Specialized genetic operators in drinking water distribution systems control

Arkadiusz Ciminski[1], Kazimierz Duzinkiewicz[2]

[1,2] Department of Control Systems Engineering
Faculties of Electrical and Control Engineering
Gdansk University of Technology
ul. Narutowicza 11/12, Gdańsk
[1] a.ciminski,[2] k.duzinkiewicz@ely.pg.gda.pl

Abstract. Model-based predictive control (MPC) is an effective method for control of the large scale systems. The method relying on repeating applying the first element of the calculated control sequence to the system, based on the model of the system and available system output measurements. A time duration of control calculation is a crucial criterion for applying this method. In this paper effective algorithm of control the drinking water distribution system (DWDS) is presented. Algorithm is based on genetic algorithm (GA), specialized genetic operators (SPO) and simulator Epanet. To improve the GA convergence, specialized genetic operators based on system operator knowledge of practical system control are proposed. Effectiveness of proposed specialized genetic operators on the example DWDS of the Chojnice city is presented.

1 Introduction

Model-based predictive control is an effective method for control the large scale systems. Method based on solved offline control task over the control horizon using current and past measurements as well as the system model. Only a first element of calculated control sequence is applied to the system. At the next sampling instant based on new process output measurements whole procedure is repeated. Control sequence is obtained by solving the control task with the weighted cost function compound of control cost and differences between predicted output and set-point trajectories. In this paper effective control algorithm of optimizing MPC algorithm is proposed. Cost function is reduced to costs of control, only. The control task is constrained by: system model, output inequalities, state and control sequence.

In control process of large scale systems a crucial criterion of effective applying the MPC is solving the control task within the time period determined by prediction step. A DWDS is a representative of the large scale systems. There are two major aspects in control of DWDS: quantity (hydraulic) and quality (disinfectant concentration). In paper a quantity aspect is considered, only. The allowed time period for solving control task in DWDS quantity is determined by the length of discretization step (hydraulics step) of system model. Length of hydraulic step depends on rate of system disruption (water consumers) and is within borders (0.5 - 2 h). For DWDS with numerous control variables, solving control task in the time period of hydraulic step is difficult or even impossible. Therefore in papers [3,7,9] using whole available knowledge about system e.g. system model, using distinctive features of the system, is used.

In paper effective solving control task algorithm based on GA, specialized genetic operators (SGO) and DWDS simulator Epanet, is presented. In order to reduce the solving time, the algorithm utilizes operator heuristic knowledge about system manual control.

Presented method uses AG with SGO as an optimizer for solving control task and SDWP simulator Epanet [8] as a source of information about the quality and admissibility of control sequence. On SWDP of Chojnice city model is showed that AG with SGO reduces control calculation time, is presented.

2 DWDS description

2.1 DWDS model

DWDS hydraulic model can be described in a form of differential-algebraic equation set over modeling horizon $\Xi_m = [t_n, t_n + H_m]$ (t_n - initial moment, H_m - length of the modeling horizon) with discretization step T_h equal to hydraulic step. Model consists of three parts: (i) linear static – conservations of water mass in nodes; (ii) nonlinear static – conservation of energy on connection elements (pipelines, valves, pumps); (iii) nonlinear dynamic – conservations of water mass tanks. Model can be presented in a form:

$$\begin{cases} A_L \cdot s(k) = 0 \\ f_{NL}(s(k)) = 0; \qquad k = 0,1,... \\ h_z(k+1) = \Psi(s(k)) \\ h(t_n) = h_{z,0} \end{cases} \tag{1}$$

,where s - characteristic variable vector of the system compound of subvectors: u - control vector (pumps and valves), d - unmeasured disturbance vector (water consumption), y - output vector (pressure in node h , flow in pipelines q , water velocity in pipelines v), h_z - state vector (water level in tanks); $h_{z,0}$ - tanks water level at initial t_n , k - discreet sampling instant $k = T_h \cdot t$.

