NATURAL GAS PREDICTION IN SLOVENIAN INDUSTRY USING GENETIC PROGRAMMING – CASE STUDIES

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Abstract

In accordance with Energy Agency of the Republic of Slovenia regulations, each natural gas supplier regulates and determines the charges for the differences between the ordered (predicted) and the actually supplied quantities of natural gas. Yearly charges for these differences represent up to 2% of supplied natural gas costs. All the natural gas users, especially industry, have huge problems finding the proper method for efficient natural gas consumption prediction and consequently, decreasing of mentioned costs. In this paper the prediction of the natural gas consumption in Štore Steel ltd. (steel plant) and Cinkarna ltd. (chemical processing plant) is presented. Based on production data several models for natural gas consumption have been developed using genetic programming method. The developed approach is extremely practical.

Keywords: natural gas consumption prediction, chemical processing, modeling, genetic programming

1. INTRODUCTION

Natural gas represents most environmentally preferred source of fossil fuel. Slovenia depends almost entirely on natural gas supplied from abroad (Russia, North Africa). Natural gas is transmitted over the gas pipelines in its gaseous state. The participants of the natural - gas market in Slovenia are the traders and the suppliers delivering natural gas to the customers. Natural gas is transmitted to the customers over the transmission and distribution networks by the system operators. The customers have the option to choose their supplier. Each supplier regulates and determines the additional charging for gas-related imbalances between the ordered and the supplied quantities [1].

The article presents an attempt for reducing additional charging for gas-related imbalances between the ordered and the supplied natural gas quantities for two large companies in Slovenia: Štore Steel ltd. (steel plant with more than 500 employees) and Cinkarna ltd. (chemical processing company with approximately 1000 employees). Differences between the ordered and the supplied natural gas quantities and corresponding charging depend on the precision of natural gas consumption prediction. In the paper natural gas consumption prediction using genetic programming method is presented.

2. NATURAL GAS ORDERING PROCEDURE

According to the contract between the supplier and natural gas user by 10 AM each Thursday the ordered natural gas quantities for the next week are to be reported to the natural gas supplier. Already ordered quantities can be changed by 10 AM one day before the actual supply; there is no charge if the change is made in time. The ordered quantities are provided by the specialist responsible for natural gas consumption based on his experience and with the help of the in-house applications or databases. The usual procedure is to collect the actually supplied natural gas quantities for the past days and check for deviations in production. Accordingly, the official prediction for the entire next week is formed. In the case of very large production variations also the already ordered natural gas quantities is changed by 10 AM one day before the actual supply [1].

3. GENETIC PROGRAMMING BASED PREDICTION OF NATURAL GAS CONSUMPTION

Genetic programming is probably the most general evolutionary optimization method [2-4]. The organisms (Figure 1) that undergo adaptation are in fact mathematical expressions (models). The prediction consists of the available function genes (i.e., basic arithmetical functions) and terminal genes (i.e., independent input parameters, and random floating-point constants). Usually the models consist of the following function genes: addition (+), subtraction (-), multiplication (*) and division (/), and terminal genes (e.g. x, y, z).

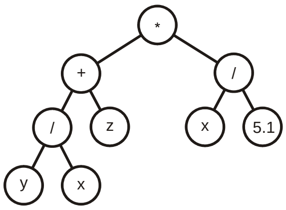

Figure 1 – Random program tree - organism

Random computer programs of various forms and lengths are generated by the means of the selected genes at the beginning of the simulated evolution. The varying of the computer programs is performed by means of the genetic operations (e.g. crossover, mutation) during several iterations, known as generations. After the completion of the variation (Figure 2) of the computer programs a new generation is obtained. Each generation is compared with the experimental data. The process of changing and evaluating organisms is repeated until the termination criterion of the process is fulfilled. The maximum number of generations is chosen as a termination criterion in the present algorithm.

