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A distributed In-Transit Processing Infrastructure for Forecasting Electric Vehicle Charging Demand

DPMSS'13 Delft

2nd International Worshop on Data-intensive Process Management in Large-Scale Sensor Systems: From Sensor Networks to Sensor Clouds

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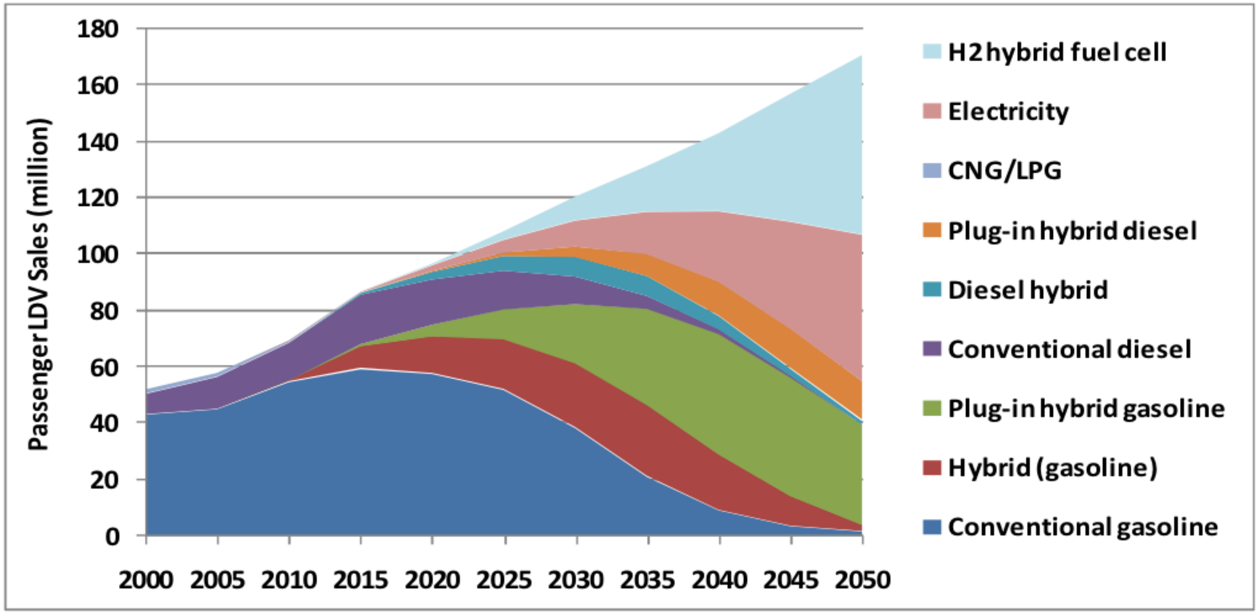
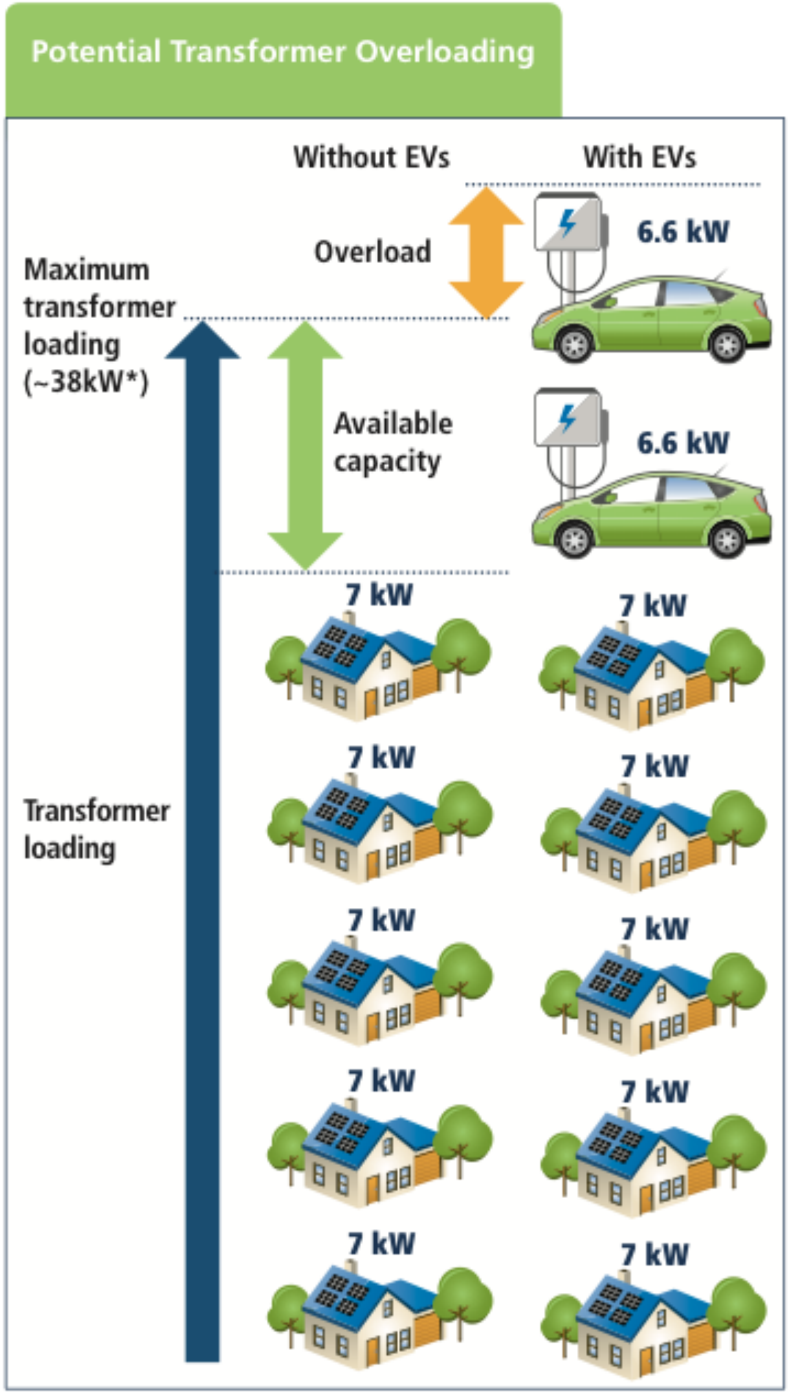
Motivation

- 72% of global oil demand correspond to transportation.
- Economic, security, and environmental pressures to electrify transportation



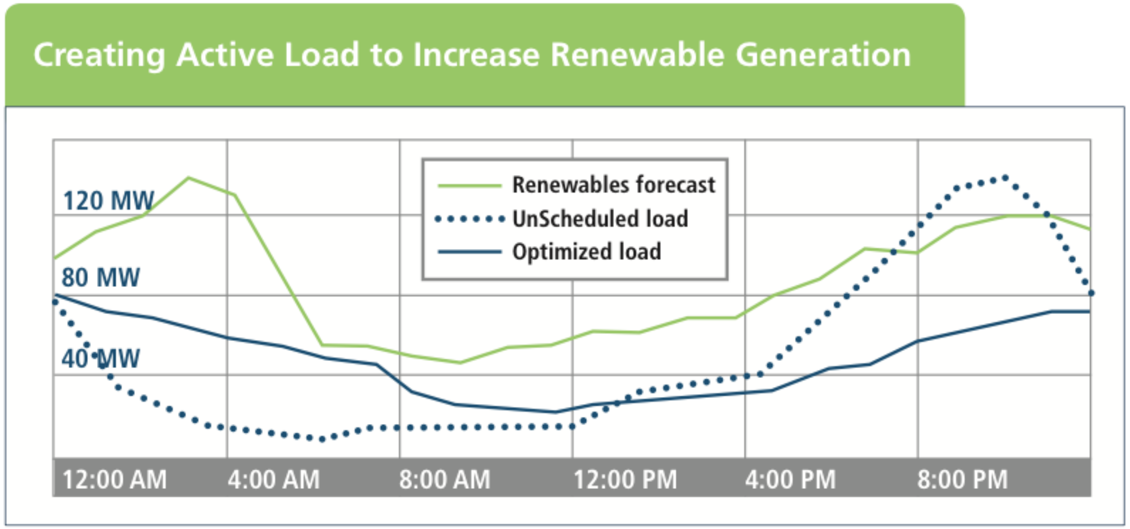
Impact on the grid

- A single EV plugged into a fast charger can double a home's peak electricity demand.
- Most serious concern utilities have is controlling when EV load is applied to their grid.
  - Most consumers will charge when they get home from work
  - Just one or two active (L2) charger could overload a transformer, creating reliability problems in 40% of US distribution transformers.