2.2 Control of DWDS

There are two major aspects in DWDS control: quantity (hydraulics) and quality over prediction horizon $\Xi_p = [t_n, t_n + H_p]$ (where H_p - length of prediction horizon). Because of differences in dynamics of hydraulics and quality, effective DWDS control is realized in a frame of suboptimal two layer hierarchical control structure [2,4]. At the upper control layer hydraulics control and coarse values of quality control are appointed. In the lower (correction) layer a correction of quality control, obtained from upper layer is realized. In the paper only hydraulics control at the upper layer is considered over control horizon $\Xi_u = [t_n, t_n + H_u]$, where H_u - length of control horizon with assumption that $\Xi_u = \Xi_p$ and $H_u = H_p = 24$ hours.

2.3 System constraints

In DWDS control problem there exist four major constraints on:

- head at water monitoring nodes $h_d(\Xi_p) \in \left[h_d^{\min}(\Xi_p), h_d^{\max}(\Xi_p)\right]$, d $\in$ D where D – water consumptions nodes index set;
- head change at water monitoring nodes $\underset{k \in 1, H_p - 1}{\forall} \Delta h_d(k, k+1) = \left|h_d(t_n + k) - h_d(t_n + k + 1)\right| \le \Delta h^{\max}$ where $\Delta h^{\max}$ - maximum pressure change;
- water tanks level– $h_z(\Xi_p) \in \left[h_z^{\min}(\Xi_p), h_z^{\max}(\Xi_p)\right]$, $z \in Z$ (Z – water tanks index set);
- initial $h_z(t_n)$ and final $h_z(t_n + H_p)$ water tanks level must be equal $\Delta h_z(t_n, t_n + H_p) = h_z(t_n) - h_z(t_n + H_p) = 0$.

Set of system constraints is given as $\overline{\overline{Y}}$.
Output and state trajectories $Y(\Xi_p) = \{h_d(\Xi_p), h_z(\Xi_p)\}$ must satisfy the system constraints:

$$Y(\Xi_p) \in \overline{\overline{Y}}(\Xi_p) \tag{2}$$

Input control variables constraints are given as:

$$U(\Xi_u) \in \left[U^{min}(\Xi_u); U^{max}(\Xi_u)\right]; \ U \in R_+ \tag{3}$$

In this paper the pump control is considered, only.

3 Formulation of DWDS optimizing control problem

Effective DWDS hydraulics control is based on optimizing predictive control algorithm. In this paper control problem is formulated as follows:

$$\begin{aligned} &Find \quad U(\Xi_u) = \underset{U(\Xi_u)}{argmin}\, E(U(\Xi_u)) \\ &subject\ to: (1) - (3) \end{aligned} \tag{4}$$

Control problem (4) is difficult to solve because of non-convexity, nonlinearity and existence of hybrid variables (continues and discrete) in the problem. In the literature [1, 3, 6,7, 9] many methods of solving control problem (4), are presented. In paper [3] control method based on GA and DWDS Epanet [9] simulator, is presented.

In this paper in order to increase the effectiveness of method presented in [3] additional SGO is proposed. This operators are based on system operator knowledge about manual system control.

4 Proposed method of solving optimizing DWDS control problem

4.1 Solving optimizing control problem of DWDS

In this paper optimization problem (4) using the AG with SGO and the DWDS simulator Epanet, is solved. Algorithm structure and scheme of information exchanging is shown in Figure 1.

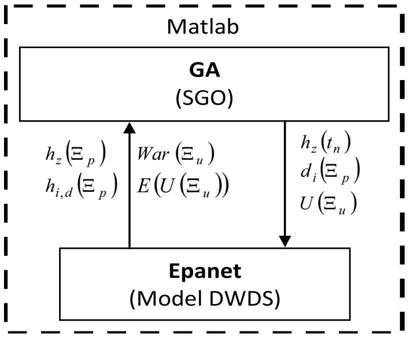

Figure 1. Algorithm structure and scheme of information exchanging

The basic AG task is to generate possible problem solutions $U(\Xi_u)$ based on evolution rules (mutation, crossing, selection, elitism) and evaluate fitness function. Epanet simulator task is to check control admissibility and quality of model output $h_{i,d}(\Xi_p)$ and state $h_z(\Xi_p)$ and calculate energy consumed by system pumps $E(U(\Xi_u))$. Simulator work based on: system model (1), control sequence $U(\Xi_u)$, output system measurement $h_z(t_n)$ and prediction of water demands $d_i(\Xi_p)$. Additionally, simulator generates warnings (results of the simulation) in the form of numerous vector (each vector element for every simulation step time k).

