ISSN 1392 – 1215 ELECTRONICS AND ELECTRICAL ENGINEERING 2012. No. 4(120)
ELEKTRONIKA IR ELEKTROTECHNIKA

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AUTOMATIZAVIMAS, ROBOTECHNIKA

Challenges for Load Distribution Optimizer in Heat Exchanger Stations

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crossref http://dx.doi.org/10.5755/j01.eee.120.4.1455

Introduction

Currently, virtually everyone is under pressure to reduce their energy consumption and consequently contribute to the global reduction of CO_2 emissions. The associated savengs are highly attractive incentive for facility managers. Typically, heat claddings have either been already installed or are too expensive and will not be installed. Therefore, novel production optimizing systems for heating are increasingly attractive for both researchers and users.

Previous research has shown that the efficiency of heat exchange stations (HES) with heat exchanger cascades can be significantly increased (up to doubled) if the load is optimally distributed among individual heat exchangers in the cascade compared to the standard load distribution used currently [1]. The idea in [1], exploits the relationship between the load of a heat exchanger and its efficiency. The efficiency decreases exponentially with the increase of input power [1].

However, reference [1] provided only theoretical framework for such optimization. Whilst, the results are valid, implementation in real systems faces some additional challenges. These challenges must be discussed and addressed before a demonstrator of such optimizer can be deployed. Such discussion is the main topic of this paper. The main challenges are addressed and system architecture of the optimizer is presented.

The structure of the paper is following. Firstly, the conclusions of [1] are, for the sake of clarity, shortly summarized. Secondly, the issue of real time data acquisition, processing and control are discussed and addressed with an empirical predictive tool. Then, the issue of reliability of measurement instruments is discussed. Finally, the system architecture is presented.

Optimum load distribution in heat exchanger cascades

District heat exchanger stations typically employ a cascade of heat exchangers that operate in parallel as depicted in Fig. 1. [1].

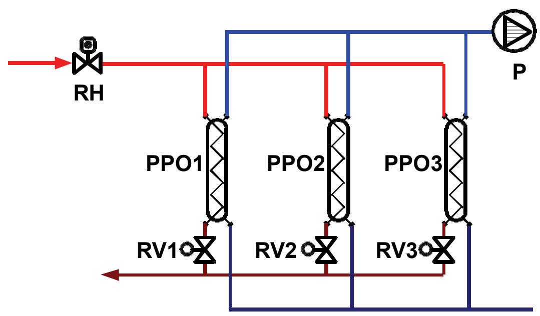

Fig. 1. Heat Exchanger Cascade in a typical HES

Reference [1] explored the efficiency of individual heat exchangers as a function of input power with the conclusion that following empirical model is suitable for the description

$$\eta = A \cdot e^{B \cdot W_1}, \quad (1)$$

where A, B are model coefficients specific for each heat exchanger and depending on settings such as temperature of output water to the secondary circuit; B is typically negative; η is the efficiency; W_1 is the input power.

The aim is the optimization of the individual loads so that total efficiency of the heat exchanger cascade, which can be expressed as shown in Eq. (2), is maximized

$$\eta_{total} = \frac{\sum_{i=1}^{N} W_{1,i} \cdot A_i e^{B_i \cdot W_{1,i}}}{\sum_{i=1}^{N} W_{1,i}}. \quad (2)$$

where index i represents individual heat exchanger in the cascade; N stands for the total number of heat exchangers in the cascade.

The optimization of total efficiency (2) must be performed for the output power that corresponds to the power consumption

$$W_{cons} = \eta_{total} \sum_{i=1}^{N} W_{1,i}. \quad (3)$$

Predictive estimation of energy consumption

One of the main challenges of the optimizer is the fact that the power consumption W_{cons} is unknown at the moment of the optimization. Thus in real systems, the objective is to determine the load distribution that will be optimal for an estimate of the power consumption W_{cons}. As a result, a predictive estimation algorithm must be employed.

Prediction of heat consumption by either a district or even the whole town has been addressed by many researchers for more than a decade, e.g. [2]. Quite often, the researchers have succeeded in their endeavours and their systems not only predict the consumption precision, but they have already reached the stage of real industrial applications, e.g. [3] or the system developed by the authors [4]. Core idea of those works is that if a heat producer can precisely anticipate the consumption within the receding horizon of few days, they can optimize their production planning to reduce their costs. However, these systems are aimed for large facilities of heat producers.

