SON Conflict Resolution using Reinforcement Learning with State Aggregation

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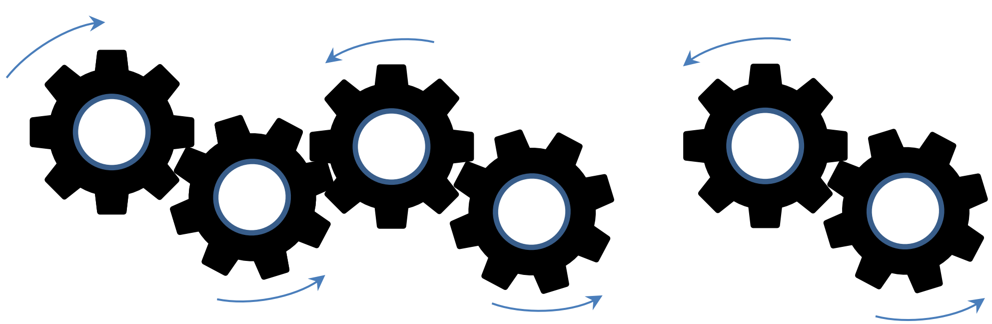
Presentation agenda:

- Introduction
- System Description: SONCO, parameter conflicts
- Reinforcement Learning
- State Aggregation
- Simulation Results
- Conclusions and Future Work

Introduction to SON & SON Coordination

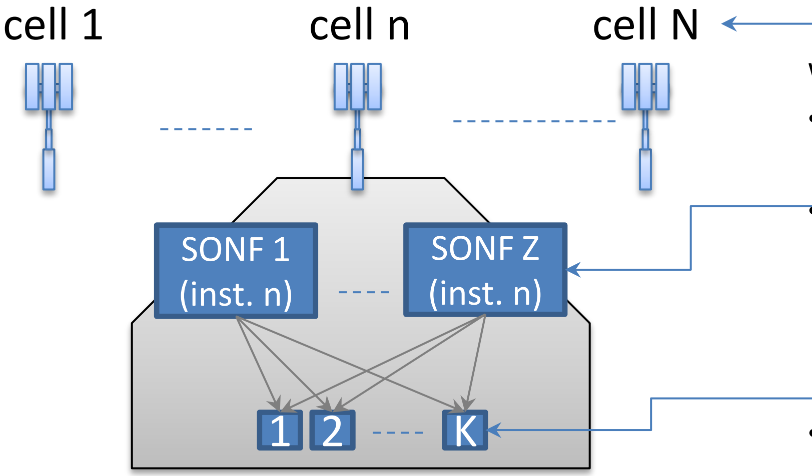
- Self Organizing Network (SON) functions are meant to automate network tuning (e.g. Mobility Load Balancing, Mobility Robustness Optimization, etc.) in order to reduce CAPEX and OPEX.
- A SON instance is a realization/instantiation of a SON function running on one (or several) cells.
- In a real network we may have several SON instances of the same or different SON functions, this can generate conflicts.
- Therefore we need a SON COordinator (SONCO)



SON instance 1
(e.g. MLB instance)

SON instance 2
(e.g. MRO instance)

System description



We consider:

- N cells. (each sector constitutes a cell)
- Z SON functions (e.g. MLB*, MRO*), black-boxes
  – each of which is instantiated on every cell, i.e. we have NZ SON instances
  – SON instances are considered as black-boxes
- K parameters on each cell tuned by the SON functions (e.g. CIO*, HandOver Hysteresis)

❑ The network at time t:

$P_{t,n,k}$ - the parameter k on cell n

❑ The SON at time t:

$U_{t,n,k,z} \in [-1;1] \cup \{void\}$- the request of (the instance of) SON function z targeting $P_{t,n,k}$

– $U_{t,n,k,z} \in [-1;0)$, $U_{t,n,k,z} \in (0;1]$ and $U_{t,n,k,z} = 0$ is a request to decrease, increase and maintain the value of the target parameter, respectively