4.2 Genetic algorithm

4.2.1 Formulation of optimizing DWDS control problem using GA

The most difficult problem in applying AG to constrained optimization problem is how to handle constraints. In this paper optimization problem (4) is transformed into an unconstrained optimization problem with exterior penalty function in a form:

$$\begin{aligned} &Find \quad U(\Xi_u) = \underset{U(\Xi_u)}{argmin}\left(E(U(\Xi_u)) + F_p(Y(\Xi_p), U(\Xi_u))\right) \\ &subject \quad to: \ (3) \end{aligned} \tag{5}$$

Penalty function $F_p(Y(\Xi_p), U(\Xi_u))$ is a weighted sum of 5 functions (for transparency arguments of individual member functions are omitted):

$$F_p = w_1 \cdot F_{model} + w_2 \cdot F_d + w_3 \cdot F_\Delta + w_4 \cdot F_{eq} + w_5 \cdot F_z \tag{6}$$

,where: $F_{model}, F_d, F_\Delta, F_z, F_{eq}$ - appropriately functions of constraints: model, pressure and pressure increment in water monitoring nodes, water tanks, initial and final water storage in water tanks equality; w_i - weights $i = \overline{1,5}$.

4.2.2 Specimen structure

The GA maintains a population S^t of individuals s_n^t ($n = \overline{1, N}$) for t - th generation. Each specimen s_n represents solution of the control problem (4) $U(\Xi_u)$ $(s_n = U(\Xi_u))$. Every specimen consists of m subvectors $u_m(\Xi_u)$, representing m - th pump and valves control sequence over Ξ_u. Specimen structure is shown in Figure 2.

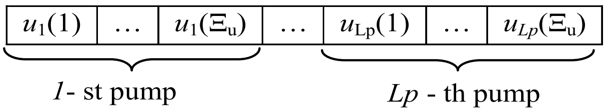

Figure 2. Specimen structure

4.3 Heuristic knowledge implementation as a genetic operators

For solving optimization problem (5) a real-number GA, was applied. However, genetic algorithm with implemented genetic operators (crossover – "sbx", mutation – "random", selection – "tournament") [5] did not work satisfactory. Solutions didn't meet the set of system constraints and moreover, computation time was too large (over 45 min.). In order to shorten the computation time, 7 specialized genetic operators, is proposed. These operators reflect the system operator knowledge regarding its control with help of simulator Epanet.

Two operators are consequences of warning messages (in a form of numeric vector *War*) generated by simulator Epanet when problem are encountered when running a hydraulic analysis [8]. First warning message is an announcement of pump choking (in system is pressure larger that this pump can produce) and the second warning message is an announcement about the negative pressure in some of DWDS nodes. If an analysis is running successfully then warning message at k - th hydraulic step is equal to zero *(War(k)=0)*. Five other operators appears directly from system constraints (2) (4 operators) and from cost function of optimizing control problem (4).

In this paper SGO are associated with pumps. However, it is possible to create the analogous SGO for all pumps and valves existing in DWDS.

Details of presented SGO (for every k -th step time, n -th specimen and t -th GA generation):

a) *Pump choking* – if j -th pump is chocking increase this pump speed by a small value η - SGO $s_n^t((j-1)\cdot H_u + k) = s_n^{t-1}((j-1)\cdot H_u + k) + \eta, \eta > R_+$.
b) *Negative pressure* - if at d -th monitoring node pressure is below 0 increase j -th pump speed, supplying water area containing this monitoring node, by a small value ε – SGO $s_n^t((j-1)\cdot H_u + k) = s_n^{t-1}((j-1)\cdot H_u + k) + \varepsilon, \varepsilon > R_+$.

c) *Monitoring node pressure* – if at d -th monitoring node pressure is below bottom constraint $h_d(k) < h_d^{\min}(k)$ (above upper constraint $h_d(k) > h_d^{\min}(k)$) then increase (decrease) j -th pump speed, supplying water area containing this monitoring node, for a small value ς - SGO $s_n^t((j-1)\cdot H_u + k) = s_n^{t-1}((j-1)\cdot H_u + k) \pm \varsigma, \varsigma > R_+$.