Up to date, we are not aware of any production optimization based on consumption prediction applied on the devices of the consumer. Quite simply, all the published models known to the authors predict the time distribution of energy consumption while depending on acquisition of accurate weather forecast information. Such information is easily accessible on the internet. However, compared to times when the development of predictive based production optimizers started, currently the costs of downloading this piece of information is marginal. Thus, it is feasible to consider implementation of such system even to smaller facilities such as local heat exchanger stations.

Accurate prediction of heat consumption is the most crucial component of a predictive production optimizer. Before a predictive model of heat consumption can be designed, the consumption must be analyzed. A sample heat consumption comparison to an average outdoor temperature is presented in Fig. 2. A sample daily load diagram is then presented in Fig. 3.

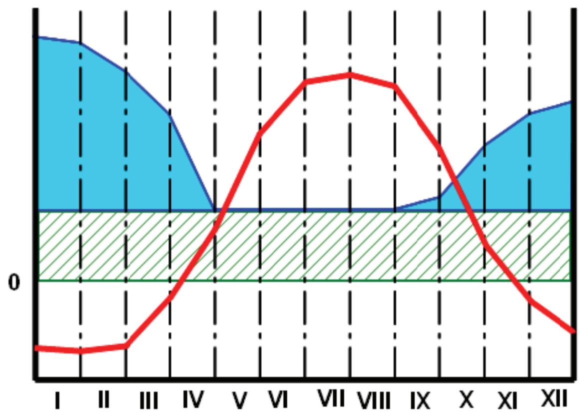

Fig. 2. Outdoor temperature and heat consumption during a year

As one can see in Fig. 2, the total consumption consists of two components(in full blue): a constant component (in green hatched) which corresponds to demand independent on outdoor temperature – e.g. hot water preparation; a variable component (in blue) which correlates well with the outdoor temperature.

In many ways, consumption of smaller block is similar to a consumption of whole district, town or city. Therefore, similar predictive models can be applied. In our work, analysis revealed that we can employ a model that we developed for large heat plant and presented earlier e.g. in [4].

For the sake of clarity, this model is shortly presented here. The basic model itself consists of two additive components. The first component is called temperature component and it depends on Temperature Function, a function derived from outdoor temperature. This component should mainly describe the heating and thermal losses in a building. The second component depends only on time. It describes periodic behaviour of occupants. For instance, hot water demand increases in the mornings and in the evenings. Additionally, people tend to turn heating off or reduce it over night. This behaviour is described by a periodic (or seasonal) component that when added to the first component corrects it in order to better fit the real life behaviour.

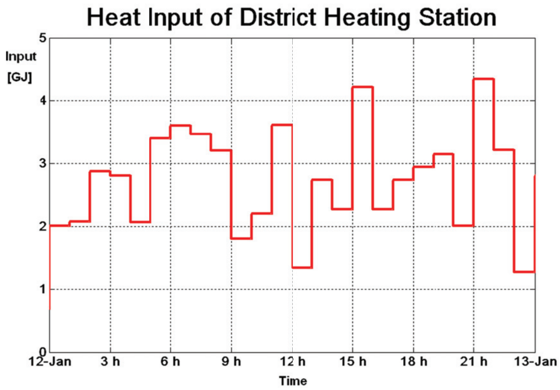

Fig. 3. Day heat consumption

As mentioned above, the temperature component depends on the temperature function. The temperature function is a new function that combines outdoor temperature (OT) and local legislation. This function is called temperature function (TF) [4] and is defined as follows:

$$\begin{cases} TF = 13 - OT, & if\ \overline{OT(48h)} < 13°C, \\ TF = 0, & if\ \overline{OT(48h)} \geq 13°C. \end{cases} \tag{4}$$

The TF is zero when the average outdoor temperature over the last two days is above 13°C. In such a case, the heating can according to Czech legislation be turned off and it usually is. In the other case, the TF is basically a reverse of the outdoor temperature. Temperature function and heat consumption are presented in Fig. 4.

It must be mentioned that the outdoor temperature OT used in the model is in fact a value obtained from weather forecast. Only then, the model can be used for prediction properly.