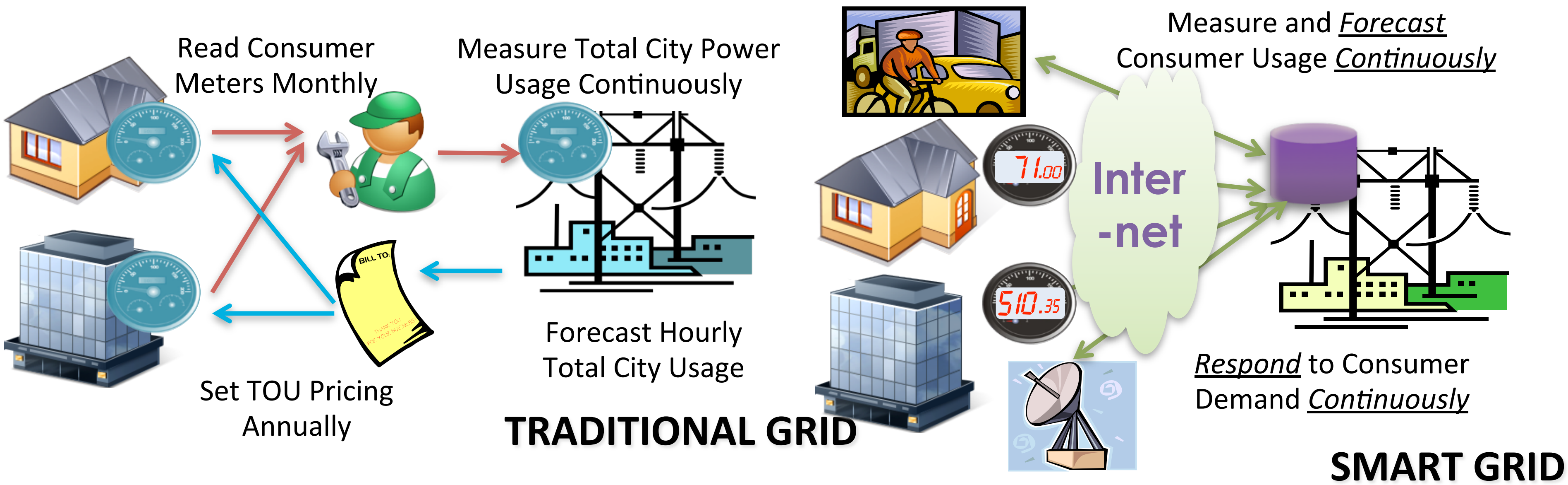


Utility Challenges

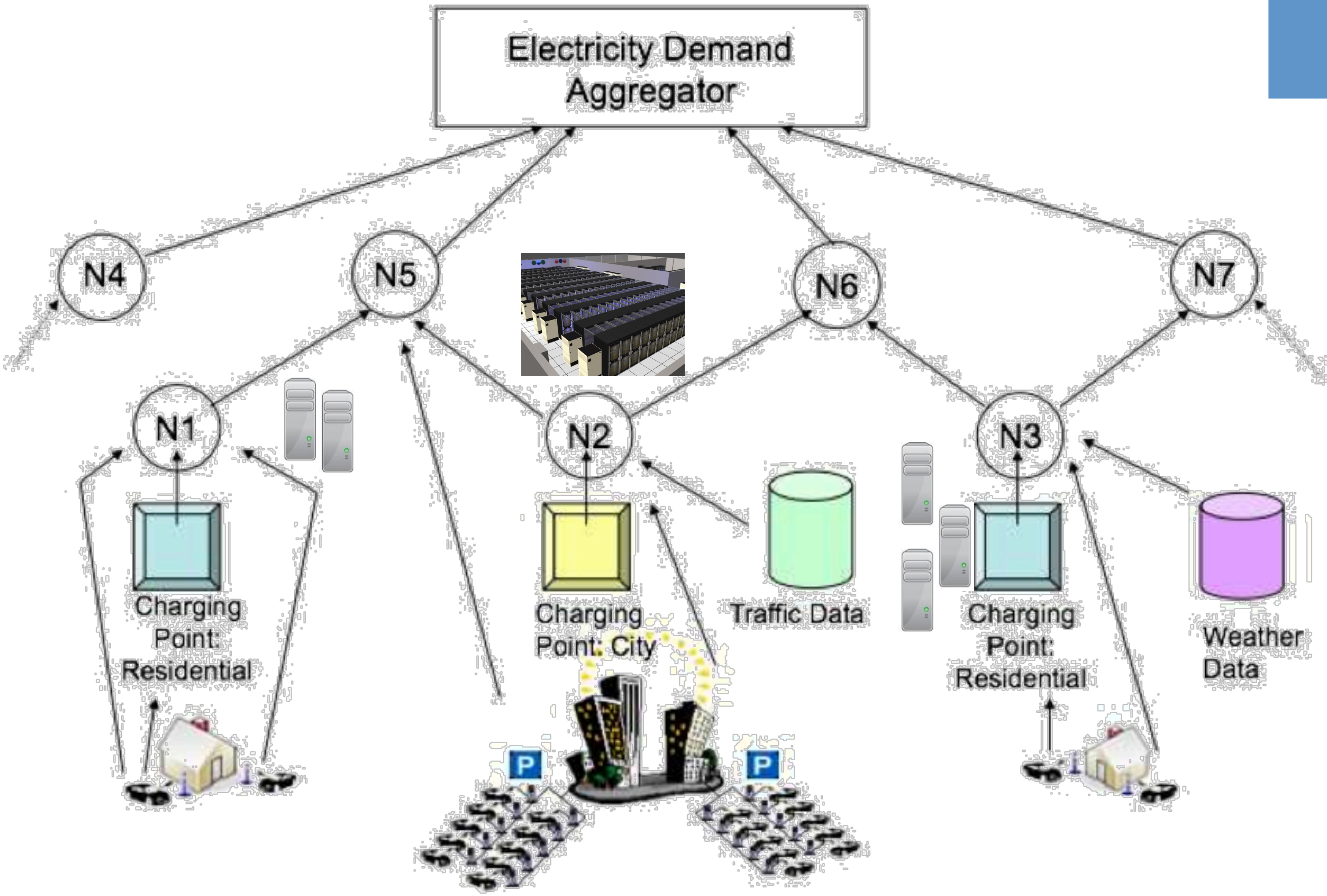
- Utilities can mitigate the impact of charging stations on the grid
  - Distributing charging requirements over time, utilities can maximize the utilization of their infrastructure
  - Leverage EVSE communication investment for other energy initiatives.



