OPTIMIZATION OF RIPPLE CONTROL SWITCHING TIMETABLES FOR DAILY LOAD BALANCING AND MINIMIZATION OF IMBALANCE ENERGY

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ABSTRACT

In this paper the effective usage of Ripple Control Systems (RCS) is investigated from the point of view of daily load balancing. A computer simulation model is developed to be able to study the power consumption of RCS-controllable groups and their impact on the daily load curve. The design of an appropriate switching pattern is formulated as an optimization problem with the objective of achieving the highest possible minimal daily load constrained by duration of service and derivative conditions.

After the decomposition of the problem a fuzzy logic and genetic algorithm based optimization method is developed. The efficiency of the method is shown comparing different switching patterns by computer simulations.

A similar method is developed for the minimization of imbalance energy, i.e. the difference between the forecast and real energy demand.

I. INTRODUCTION

By the end of the 20th century, before privatization of the energy industry in Hungary the system of Ripple Control Systems (RCS) had been installed in order to be able to fill up load valleys by remotely switching on and off storage heaters from the dispatcher centers of the utility companies. A two-tariff system has been established, supplying energy mainly for the switchable hot water electric boilers and heaters considerably cheaper in off-peak time than for the non-switchable consumers.

Recently the former utilities turned into Distribution System Operators (DSO) and changed their switching patterns so as to keep the deviation from their schedule as low as possible (still providing at least 8 hours switch-on time for the remotely switchable consumers). This interest contradicts the interest of the Hungarian Independent System Operator, which is still balancing the load valleys so that no block of the nuclear power plant Paks has to lower its production during the night.

The present practice of RCS control does not make the most of its possibilities, though it could do so fairly easily and without conflicting with the interests of the consumers.

In this paper various possible RCS switching patterns are analyzed and compared based on computer simulations. For the simulations it is necessary to know :

- the change of power demand due to switching on a group of RCS-controllable consumers
- and also the power consumption without the switchable consumers (called "undistorted load curve")

This issue is addressed in Section II.

During the simulations the load time functions of the RCS-groups is superposed on the undistorted load curve according to various RCS programs, and so the efficiency of those programs in the load-balancing can be analyzed. Important constraints to be satisfied are:

- the change of the total load of the Hungarian system due to RCS switching is not allowed to exceed 90 MW within a 5-minute interval,
- every group has to be switched on at least 8 hours a day,
- the double tariff system according to peak and off-peak times is not subject to change.

These constraints along with the demand for a highest possible minimal load formulate an optimization problem for the switching pattern. The total length of the off-peak tariff time during one day is 15 hours: 13.00 to 17.00 and 20.00 to 07.00 in winter and 14.00 to 18.00 and 21.00 to 08.00 in summer. Considering that the switching patterns are determined in a 5 minute resolution, this yields a total of 180 possible switching instants. Further considering that there are several dozens of switchable groups yields a pattern to be optimized depending on several thousand variables; these variables are binary: either a group is on or off during a 5 minute period.

In Sections IV and V a soft-computing based optimization method is developed, which allow the fuzzy formulation of the above mentioned objective and constraints. Section VI presents a method for the on-line modification of the switching pattern for the purpose of reduction of imbalance energy.

II. DETERMINATION OF THE UNDISTORTED LOAD CURVE

Some DSO-s have performed systematic measurements of their RCS-groups and obtained detailed information on the power consumption of each group. These results match with the following theoretical assumption: the individually set switch-off temperatures and the actual amount of heat, stored in each electric boiler result in a nearly exponentially decreasing time-function of the consumed power of a controlled group.

The time-function of the power consumption of an RCS-controlled group can be approximated as:

$$P(t) = P_0 e^{-\frac{t-t_0}{\tau_1}} - P_0 e^{-\frac{t-t_0}{\tau_2}} \quad (1)$$

where t_0 is the switch-on time, and P_0 is the nominal total load of the group. In the second term τ_2 determines the rise-time constant, while τ_1 determines the fall-time constant of the double-exponential curve.

At those DSO-s where no detailed RCS-measurements are available, the following method is used: the undistorted load-curve is assumed to be linear during a certain time-period, that is, the total power consumption can be expressed as

$$P(t) = P_0 e^{-\frac{t-t_0}{\tau_1}} - P_0 e^{-\frac{t-t_0}{\tau_2}} + m \cdot t \quad (2)$$

where m is a constant slope. The switch-on instant t_0 is found as an abrupt increase of the total consumption, and the other four parameters are determined by a curve-fitting method, so that

$$f(P_0, \tau_1, \tau_2, m) = \sqrt{\sum_{t_0}^{t_{max}} \left(P_{measured}(t) - P(t)\right)^2} \quad (3)$$

be minimal. The instant t_{max} is either the switch-on time of the next group or the switch-off time of the same group. The undistorted load curve is then approximated as the difference of the measured load curve and P(t) as in (1). This method can be somewhat inaccurate since the linearity assumption in (2) may not hold, and since t_{max} may be close to t_0.

The result of the above method is shown in Fig.1.