– $|u|$ signifies the criticalness of the update, i.e. how unhappy the SON instance is with the current parameter configuration

– we consider that u may also be $void$ for the case when a SON function is not tuning a certain parameter

❑ The SONCO at time t:

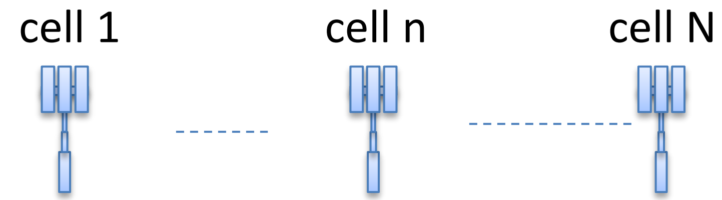
$A_{t,n,k} \in \{\pm1,0\}$- the action of the SONCO

– if $A_{t,n,k} = 1$/ $A_{t,n,k} = -1$ means that we increase/decrease the value of $P_{t,n,k}$ only if there exists a SON update request to do so, else we maintain the value of $P_{t,n,k}$.

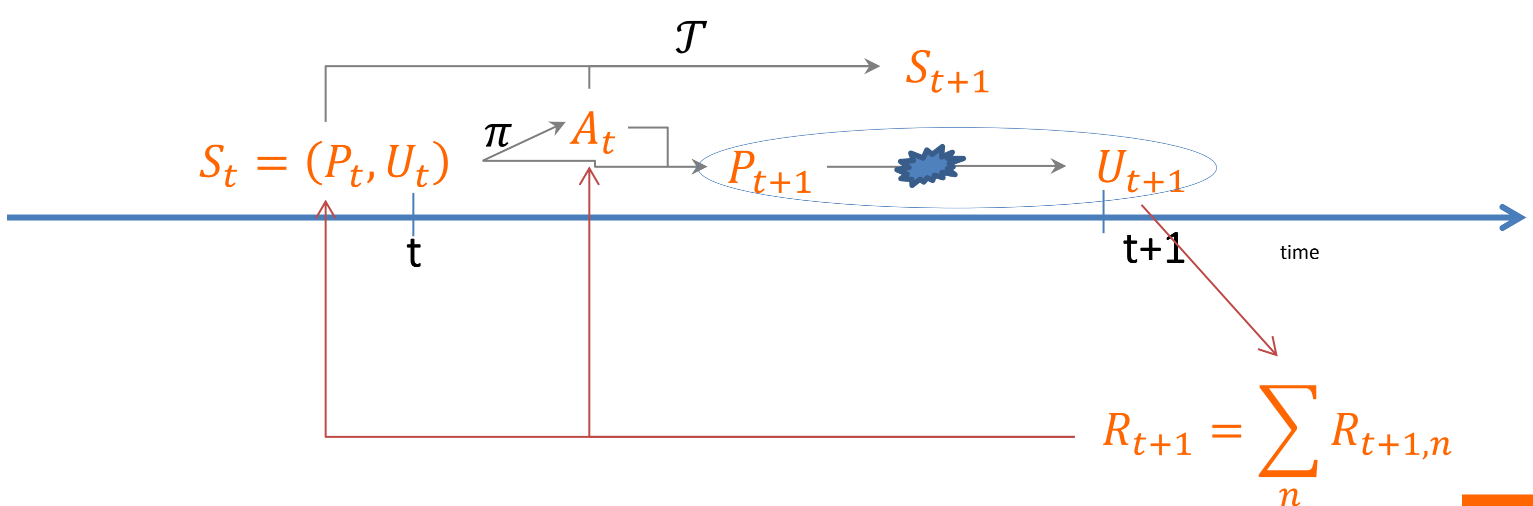
- targets to arbitrate conflicts caused by requests targeting the same parameters