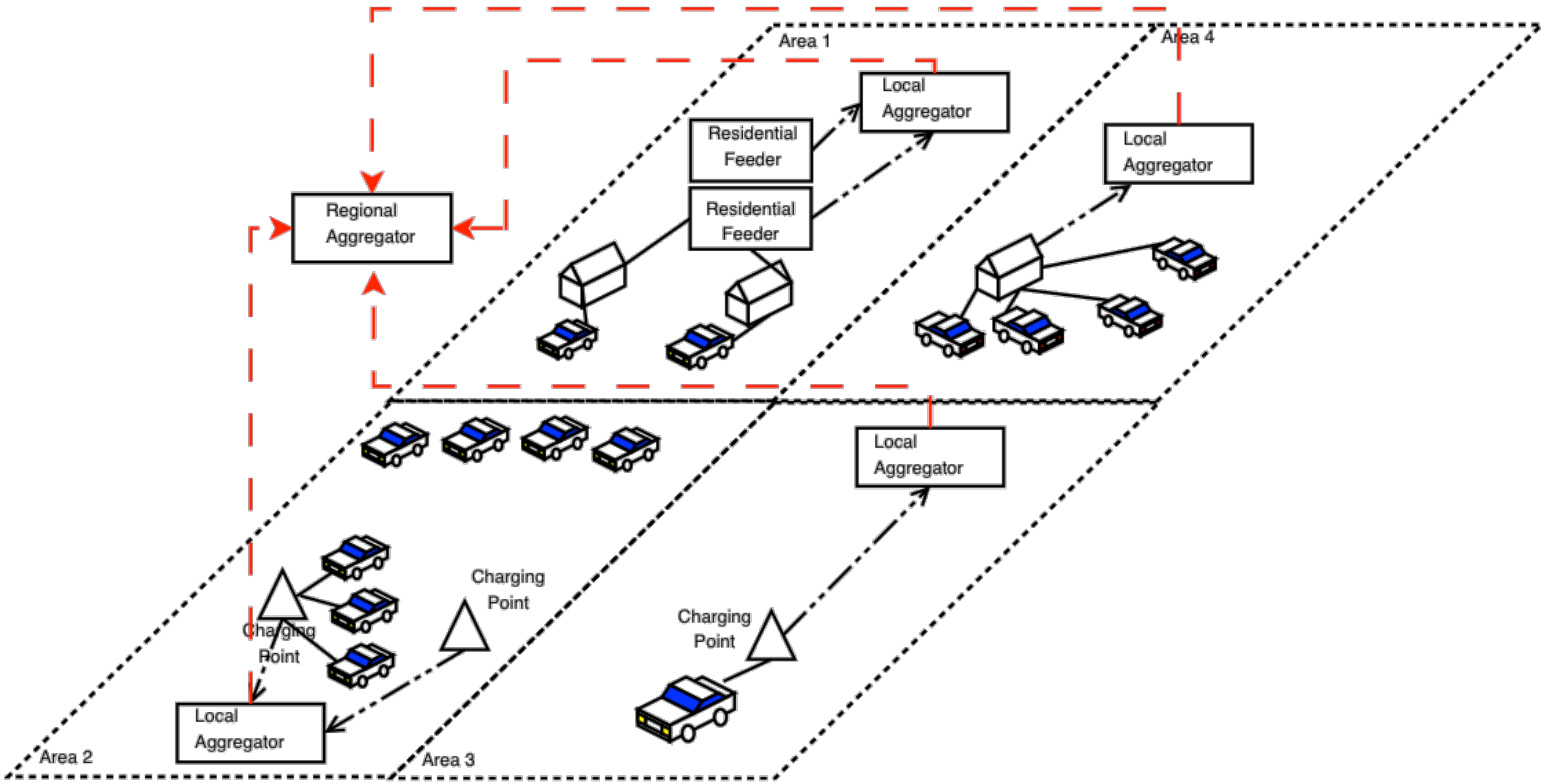
Transition to a *Smart* Grid



- **Smart meters**
  - Bi-directional, realtime communication between utility & consumer

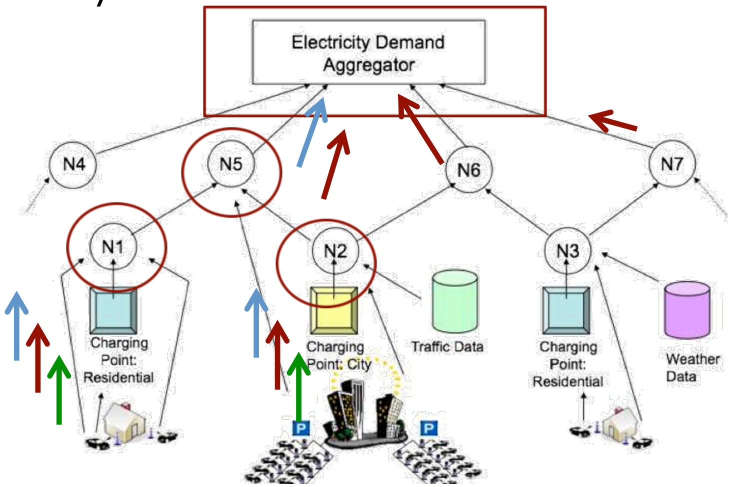

Electricity Demand Aggregator
N4
N5
N6
N7
N1
N2
N3
Charging Point: Residential
Charging Point: City
Traffic Data
Charging Point: Residential
Weather Data
P
P

Hierarchical Division



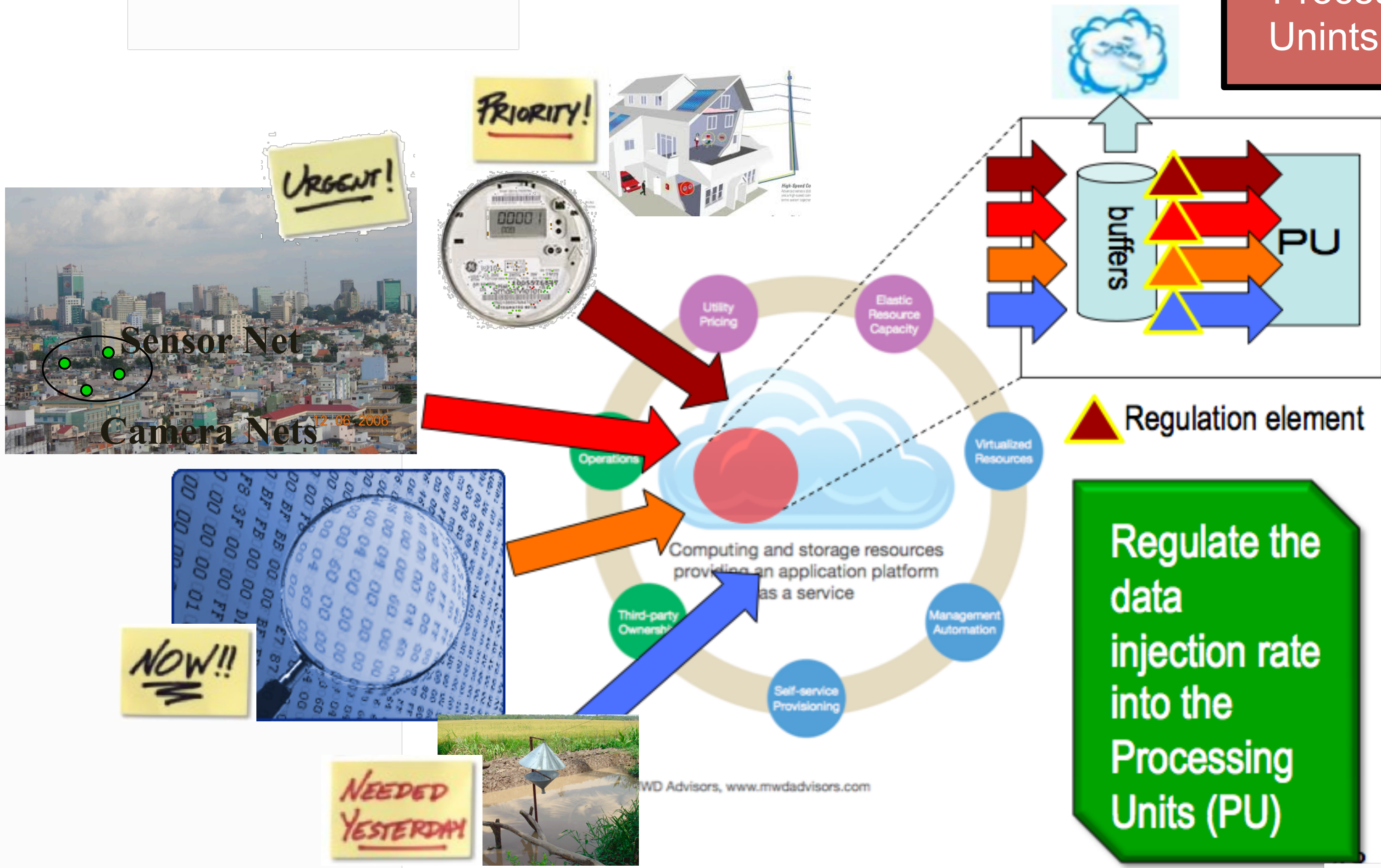
Data management and computation requirements