d) *Monitoring node pressure difference* – if at d -th monitoring node pressure difference in following time steps $[k\text{-}1, k]$ – th is bigger then maximum pressure difference: $\Delta h_d^{\max}$ - $h_d(k-1) - h_d(k) < -\Delta h_d^{\max}$ $\left(h_d(k-1) - h_d(k) > \Delta h_d^{\max}\right)$ then increase (decrease) j -th pump speed, supplying water area containing this monitoring node, for a small value ς - SGO $s_n^t((j-1)\cdot H_u + k) = s_n^{t-1}((j-1)\cdot H_u + k) - \theta; \theta > R_+$.

e) *Water tank level* - if at z -th tank water level is below lower constraint $h_z(k) < h_z^{\min}(k)$ (above upper constraint $h_z(k) > h_z^{\min}(k)$) then increase (decrease) j -th pump speed at previous time step, supplying water area containing this tank, for a small value τ - SGO $s_n^t((j-1)\cdot H_u + k - 1) = s_n^{t-1}((j-1)\cdot H_u + k - 1) \pm \tau, \tau > R_+$.

f) *Initial an final water tank level* - if at z -th tank, final $h_z(t_n + H_p)$ water tanks level is below initial level $h_z(t_n) < h_z(t_n + H_p)$ (is bigger then initial $h_z(t_n) > h_z(t_n + H_p)$) level then increase (decrease) j -th pump speed in previous 3 time steps, supplying water area containing this tank, for a small value $\overline{\rho}$ - SGO $s_n^t\left(\overline{(j\cdot -1)\cdot H_u - \rho, (j\cdot -1)\cdot H_u}\right) = s_n^{t-1}\left(\overline{(j\cdot -1)\cdot H_u - \rho, (j\cdot -1)\cdot H_u}\right) \pm \overline{\rho}, \dim(\overline{\rho}) = 3$.

g) *Minimizing energy cost* – within the time intervals when electric energy is low $\Xi_{low} = \left\lfloor t_n + H_{low}^{min}, t_n + H_{low}^{max} \right\rfloor$ (high - $\left(\Xi_{high} = \left\lfloor t_n + H_{high}^{\min}, t_n + H_{high}^{\max} \right\rfloor\right)$) increase (decrease) j -th pump speed, for a small value $\overline{\sigma}$ - SGO $s_n^t((j-1)\cdot H_u + \Xi_{low}) = s_n^{t-1}((j-1)\cdot H_u + \Xi_{low}) + \overline{\sigma}$, $s_n^t((j-1)\cdot H_u + \Xi_{high}) = s_n^{t-1}((j-1)\cdot H_u + \Xi_{high}) - \overline{\sigma}; \overline{\sigma}_{low}, \overline{\sigma}_{high} > R_+$.

Small values $\varepsilon, \eta, \varsigma, \overline{\rho}, \tau, \theta, \overline{\sigma}$ are randomly generated within assumed borders.

5 Simulation example

5.1 Description of the system model

The Chojnice DWDS serves as a testing example for optimizing predictive control algorithm. Model structure is shown in Figure 3.

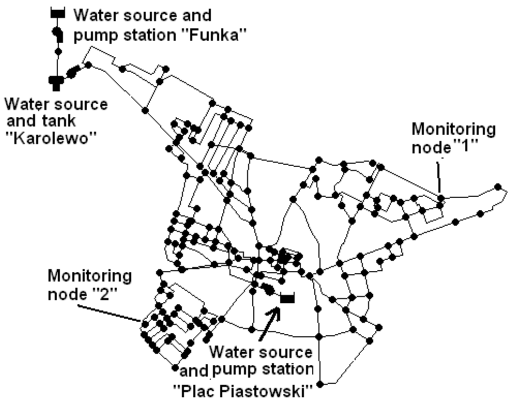

Figure 3. Test model of Chojnie city

Test model Chojnice DWDS consists of 177 nodes, 271 pipelines, 2 water sources, 3 pump stations and 1water tank. Hydraulic step is 1 hour and length of prediction and control horizon are 24 hours. Pump stations "Karolewo" and "Plac Piastowski" supply water to area with "Monitoring nodes 1 and 2 respectively". Limits on pressure and its increment at "Monitoring nodes 1 and 2" are on value from 185 up to 210 [m] and 3 [m/h], respectively. pressure in tank "Karolewo" is limited to the value from 167.2 up to 170.8 [m]. During 8 am – 12 am and 4 pm – 10 pm electric energy cost 0.24 zl/kWh and rest of a day is 0,12 zl/kWh.