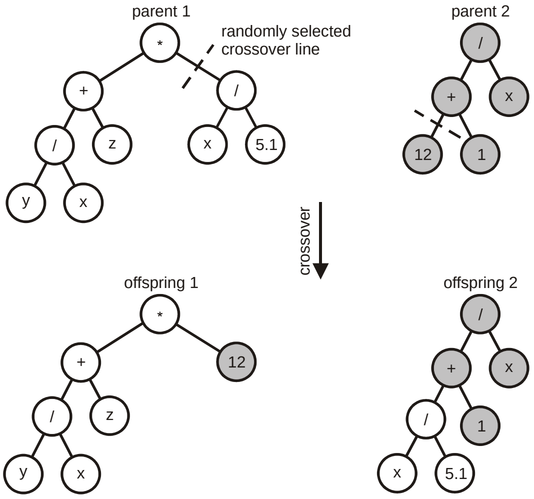

Figure 2 – Genetic programming crossover

The following evolutionary parameters were selected for the process of simulated evolutions: 1000 for the size of the population of organisms, 100 for the maximum number of generations, 0.4 for the reproduction probability, 0.6 for the crossover probability, 6 for the maximum permissible depth in the creation of the population, 10 for the maximum permissible depth after the operation of crossover of two organisms, and 2 for the smallest permissible depth of organisms in generating new organisms. Genetic operations of reproduction and crossover were used. For selection of organisms the tournament method with tournament size 7 was used.

For the fitness function Δ average relative deviation between predicted and experimental data was selected. It is defined as:

$$\Delta = \frac{\sum_{i=1}^{n} \left| E_i - P_i \right|}{E_i \cdot n}, \tag{1}$$

where n is the size of monitored data and E_i and P_i are the actual and the predicted natural gas consumption, respectively.

The AutoLISP based in-house genetic programming system was run 100 times in order to develop 100 independent civilizations. Each run lasted approximately 5 hours on a 3.0 GHz processor and 4 GB of RAM.

3.1 Natural gas consumption prediction in *Štore Steel* ltd.

Štore Steel Ltd. (Figure 3) is one of the biggest spring steel producers in Europe. It's natural gas consumption represents approximately 1.10% of Slovenia's natural gas consumption.

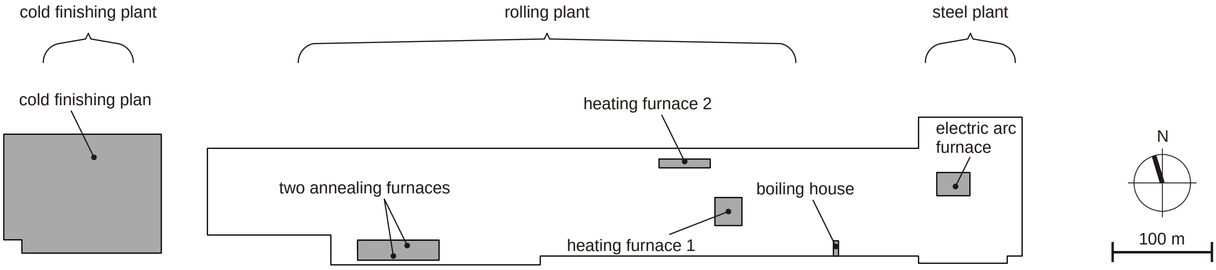

Figure 3 – *Štore Steel* layout

The following data was collected based on the actual ordering:

- drawing plant shifts [number of shifts] (*shifts*),
- steel plant production [number of batches] (*batches*),
- rolling plant production [t] (*tons*),
- annealing furnace #1 production [t] ($anneal_1$),
- annealing furnace #2 production [t] ($anneal_2$) and
- date (*month*).

The best model for NG consumption prediction in Cinkarna ltd. is:

$$\begin{gathered} 9665.77+3024\cdot anneal_1+3417.08\cdot shifts-2899.81\cdot month+\\ 33.972\cdot tons+790.126\cdot batches+\\ \frac{\left(\begin{gathered} anneal_1+\frac{-3.67\cdot shifts+0.04299\cdot tons}{anneal_1+shifts}+\frac{624299}{tons}+\\ \frac{3417.08\cdot tons+790.126\cdot batches}{-2899.81\cdot shifts+33.972\cdot tons}+\\ \frac{\frac{790.126\cdot tons}{shifts+roll}+791.126\cdot batches}{shifts}+\\ shifts\left(\begin{gathered}\frac{anneal_1(shifts+33.972\cdot tons+790.126\cdot batches}{anneal_1\cdot shifts+790.126\cdot tons}+\\ \frac{tons(2699920\cdot tons+624299\cdot batches)}{(2899.81\cdot shifts-33.972\cdot tons)^2 batches}\end{gathered}\right)\end{gathered}\right)}{shits+batches}\end{gathered} \tag{2}$$

with average relative deviation between predicted and experimental data 9.30%.