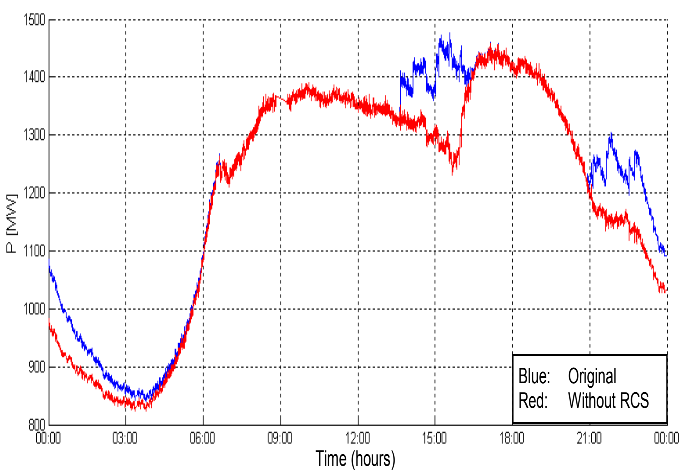

Fig.1. The measured and the undistorted load curve of one of the six Hungarian DSO-s

Fig. 1. shows that the switching pattern used makes a rather low contribution to filling up the minimum load valley around 4 a.m. The same result can be gained by considering the total daily load curve of the Hungarian system.

III. SIMULATION METHOD

The method described in previous Section yields a set of (P_0, τ_1, τ_2) triplets, one for each switchable group. The sample-time of the measurements used was 6 s, and for each τ_2 approximately half a minute was obtained. During the simulations described in Sections IV to VI the sample time is set to 5 minutes, so that τ_2 and the second term in (1) are neglected.

When a group is switched on, its power consumption is approximated as

$$P(t) = P_{on} e^{-\frac{t-t_{on}}{\tau_{on}}} \quad (4)$$

where t_{on} is the instant of switching on, and P_{on} is the initial power consumtion of the group. When a group is switched off, the power it would initially consume if it was switched on again is simulated as:

$$P(t) = P_{off} + (P_g - P_{off})(1 - e^{-\frac{t-t_{off}}{\tau_{off}}}) \quad (5)$$

where P_{off} is the power consumed right before the instant of switching off, t_{off}. P_g is the nominal load of the group, the power it would consume when switched on for the first time in the afternoon off-peak time. P_g was either available from the DSO-s or it was determined based on the results in Section II.

The parameters τ_{on} and τ_{off} are also determined based on the results in Section II, but the following additional information is used: measurements reported in [1] show that the instantaneous domestic hot water usage (l/min) in a large area of consumers has two daily maxima: one at approx. 7 a.m. and one at 8 p.m.

It is feasible – though this still needs to be further investigated – that the boilers will reach their switch-off temperature faster if less hot water is used. Therefore τ_{on} and τ_{off} are considered to be changing during the simulations, see Figs. 2 and 3.

Simulations are started at the beginning of the afternoon off-peak tariff time.

In this paper two scenarios are considered. In the first case the whole RCS-controlled load of 1400 MW can be used by the Independent System Operator (ISO) for the daily load-balancing purpose. This is a rather hypothetical case since the RCSs are property of the DSOs.

In the second case the ISO is hiring a part of the RCS capacity from the DSOs (representing a total load of 500 MW) and switching them according to its own pattern.

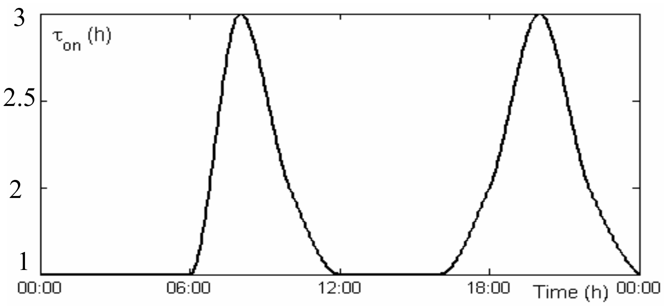

Fig.2. Daily variation of parameter τ_{on} (in the range of 1 to 3 hours)

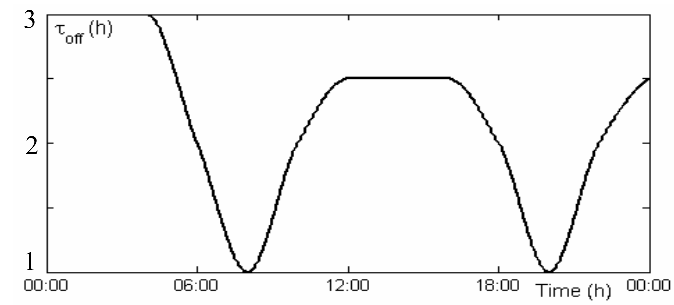

Fig.3. Daily variation of parameter τ_{off} (in the range of 1 to 3 hours)

In the next Sections a method for the automatic generation of the switching pattern is shown, which is achieved by the decomposition of the original optimization problem in two sub-problems.

IV. FUZZY LOGIC BASED OPTIMIZATION OF THE SWITCHING PATTERN TO FOLLOW A PRE-DEFINED LOAD CURVE

In this section a fuzzy logic based optimization method is shown which allows the generation of a switching pattern so that the total consumption of the RCS groups follows – as long as possible – a pre-defined curve.

In each 5 minute interval t a set-point, $P_{Goal}(t)$ is given. The groups that will be on during one interval are selected as follows.

Let TT_i denote the total time the *i-th* group has already been switched on since the simulation was started. This quantity is fuzzified using a membership function μ_{time} as seen on Fig. 4. This membership function shows how important it is to switch on a group to be able to provide long enough supply.

Also the power $P(t)_i$ that the *i-th* group would consume if it was on is calculated for each i, see (4) and (5).

Precedence among the switchable groups is defined based on μ_{time}, and the groups that have the same μ_{time} are ranked based on their power $P(t)_i$. The higher this power the higher the precedence.