- **Handling concurrent heterogeneous data streams**: Different rate, frequency and sample size. For example: vehicle and charging point data, weather and traffic agencies, etc.
- **Different** data stream **relevance**, with **behaviour** of varying complexity, different computational complexity.
- **Different Quality of Service (QoS)** constraints to limit data loss and latency.
- **Sharing computational** resources in a elastic way in each node

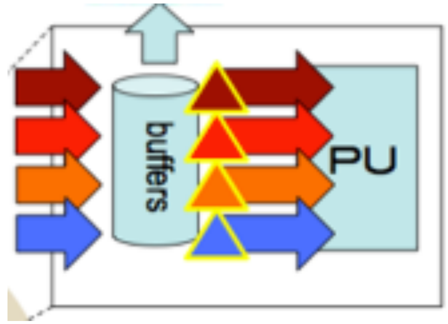


QoS on Clouds: General Picture

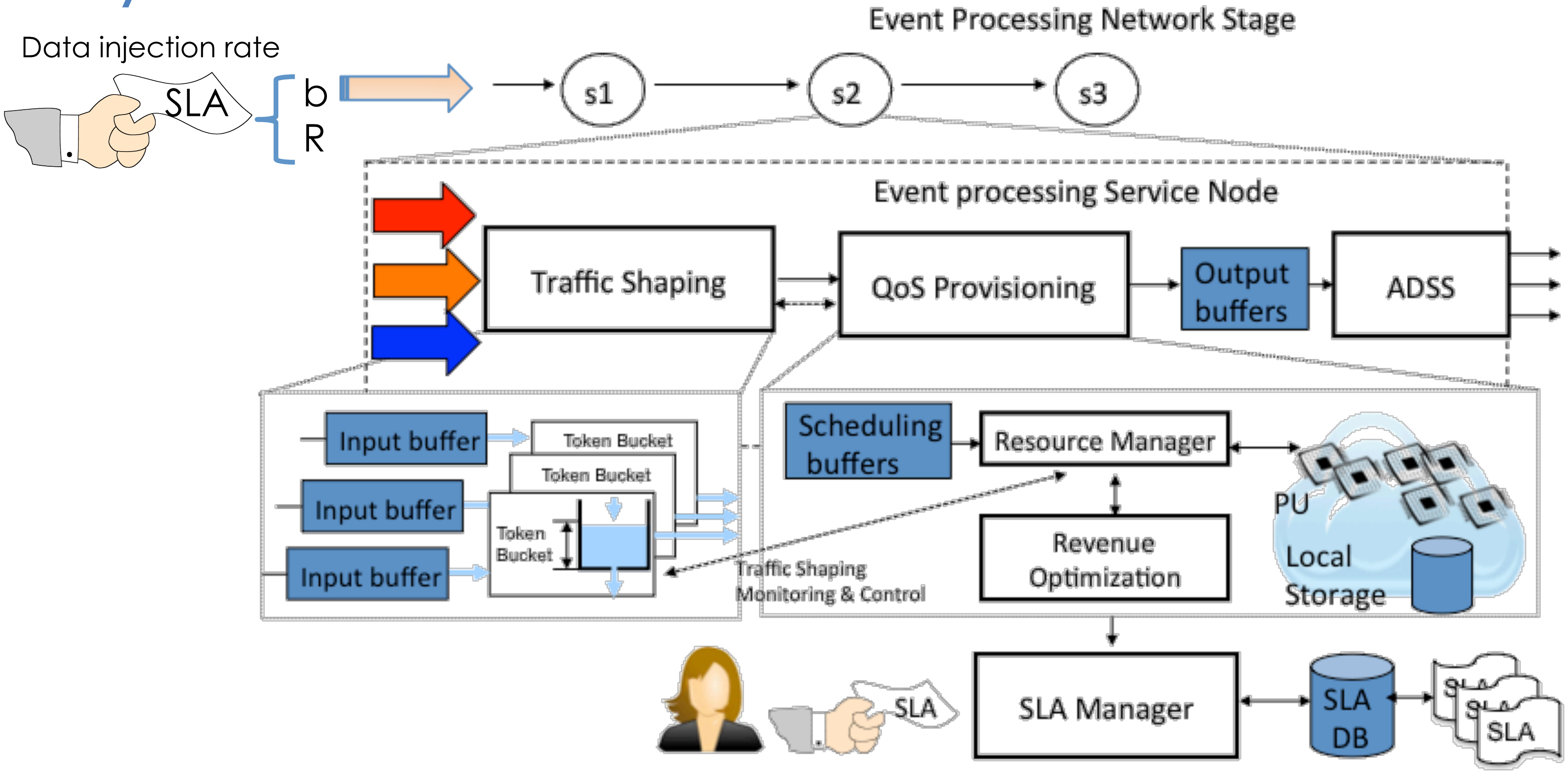
Regulate the number of Processing Unints (PU)



Regulate the data injection rate into the Processing Units (PU)



