Using Message-passing DCOP Algorithms to Solve Energy-efficient Smart Environment Configuration Problems

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Context: Internet-of-Things

- Huge (marketing ?) trend today
- 25 billion of connected objects in 2020 ? (Gartner)
- Hardware and communication is cheaper and cheaper
- Contrained devices
  - limited cpu and memory resources
  - limited communication capabilities
- Coordination mostly centralized and cloud-based

Coordination in the IoT

What is the best approach for IoT ?

- Decentralized coordination
  - no central point of failure
  - no communication bottleneck
  - better scaling, locality of interaction
- Distributed Constraints Optimization Problem
  - Distribute the computations directly on the devices
- Application on Smart Environments / Smart Home

DCOP

Distributed Constraints Optimization Problem

A DCOP is a tuple $\langle \mathcal{A}, \mathcal{X}, \mathcal{D}, \mathcal{C}, \mu \rangle$, where:

- $\mathcal{A} = \{a_1, \ldots, a_{|A|}\}$ is a set of agents;
- $\mathcal{X} = \{x_1, \ldots, x_n\}$ are variables;
- $\mathcal{D} = \{\mathcal{D}_{x_1}, \ldots, \mathcal{D}_{x_n}\}$ is a set of finite domains, for the x_i variables;
- $\mathcal{C} = \{c_1, \ldots, c_m\}$ is a set of soft constraints, where each c_i defines a cost $\in \mathbb{R} \cup \{\infty\}$ for each combination of assignments to a subset of variables;
- $\mu : \mathcal{X} \rightarrow \mathcal{A}$ is a function mapping variables to their associated agent.

A *solution* to the DCOP is an assignment to all variables that minimizes $\sum_i c_i$.

SECP Model

Actuators:
Connected light bulbs, TV, Rolling shutters, ...

Sensors:
Presence detector, Luminosity Sensor, etc.

Physical dependecy Models:
E.g. Living-room light model

User Preferences:
expressed as rules ;

$$
\begin{array}{lllr}
\texttt{IF} & \texttt{presence\_living\_room} & = & \texttt{1} \\
\texttt{AND} & \texttt{light\_sensor\_living\_room} & < & \texttt{60} \\
\texttt{THEN} & \texttt{light\_level\_living\_room} & \leftarrow & \texttt{60} \\
\texttt{AND} & \texttt{shutter\_living\_room} & \leftarrow & \texttt{0}
\end{array}
$$

SECP Model

Actuators:

- *Decision* Variable x_i, Domain $\mathbf{x}_i \in \mathcal{D}_{x_i}$
- Cost function$c_i : \mathcal{D}_{x_i} \to \mathbb{R}$

Sensors:

- *Read-only* Variable s_l, Domain $\mathbf{s}_i \in \mathcal{D}_{s_l}$

Physical dependecy Models:

- Give the expected state of the environment from a set of actuator-variables influencing this model
- Variable y_j representing the *expected* state of the environment
- Function $\phi_j : \prod_{\varsigma \in \sigma(\phi_j)} \mathcal{D}_\varsigma \to \mathcal{D}_{y_j}$

User Preferences:

- Utility fonction u_k
- Distance from the current expected state to the target state of the environnement

Formulating the SECP as a DCOP

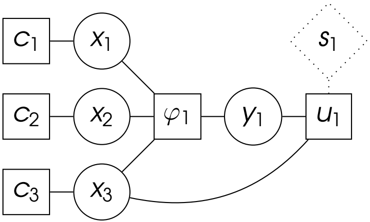
- Optimization problem

$$\underset{x_i \in \nu(\mathfrak{A})}{\textbf{minimize}} \sum_{i \in \mathfrak{A}} c_i \quad \text{and} \quad \underset{\substack{x_i \in \nu(\mathfrak{A}) \\ y_j \in \nu(\Phi)}}{\textbf{maximize}} \sum_{k \in \mathfrak{R}} u_k$$

$$\textbf{subject to} \quad \phi_j(x_j^1, \ldots, x_j^{\overline{\phi_j}}) = y_j \quad \forall y_j \in \nu(\Phi)$$

- Mono objective DCOP :

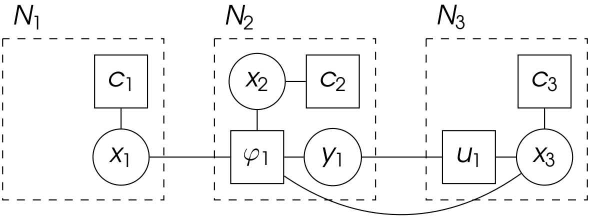
$$\underset{\substack{x_i \in \nu(\mathfrak{A}) \\ y_j \in \nu(\Phi)}}{\textbf{maximize}} \quad \omega_u \sum_{k \in \mathfrak{R}} u_k - \omega_c \sum_{i \in \mathfrak{A}} c_i + \sum_{\varphi_j \in \breve{}} \varphi_j$$