As can be seen from Fig. 4, the heat consumption and Temperature Function are highly correlated. Thus, a polynomial regression model can be anticipated

$$P_2 = a_0 + a_1 \cdot TF + a_2 \cdot TF^2 + \ldots + a_k \cdot TF^k , \tag{5}$$

where P_2 stands for output power [W]; a are model coefficients; TF is the temperature function.

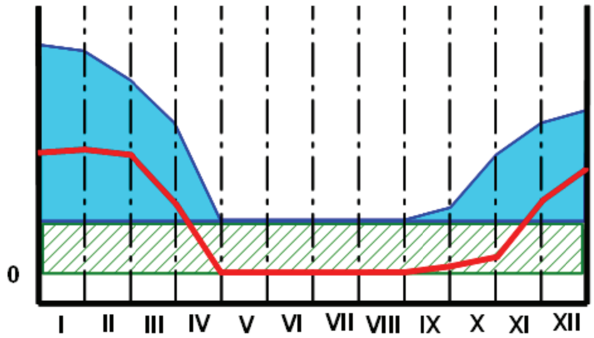

Fig. 4. Temperature function and heat consumption during a year

The power of regression may differ from building to building. However, statistical analysis shows that typically, quadratic term is the highest term required.

In typical prediction, the coefficients of the temperature component are calculated first based on the past values. Secondly, the error between the temperature coefficient and actual consumption is processed to calculate the coefficients of the periodic component. The error is averaged over a number of periods (weeks) and a sample week correction is obtained.

A basic problem of model described above is the fact that such model is not dynamic and cannot react to changes of the systems – e.g. new thermal insulation, change of occupants´ habits etc. Thus, it is only implemented as a core of an adaptive algorithm. Weekly, the model computes new model parameters to adapt itself for the new prediction over the upcoming week. Every week, three sets of parameters are calculated. These are based on vectors of past values with varying length. The parameters based on the longest vector can average out random short term variations. However, it takes it the longest time to adapt to a change in the system. For the shortest interval, the situation is the exact opposite. The middle length vector is a compromise.

The precision of prediction based on each of the three parameter set is determined and the set that performs the best over a sample interval is selected.

Analysis based on a limited number of buildings show that this algorithm is very suitable not only for large districts or towns [4] but also for smaller facilities such as blocks or larger buildings.

Reliability of measurements

The proposed system and its efficiency will strongly rely on the reliability of measurement devices as the measured values will be crucial for model estimation in the case of the consumption prediction as well as in the case of the heat exchanger efficiency estimation.

The first issue is represented by random software errors that are omnipresent in most industrial devices. The complexity of error detection will vary depending on the measured quantity. Whilst some errors, e.g. incorrect reading of the volume meter (see Fig. 5) can be detected easily, other errors will require more sophisticated algorithms e.g. [5]. This applies e.g. to the error in efficiency estimation of the heat exchanger that has two causes. Firstly, industrial devices typically do not posses perfect synchronization between the measurements for primary and secondary circuit as the synchronization is not essential for consumption measurement. Secondly, model from [1], whilst sufficient for significant efficiency increase, does not include the dynamics of the heat exchanger [6]. However, consideration of the dynamics is not essential given that in real implementation the optimization is performed towards estimated power consumption. In other words, the estimate of the power consumption is expected to introduce more uncertainty than the estimation of model parameters from (1).

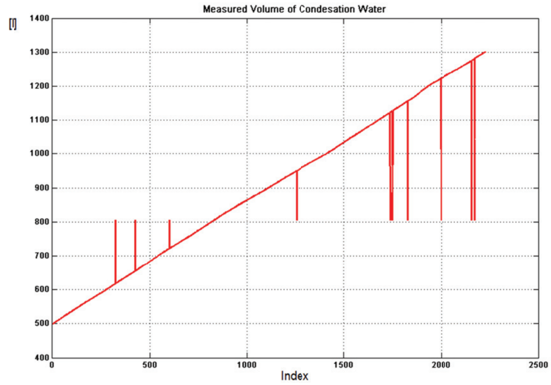

Fig. 5. Measured volume of condensation water

This quantity should be a non-decreasing function. Peaks correspond to an error caused by interference between the measurement device and the central data acquisition unit.