5.2 Simulation result

Comparison of arithmetic means (20 simulation runs) of GA with SGO and GA with "classical" operators cost functions is shown in Figure 4.

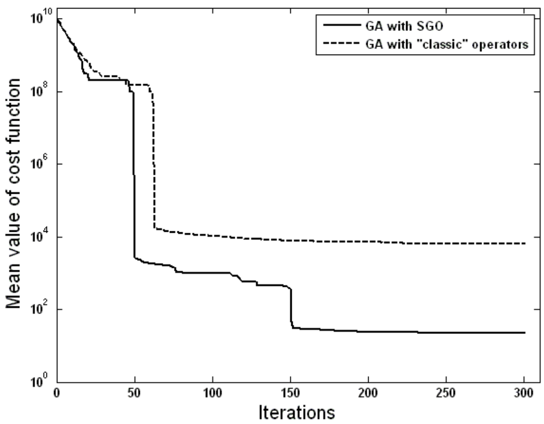

Figure 4. Comparision arithmetic means of cost functions

See that cost function coming from AG with classical operators lays considerably higher then this from AG with SGO. This is a result of problems with meeting the limits on tank levels and node pressures (penalty function). The AG with SGO fulfills all the restrictions quite well. Moreover the computational time was much shorter (20 min) comparing to classic AG (45 min).

The simulations was made in Matlab/Simulink 7.1 environment on a computer classes PC with the XP operating system (Service Pack 2), RAM 1 GHz, Pentium 4.3 GHz.

6 Conclusion

In the article an algorithm of solving the optimization task of control the SDWP was proposed. Usage of the specialized genetic operators based on operators knowledge, has improved presented control algorithm. Performed simulations based, on the SDWP model of Chojnice have demonstrated an increase of effectiveness of proposed method comparing to AG with „classical" operators.

Bibliography

[1] Brdys, M. A., Ulanicki, B. (1994): "*Operational control of Water Systems: Structures, Algorithms and Applications",* Prentice Hall, New York, London, Toronto, Sydney, Tokyo;

[2] Brdys, M.A., Chang, T., Duzinkiewicz, K. and Chotkowski, W. (2000): "*Hierarchical control of integrated quality and quantity in water distribution systems",* Proc. of the A.S.C.E. 2000 Joint Conference on Water Resources Engineering and Water Resources Planning and Management , Minneapolis, Minnesota, July 30-August 2.

[3] Drewa, M., Brdys, M. A., Ciminski, A. (2007): *"Model predictive control of integrated quantity and quality in drinking water distribution systems",* 8th IFAC International Symposium on Dynamics and control of Process Systems, Cancun, Mexico, June 6-8, 2007;

[4] Duzinkiewicz, K. (2005): „*Zintegrowane sterowanie systemami zaopatrzenia w wodę pitną"*, Praca habilitacyjna, Wydawnictwa Naukowo-Dydaktyczne Akademii Górniczo-Hutniczej w Krakowie (in polish);

[5] Gen, M., Cheng, R. (2000): *„Genetic algorithm and engineering optimization"*, John Wiley & Sons, Inc,

[6] Jowitt, P.,W., Germanopoulos, G., (1992): *"Optimal pump scheduling in water-supply networks"*, Journal of Water Resources Planning and Management ,118 (4),406-422;

[7] Martinez, F., Hernandez, V., Alonso, J., M., Rao, Z., Alvisi, S., (2007): *"Optimizing the operation of the Valenci a water- distribution network"*, Journal of Hydroinformatics, (67-78), 09.1 2007;

[8] Rosmman, L.A., (2000): *„EPANET 2 User Manual"*, EPA/600/R-00/057,September 2000;

[9] Shamir, U., Salomons, E., (2008): *„Optimal Real-time Operation of Urban Water Distribution Systems Using Reduced Models"*, Journal of Water Resources Planning and Management , 134(2), 181-185;