Annals of DAAAM for 2010 & Proceedings of the 21st International DAAAM Symposium, Volume 21, No. 1, ISSN 1726-9679
ISBN 978-3-901509-73-5, Editor B. Katalinic, Published by DAAAM International, Vienna, Austria, EU, 2010
Make Harmony Between Technology and Nature, and Your Mind will Fly Free as a Bird
Annals of DAAAM International

USING PSO ALGORITHM FOR PARAMETER IDENTIFICATION OF SIMULATION MODEL OF HEAT DISTRIBUTION AND CONSUMPTION IN MUNICIPAL HEATING NETWORK

KRAL, E[rik]; DOLINAY, V[iliam]; VASEK, L[ubomir] & VARACHA, P[avel]

Abstract: *This paper describes application of the Particle Swarm Optimization (PSO) algorithm for the parameters identification of simulation model and for the prediction of the mass flow and supply temperature of the water. Simulation model represents the heat distribution and consumption in municipal heating network and is based on the discrete simulation. Estimated parameters are heat transfer coefficients and daily load profiles. The results of experiment at combined heat and power (CHP) plant are presented.*
Key words: *PSO, district heating, identification, simulation*

1. INTRODUCTION

There are many different approaches to simulation models and operational optimisation of district heating networks (Helge et al., 2006; Balátě et al., 2008) and Heat-load modelling (Heller, 2002). Our approach is to use data mining methods combined with simple model of heating network. The advantage is that we can avoid complex modelling. Model parameters are estimated by means of an evolution algorithm. After initial 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 the problem to be optimized.

This paper briefly describes simulation model, PSO variant, stopping criterion and fitness function. The algorithm was successfully applied in the experiment at combined heat and power (CHP) plant and results are presented. Finally, future research plans and limitation are presented.

2. SIMULATION MODEL

The heat distribution simulation model is described as a set of section and nodes, where each section is linked:

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

These groups of parameters are to be estimated by means of the PSO:

- the heat transfer coefficient in the section S_i of the input pipes (depends on ambient temperature),
- 24 hour load coefficients (daily load profiles) and
- other input coefficients: wind direction and speed, solar radiation, humidity, cold-water temperature.

PSO is also used for prediction of mass flow of the water and supply temperature at the heating plant.

These input data are known:

- the mass flow of the water (G),
- the supply temperature at the heating plant (T_S),
- the return temperature at the heating plant (T_R),
- reference water temperatures at some nodes and
- weather data (ambient temperature *Tex*, wind intensity and direction, ...).

For the control of CHP plant, model parameters are identify from the reference day by means of ambient temperature prediction.

3. PARTICLE SWARM OPTIMIZATION

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

3.1 PSO variant

We use this PSO variant

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

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

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* is 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.

3.2 Fitness function

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

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

Where *n* is the number of samples.

3.3 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 certain amount of best particles is below a threshold *m* or the maximum number of iteration is reached:

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

4. IMPLEMENTATION

PSO is implemented in JAVA in this 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 return 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 in the means of particle number with particle.

This solution enables parallel implementation of PSO algorithm. There is a peer application (Simulator multithread) that runs simulations in separate threads and runs PSO functions. There is also online database connection to weather data provider and to power plant database of measurements.

5. RESULTS

The algorithm was successfully evaluated in experiment at combined heat and power plant in Czech Republic. Figure 1 shows comparison between return temperatures T_R of reference day, simulation results and measured data.

Experiment procedures:

- Input parameters estimation using PSO.
- Estimation of the reference day by means of ambient temperature prediction.
- Prediction of supply and return temperature at the heating plant using PSO
- Measuring return temperature and comparison with predicted.

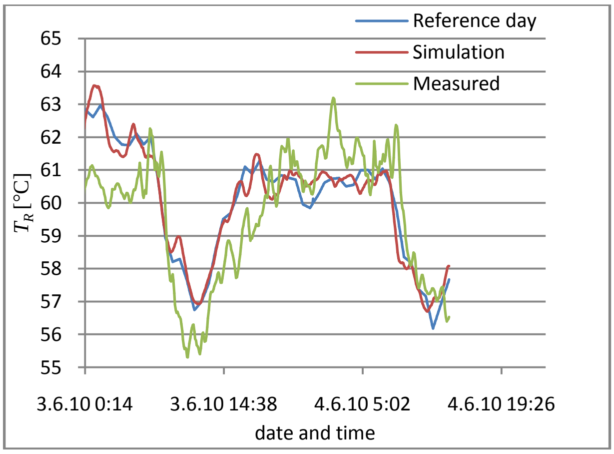

Fig. 1. Experiment results (comparison of return temperatures)

6. FUTURE RESEARCH PLANS AND LIMITATIONS

The main limitation of our research is that we still cannot simulate pressure difference between the supply and return line. Our future research plans are further estimation of the significance of heat load components (space heating for buildings, domestic hot-water preparation, distribution loss, Additional work-day loads) and significance of input parameters, such as ambient temperature, cold-water temperature, solar radiation, wind and humidity. We also investigate possibility that PSO will estimate section, nodes and links itself.

The second area of research plans is to implement cost optimization, so the PSO algorithm could find most efficient control strategy for power plant. This is most challenging task in combined heat and power production.

7. CONCLUSION

This paper describes application of the Particle Swarm Optimization (PSO) algorithm for parameters identification of simulation model and for the prediction of the mass flow and supply temperature of the water. Simulation model represents heat distribution and consumption in municipal heating network. Our approach is to use data mining methods combined with simple model of heating network. Simulation model was successfully evaluated in experiment at combined heat and power plant in Czech Republic. Our future research plans are further estimation of the significance of heat load components and significance of input parameters

8. ACKNOWLEDGEMENTS

The financial support from the research project NPVII-2C06007, by the Czech Republic Ministry of Education is gratefully acknowledged.

9. REFERENCES

Balate, J., Navratil P.; Chramcov, B. (2008). Qualitatively-quantitative method of heat power in the hot water supply for the district heating system. In: *ARTEP 2008*, TU Kosice

Král, E.; Vašek, L. ; Dolinay V. ; Vařacha P. (2010). Usage of PSO Algorithm for Parameters Identification of District Heating Network Simulation Model. *Proceedings of the 14th WSEAS International Conference on Systems.* Corfu Island, Greece

Helge, L.; Benny, B.; Michael, W (2004). A comparison of aggregated models for simulation and operational optimisation of district heating networks, *Energy Conversion and Management*, Volume 45, Issues 7-8, May 2004, pp. 1119-1139, ISSN 0196-8904

Kennedy, J.; Eberhart, R. (1995). Particle Swarm Optimization. *Proceedings of IEEE International Conference on Neural Networks*. IV. pp. 1942-1948

Martí, L.; García, J.; Berlanga, A.; Molina, M. (2009). An approach to stopping criteria for multi-objective optimization evolutionary algorithms: the MGBM criterion. In *Proceedings of the Eleventh Conference on Congress on Evolutionary Computation* (Trondheim, Norway, May 18 - 21, 2009). IEEE Press, Piscataway, NJ, 1263-1270

Vařacha, P. (2009). Impact of Weather Inputs on Heating Plant - Agglomeration Modeling. *Proceedings of the 10th WSEAS International Conference on Neural Networks*, Mastorakis, N., pp. 159-162, ISBN 978-960-474-065-9, Prague