Usage of PSO Algorithm for Parameters Identification of District Heating Network Simulation Model

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Abstract: - This paper describes usage of the Particle Swarm Optimization for parameters identification of simulation model of heat distribution and consumption in municipal heating network. The simulation model is based on the discrete simulation and PSO is used for identification of model parameters from input dataset.

Key-Words: district heating, simulation model, particle swarm optimization, heat-load modelling

1 Introduction

This paper describes usage of the Particle Swarm Optimization (PSO) for parameters identification of simulation model of heat distribution and consumption in municipal heating network. The algorithm was implemented in JAVA language and was successfully applied in real experiment at combined heat and power (CHP) plant. This paper briefly presents simulation model, PSO variant, stopping criterion and fitness function. Finally the experiment results are presented.

2 Simulation model

There are many different approaches to simulation models and operational optimization of district heating networks (Helge et al., 2006; Balate et al., 2008) and Heat-load modelling (Heller, 2002).

Our approach is to use data mining methods combined with simplified physical model of real heating network. There is no need to have detailed information about network and parameters of the model. Parameters are estimated by means of an evolution algorithm from operational dataset and meteorological data.

The heat distribution simulation model is described as a set of section and nodes, where each section is linked, see the figure 1.

Where

C	is the consumer,
N	is the node,
S	is the section and
SP	is supply (source).

Consumer, node, section and supply have specific transfer function.

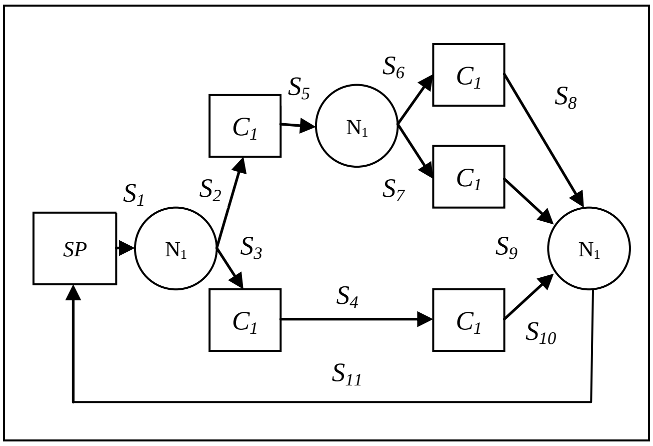

Fig. 1. Example of the heat distribution and consumption model

2.1 Model Parameters for Identification

These parameters are to be estimated:

- the heat transfer coefficient in the sections *S*
- 24 hour load coefficients for one-day prediction
- Wind, solar radiation and other parameters.

These input data are known:

- the mass flow of the water,
- the supply temperature at the heating plant (*TS*),
- the return temperature at the heating plant (*TR*),
- reference water temperatures at some nodes and
- meteorological data (measured and predicted)

Process of identification of model parameters for one-day prediction can be described in three steps:

1. The reference day is found in operational dataset by means of predicted ambient temperature
2. Model parameters are estimated from reference day.
3. Estimated parameters are used for modeling and control of predicted day.

3 Problem Solution

After experiments with Differential Evolution, Self-Organizing Migrating Algorithm, Neural Networks (Vařacha, 2009) and Levenberg–Marquardt algorithm, the Particle swarm algorithm was chosen as the numeric optimization algorithm suitable for problem without explicit knowledge of the gradient of function to be optimized.

3.1 Particle swarm optimization

PSO was first introduced in (Kennedy & Eberhart, 1995) and was successfully applied on many optimization problems.

We use these PSO variant:

$$v'_{i,j} = \omega v_{i,j} + c_1 r_1 \left(global\ best_j - x_{i,j}\right) + c_2 r_2 \left(local\ best_{i,j} - x_{i,j}\right) \qquad (1)$$

$$x'_{i,j} = x_{i,j} + v'_{i,j} \qquad (2)$$

Where:

n	is the number of particles, i = 1,…,n
m	is the dimension, j = 1, …, m
$x_{i,j}$	is the particle position
$x'_{i,j}$	is the updated particle position
$v_{i,j}$	is the particle velocity
ω	is the inertia component
c_1	is the social component
c_2	is the cognitive component
r_1, r_2, r_3	are uniform random numbers $\langle 0,1 \rangle$
$global\ best_j$	is the best global position
$local\ best_{i,j}$	is the best local particle position

The number of particles *n* we usually set two times more than dimension *m*. Inertia component ω is set about 0.8, social component c_1 is set about 1.4 and cognitive component c_2 is set about 0.6.

The fitness function is the minimum of the sum of squared residuals of measured and simulated return temperatures:

$$\sum_{i=0}^{n} \left(T_R measured(i) - T_R simulated(i)\right)^2 \qquad (3)$$

Where *n* is the number of samples.

3.1.1 Stopping criterion

We use MaxDistQuick as a stopping criterion as described in (Martí et al., 2009). The optimization is stopped if the maximum distance of the major part of particles is below a threshold *eps* or the maximum number of iteration is reached:

1) Particles are sorted by the means of their quality (value of fitness function).
2) The subset of best *n* particles is chosen.
3) The Euclidean distance from best particle is estimated for each particle in subset.
4) Algorithm stops if the maximum distance in subset is below the threshold *eps*.