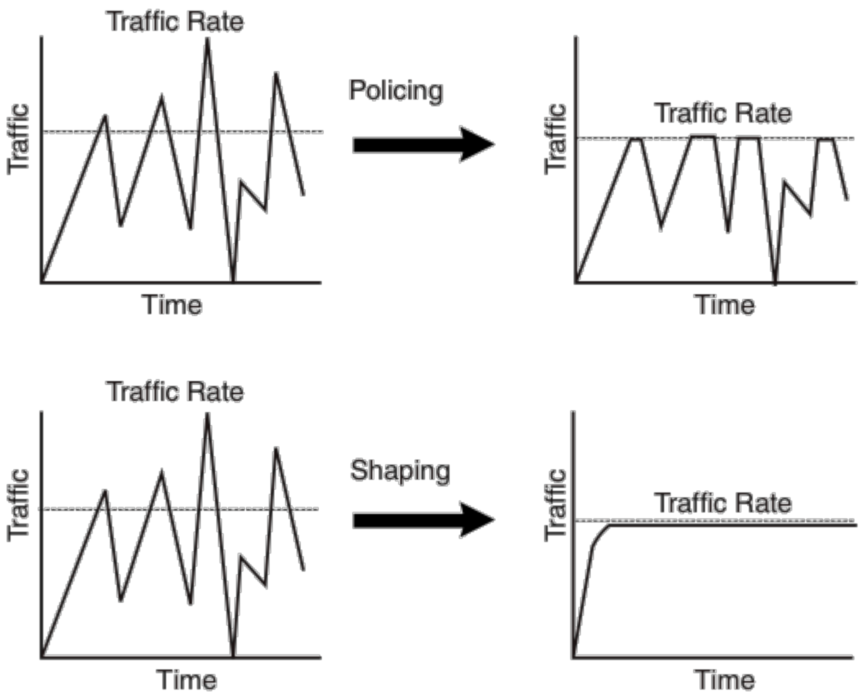
System Architecture



- 3 key components / node: Token Bucket, Processing Unit & output streaming

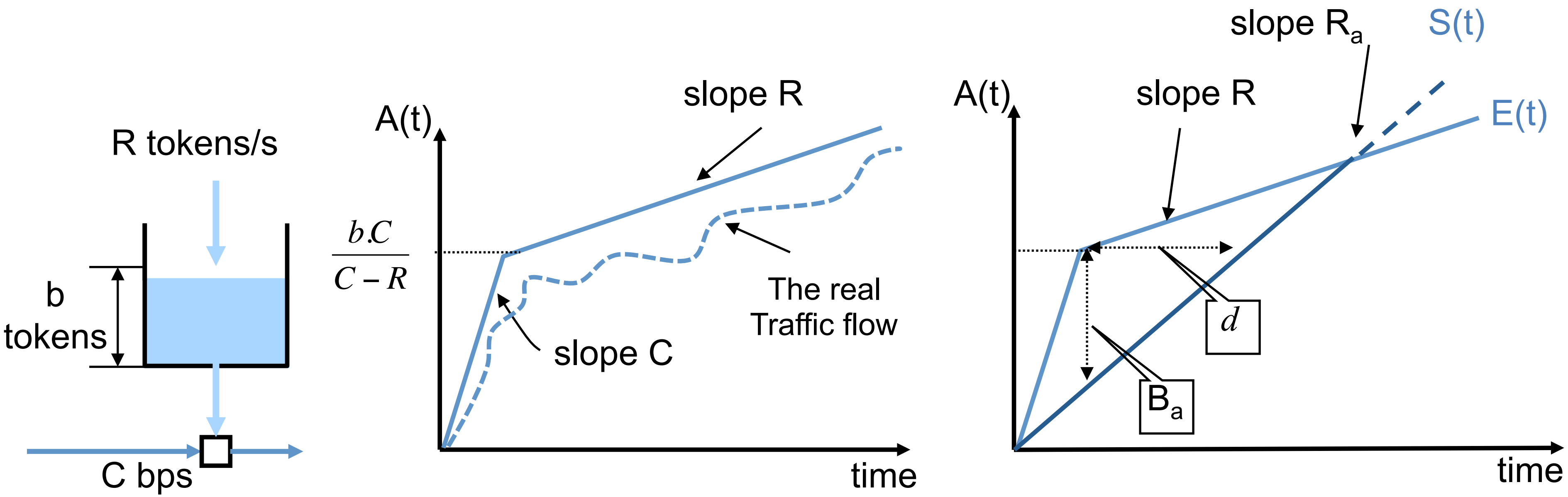
Token Bucket (shaping traffic)

Traffic shaping component allows **to control the traffic** going out this component in order **to match** its **flow** to the processing speed of **available resources** and to ensure that the traffic conforms to policies contracted for it



- A **policer** typically drops excess traffic.
- A **shaper** typically delays excess traffic using a buffer to hold data and shape the flow when the data rate of the source is higher than expected.

Token Bucket (shaping traffic)

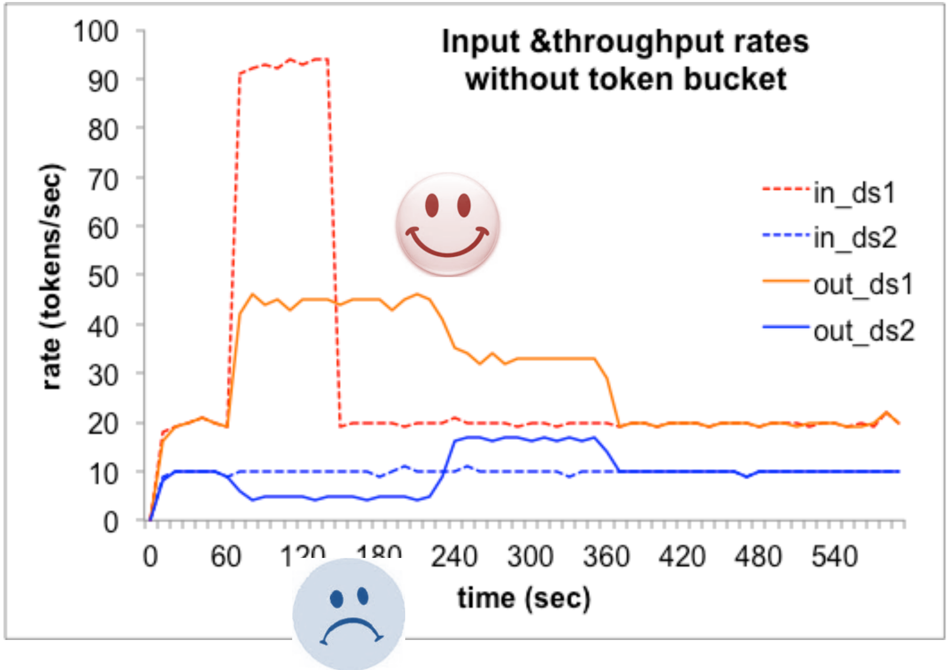


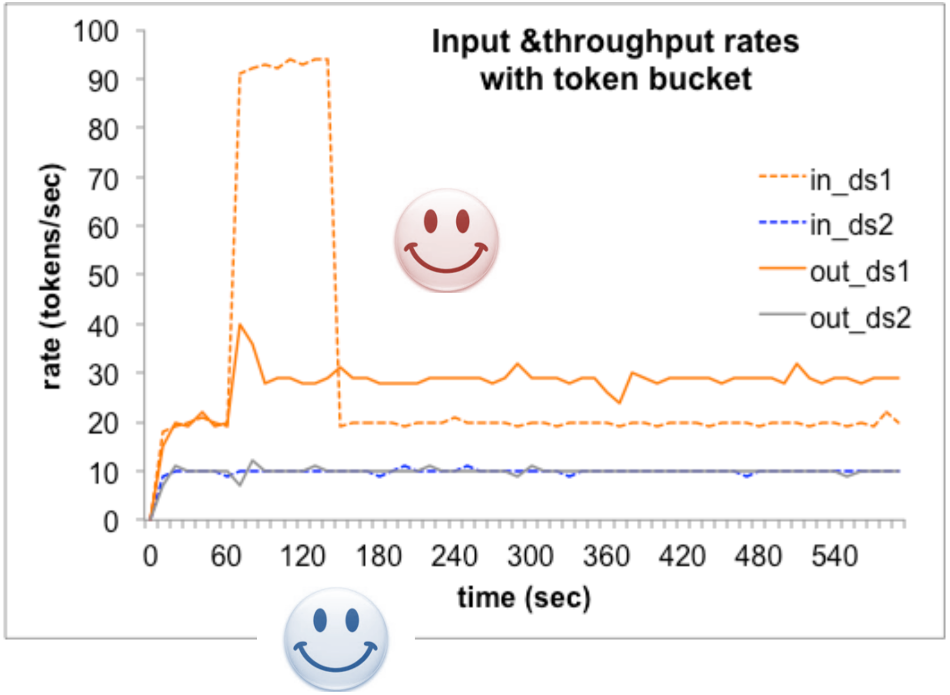
A(t): Amount of data arriving up to time t