(*) MLB = Mobility Load Balancing; (*) MRO = Mobility Robustness Optimization; (*) CIO = Cell Individual Offset

MDP formulation



- State: $S_t = (P_t, U_t)$
- Action: $A_t \in \{\pm 1, 0\}^{NK}$
- Transition kernel:
  - $P_{t+1} = g(P_t, U_t, A_t)$ (where g is a deterministic function)
  - $U_{t+1} = h(P_{t+1}, \xi_{t+1})$, i.e. is a "random" function of P_{t+1}, and some noise ξ_{t+1}



$$e.g.\ R_{t+1,n} = \max_{k,z} \left| U_{t+1,n,k,z} \right|$$

Target: optimal policy, i.e. best A_t

- we define discounted sum regret (value function):

$$V^{\pi}(s) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t R_t \,|S_0 = s\right], 0 \leq \gamma \leq 1$$

- the optimal policy π^* is the policy which is better or equal to all other policies:

$$V^{\pi^*}(s) \leq V^{\pi}(s), \qquad \forall s$$

- the optimal policy can be expressed as

$$\pi^*(s) = \underset{a}{\operatorname{argmin}}\, Q^*(s,a)$$

where $Q^*(s,a)$ is the optimal action-value function:

$$Q^*(s,a) = \mathbb{E}_{\pi^*}\left[\sum_{t=0}^{\infty} \gamma^t R_t \,|S_0 = s, A_0 = a\right]$$

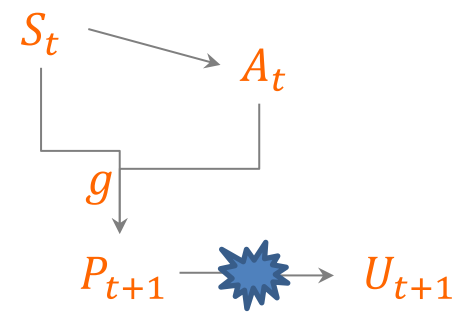
- We only have partial knowledge of the transition kernel ➔ Q^* cannot be calculated it has to be estimated (Reinforcement Learning). For example we could use Q-learning. BUT: we have deal with the complexity issue

Towards a reduced complexity RL algorithm

Main idea : exploit the particular structure/features of the problem/model:

- Special structure of the transition kernel:

$$P_{t+1} = g(S_t, A_t)$$
$$U_{t+1} = h(P_{t+1}, \xi_{t+1})$$



- the regret:

$$R_{t+1} = \sum_{n \in \mathcal{N}} R_{t+1,n}$$

only depends on

The consequence is:

$$Q(s,a) = \sum_{n \in \mathcal{N}} W_n(p'), p' = g(s,a)$$

The complexity is reduced as now we can learn the W-function instead of the Q-function, (the domain of $(s,a) = ((p,u),a)$ is smaller than the domain of $g(s,a) = p$)

Still not enough, but…

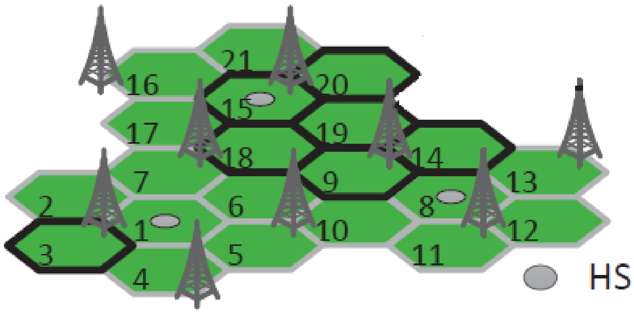
- ❑ The complexity is still too large as the domain of $\mathrm{p}' = g(s, a)$ scales exponentially with the number of cells.

➔Use state aggregation to reduce complexity.