3.1.2 Implementation

PSO is implemented in JAVA language in this main function structure:

• Initialization - this function initializes all parameters and runs only once at the start of the algorithm.

• Update particles positions - this function calculates new positions of particles and returns true if the algorithm should stop.

• Get updated position - this function returns positions of one particle that should be evaluated together with particle number.

• Set fitness function value for particle - this function receives value of the fitness function and pairs this value by the means of particle number with particle.

This solution enables parallel implementation of PSO algorithm (Figure 2). There is a peer application that runs simulations in threads and runs PSO functions.

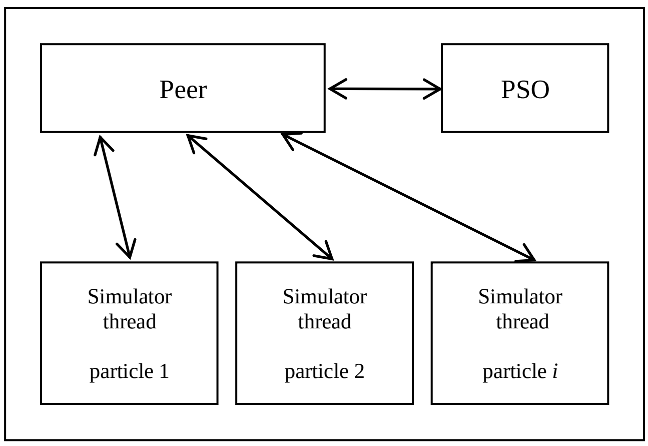

Fig. 2. Parallel implementation

4 Results

The algorithm was successfully tested in real experiment at CHP plant in Czech Republic. Figure 3 shows comparison between return temperatures TR of reference day, simulation and measured data.

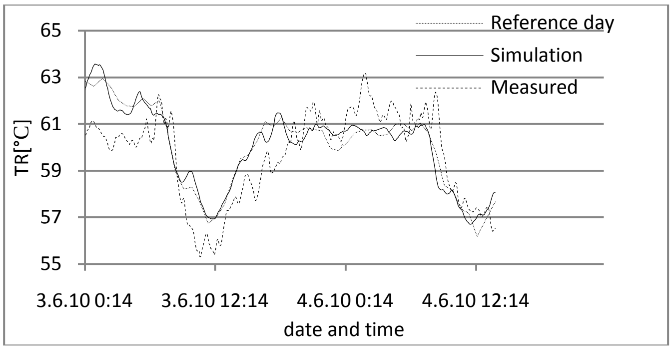

Fig. 3. Experiment results

Figure 4 describes fitness function convergence rate and figure 5 describes MaxDistQuick distance rate. Identification was run 10 times with these parameters settings:

n	54
m	27
ω	0.8
c_1	1.8
c_2	0.6
eps	0.2

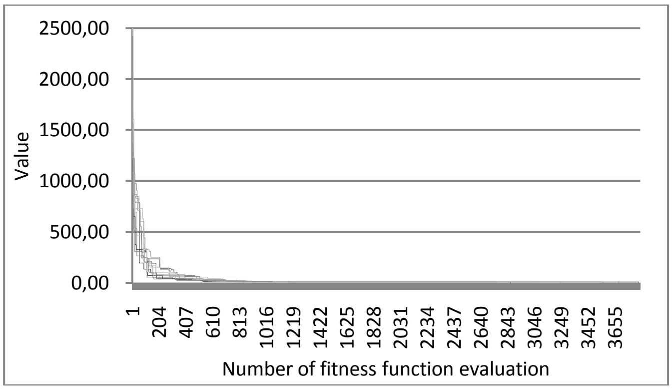

Fig. 4. Fitness function convergence

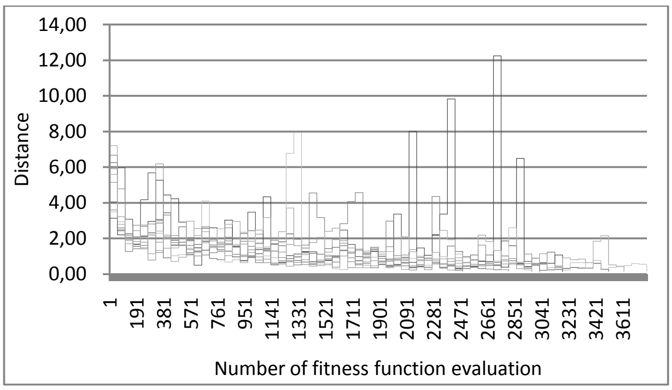

Fig. 5. PSO MaxDistQuick distance

5 Conclusion

This paper describes usage of the Particle Swarm optimization (PSO) for parameters identification of simulation model of heat distribution and consumption in municipal heating network. PSO was successfully applied in this optimization problem. The algorithm was implemented in JAVA and tested in real experiment in combined heat and power plant. The stopping criterion and component setting was proved to be very stable and algorithm itself very reliable.

5 ACKNOWLEDGEMENTS

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