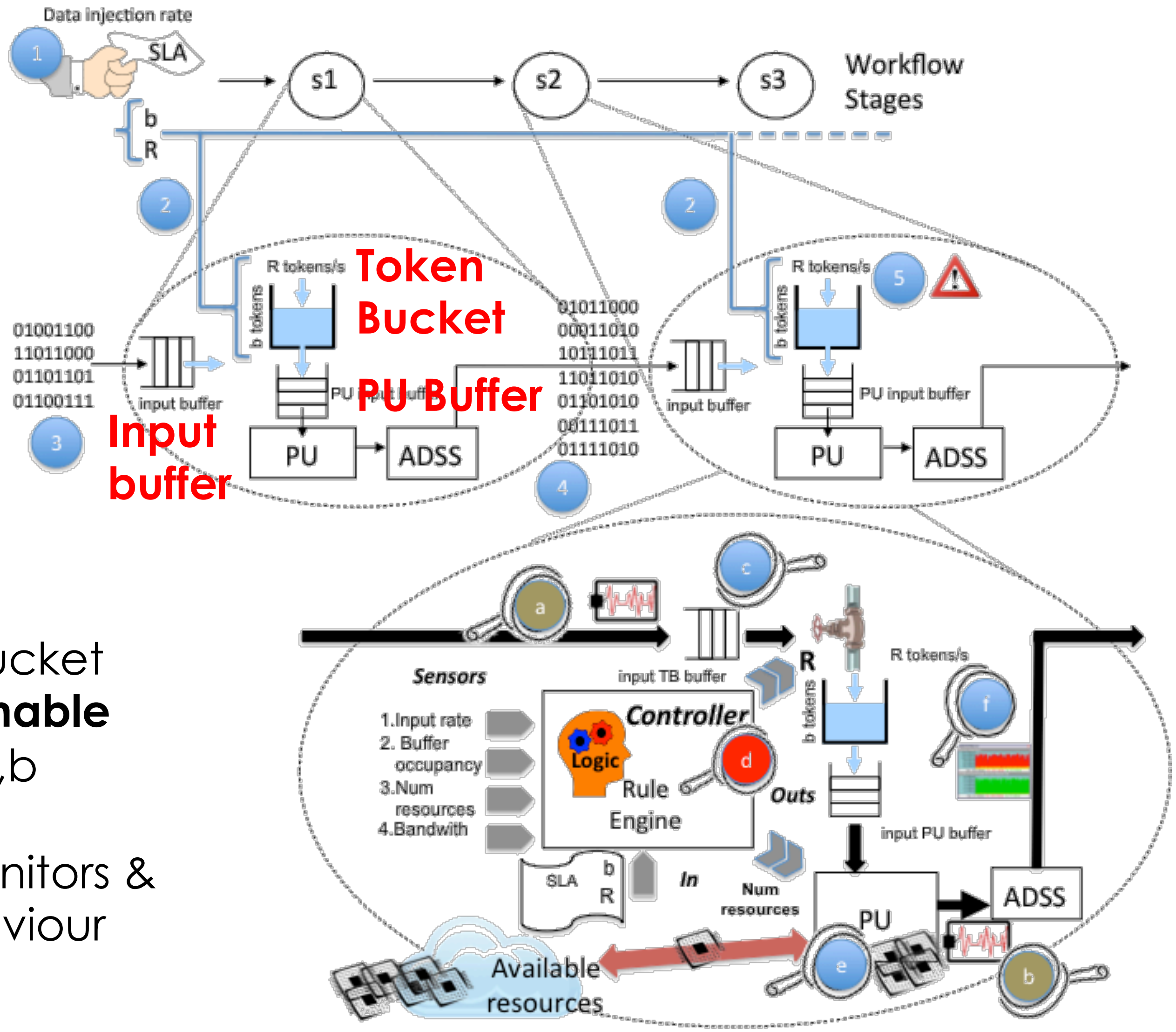
Two key parameters of interest:

- **R**: Also called the **committed information rate** (CIR), it specifies how much data can be sent or forwarded per unit time on average
- **B**: it specifies **for each burst how much data can be sent** within a given time without creating scheduling concerns

Token Bucket (shaping traffic)







Each token bucket provides us **tunable** parameters: R,b

Controller: monitors & modifies behaviour

Control for Elastic SLA definitions

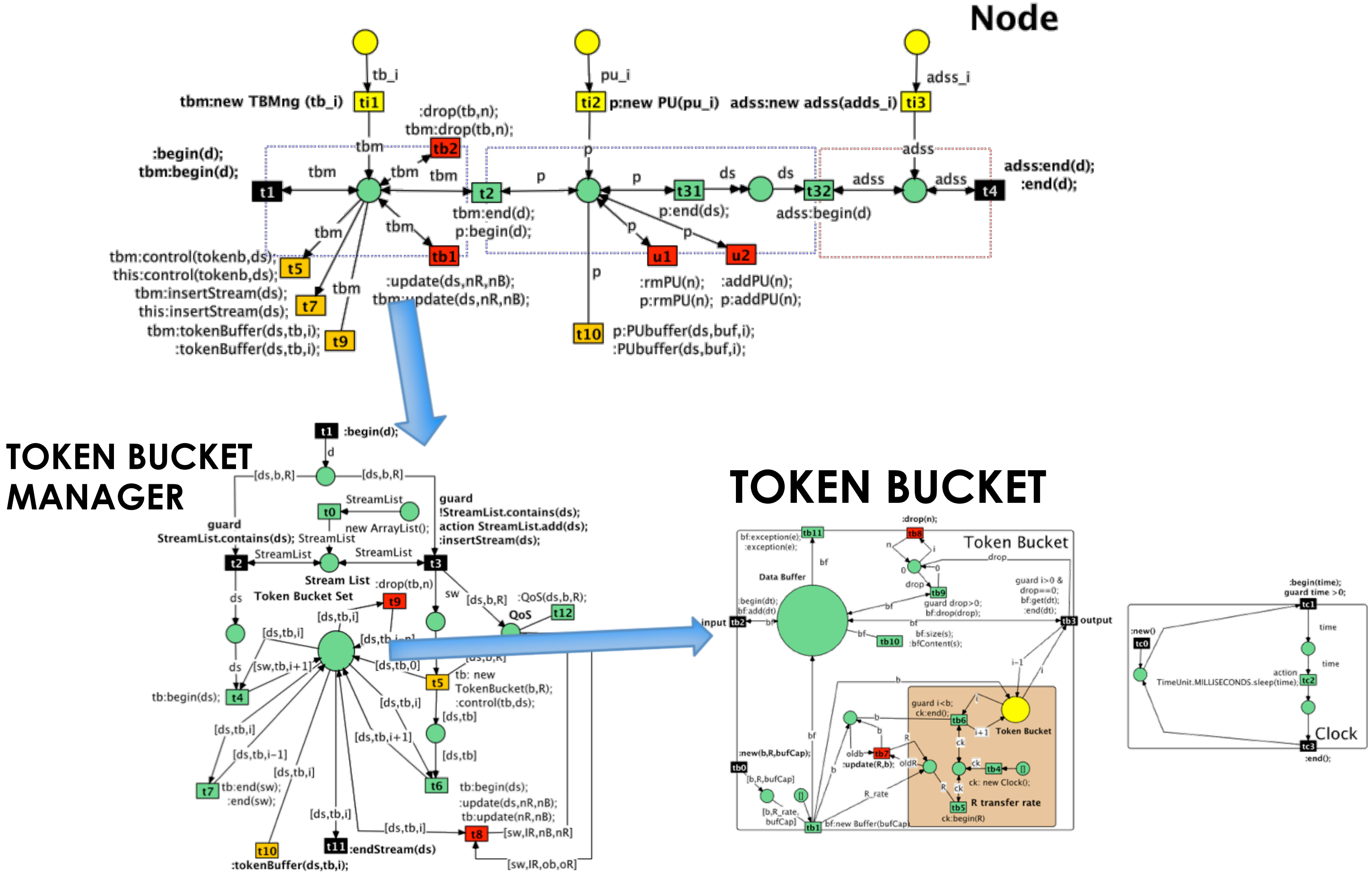
Controller: monitors & modifies behaviour

