study 1: Networks for predicting consumption

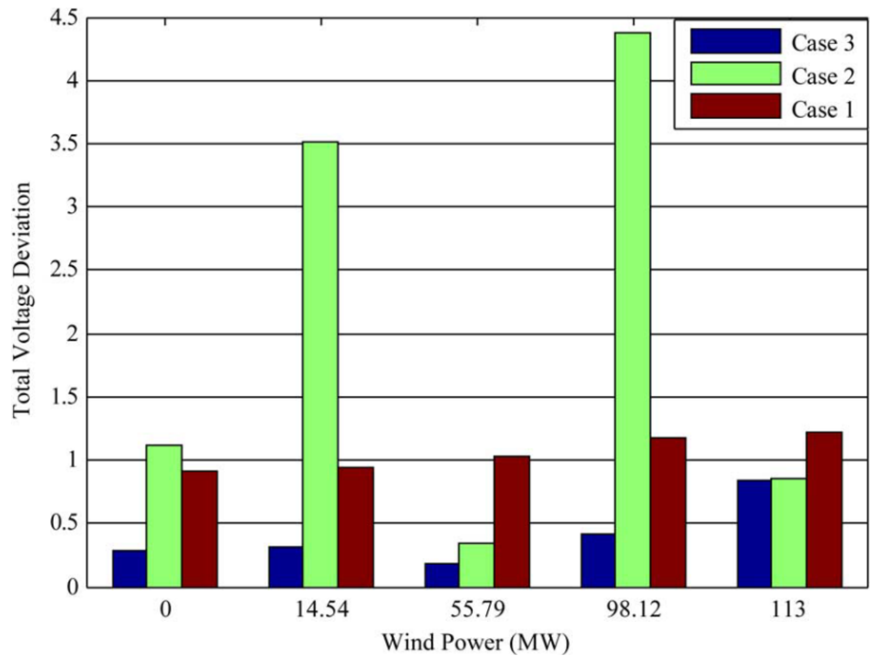
- Compared LSTM to other 'traditional algorithm types' for load forecasting
- France Energy metropolitan data
- Forecasting on a 2 week daily horizon
- 0.6% mean error in predicted consumption



Bouktif et al., 2018: Energies, 11, 1636

Case study 2: Swarms for allocating energy storage systems

- ESS improve power cost and voltage profile
- Improper placement increase cost and stability risk
- PSO used to search for optimal placement and sizing of ESS in a wind power system
- Using PSO tested against the IEEE 30-bus benchmark
- Considers the entire wind power distribution, unlike most other methods
- $606,528/year saving in operational cost
- Minimised voltage deviation



Wen et al., 2015: IEEE Transactions on Power Systems: 30 (2) 644 - 652

Thank you for listening

Please visit www.t-dab.com

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