The groups that will be switched on during the next 5-minute interval t are selected from the beginning of the precedence queue as long as their total load

$$P_{sum,k}(t) = \sum_{i=1}^{k} P(t)_i \qquad (6)$$

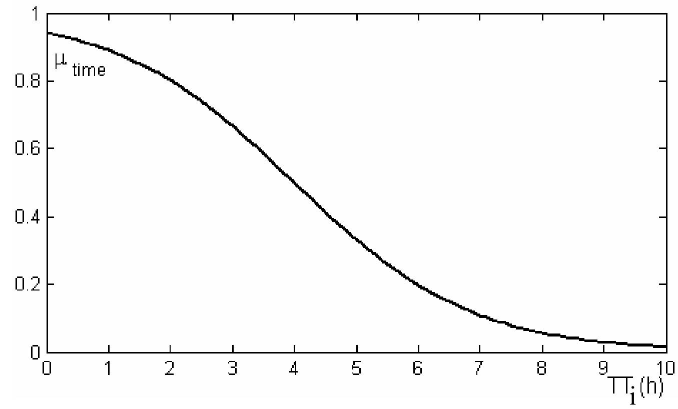

Fig. 4. Membership function μ_{time}

is not greater than $P_{Goal}(t)$, where k denotes the number of the last group selected so far. For the next group ($k+1$) in the precedence queue

$$\Delta P_{k+1}(t) = P_{sum,k+1}(t) - P_{Goal}(t) \qquad (7)$$

and

$$P_{change}(t) = P_{sum,k+1}(t) - P_{sum}(t-1) \qquad (8)$$

are calculated, where $P_{sum}(t-1)$ denotes the total switched-on power in the previous 5-minute interval.

Two membership functions are defined for the quantities calculated in (7) and (8) as shown in Figs. 5 and 6. The lower the membership degrees $\mu_{\Delta P}$ and $\mu_{Pchange}$, the higher the acceptability of ΔP_{k+1} (deviation from the set-point) and P_{change} (change compared to the previous interval) which would be caused by switching on also group $k+1$ besides the first k groups in the precedence queue.

The $(k+1)^{st}$ group is selected to be switched on if

$$\mu_{time,k+1} > MAX(\mu_{\Delta P}, \mu_{Pchange}) \qquad (9)$$

If so, the next, $(k+2)^{nd}$ group is considered, the quantities in (6) to (8) and the membership degrees according to Figs. 5 and 6 are recalculated and the decision is made for group $k+2$ according to (9), and so on.

If (9) is false, the selection for the actual 5-minute interval is done, and one can go over to the next interval *t+1*.

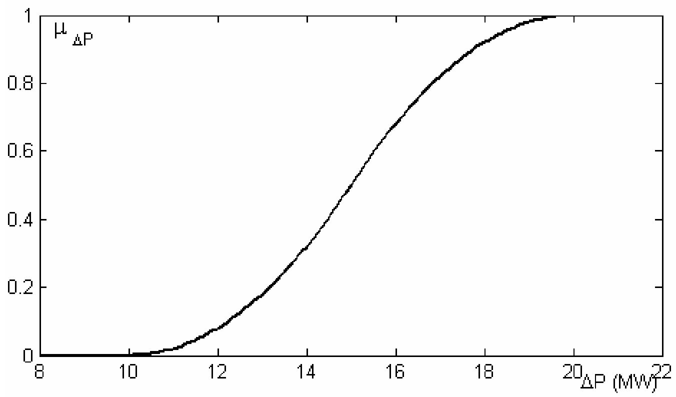

Fig. 5. Membership function $\mu_{\Delta P}$

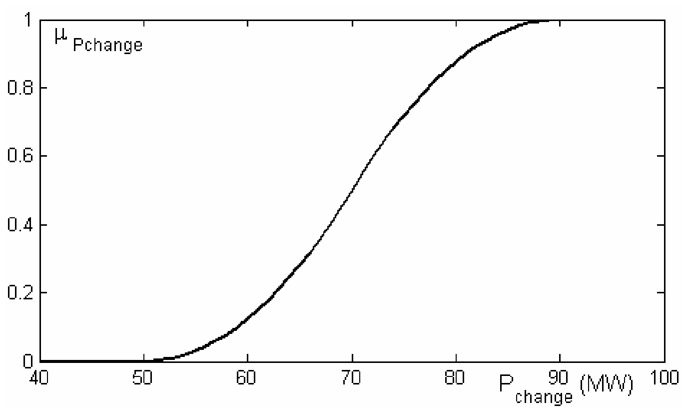

Fig. 6. Membership function $\mu_{Pchange}$

The result of the above optimization process is shown in Figs. 7 and 8 for a heuristically defined P_{Goal} time function. If the whole RCS load of 1400 MW is under control of the ISO, the result is plotted in Fig. 7 (for the sake of simplicity 50 groups of equal load are assumed).

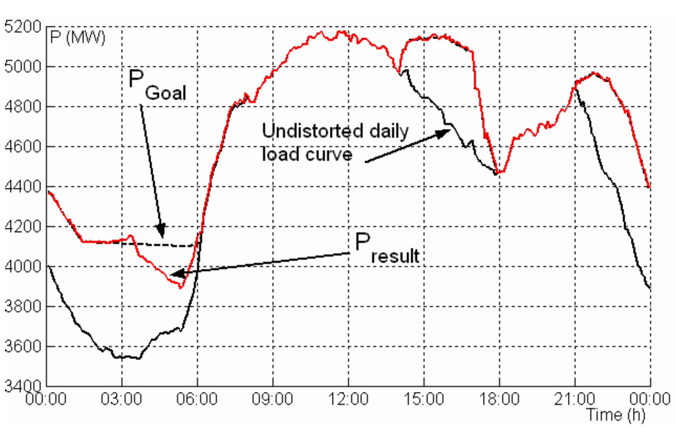

Fig. 7. Result of the optimization process: the undistorted daily load curve for a summer weekday, P_{Goal} and the resulting load curve if 1400 MW RCS load is used

All the groups are switched on only for approx. 6.5 hours and P_{change} exceeds -90 MW right before 18:00. The minimal daily load is 3885 MW.