- **Token bucket behaviour** is regulated by **b, R** parameters
- **SLAs** can specify **more flexible behaviours** allowing the **controller** to take different **actions** when a threshold is reached
  - **Load-shedding:** drop data stored by the token bucket buffer
  - **Modify** the mean injection rate **R**

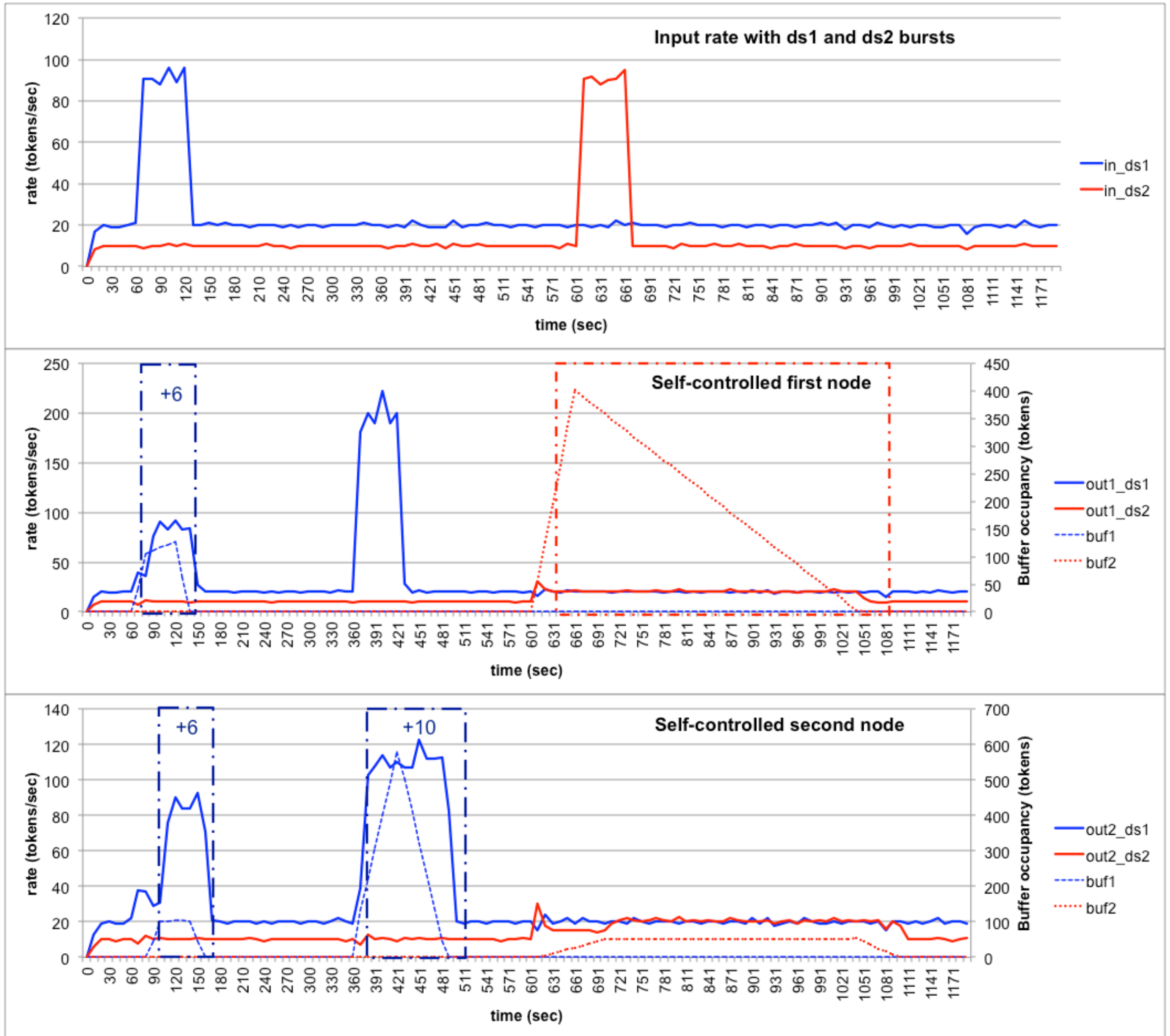
Business rules

	Pattern	Action
1	**E:** B_i over threshold **C:** SLA_i allows control the addition of N_i resources	$\Delta NumRes_{ij} = min(N_i, (\lambda_{ij} - R_{ij})/\hat{\delta_{ij}})$ $\Delta R_{ij} = \lambda_{ij} - R_{ij}$
2	**E:** B_i over threshold **C:** SLA_i allows control the use of free resources	$\Delta R_{ij} = \sum_{i=1}^{n} NumRes_{ij} * \hat{\delta_{ij}} - \sum_{i=1}^{n} R_{ij}$
3	**E:** B_i over threshold **C:** SLA_i allows control to drop D_{ij}	$B_{ij} = B_{ij} - D_{ij}$
4	**E:** Throughput degradation **C:** SLA_i allows control to add N_i resources	$\Delta NumRes_{ij} = \sum_{i=1}^{n} R_{ij}/\delta_{ij} - \sum_{i=1}^{n} R_{ij}/\hat{\delta_{ij}}$
5	**E:** B_i above threshold **C:** Contolled Stream	$\Delta R_{ij} = 0$ $\Delta NumRes_{ij} = 0$
6	**E:** Overthrow **C:** Contolled Stream	$\Delta NumRes_{ij} = 0$