3.2 Natural gas consumption prediction in Cinkarna ltd.

Cinkarna Ltd. is a chemical processing company in Slovenia and the country's largest manufacturer of titanium oxides (TiO_2). Cinkarna Ltd. has an average annual natural gas consumption of 12.7 MIO Sm^3, which represents approximately 1.47% of Slovenia's natural gas consumption. The Cinkarna Ltd. layout is presented in (Figure 5). There are 5 main production units:

- TiO_2,
- Metallurgy,
- Chemistry,
- Graphics, and
- Maintenance and energy.

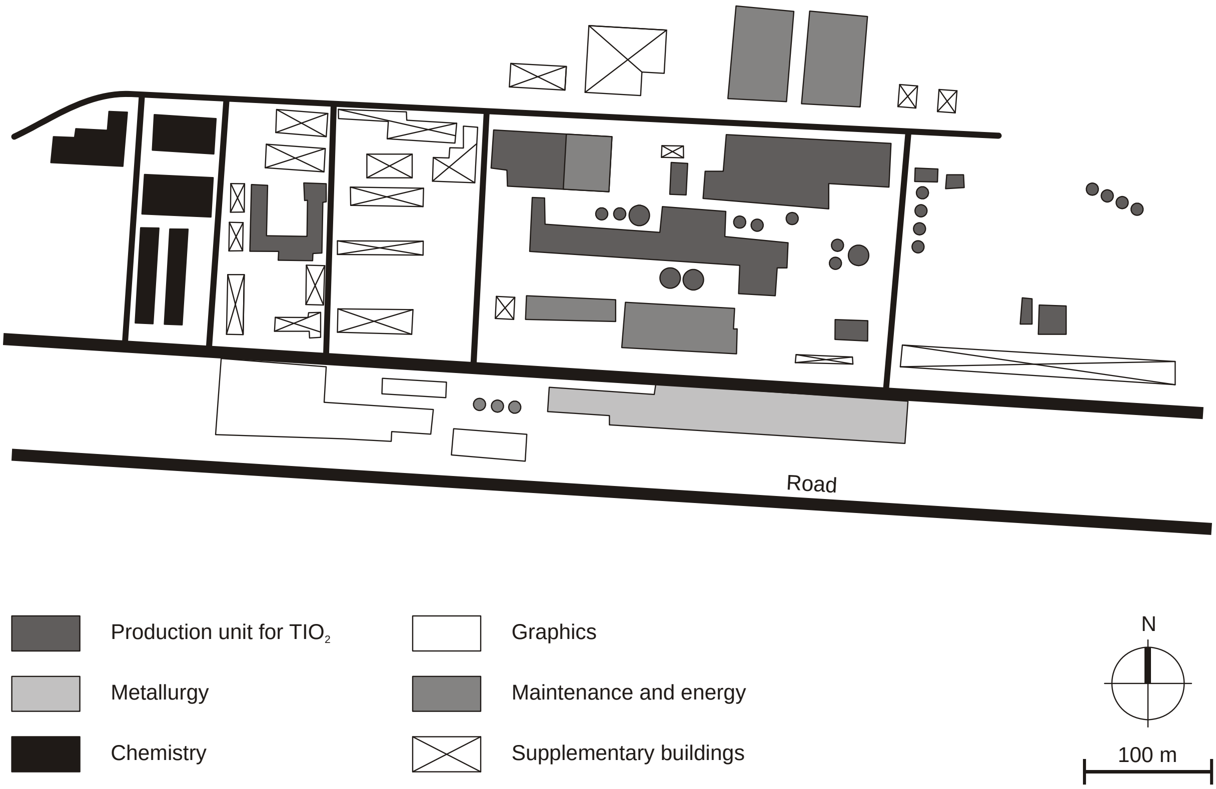

Figure 5 – *Cinkarna* ltd. layout

The following data was collected:

- the actually supplied quantities [Sm^3] for the previous 5 days (*DAY*1, *DAY*2, *DAY*3, *DAY*4, *DAY*5),
- planned working hours of steam boilers 1 and 2 [h] (*STEAM*1 and *STEAM*2),
- planned sulfur acid production working hours [h] (*ACID*),
- planned daily TiO_2 production [tons] (*TIO*2),
- predicted average daily temperature for the (next) day of gas consumption [°C] (*TEMP*) and
- actual natural gas consumption.