If only 500 MW of the total RCS-controlled groups are used (20 groups of equal load are assumed), the result for the same $P_{Goal}(t)$ is shown in Fig. 8.

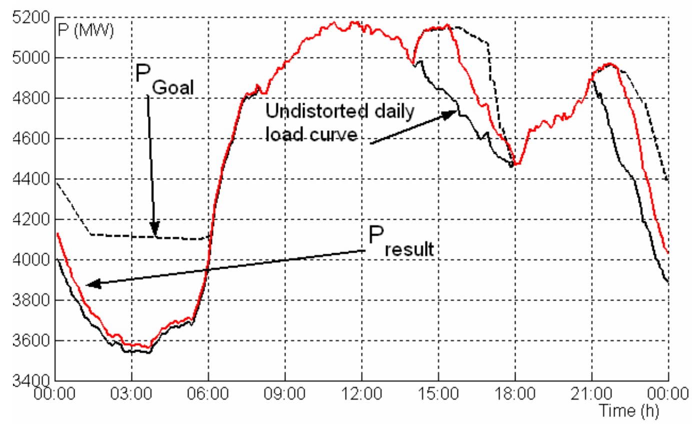

Fig. 8. Result of the optimization process: the undistorted daily load curve for a summer weekday, P_{Goal} and the resulting load curve if 500 MW RCS load is used

All the groups are switched on for more than 12 hours (even in the afternoon they all receive a gap of more than 3 hours) and - 60 MW < P_{change} < 73 MW during the whole day.

It can be observed that e.g. after 22:00 all the groups are switched on but their total load is quickly decreasing so that they hardly contribute to the increasing of the minimal load.
In both cases a more clever definition of the $P_{Goal}(t)$ curve is necessary which is done as described in the next Section.

V. FUZZY GA-BASED OPTIMIZATION OF THE LOAD CURVE

In this section the automatic optimization of the $P_{Goal}(t)$ curve is described, which yields a $P_{Goal}(t)$ time function that together with the switching pattern optimized by fuzzy logic as described in Section IV, will result in a highest possible minimum of the daily load curve.

For this purpose $P_{Goal}(t)$ will be represented by its values at the peak load hours (14:00,15:00, and so on) of the off-peak tariff zone. For the time-points representing 5-minute intervals between two neighboring hours linear interpolation is used, for time-points in the peak tariff zone the $P_{Goal}(t)$ is not defined since no RCS group will be switched on at that time.

To be optimized are therefore 15 values of $P_{Goal}(t)$. The lower bound of these variables is 0 MW, the upper bound depends on how large the peak load is allowed to be; in the simulation 400 MW is used in the afternoon and at 21:00 and the total RCS load (500 MW or 1400 MW) for the other points.

The optimization is performed using a Genetic Algorithm (GA); in the terminology of GAs an "individual" is one set of the 15 variables (representing one $P_{Goal}(t)$ function), the "fitness" of an individual is a performance index, based on which the individuals are compared.

For each individual $P_{Goal}(t)$ is calculated using the interpolation described above, and then the Fuzzy Logic based optimization of the switching pattern is performed as in Section IV. This switching pattern results in a time function $P_{result}(t)$, the minimum of which is intended to be maximized. A membership function μ_{MIN} for $\min_t\{P_{result}(t)\}$ is defined as in Fig. 9.

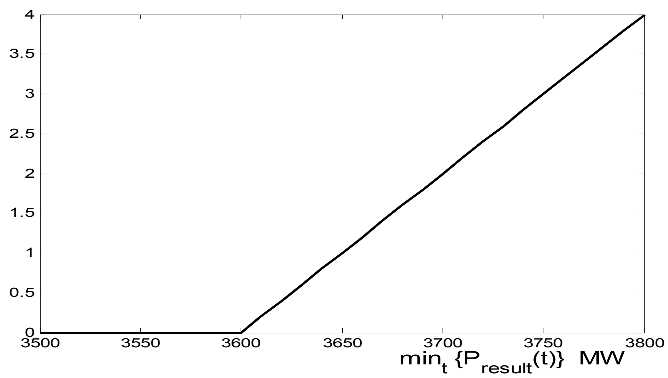

Fig. 9. Membership function μ_{MIN}

The "8 hour" and "90 MW" constraints are also fuzzified, but the membership functions (see Figs. 10 and 11) are different for this optimization process from the ones described earlier.

The fitness of an individual is now defined as:

$$F = \mu_{MIN} \cdot \mathrm{MIN}\{\underset{i}{\mathrm{MIN}}\{\mu_{time}^{(i)}\}, \underset{t}{\mathrm{MIN}}\{\mu_{Pchange(t)}\}\} \quad (10)$$

where i denotes the number of the group and t is the time for each 5-minute interval.

