

A Fog Computing Service Placement for Smart Cities based on Genetic Algorithms

Claudia Canali, Riccardo Lancellotti

University of Modena and Reggio Emilia

Department of Engineering "Enzo Ferrari"

Background and motivation



Cyber-physical environments driven by geographically distributed sensors

Increasing amount of information to be filtered and processed

Excessive delay and scalability issues for some applications:

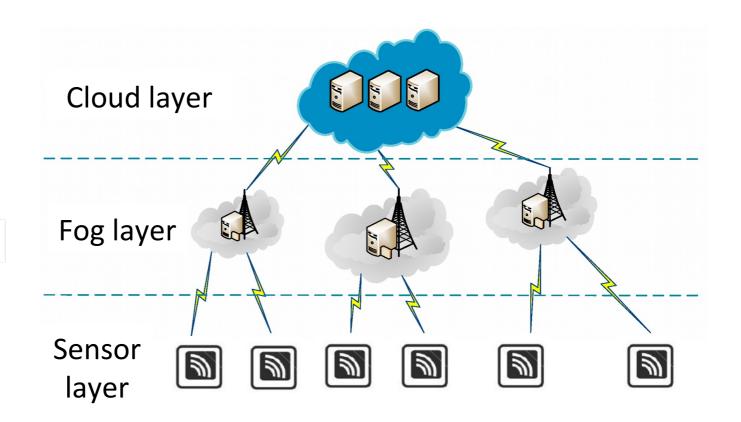
- Applications requiring very low and predictable latency (traffic control, support for autonomous driving)
- Geo-distributed applications (pipeline monitoring, sensor networks to monitor the environment)
- Fast mobile applications (smart connected vehicle, connected rail)
- Large-scale distributed control systems (smart grid, smart traffic monitoring)

Fog Computing



- Intermediate layer of fog nodes close to the sensors
- Services moved to the edge of the network: filtering, aggregation and/or latency critical tasks

Goal: improve latency and scalability



State of the art



- New challenges
- Existing studies:
 - Focus on the level between Fog and Cloud layers
 - Optimizing allocation of processing tasks on cloud infrastructure
 - Solutions exploiting fog-to-fog nodes communication
- Less covered issue

Mapping sensor data flows over fog nodes

- Common assumption:
 - Fog nodes directly communicate with sensors single-hop wireless connections
- Critical task to reduce global latency and processing time for high QoS in terms of response time

Problem definition



- Smart city scenario:
 - City monitoring application (e.g., traffic intensity, air quality, ...)
 - Data collected in the Cloud infrastructure for value-added services (e.g, traffic or pollution forecast)
- Three layers:
 - Sensor layer of wireless sensors
 - Fog layer for preliminary data pre-processing (filtering, aggregation) or anomaly detection
 - Cloud layer as final data destination of refined data samples (analysis and storage)
- Mapping sensor data flows over the fog layer

Contributions



Twofold contribution:

- Optimization model for mapping incoming workload over fog nodes
 - Latency due to communication
 - Processing time due to local load
- 2) Heuristic to solve the optimization problem in a scalable way
 - Genetic Algorithms (GAs)

Realistic scenario

Smart city environment

Geographic testbed based on realistic scenario of Fogarchitecture in a small-sized city in Italy

Problem modeling



- Set of S sensors
- Sensors produce data at a steady rate: frequency λ_i for sensor i
- Fog layer: F nodes
- One cloud data center

Goal: guarantee a fast response

- Response time contributions:
 - Network-based latency $\delta_{i,j}$ of communication between sensor i and fog node j
 - Network-based latency $\boldsymbol{\delta}_j$ of communication between fog node j and the cloud data center
 - Processing time on fog node: 1/μ_i time to process a data packet on node j and the data rate λ_i arriving at fog node j

Optimization model



- Mapping incoming workload over fog nodes
- Assumption: all data of a sensor are sent to the same fog node
- Main decision variable: matrix X of boolean flags x_{i,j}

$$x_{i,j} = \begin{bmatrix} 1 & \text{if sensor i is sending data to fog node j} \\ 0 & \text{otherwise} \end{bmatrix}$$

$$\min obj(X) = \sum_{i \in \mathcal{S}} \sum_{j \in \mathcal{F}} x_{i,j} \cdot \left(\frac{1}{\mu_j - \lambda_j} + \delta_{i,j} + \delta_j \right)$$