Computation distribution

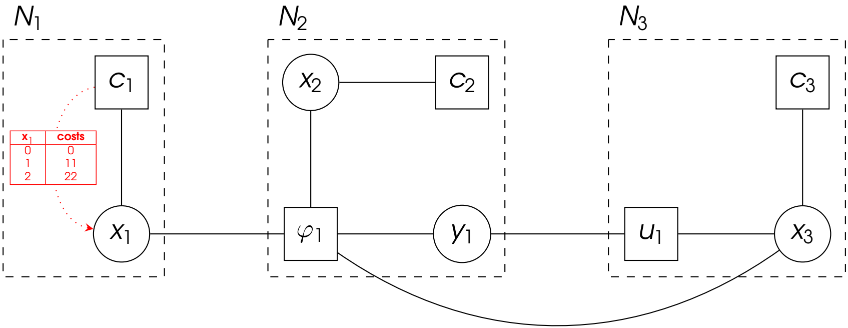
Allocating computation to agents

- Optimal Distribution : graph-partioning, NP-complete
- Simple heuristic:
  - No computation on sleepy devices (sensors)
  - Computation should be close the the impacted variables
  - Spread the computation load amongst agents



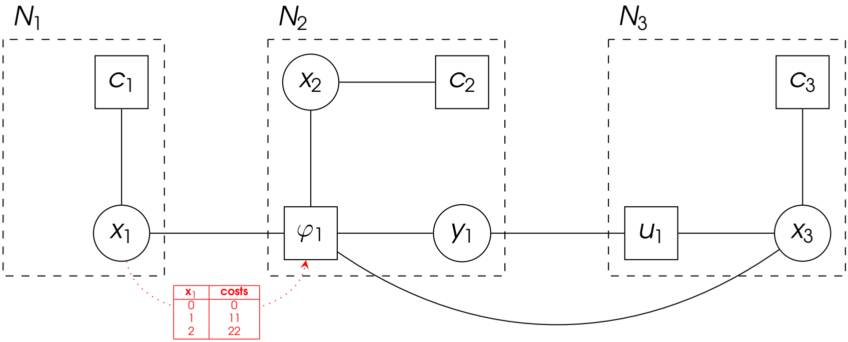
Solving the SECP

Message passing protocol for optimization



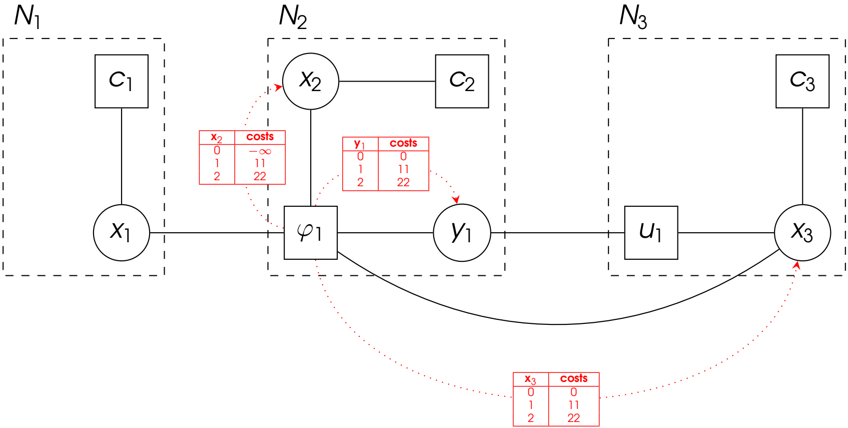
Solving the SECP

Message passing protocol for optimization



Solving the SECP

Message passing protocol for optimization

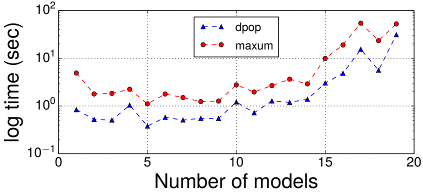


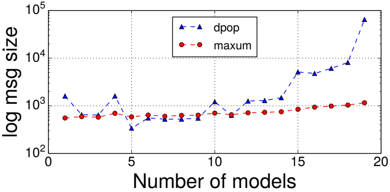
Experimental Setup

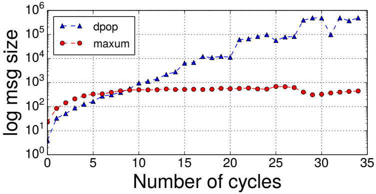
- Randomly generated instances
- Connected graphs only
- 3 experiments:
  - Growing number of models (10 actuators and 5 rules)
  - Growing number of rules (10 actuators and 5 models)
  - Growing number of cycles
- We solve the DCOP with two algorithms : Max-Sum and DPOP
  - DPOP is complete and serves as a references for optimality
  - Max-Sum is approximate but light-weight

Results: DPOP vs. Max-Sum

- Dpop is a bit faster
- Max-Sum generate much less message-load
- Max-Sum is almost always optimal
- Complexity depends on the number of cycles







Conclusions

Summary

- The SECP model is a viable approach for decentralized autonomous coordination in Smart Environments
- The Max-Sum algorithm is well suited for the constrainted devices in these environments

Perspectives

- Learning the physical models
- Tailor-made Max-Sum derivative for this application domain-specific characteristics
- Explore the Multi-objective DCOP framework
- Consider the dynamic acpect of the environment and the resilience of the approach.

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