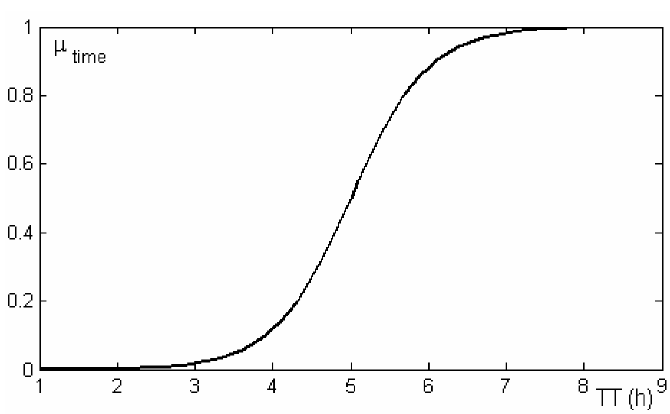

Fig. 10. Membership function μ_{time}

The Genetic Algorithm searches for the maximum of F varying the 15 parameters that define $P_{Goal}(t)$. In such a way the "8 hour" and "90 MW" constraints are transformed to be part of the objective function.

The result of the optimization can be observed in Fig. 12 (with 1400 MW RCS load) and Fig. 13 (with 500 MW RCS load).

If using 50 equal groups with a total load of 1400 MW, each group is switched on for 8 hours and 5 minutes or 8 hours and 10 minutes (even in the afternoon they all receive a gap of 1 hour and 20 minutes) and - 80 MW < P_{change} < 80 MW during the whole day, except one single 5-minute interval when P_{change} is -94 MW. The minimal daily load is raised to 3955 MW.

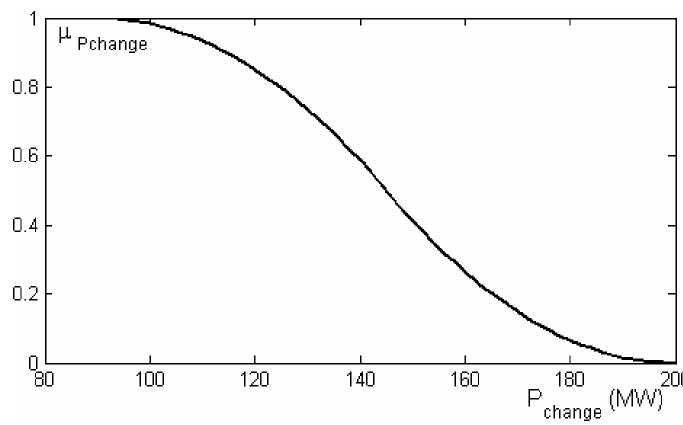

Fig. 11. Membership function $\mu_{Pchange}$

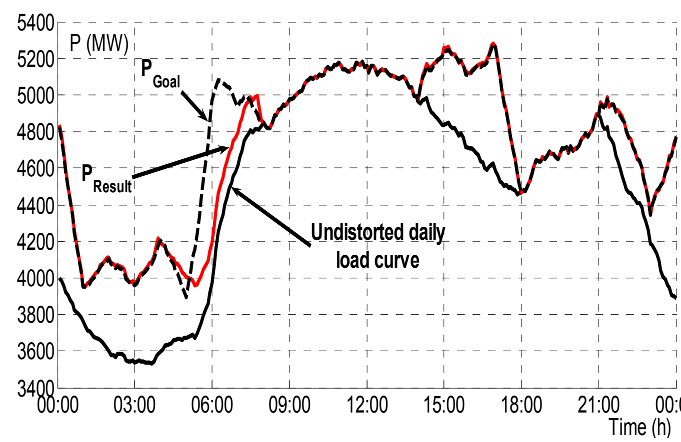

Fig. 12a. Result of the optimization process: the undistorted daily load curve for a summer weekday, P_{Goal} and the resulting load curve if 1400 MW RCS load is used

If using only 20 equal groups with a total load of 500 MW, each group is switched on for 8 hours or 8 hours and 5 minutes (even in the afternoon they all receive a gap of more than 1 hour and 40 minutes).

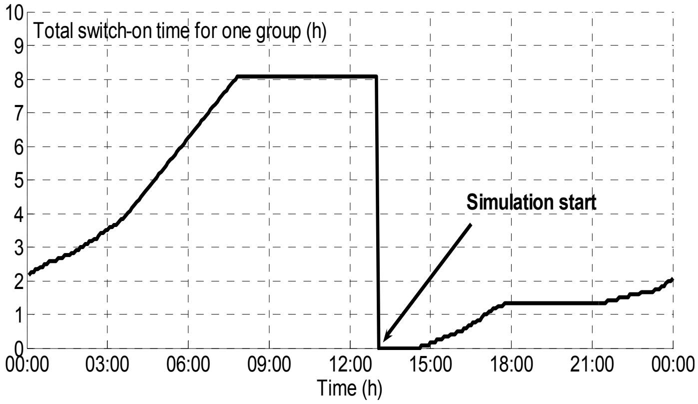

Fig. 12b. Result of the optimization process: the total switch-on time for one RCS group, if 1400 MW RCS load is used

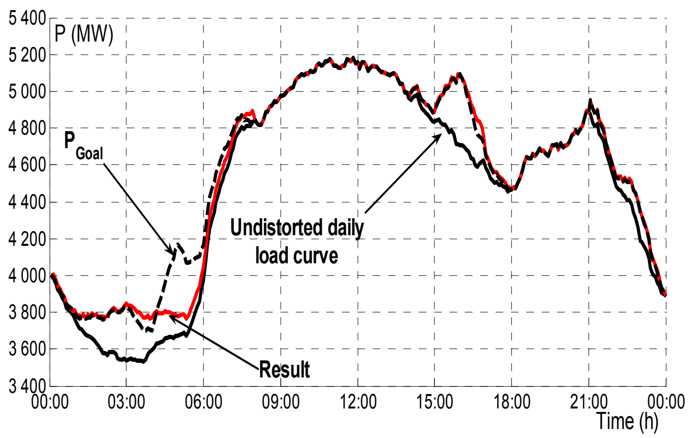

Fig. 13. Result of the optimization process: the undistorted daily load curve for a summer weekday, P_{Goal} and the resulting load curve if 500 MW RCS load is used

During the whole day - 66 MW < P_{change} < 73 MW and the minimal daily load is increased to 3766 MW.