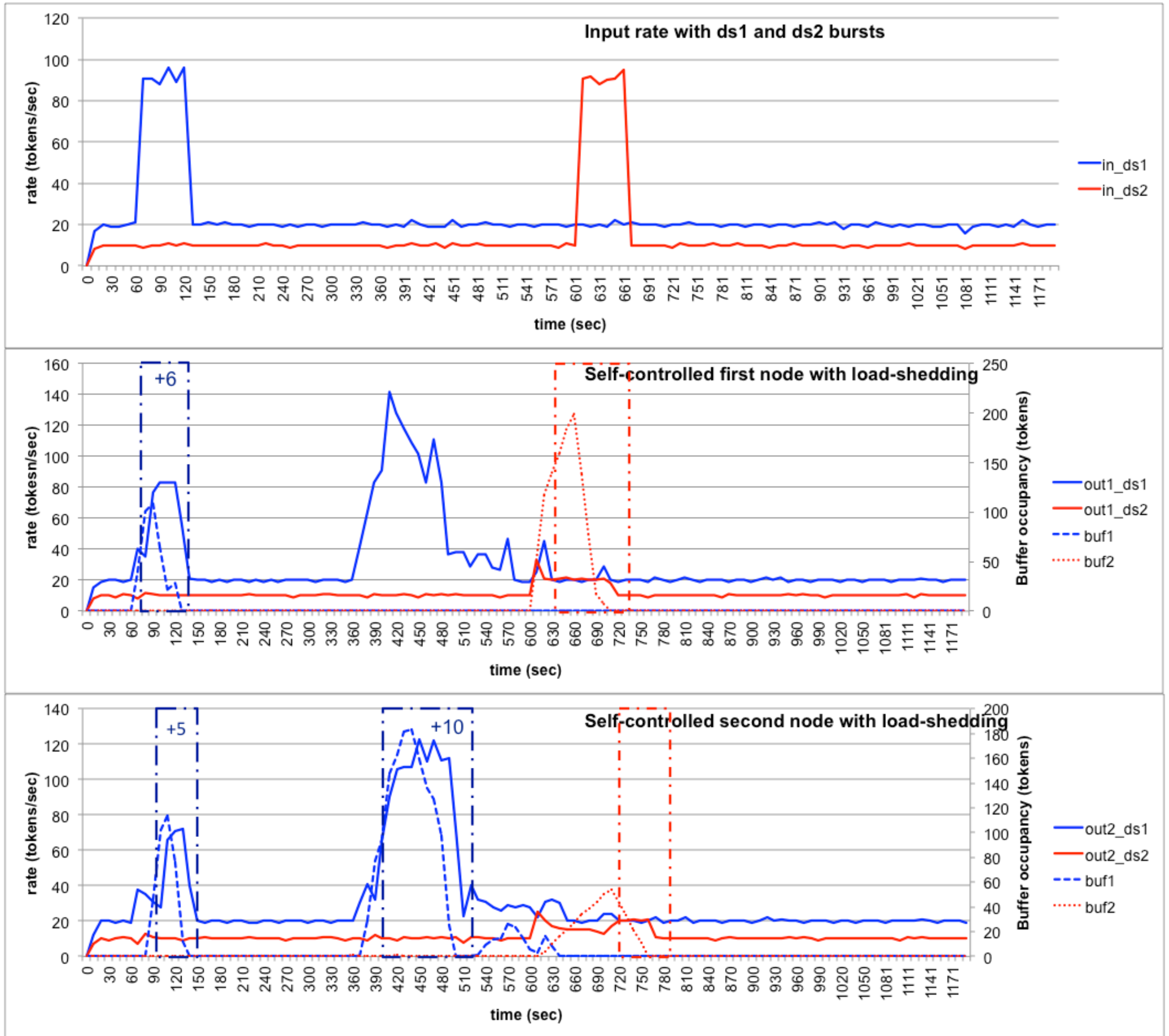
PETRI NET MODELS



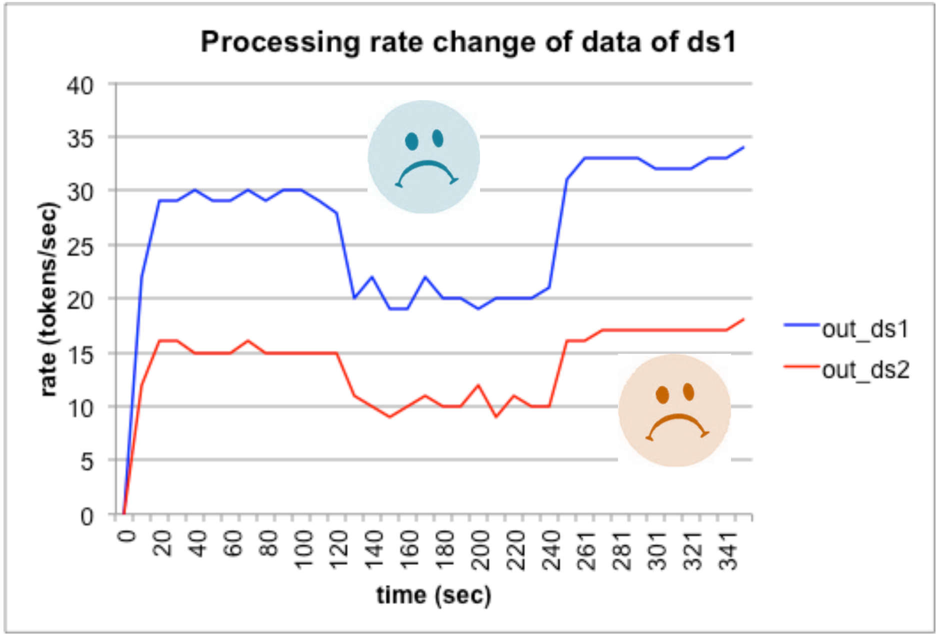
Self adaptation with different performance constraints

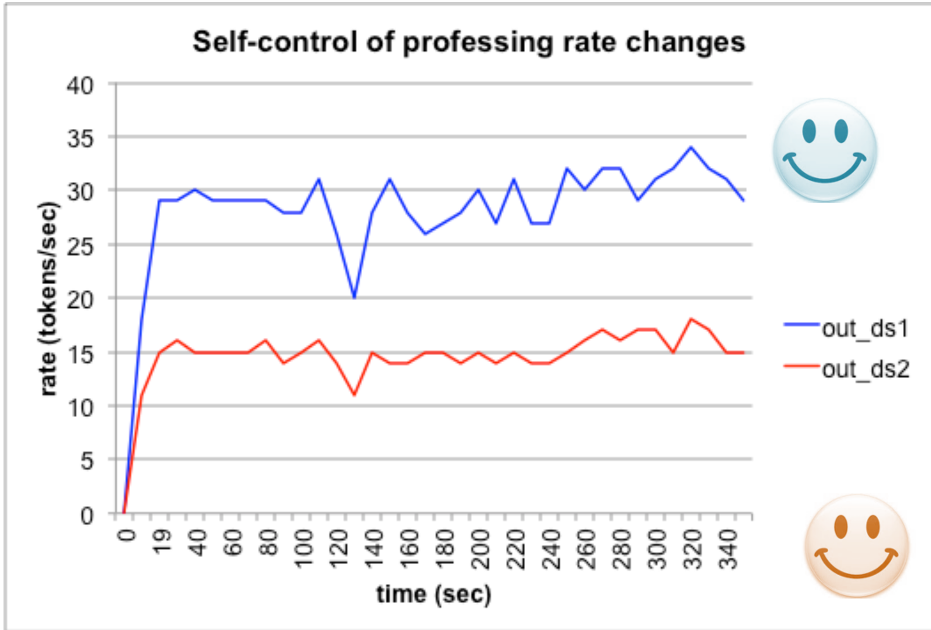


Load-shedding (dropping data)



Processing rate change





Conclusion & Future work

Conclusion

- **EV vehicles load forecast and Identify Charging Schedules for EVs requires to control the data injection rate**
- **Token bucket parameters** can provide a flexible injection of bursty data isolating each data stream.
- **Business rules** can adapt token Bucket parameters to control data stream priorities.

Future Work

- **Develop efficient mechanisms**
  - Token bucket models that implement business strategies
- **Validation in real scenarios**: Smart grid, sensor network, Ev charging schedules

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