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Waste-to-Energy Plant Operation Planning based on Stochastic Simulation

Michal Touš*, Martin Pavlas, Petr Stehlík

Institute of Process and Environmental Engineering, Faculty of Mechanical Engineering, Brno University of Technology, Technická 2896/2, 616 69 Brno,Czech Republic
tous@fme.vutbr.cz

In many cases, waste-to-energy (WtE) plants are combined heat and power producers. They are often integrated into a central heating system and they also export electricity to a grid. Therefore, they have to plan their operation for the next day, next month, etc. However, it may be a challenging task due to stochastic nature of some input variables such as varying lower heating value of waste, boiler performance resulting in fluctuating steam parameters, irregular internal steam consumption or its export. This paper presents a novel tool for a WtE plant operation planning under uncertainty. The crucial part of the tool is a stochastic model of a technology. The stochastic model was developed using operational data from an existing plant. The model was then implemented into simulation tool and well-known Monte Carlo simulation method was applied. Utilization of simulation results for operation planning is described on an example and the contribution of stochastic approach is evaluated using historical data.

Introduction

This paper deals with heat and electricity production planning in a short-term horizon (one day) in an existing waste-to-energy plant. The operator of WtE plant has to estimate the amount of heat dispatched to a district heating system (more or less fixed – see section 2) and the amount of electricity dispatched to a grid. If the plan is not fulfilled, there are financial penalties according to a contract on deliveries. Complex nature of WtE plant technology and some uncertainties (lower heating value of waste, irregular steam extraction) make the operation planning complicated. In case of the investigated existing plant, the planning is based on previous experience and on a simple utilization of historical data. In this paper, we present simulation-based planning of heat and electricity delivery applying stochastic model of the existing WtE plant. The model is based on operational data using linear regression (LR) and artificial neural network (ANN) modelling.

Based on our literature search, improvements in energy management based on simulation and optimization are discussed a lot. Salgado and Pedrero (2008) presented a review on short-term operation planning on CHP systems. They concluded that stochastic models should be included more frequently. Short-term operation planning is also typical for some renewable energy systems (solar, wind). Nemet et al. (2012) presented a paper dealing with an increase of solar energy in order to minimize utility consumption by rescheduling. Pereira et al. (2014) introduced a mixed integer nonlinear programming model to manage power system including wind power plants.

A good mathematical model describing the system and related aspects is essential. According to Smith et al. (2013), data-based (statistical) models are preferred in circumstances where computation time is important, when phenomena or properties affecting the process are not fully known, or when the scope of application does not require extensive deterministic models. In scientific papers, we can find researches using analytical models of WtE plant operation; Kropáč et al. (2012) investigates hazardous waste incineration from energy production point of view using balance model developed in W2E software and Šomplák et al. (2013) uses balance model for basic design optimization of a new WtE plant. According to our literature search, data-based modelling of WtE plant operation has not been published yet. Similarly

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focused research was presented by Bunsan et al. (2013) where ANN model is used for dioxin emission production prediction to plan strategies for pollution reduction.

We usually use combination of analytical models and data-based models. Our literature search in the field of data-based modelling of process units has shown that linear regression models and artificial neural network models seem to be the most frequently used, e.g. Mohonraj et al. (2012) presented a review of more than one hundred applications of ANN. In comparison with LR models, ANN models can successfully identify nonlinear relations between considered variables and are generally very suitable for regression-type problems. On the other hand LR models show a lower level of complexity than ANN models, which can be advantageous in further applications.

The next section describes the model development of the WtE plant operation. The third section deals with simulation tool utilizing the model and application of the simulation tool is presented in the following section. The final section provides major conclusions.

Stochastic simulation model of waste-to-energy plant

The simplified flow sheet of investigated technology (steam cycle only) is shown in Figure 1. The plant with the waste treatment capacity of 300 kt/y serves a city with 1 million inhabitants. There are four boilers with waste treatment capacity of 15 kt/h each. They produce steam with temperature of 230 °C and pressure of 1.2 MPa. Part of steam exiting boilers is utilized in technology and part is exported. Afterwards, it goes to the condensing steam turbine with one deregulated extraction. Steam from the extraction is used for feed water pre-heating and for district heating. Steam from turbine is condensed in the condenser. Dashed line represents steam by-pass which is used for steam turbine regulation.