Both values allow the normal operation of the nuclear power plant.

VI. IMBALANCE ENERGY MINIMIZATION

In this section a similar method to that described above is developed for the minimization of imbalance energy, i.e. the difference between the forecasted and real energy demand. Suppose there exists a pre-defined RCS switching pattern (e.g. one defined as above), and it has to be modified on-line so as to

– decrease imbalance energy, and at the same time

– keep the deviation from the original switching pattern as low as possible.

In this section we use real data of one DSO having 80 RCS groups, in the range of 0.53 MW to 8.38 MW.

The length of Accounting Time Interval (ATI) is 15 minutes, and switching of the controlled groups is done at the beginning of every 5-minute Sampling Time Interval (STI). Therefore the first task is to predict the imbalance energy three times for the ATI. For the present simulations imbalance power is used, i.e. the average power that is obtained by dividing imbalance energy by 15 minutes. The estimation can be done for example using a neural network, as described in an earlier study [2]. In the present work known historical imbalance power data is used for the simulations. In ATI *a* the estimation of imbalance power $\widetilde{\mathrm{P}}$ in the 1st 5min. interval is being made as follows:

$$\widetilde{P}(t,a) = \frac{1}{3}\big(P(a-3) + P(a-2) + P(a-1)\big) \qquad (11)$$

where P(a-k) denotes the known imbalance power *k* ATIs before *a*;

- in the 2nd 5min. interval the estimation is the sum of P(a) and a random noise with Gaussian density, having a variance of 5 MW;

- in the 3rd 5min. interval the estimation is the sum of P(a) and a random noise with Gaussian density, having a variance of 2.5 MW;

Let $\mathrm{TTD_i(t)}$ denote the Total Time of Deviation of RCS-group *i* from the original switching pattern at STI *t*. If for example at a certain STI *t* the group *i* should have been on, but it had to be kept off for the sake of decreasing imbalance power, then $\mathrm{TTD_i(t)}$ is decreased by 5/60 hours.

The Sum of $\mathrm{TTD_i(t)}$, i.e.

$$\mathrm{STTD_k(t)} = \sum_{i=1}^{k} \mathrm{TTD_i(t)} \qquad (12)$$

is fuzzified using a membership function $\mu_{TTD}(k)$ as shown in Fig. 14.

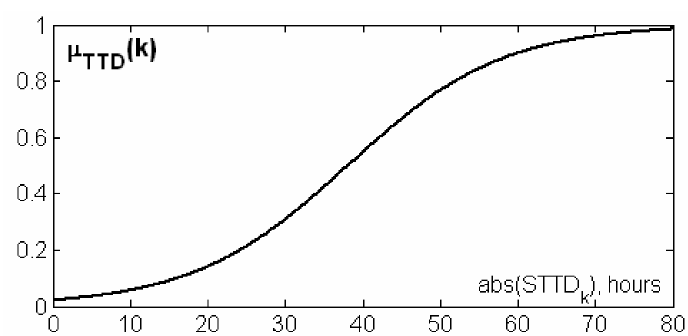

Fig. 14. Membership function for abs($\mathbf{STTD_k}$)

If in a 5-minute interval *t* the groups 1 to *k* are switched on, a total load of

$$P_{sum,k}(t) = \sum_{i=1}^{k} P(t)_i \quad (13)$$

is obtained.

Another membership function is defined for the deviation from the goal, which is $\widetilde{P}(t,a)$. Let

$$DP(t) = \widetilde{P}(t,a) - P_{sum,k}(t) \quad (14)$$

Then μ_{DP} is defined as in Fig. 15.

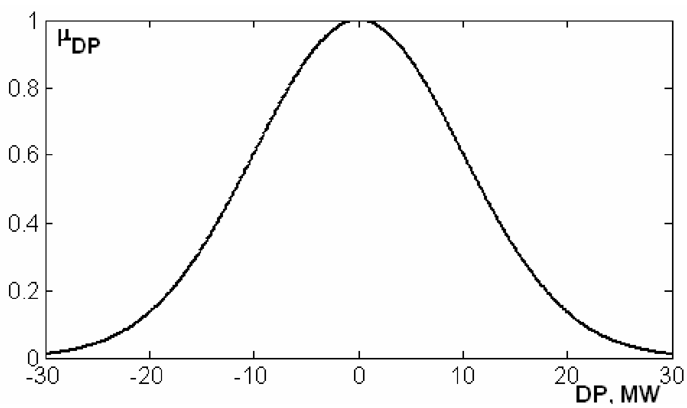

Fig. 15. Membership function for DP

The algorithm of selection of groups to be switched on is outlined as follows. Let OOP(t) denote the set of groups, that were supposed to be switched on at STI *t* according to the original switching pattern, and NOOP(t) denote the set of all other groups.