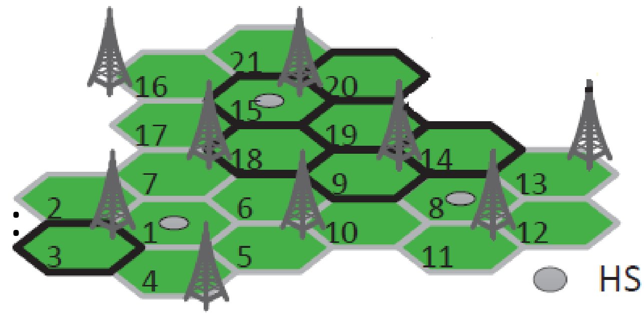
$$W_n(p) \approx \bar{W}_n(\bar{p}_n)$$

$\bar{p}_n$ contains the parameters of cell n and its neighbors, which are the main cause of conflict.

e.g. in our example: keep the CIO and eliminate the Handover Hysteresis.



Application example



Some scenario details:

- 2 SON functions instantiated on each and every cell :
  - **MLB ($z = 1$)**: tuning the CIO ($k = 1$)
  - **MRO ($z = 2$)**: tuning the CIO ($k = 1$) and the HandOver Hysteresis ($k = 2$)

- we have a **parameter conflict** on the CIO

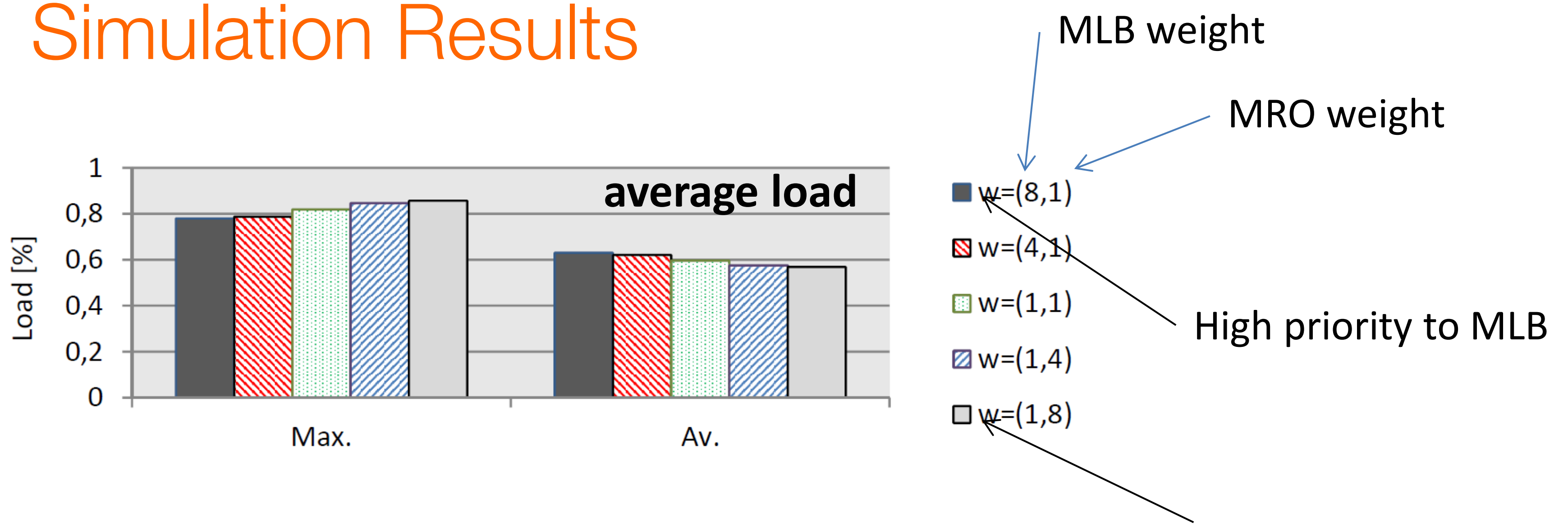
- the regret is a sum of sub-regrets calculated per cell $R_{t,n} = \max_{k,z} |U_{t,n,k,z}|$ ➔ W_n $(n \in \mathcal{N})$