We consider two energy outputs to be planned - heat delivery to the district heating system and electricity delivery to the grid. The planning of heat delivery has several levels. One year heat delivery (agreed in a contract) is divided into months (higher in winter, lower in summer) and consequently into weeks and days. So the operator knows the amount of heat to be delivered on the next day and has to decide about the next day electricity delivery. It means that the entire process of steam production and utilization has to be predicted. It can be done with mathematical model comprising sub-models of important parts of technology.

All included sub-models are summarized in Table 1. First of all, we have to predict amount of steam produced in boilers (1, 2, 3, 4). Then, there are steam extractions for boiler on-line cleaning blow-off (5), for deaeration (6) and for external technology (7). Remaining steam flow is then utilized in steam turbine for heat and electricity production. The model has to address steam parameters changes on deregulated turbine extraction. The heat delivery is agreed by the plan and we have to calculate the amount of steam used for this. The required steam flow is calculated based on steam enthalpy in deregulated extraction (8), which depends on extraction pressure and temperature, and enthalpy drop in a heat exchanger for district heating system (11). Since the extraction pressure is measured we can develop a model to predict the

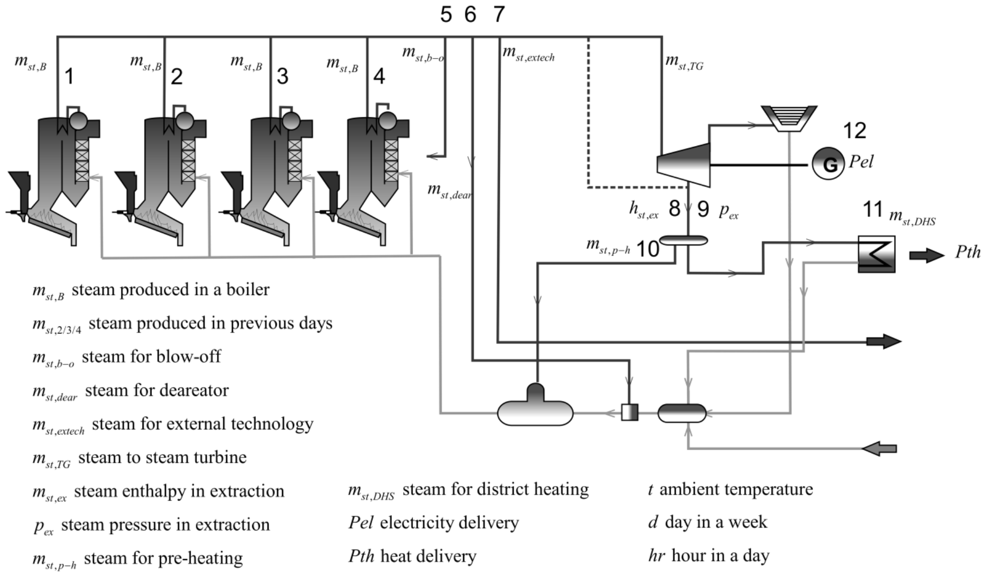

Figure 1: Simplified flow-sheet of WtE technology (dark lines represent steam, light lines represent water)

extraction pressure (9). The steam from extraction is then divided to steam for feed water pre-heating (10) and steam for district heating system (11). Having all the models (1-11), we can predict all steam flows and we can calculate electricity production on the steam turbine (12). We do not assume by-pass utilization because it is not desired (steam is not used in combined heat and power production). In real operation, the by-pass is used to decrease amount of steam to steam turbine when the electricity production/delivery is significantly higher than the planned electricity production/delivery (otherwise there are penalties).

Let us have a look at the turbine model in more details. The extraction pressure is a function of amount of steam at the turbine inlet and amount of extracted steam. The amount of extracted steam is given by enthalpy (to meet the heat delivery), which is a function of extraction pressure and temperature. Therefore, we have a cycle in the model and we need an iterative algorithm to perform a simulation. Now, we need an approach for enthalpy calculation. We have two options how to calculate the enthalpy. For both options, the turbine is divided into two stages – before and after extraction. The first option is to implement a basic thermodynamic model of the stage before extraction. The other option is to develop a regression model where enthalpy is a function of the extraction pressure. The first option is much more challenging mainly due to necessary implementation of steam tables. The other option provides much easier way – a regression function for enthalpy depending on the extraction pressure. We need a thermodynamic model as well but only to generate data for the regression function fitting. So we can use any software enabling steam turbine simulation (e.g. Aspen, Chemcad, W2E) to generate data. The best form of the regression function is a power function $h_{ex} = a \cdot p_{ex}^{b} + c$. Figure 2 shows that the fitting is very accurate.