IF $\widetilde{P}(t,a) > 0$, THEN

1. Switch ON each group *i* for which $i \in ON_1$, where $ON_1 \equiv OOP(t)$
2. Switch ON each group *i* for which $i \in ON_2$, where $ON_2 = \{i : TTD_i(t) < 0 \text{ AND } i \in NOOP(t)\}$
3. IF $\widetilde{P}(t,a) > \sum_{i \in ON_1 \cup ON_2} P(t)_i$, THEN
   a. $ON_3 = \{i : TTD_i(t) \geq 0 \text{ AND } i \in NOOP(t)\}$
   b. sort ON_3 in ascending order of $TTD_i(t)$, *i* in ON_3
   c. switch ON groups $i = 1..k$ in ON_3 until $MAX\left((1-\mu_{TTD}(k)) * \mu_{DP} \right)$ is reached. Truncate ON_3 to $i = 1..k$. **STOP.**
4. IF $\widetilde{P}(t,a) < \sum_{i \in ON_1 \cup ON_2} P(t)_i$, THEN
   a. $OFF_4 = \{i : TTD_i(t) \geq 0 \text{ AND } i \in OOP(t)\}$
   b. sort OFF_4 in descending order of $TTD_i(t)$, *i* in OFF_4
   c. switch OFF groups $i = 1..k$ in OFF_4 until $MAX\left(\mu_{TTD}(k) * \mu_{DP} \right)$ is reached. Truncate OFF_4 to $i = 1..k$.
5. IF still $\widetilde{P}(t,a) < \sum_i P(t)_i$ for $i \in ON_1 \cup ON_2, \text{AND } i \notin OFF_4$, THEN
   a. $OFF_5 = ON_2$
   b. Sort OFF_5 in ascending order of $TTD_i(t)$, *i* in OFF_5
   c. switch OFF groups $i = 1..k$ in OFF_5 until $MAX\left((1-\mu_{TTD}(k)) * \mu_{DP} \right)$ is reached. Truncate OFF_5 to $i = 1..k$ **STOP.**

For $\widetilde{P}(t,a) < 0$ a similar algorithm has to be applied, with respective changes.

The result of the algorithm is shown in Fig. 16.

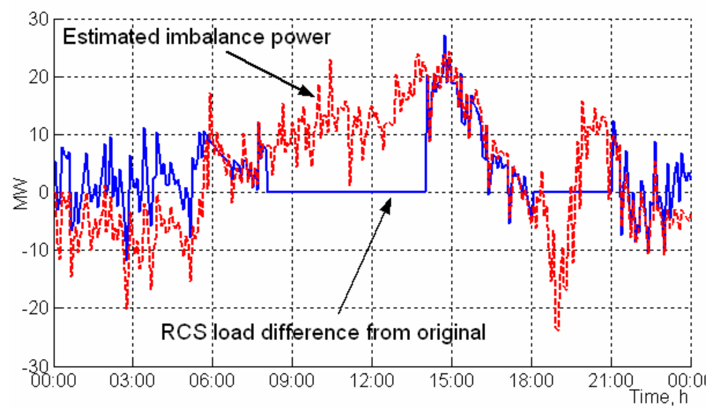

Fig. 16. Simulation results of the presented imbalance energy minimization

It can be observed, that the imbalance power is well served by the RCS loads as long as the deviation from the original switching pattern does not prevent them from doing so.

The simulation showed a decrease in the imbalance energy by 30 % in the off-peak tariff time. At the same time the customers in each RCS group received more than 8 hours of supply, the highest deviation was about 35 minutes.

VII. STEPS FORWARD

The exponential load model presented in Section II. of this paper sometimes appears to be inaccurate in the early morning hours. By this time usually all the groups had been already switched on, so – according to the above model – the total RCS load should be decreasing. In fact an increase can be observed due to the increasing water demand. (See bottom of Fig.19.)

This phenomenon can be well modeled as described in [3]. The drawback of this model is that one has to solve a system of coupled partial differential equations (Fokker-Planck type), and that very rough simplifications are needed when trying to use the model for an optimal load-management strategy [4].

Therefore a new approach is proposed in this paper to model aggregate water heating loads, which is based on the Preisach-type hysteresis model used in magnetics.

If the temperature of a single water heater is denoted by $x(t)$, we can write [3]:

$$C\frac{dx(t)}{dt} = -a'\big(x(t) - x_a(t)\big) - c'_e\, q'(t)\big(x_d - x_{in}\big) + R'm(t)b(t) \quad (15)$$

The variables in Eq. (15) are defined as follows

- C: tank thermal capacity (Joules/°C)
- $x_a(t)$: ambient temperature (°C) at time t
- x_d: desired outlet water temperature (depends on customer)
- x_{in}: inlet temperature (°C)
- a': thermal resistance of tank walls (a function of water heater insulation (Watts/°C)
- m(t): thermostat binary state (1 for on, 0 for off) at time t
- q'(t): hot water rate of extraction (m^3/sec) at time t
- b(t): the on-off control possibly applied by the utility within a load management program (1 for on, 0 for off)
- c'_e: specific heat constant for water (Joule/m^3 °C)
- R': power rating of the heating element (Watts).

The thermostat can be modeled as a simple hysteresis:

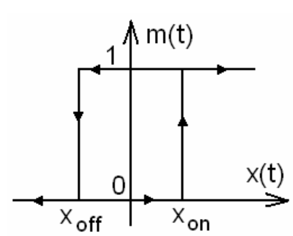

Fig. 17. Thermostat model

IF $x(t) > x_{on}$ (= $x_{set} + x_{hist}$) THEN m(t) = 1
IF $x(t) < x_{off}$ (= $x_{set} - x_{hist}$) THEN m(t) = 0,
where x_{set} and x_{hist} are the set-point and the half-hysteresis (usually 2-3 °C) of the thermostat, respectively.

The total load of an RCS group is composed of N such water heaters, where N can be estimated from utility data.
The proposed aggregate load model also uses Eq. (15), with following modifications:

- x(t) is the average temperature of N water heaters
- m(t) can take any value between 0 and 1, and represents the fraction of water heaters in the "on" state at time t
- q'(t) is the total hot water demand of the whole group
- c, a' and R' are average values
- the total load is obtained by $N \cdot R'm(t)b(t)$

The key issue is to model the aggregate hysteresis property of the heaters, i.e. the dependence of m(t) on x(t). This is done by using the Preisach model known from magnetic hysteresis computation.