Processing time derived from Little's result applied to a M/G/1 model

subject to:

$$\lambda_j = \sum_{i \in \mathcal{S}} x_{i,j} \cdot \lambda_i \quad \forall j \in \mathcal{F},$$

$$\sum_{j \in \mathcal{F}} x_{i,j} = 1 \quad \forall i \in \mathcal{S},$$

$$\lambda_j < \mu_j \quad \forall j \in \mathcal{F},$$

$$x_{i,j} = \{0,1\}, \quad \forall i \in \mathcal{S}, j \in \mathcal{F},$$

(4) Boolean nature of decision variables

Heuristic algorithm



- Solution based on Genetic Algorithms (GAs)
 - Viability evaluation
- Population of individuals
 - Each individual represents a candidate solution encoded in a chromosome
 - Chromosome composed by a fixed number of genes
 - Genes represent the single parameters characterizing a solution
- Population of individuals initialized randomly
- Fitness function applied to each individual
 - Describing the objective function of the optimization problem
- Evolution of population (set of generations) to improve the fitness of the population
- Three operators: mutation, crossover, selection

Mutation and Crossover

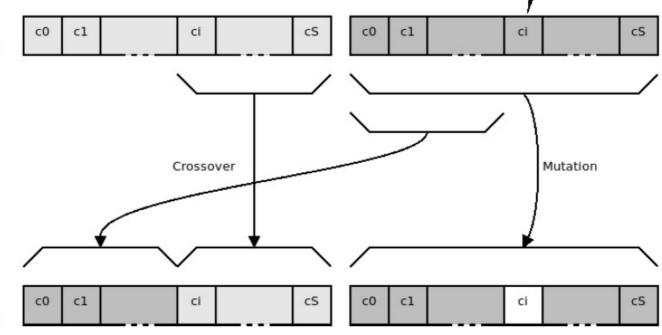
K+1-th

generation



- Mutation: change of single or group of genes in a chromosome
 - Main parameter: probability to select an individual to perform mutation on one of its genes P_{mut}
- Crossover: merge of two individuals by exchanging part of their chromosome

• Main parameter: probability to select individuals as parents P_{cross} _{kth} $rac{1}{1}$ $rac{1}$ $rac{1}$ $rac{1}{1}$ $rac{1}$ $rac{1}$ r



Mutation

Selection



- Selection: selection of individuals passing to the next generation
 - Stable population size over generations
- Approach:
 - Fitness function applied to each individual (including new ones)
 - Probability of being selected for the next generation proportional to fitness value

Solution encoding



- A solutions encoded as a chromosome
- Chromosome: a set of S genes, with S number of sensors
- Gene: an integer number from 1 to F, with F number of fog nodes
- The ith gene in a chromosome:
- Objective function used as basis $c_i = \{j: x_{i,j} = 1\}$
- Direct mapping between chromosomes and solutions of optimization problems - constraint (2)
- Constraints satisfied by the encoding except (3) on fog nodes overload
 - Embedded in the fitness function through penalty on overloading individuals

Experimental testbed



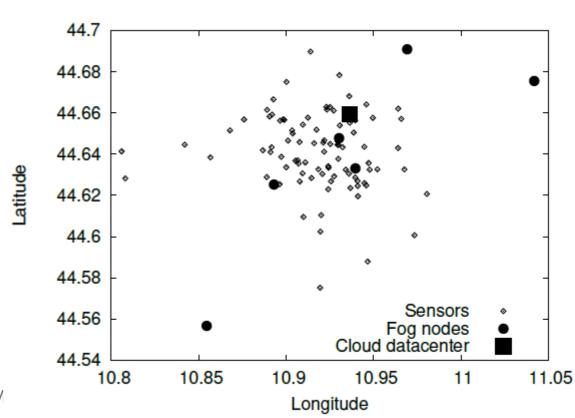
- Realistic based on the small city of Modena Italy (180.000 inhabitants)
- Assumption: support for traffic monitoring application
- Sensors: on main streets, collecting data on traffic measures (90)
- Fog nodes: buildings hosting municipality offices (5)
- Municipality data center (1)
- Euclidean distance to model communication latency

$$\lambda_i = 1, \ \forall \ i \in S$$
 $\mu_i = 100, \ \forall \ j \in F$

Optimization problem:

