

An Intelligent Prediction of Self-produced Energy

Ayca Altay and Aykut Turkoglu

Abstract The need for energy has been aggressively increasing since the industrial revolution. An exponential growth of industrial and residential power use is encountered with the technological revolution. Cogenerated and self produced energy is a solution that allows the reuse of heat produced, decreases transmission investments, and reduces carbon emissions and decreases dependency on energy resource owners. The mass production sites, health centers, big residential sites and more can use the system. In this chapter, the focus is given to industrial auto-producers. Power market balance is based on the day-ahead declarations; therefore, the production is to be planned in detail to avoid penalties. A recurrent Artificial Neural Network model is constructed in order to predict the day ahead energy supply. The model considers energy resource price, demand from multiple sites, production cost, the amount of energy imported from the grid and the amount of energy exported to the grid. In order to achieve the energy production rate with the least error rate possible, an energy demand forecasting model is constructed for a paper producing company, using a Nonlinear Autoregressive Exogenous Model (NARX) network implemented in Matlab. Three parameters of the forecasting model are tuned using the Particle Swarm Optimization (PSO) algorithm: the number of layers, the number of nodes in hidden layers and the number of delays in the network. Error level is measured using the Minimum Absolute Percentage Error between the predictions and the actual output. Results indicate that NARX is an appropriate tool for forecasting energy demand and the algorithm yields better results when the system parameters are tuned.

Keywords Energy • Self-produced • Cogeneration • Neural networks

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1 Introduction

Energy and its demand is one of the most important topics of humanity through ages. Especially from the beginnings of the industrial revolution, increasing demand of the energy from both industrial and residential sites still has been growing continuously (Olah 2005). Newly developed technologies enable the construction of new energy production plants and facilities to be put into practice, in either large or micro scale projects (Afgan and Darwish 2011). Up to last few decades, majority of the energy sources that are required for energy production have been supplied from controversial sources like fossil fuels, and, electricity and thermal energy have been considered isolated from each other and that is why generated in the separate facilities. The most common and obvious example of separated generation is that in residential sites central heating system produces steam and a coal plant generates electricity to supply electricity to same consumption area. This separate production, however, requires to consume more resources than combined facilities that supply desired electricity and thermal power; causing money and temporal lost and environment contamination. Cogeneration, which is the process of producing several forms of energy from the same energy source, is one of the solutions to the increasing energy demand and known as an effective state-of-the-art way of generating electricity and heat at the same time (Kanoglu and Dincer 2009; Panno et al. 2007). These systems are proven to be advantageous in technical, environmental and economic terms. Simultaneous generation of different energy forms (i.e. electric and heat) in one combined production system enables efficiency in fuel use; since conventional electric energy producing systems “waste” the produced heat (Mostofi et al. 2011). Less fuel is required to generate the same amount of energy compared to conventional systems (Afgan and Darwish 2011). Cogeneration systems also offer a high energy transformation option, consequently contributing to the decrease in the emission that cause the majority of the green house effects (Benelmir and Feidt 1998; Mancarella and Chicco 2008). Even though the investment costs are higher than traditional energy systems, cogeneration systems are known to have short return-on-investment periods through maximal exploitation of the energy resource and less fuel requirement, which makes them economically efficient (Benelmir and Feidt 1998; Kanoglu and Dincer 2009).

Aforementioned benefits of cogeneration systems has yielded a huge progress in their implementations. This progress has also yielded a parallel increase in the number and context of researches in academia. Pioneering studies grant a broader overlook on their economical and environmental effects alongside the advantages they bring (Benelmir and Feidt 1998; Strickland and Nyboer 2001) and the initiation of their technologies (Cardona and Piacentino 2003; Hochenauer et al. 2004). Conceivably, recent studies focus on latest and more advanced technologies in cogeneration systems (Mostofi et al. 2011; Zabihian et al. 2012; Ahrenfeldt et al. 2013) and their management related challenges such as sustainability and design (Afgan and Darwish 2011; Abdelhady et al. 2014; Marshman et al. 2010).

In order to improve the efficiency of such systems, cogenerated self-energy production comes up to practice which require minimized electricity grid, reduce transmission losses, enhance greater operation and consumption flexibilities. One of the main management issues of self-produced cogeneration systems involve the production planning and scheduling of an established plant (Maifredi et al. 2000). In order to implement the means for deriving the optimal energy production scheduling, grasping the information on the energy demand for the upcoming period is essential (Aik et al. 2007). However, energy systems cannot be fully executed on pre-orders since the systems involve great deal of uncertainty. Hence, energy demand prediction becomes elemental for cogeneration system implementations.

This chapter focuses on industrial auto producers which use cogeneration technology together with self-energy production. Due to indispensable advantages of cogeneration production, this chapter aims to forecast the energy demand by constructing a Neuro-PSO (which will be referred as PSO-NARX) model considering variables such as natural gas prices, production cost or amount of energy produced and exported, so that a more accurate schedule can be achieved. The next section provides a broad literature review on cogeneration system overview and demand forecasting, whereas the methodology is presented in the third section. A real-world application is given in the next section together with its results. Finally, the last chapter presents conclusions brief and proposals on further research.