The classical Preisach model (see [5] or [6]) is based on the assumption, that the magnetic material is composed of domains, all subjected to the same magnetic field, behaving like the so-called hysteron in Fig. 17. Another assumption is that the x_{on} and x_{off} values of the hysterons are not equal among the domains, but are distributed on a certain range (between x_{min} and x_{max}). This distribution can be described by a density function $\mu(x_{off}, x_{on})$ above the $x_{off} - x_{on}$ plane. Since $x_{on} > x_{off}$ always holds, the density function is restricted to the upper triangle of the plane (see Fig. 18.)

The aggregate behavior of the material is determined by the history of excitation (magnetic field) and its actual value. The history is represented by a terragonal line, which consists of the extreme turning points of the excitation. This line divides the triangle in an upper (S-) and a lower (S+) domain. The output (magnetization) is obtained by Eq.(16).

$$m(t) = \iint_{S+(t)} \mu\big(x_{off}, x_{on}\big)dx_{off}\,dx_{on} - \iint_{S-(t)} \mu\big(x_{off}, x_{on}\big)dx_{off}\,dx_{on} \quad (16)$$

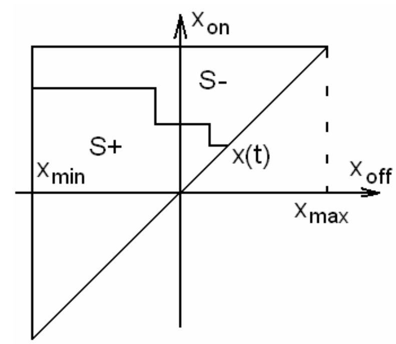

Fig. 18. The Preisach hysteresis model

The analogy between magnetic material and the aggregate hysteretic behavior of the water heaters is obtained by matching the magnetic field to the average temperature of the water heaters, and magnetization to the fraction of water heaters in the "on" state.

Fig.19. shows results obtained by the simulation of 1000 individual water heaters, compared to the results obtained by the Preisach-based model, after a simple identification of $\mu(x_{off}, x_{on})$.

A very good accordance can be observed in the first diagram. Of course an extensive identification algorithm still has to be developed, and the usability of the model has to be demonstrated from the point of view of power management. These results will be reported on in a later paper.

VIII. CONCLUSIONS

In this paper the effective usage of Ripple Control Systems (RCS) is investigated from the point of view of daily load balancing and imbalance energy minimization. A computer simulation model is developed to be able to study the power consumption of RCS-controllable groups and their impact on the daily load curve. The design of an appropriate switching pattern is formulated as an optimization problem with the objective of the highest possible minimal daily load constrained by duration of service and derivative conditions. After the decomposition of the problem a soft-computing-based optimization method is developed. The result of the optimization process can be influenced by a small number of parameters which define the membership functions, i.e. the importance (severity) of the constraints and objectives. The tool developed is efficient in generating the optimal switching pattern and different market conditions and constraints can easily be taken into consideration.

A further result reported on in this paper is an algorithm that is capable to modify on-line an existing switching pattern,

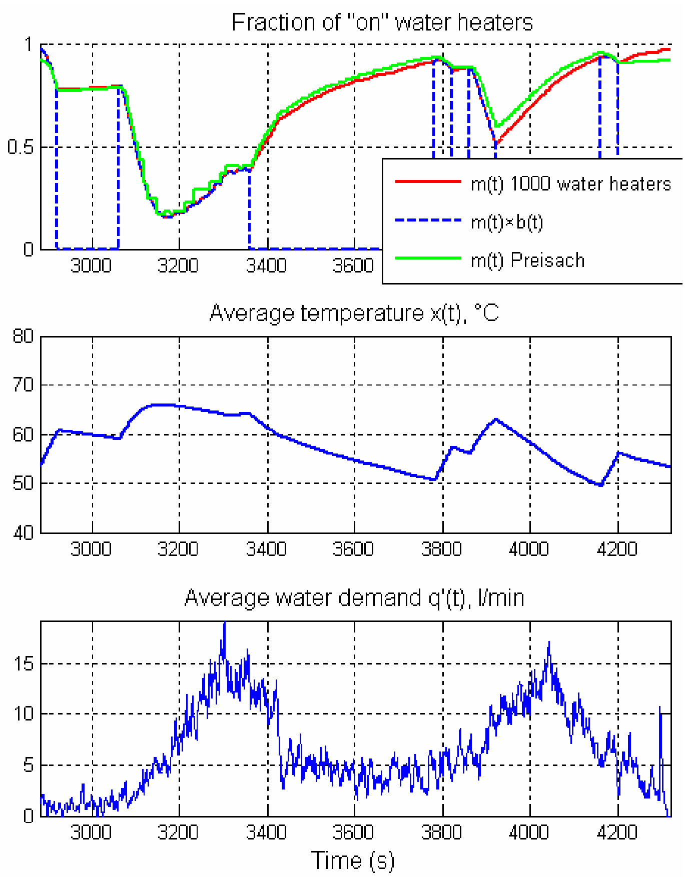

Fig. 19. Comparison of the Preisach model to the simulation of 1000 individual water heaters

so that the modification is slight but effective in decreasing imbalance energy, which is a great concern of utilities.

First results on the applicability of the Preisach-type hysteresis model to aggregate water heater load modeling are also shown.

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BIOGRAPHY

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