AMPL / CPLEX

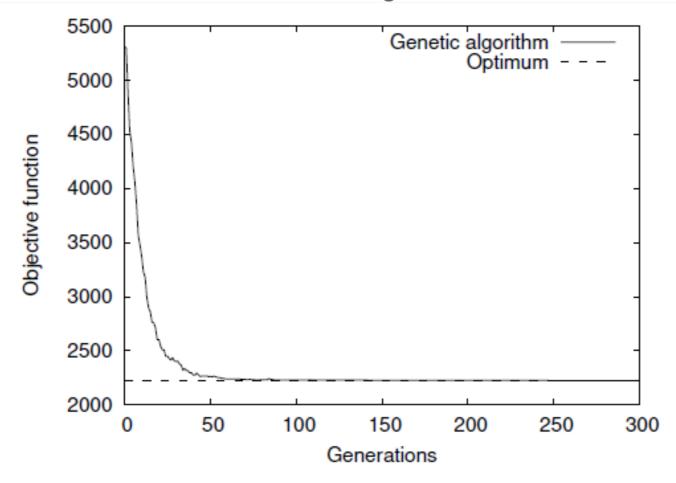
 GA: Distributed Evolutionary Algorithms in Python



Genetic algorithm performance



- Fast Convergence (<1% between fitness and optimal values)
- Execution time: one order of magnitude lower for convergence



Sensitivity Analysis



Evaluating stability of the results against main parameters variance

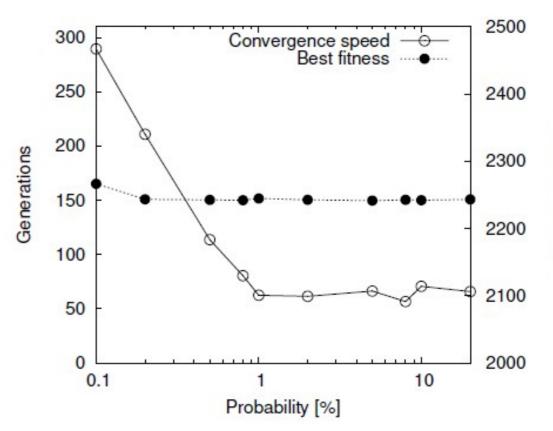
1) Probability of selecting an individual for a crossover operation P_{cross} [0.1%, 20%]

Number of generations

- Non-negligible dependence
- Stability for P_{cross} > 1%

Best fitness value

Stable



Objective function

Sensitivity Analysis



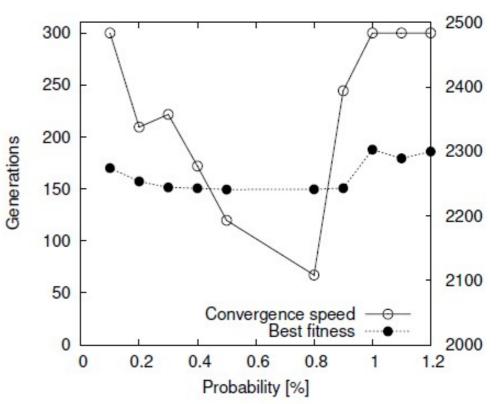
2) Probability of selecting an individual for a mutation operation P_{mut} [0.1%, 1.2%]

No converge within the threshold (300 generations) for very low (0.1%) and high values (>1%) of P_{mut}

V-shaped curve with point of fast convergence close to 0.8%

Low P_{mut} : low possibility to explore solution space

Hit P_{mut} : late convergence due to fast changes in population



Objective function

Concluding remarks



- Scenario: Fog Computing for smart city applications
- Challenge: mapping sensors data flows over fog nodes
- Contributions: optimization model and GA-based heuristic
- Results:
 - GA-based heuristic is a viable solution
 Reach optimal solution in presence of a complex problem with integer programming and non-linear objective function
 - Sensitivity analyis on main parameters
- Future directions:
 - More complex scenarios involving dynamic changes in workload
 - Sensors mobility
 - Adaptive sampling techniques at the sensor level



Thanks for your attention!