The best model for natural gas consumption prediction in *Cinkarna* ltd. is:

$$
\begin{aligned}
&\mathrm{DAY5}+\mathrm{TIO2}+\frac{\mathrm{DAY2}^{2}}{\mathrm{ACID}\,(2\,\mathrm{ACID}+\mathrm{TEMP})\,\mathrm{TIO2}\,(\mathrm{ACID}+\mathrm{DAY2}+\mathrm{TEMP}+\mathrm{TIO2})}-\\
&\frac{-\mathrm{DAY1}-3\,\mathrm{DAY4}+4\,\mathrm{DAY5}-3\,\mathrm{TIO2}}{-\frac{\mathrm{DAY2}}{\mathrm{TIO2}}+\mathrm{TIO2}}+\frac{2\,\mathrm{ACID}-\mathrm{DAY1}-\mathrm{DAY4}+2\,\mathrm{DAY5}+\mathrm{TEMP}+\mathrm{TIO2}-\frac{-\mathrm{DAY2}+\mathrm{TIO2}}{\mathrm{ACID}^{2}\,\mathrm{TIO2}}}{\mathrm{ACID}-\frac{\mathrm{DAY2}}{\mathrm{ACID}\,\mathrm{TIO2}}+\mathrm{TIO2}}-\\
&\frac{-\mathrm{DAY1}+\frac{\mathrm{DAY2}}{\mathrm{ACID}}+\mathrm{DAY5}}{\left(\mathrm{TIO2}-\frac{\mathrm{ACID}-\mathrm{DAY1}-\mathrm{DAY4}+2\,\mathrm{DAY5}+\mathrm{TEMP}-\mathrm{TIO2}}{-\frac{\mathrm{DAY2}}{\mathrm{DAY1}}+\mathrm{TIO2}}\right)\left(\mathrm{TIO2}-\frac{-\mathrm{DAY1}-\mathrm{DAY4}+2\,\mathrm{DAY5}-\mathrm{TIO2}}{-\frac{\mathrm{DAY2}}{\mathrm{DAY4}}+\mathrm{TIO2}}\right)}-\\
&\frac{-\mathrm{DAY1}-2\,\mathrm{DAY4}+3\,\mathrm{DAY5}-3\,\mathrm{TIO2}+\frac{\mathrm{DAY2}-\mathrm{DAY5}+\mathrm{TIO2}}{\mathrm{ACID}\,\mathrm{DAY4}}}{-\frac{\mathrm{DAY2}}{\mathrm{TIO2}}+\mathrm{TIO2}}-\frac{-\mathrm{DAY1}+2\,\mathrm{DAY5}-\frac{-3\,\mathrm{ACID}\,\mathrm{DAY1}+\mathrm{DAY5}}{-\frac{\mathrm{DAY2}}{\mathrm{TIO2}}+\mathrm{TIO2}}}{\mathrm{TIO2}-\frac{\mathrm{DAY2}}{3\,\mathrm{DAY4}-2\,\mathrm{DAY5}-\mathrm{ACID}\,(-\mathrm{DAY4}+\mathrm{DAY5})+\frac{\mathrm{DAY2}}{\mathrm{ACID}\,\mathrm{TIO2}}+\mathrm{TIO2}}}-\\
&\frac{(2\,\mathrm{ACID}+\mathrm{TEMP}+\mathrm{TIO2})\left(\mathrm{DAY2}+\mathrm{DAY4}+\frac{-\mathrm{ACID}\,\mathrm{DAY1}+\mathrm{DAY5}}{\mathrm{TIO2}-\frac{\mathrm{DAY2}+\mathrm{DAY4}-2\,\mathrm{DAY5}+2\,\mathrm{TIO2}}{\mathrm{ACID}^{2}}}\right)}{-\mathrm{DAY4}+\frac{\mathrm{ACID}-\mathrm{DAY1}-\mathrm{DAY4}+2\,\mathrm{DAY5}+\mathrm{TEMP}-\mathrm{TIO2}}{\mathrm{TEMP}}+\mathrm{TIO2}+\frac{-\mathrm{ACID}\,\mathrm{DAY1}+\mathrm{DAY5}}{-\frac{\mathrm{DAY2}}{\mathrm{TIO2}}+\mathrm{TIO2}}-\frac{\mathrm{ACID}\,\mathrm{DAY1}}{-\frac{-\mathrm{DAY2}+\mathrm{DAY5}}{\mathrm{TIO2}}+\mathrm{TIO2}}}-\\
&\frac{\begin{gathered}-\mathrm{DAY1}+\mathrm{DAY5}-\frac{-\mathrm{ACID}\,\mathrm{DAY1}+2\,\mathrm{DAY4}-\mathrm{ACID}\,(-\mathrm{DAY4}+\mathrm{DAY5})+\frac{\mathrm{DAY2}}{\mathrm{ACID}\,\mathrm{TIO2}}+\mathrm{TIO2}}{-\frac{\mathrm{DAY2}}{\mathrm{TIO2}}+\mathrm{TIO2}}-\\ \frac{\mathrm{ACID}\,(\mathrm{ACID}+\mathrm{TEMP})\,(-\mathrm{ACID}+\mathrm{TIO2})\,(-\mathrm{DAY2}+\mathrm{TIO2})\left(-\mathrm{DAY1}+\mathrm{DAY4}+\frac{(-\mathrm{ACID}+\mathrm{DAY5}-\mathrm{TIO2})\left(-\frac{1}{\mathrm{ACID}}+\mathrm{TIO2}\right)}{\mathrm{DAY2}-\mathrm{DAY5}+\mathrm{TIO2}}\right)}{\mathrm{DAY2}\,(\mathrm{ACID}+\mathrm{DAY4})}+\\ \frac{\mathrm{ACID}\,\mathrm{DAY1}}{\mathrm{TIO2}-\frac{(\mathrm{ACID}+\mathrm{DAY2}-\mathrm{DAY5}+\mathrm{TIO2})\,(\mathrm{ACID}+\mathrm{DAY4}-\mathrm{DAY5}+\mathrm{TEMP}+2\,\mathrm{TIO2})}{\mathrm{DAY2}}}\end{gathered}}{\mathrm{STEAM1}}-\\
&\frac{-\mathrm{DAY1}+\mathrm{DAY5}}{\mathrm{TIO2}-\frac{2\,\mathrm{ACID}-\mathrm{DAY1}-\mathrm{DAY4}+2\,\mathrm{DAY5}+\mathrm{TEMP}+\mathrm{TIO2}-\frac{-\mathrm{DAY2}+\mathrm{TIO2}}{\mathrm{ACID}^{2}\,\mathrm{TIO2}}}{-\frac{\mathrm{DAY2}}{\mathrm{ACID}\,\mathrm{TIO2}}+\mathrm{TIO2}}-\frac{-\mathrm{DAY1}+\mathrm{DAY5}}{\mathrm{TIO2}-\frac{\mathrm{DAY5}-\mathrm{ACID}^{2}\,(-\mathrm{DAY1}+\mathrm{DAY5})}{\mathrm{TIO2}-\frac{\mathrm{DAY2}+\mathrm{DAY4}-\mathrm{DAY5}+\mathrm{ACID}\,\mathrm{TIO2}}{\mathrm{DAY5}}}}}
\end{aligned}
\tag{3}
$$