Most of the sub-systems (1-12) are described by data-based models using LR and ANN. LR models are preferred due to easy understanding and implementation. However, ANN models are necessary in case of units with more complex nature. Sub-system models are summarized in Table 1 (R – correlation coefficient, MAE – mean absolute error).

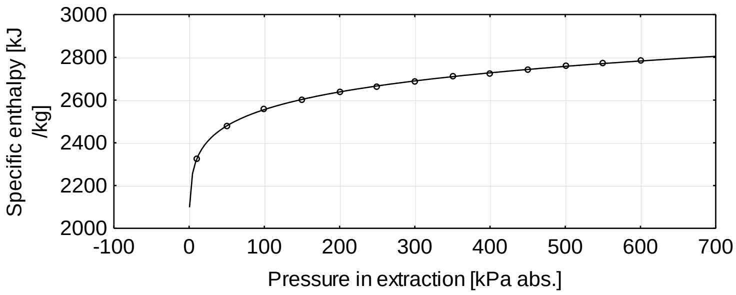

Figure 2: Specific steam enthalpy as a function of extraction pressure

Table 1: Summary of sub-systems models (for symbols see Figure 1)

Sub- system	Function	Model type	R	MAE
Steam from boiler 1	$m_{st,B} = f\left(m_{st,2}, m_{st,3}, m_{st,4}\right)$	ANN	0.81	0.82 t/h
Steam from boiler 2	$m_{st,B} = f\left(m_{st,2}, m_{st,3}, m_{st,4}\right)$	ANN	0.78	1.05 t/h
Steam from boiler 3	$m_{st,B} = f\left(m_{st,2}, m_{st,3}, m_{st,4}\right)$	ANN	0.73	0.63 t/h
Steam from boiler 4	$m_{st,B} = f\left(m_{st,2}, m_{st,3}, m_{st,4}\right)$	ANN	0.92	0.78 t/h
steam extraction for blow-off	-	Set by the operator	-	-
steam extraction for deaeration	$m_{st.dear} = f\left(\sum m_{st,B}, t, m_{st,extech}\right)$	ANN	0.86	0.46 t/h
steam extraction for external technology	$m_{st,extech} = f\left(d, hr, t\right)$	ANN	0.91	0.84 /th
steam enthalpy	$h_{st,ex} = f\left(p_{ex}\right)$	LR	0.99	0.22 kJ/kg
extraction pressure	$p_{ex} = f\left(m_{st,TG}, m_{st,DHS}, m_{st,p-h}\right)$	LR	0.99	5.4 kPa
steam for feed water pre-heating	-	Energy balance	-	-
steam for district heating system	-	Energy balance	-	-
electricity export	$Pel = f\left(m_{st,TG}, m_{st,DHS}, m_{st,p-h}\right)$	LR	0.99	0.13 MW

Looking at Table 1, goodness of fit indicators implies lower prediction accuracy in case of boilers and extraction of high-pressure steam. The reason could be either missing independent variable (model input) or randomness. In some cases, we cannot handle the first reason because not all model inputs are available (no measurement, e.g. lower heating value of waste). Therefore we assume randomness to be the only reason and we introduce stochastic part of the models:

$$predicted\ value = model\ output + random\ number \tag{1}$$

The random number is generated from a probability distribution which is given by probability distribution of residuals from the process of model development. Clearly the deviation of residuals for models with lower prediction accuracy is higher than for models with good prediction accuracy.
Stochastic model developed in previous part has to be implemented to a simulation model in order to provide appropriate support for the planning of heat and electricity production. We use sequential modular approach with aforementioned iterative calculation. The stochasticity is handled by Monte-Carlo simulation. Simulation procedure is described in Figure 3. In summary, there are usually thousands of simulation runs; each run is with different, randomly generated, numbers. The result is a random variable which has to be statistically processed.