System architecture

On the system level, the proposed optimizer consists of six modules:

- Data Acquisition Layer;
- Data Verification Module;
- System Status Module;
- Consumption Prediction Module;
- Decision making module;
- Communication Interface.

These modules and their position in the system are depicted in Fig. 6.

Data Acquisition Layer. Data Acquisition Layer represents the basic layer of the system. Set of measurement devices continuously acquires data and transmits them to the central control unit. Additionally, this module also acquires the weather forecast from the internet. Design and issues of this layer has been thoroughly studied in open literature, e.g. in [7].

Data Verification Module. Second layer of the system is a Data Verification Module. All acquired data must firstly be tested on reliability as described in preceding section.

System Status Module. Errors detected by the Data Verification Module and system failures must also be reported to the HES supervising staff so that recurring errors and their source can be detected. This is done by System Status Module.

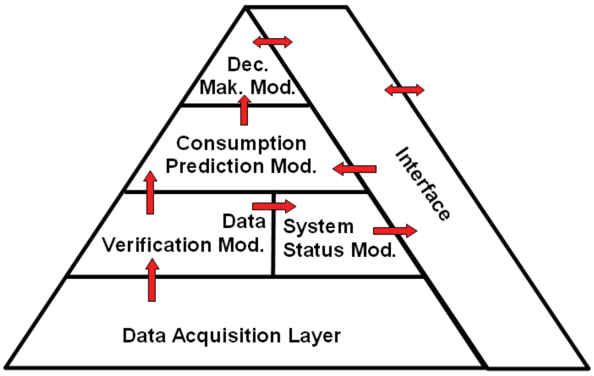

Fig. 6. Optimizer – system overview

Consumption Prediction Module. This processes the measured data and weather forecast. Production prediction described above is applied to provide a forecast over a receding horizon of few days.

Decision Making Module. This module estimates the model parameters of Eq. (1) for individual heat exchangers. These are used to distribute the load optimally using the predicted estimate of consumption and the optimization algorithm from [1].

Communication Interface. This module ensures that all the system layers communicate properly among each other and with the outside world.

Conclusions

This paper explores the challenges associated with real implementation of an algorithm that optimizes the load distribution among heat exchangers in district heat exchanger stations.

The main issues are the unknown consumption for which the optimization will have to be performed and the reliability of the measurement devices. The former is addressed by a consumption prediction algorithm that has been adapted to meet the specifics of a small district compared to a predictor for the entire city [4]. The latter is addressed by algorithms that test the reliability of the data. In case of erroneous data, the error is corrected and supervising staff is notified.

Finally, the architecture of the load distribution optimizer addressing the above mentioned issues is presented and the function of its system layers is explained.

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Received 2011 11 02
Accepted after revision 2011 12 14

J. Sipal. Challenges for Load Distribution Optimizer in Heat Exchanger Stations // Electronics and Electrical Engineering. – Kaunas: Technologija, 2012. – No. 4(120). – P. 65–68.

This paper explores the challenges associated with real implementation of an algorithm that optimizes the load distribution among heat exchangers in district heat exchanger stations. Such algorithm can significantly increase the efficiency of heat exchanger stations. However, the challenges such as unknown future consumption and uncertainty of measured data must be addressed by consumption prediction algorithm and algorithms for estimation of measurements' reliability. A system architecture that includes these algorithms is also presented. Ill. 6, bibl. 7 (in English; abstracts in English and Lithuanian).

J. Šipal. Šilumokaičių stočių apkrovos pasiskirstymo optimizavimo uždaviniai // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2012. – Nr. 4(120). – P. 65–68.

Nagrinėjami uždaviniai susiję su realiu algoritmo, optimizuojančio apkrovos tarp šilumokaičių pasiskirstymą, įdiegimu. Toks algoritmas gerokai padidina šilumokaičių stočių efektyvumą. Tačiau, tokie uždaviniai kaip nežinomas energijos suvartojimas ateityje ir matavimo duomenų neapibrėžtumas, turi būti adresuojami suvartojimo prognozavimo algoritmui ir matavimų patikimumo vertinimo algoritmams. Pateikta šiuos algoritmus turinčios sistemos architektūra. Il. 6, bibl. 7, lent. X (anglų kalba; santraukos anglų ir lietuvių k.).