where average relative deviation between predicted and experimental data is 5.40%.

4. CONCLUSIONS

Energy Agency of the Republic of Slovenia regulates and determines the charges for the differences between the ordered (predicted) and the actually supplied quantities of natural gas. Accordingly the most precise natural gas consumption prediction is appreciated. In this paper the prediction of the natural gas consumption in Štore Steel ltd. (steel plant) and Cinkarna ltd. (chemical processing plant) using genetic programming method is presented. In genetic programming system the structure, undergoing simulated evolution, is the population of mathematical models for natural gas consumption prediction. During the evolution mathematical models become more and more complex and accurate. For efficient prediction following influential parameters were used for evolving the mathematical models:

- Štore Steel ltd.:
  - drawing plant shifts,
  - steel plant production,
  - rolling plant production,
  - annealing furnace #1 production,
  - annealing furnace #2 production and
  - month of the year.
- Cinkarna ltd.:
  - actually supplied natural gas quantities for the previous 5 days,
  - planned working hours of steam boilers 1 and 2,

  - planned sulfur acid production working hours,
  - planned daily TiO_2 production,
  - predicted average daily temperature for the (next) day of gas consumption.

For each company's natural gas consumption the same AutoLISP based in-house genetic programming system was run 100 times. Consequently 2-times 100 genetic programming models for prediction of natural gas consumption were developed. Only the best two were used for analysis. The average relative deviation between predicted and actual natural gas consumption in Štore Steel ltd. and Cinkarna ltd. is 9.30% and 5.40%, respectively. With slight modifications the developed approach is extremely practical for any kind of natural gas consumption prediction.

5. REFERENCES

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