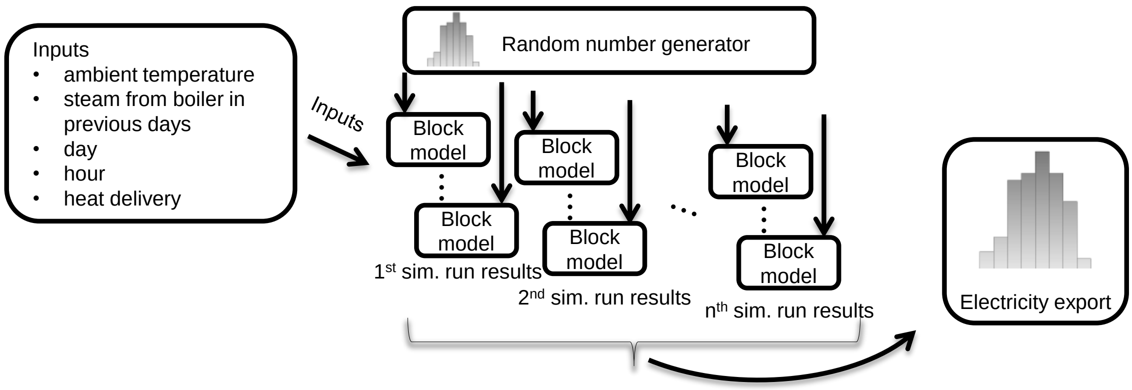

Figure 3: Scheme of the simulation procedure

Model application for energy delivery planning

In the investigated WtE plant, steam is frequently by-passed to regulate Pel. A good operation plan should provide smooth realization in real operation without utilization of by-pass because it decreases the potential for energy production in cogeneration and results in lower energy efficiency. Let us demonstrate the application of the simulation model and its benefits through a case study based on real operational data. We chose date 25/07/2013 to be planned because it represents typical operation regarding utilization of by-pass (otherwise Pel would have been outside the tolerance interval). All input data are summarized in Table 2.
Figure 4 shows comparison of real Pel, possible Pel and predicted Pel (two hours are missing due to error in measurement). The real Pel means real operation recorded in the operation log. The real Pel is fluctuating around planned Pel of 6 MW. Possible Pel means to what extent the Pel could be without utilizing by-pass and predicted Pel means the result of the simulation/prediction. Figure 4 shows Pel planned by operator and tolerance interval for Predicted Pel. We can see that Pel planned by operator is about 1 MW lower than predicted Pel. Real Pel is regulated according to it. However, without regulation (by-pass utilization) possible Pel could reach significantly higher values. Considering planning based on prediction, these values would be within the tolerance interval. As one can see, there are four points below (hour 5, 13 ,14, 17) and two above (hour 20 and 22) the tolerance interval.
The below points would mean decrease of Pth (very slight in hour 5 and 17) to increase Pel at the lower limit of the tolerance. The above points would mean only very slight utilization of the by-pass. Summarizing the results, the operation based on prediction significantly reduces utilization of by-pass. It brings approximately 12.3 MWh of electricity per day extra (about 10 % of total Pel) and fulfills the Pth plan for most of the time.

Table 2: Inputs for prediction

Input parameter	Value
Boiler 1 steam output 2/3/4 d before	35.5/35.1/35.0 t/h
Boiler 2 steam output 2/3/4 d before	35.3/37.7/8.7 t/h
Boiler 3 steam output 2/3/4 d before	0/0/0 t/h
Boiler 4 steam output 2/3/4 d before	29.8/30.6/31.6 t/h
Day	Thursday
Temperature range	19 – 27.4 °C
Heat delivery (Pth)	9 MW (constant in plan)

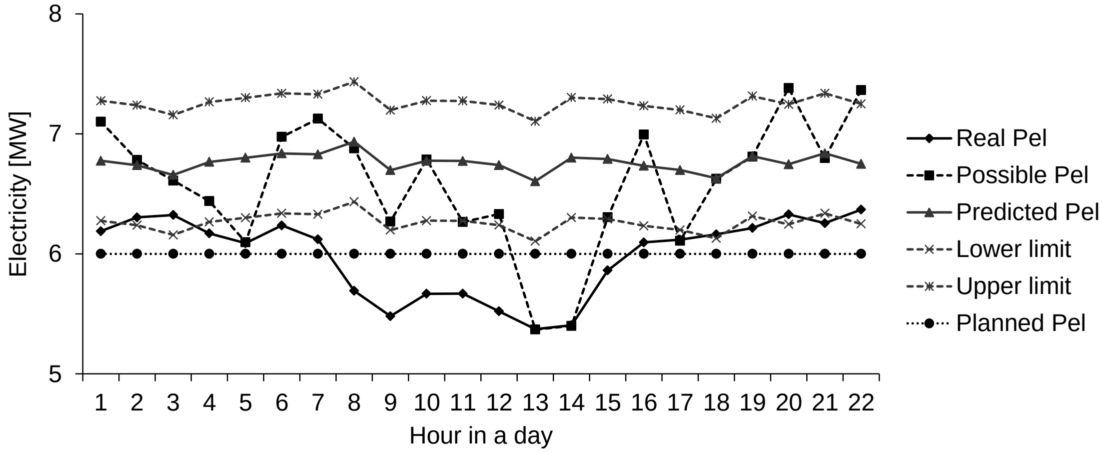

Figure 4: Comparison of next-day electricity delivery prediction with real delivery