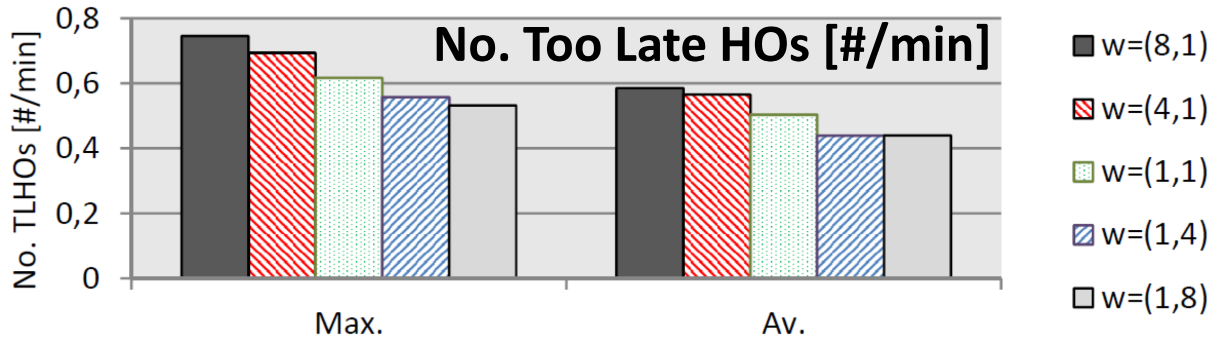
- from $W_n(p)$ to $\overline{W}_n(\bar{p}_n)$: $\bar{p}_n$ contains the CIOs of cell n and its neighbors

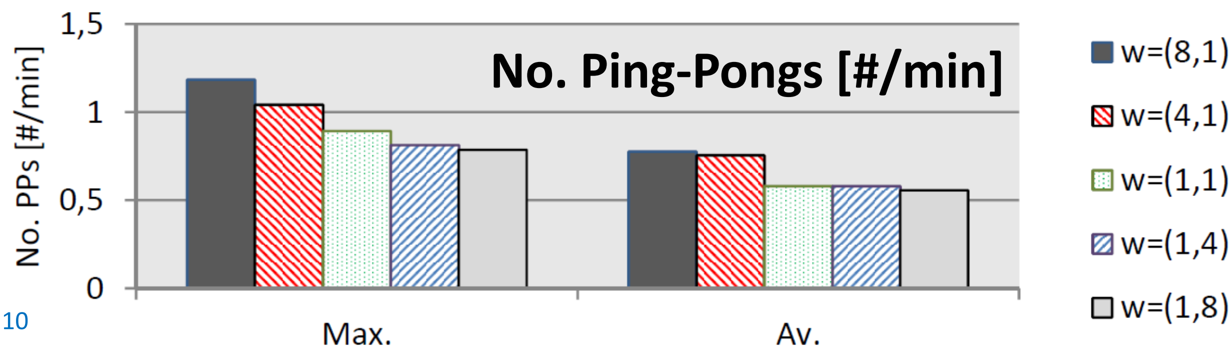
- consequence: the state space scales linearly with the no. of cells.

- to be able to favor the SON functions in calculating the regret we also associate some weights to the SON functions

Simulation Results







- we have 48h of simulations
- the results are evaluated over the last 24h, when the CIOs become reasonably stable

Conclusion and future work

- we are capable of arbitrating in favor of one or another SON function (according to the weights)
- the solutions state space scales linearly with the number of cells
- still there remains a problem on the action selection (in the algorithm we exhaustively evaluate any possible action to find the best one)

Future work:

- analyzing **tracking** capability of the algorithm,
- **HetNet scenarios,**

Questions ?

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