Now, let us show benefits of stochastic simulation model. The main advantage of stochastic approach is the possibility of risk evaluation. When considering randomly fluctuating inputs or influences we obtain very different results for Pel as shown in Figure 5a (only three scenarios chosen form one thousand). In some cases, the difference reaches almost 2 MW. Considering the tolerance interval range of 1 MW (± 0.5 MW from planned Pel), there is a risk of the real Pel being outside the tolerance interval. However, the results of all simulation runs can be statistically processed and the risk of not meeting the plan can be evaluated. Figure 5b shows cumulative distribution function of Pel obtained processing the Monte-Carlo simulation results with plotted median 6.78 MW (proposed plan) and corresponding tolerance intervals (± 0.5 MW).

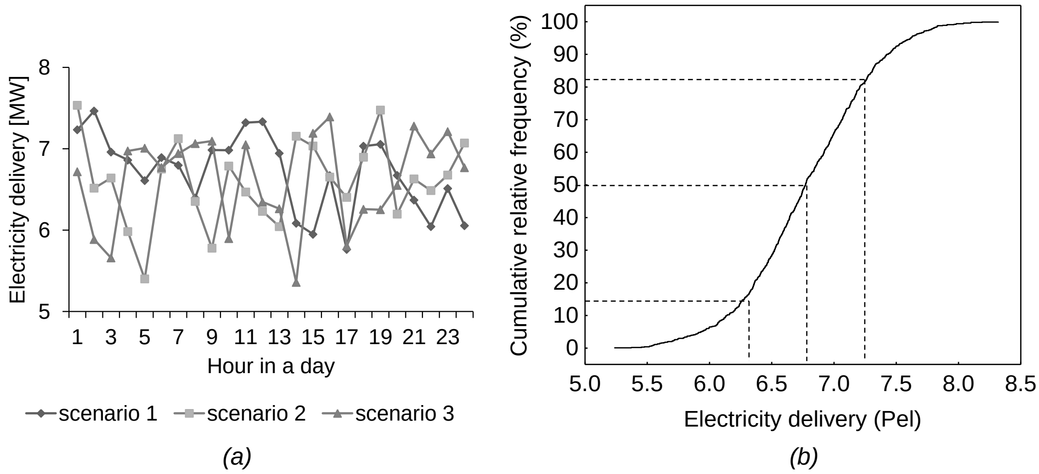

Figure 5: (a) Prediction of electricity delivery for different scenarios, (b) cumulative distribution function of electricity delivery for hour 1

It is easy to calculate probability of failing to fulfil this plan – the risk. In this case, it is about 30 %. It also corresponds to the results presented in Figure 4, where the possible Pel is outside of the tolerance interval in 6 cases from 22; it is 27 %.
It could be also beneficial to know in what range Pel could fluctuate with a given probability. For example, with probability of 90 % the range is from 6.1 to 7.5 MW. So the operator can be almost sure of the real Pel within this range. Analysis of historical data in this sense could provide the operator with crucial information for negotiation about the tolerance interval in a contract.

Conclusion

The research presented in this paper showed how the development and application of regression models may contribute to operation planning improvement in WtE plants. The operation planning of such a complex plant is very difficult without a good supportive tool. Moreover, it is tricky due to some uncertainties. The typical uncertainty is presented in boilers performance which is caused by heterogonous composition of waste. Clearly, the uncertainties can be handled applying stochastic approach. We presented a simple stochastic model and applied Monte-Carlo simulation method to predict the electricity delivery for a next day planning. The illustrative example based on real operational data showed that model-based planning provides higher energy production/efficiency and smooth operation. Moreover, when applying stochastic simulation we can estimate the probability of fulfilling the plan, which could be very helpful in negotiation about energy delivery contract. However, this should be proven by a long-term application in the existing WtE plant.

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