2 Literature Review

The patent on cogeneration systems has been a broadcast in 1980 (Graham and Rao 1980). Same year, it was offered as “a successful response to the energy crisis” (Pratt 1980) and was also applied to industrial systems (Camm 1981; Hannen and Joyce 1981). The early researches of twentieth century focus on the initiation processes and basic technologies. Fowler (1983) attempts to find the optimum location for cogeneration facilities in Chicago. Parsons (1984) introduces the concept of induction generators to cogeneration as an alternative to synchronous generators and brings out its economic advantages. Mouostafa et al. (1984) offers a new design for a solar power plant in Kuwait. At the time, feasibilities of different technologies have been evaluated. Hansen (1985) analyzes biomass to ethanol cogeneration in terms of economic feasibility, whereas Hnat and Coles (1985) analyze three types of technologies in terms of technical feasibility and conclude that the best performance to the systems with Rankine cycles using toluene. Consequently, safety and reliability issues have arisen (Nobile 1987) and smaller cogeneration systems are designed for specific occasions such as hospitals and residents (Miller and Branson 1987; Krause et al. 1988). The concept of energy parks have been introduced (Brock and Manno 1987). Additionally, in 1990, the concept of self-produced energy has been used in literature without being

introduced to a case of cogeneration yet; wood has been offered as a self-produced energy source (Burwell 1990).

With the emerging and rising awareness in emissions and renewable energy sources, studies involving cogeneration from renewable energy sources have also increased sharply where biomass is frequently considered as the renewable resource (Gustavsson and Johansson 1994; Burnham and Easterly 1994; Clark and Edye 1997). Solar cogeneration system technologies have also been enhanced and their design and technologies have been adjusted (Hollic 2000; Lindenberger et al. 2000).

The innovations and developments on cogeneration systems have been triggered with the dramatically increased consciousness in environmental challenges in the new millenium. CO₂, SO_x, and NO_x emissions have become an indispensable constraint of energy optimizations (Tsay 2003; Chen et al. 2005). The number of residential sites that execute cogeneration systems have grown at a great extent (Rosen et al. 2005; Dorer et al. 2005) together with the industrial sites. Paper and pulp industry has been the greatest benefiter of cogeneration systems at a national or a global level (Möllersten et al. 2003; Marshman et al. 2010; Cortes and Rivera 2010).

As for the case of self-produced energy, it has been involved as a decision variable indicating that it is one of the options in its earlier years (Howarth and Norgaard 1992; Pelandi and Tarallo 1999). Yet, cogenerated and self-produced energy is still an emerging field in literature. Some researchers question the feasibility of the self-energy production systems, but even those of doubtful scientists argue that they need to do further research before being disfavor of this technology. Hong et al. (2010) emphasizes that there is still a need for, yet, a lack of self produced energy systems in Taiwan and offers a system for Taiwanese textile companies. Economic and performance evaluations of these systems are most commonly inspected in recent years of academia. Cardona et al. (2012) conduct an applied study about to increase efficiency of cogeneration processes and recovery period of investment at food industry. In the study, pre-used electricity, and working hours of the plants are subjected to economic analysis however, due to insufficient percent of total cogeneration capacity it is resulted that future investment should be done to take advantage of cogeneration facilities. Torchio (2013) utilize a life cycle cost analysis to compare a cogeneration system and a separate heating system in terms of environmental and economic aspects. As a result of case study, it is conducted that net present value and payback period are two methods that could be efficiently used to compare these systems. Wang et al. (2011) administrate an industrial application to analyze technical conditions of cogeneration systems and separated production systems by pre-proposed and energy-specific feasibility and sensitivity analyses.

It is also a recognized fact that energy requirement for economic growth and wealth should be balanced with sustainable development. This fact favors the utilization renewable and hybrid technologies for sustainable development. Cakir et al. (2012) underline the sustainable effects of cogeneration power plants in their literature survey and shows the importance of cogeneration facilities in terms of

sustainable development with a case study on a hospital. Bloemhof-Ruwaard et al. (1996) examine different variations of recycling methods networks of energy flow of Europe using Linear Programming and find out that clear techniques and methods should be applied before taking environmental policy measures to ensure that pulp sector grow sustainable. Sustainability of solar and biomass cogeneration technologies are also emphasized (Buoro et al. 2012; Bettocchi et al. 2009; Bohorquez et al. 2012). Ashar et al. (2012) apply a case study using the criteria in literature to state that urban energy demand can be met fuel cell cogeneration facilities which also contributes to reduce overall greenhouse effects of environment.

In order to be able to spread usage of cogeneration facilities, efficiency (in terms of both environmental and economic), and total effectiveness of the systems should be enhanced. These enhancements are achieved using different optimization methods in. Marshman et al. (2010) construct a Dynamic Programming model to ensure that the system remains profitable. Kralj and Glavic (2009) apply Nonlinear Programming in order to increase efficiency in a cogeneration system by controlling flow rates. Streckiene et al. (2009) conduct a research over a Combined Heat and Power (CHP) plant to identify optimal size, thermal storage and flexibility by simulation. Hong et al. (2011) evaluate the energy network of Taiwan pulp industry by using energy footprint techniques and found that major losses of industry are caused from technical insufficiencies such as the incapability of the equipment. Furthermore, they offer their results for benchmarking with other methods. Popli et al. (2011) present a case study to investigate integration of trigeneration system and natural gas power plant by taking into account several criteria like OPEX and payback period of investment and conclude that waste heat recovery by CHP systems is one of the most important factors for decreasing future fossil fuel consumption of the world. Cakembergh-Mas et al. (2010) construct a Mixed Integer Linear Programming to commercial cogeneration plants in Beijing in order to evaluate the impacts of cogeneration and state that the impacts are subject to change due to municipal constraints. Cortes and Rivera (2010) carry out a paper mill case study in order to optimize economic and structural conditions of an existing natural gas CHP by a nonlinear programming model.

Scheduling is one of the most important challenges in cogeneration systems. In order to avoid excess energy production and shortages, it is essential to plan the energy production. Dotzauer and Holmström (1997) try to find general method for mathematical modeling of cogeneration plants. As a result of literature survey they find an algorithm for short term scheduling. Chen et al. (2005) has proposed an Artificial Immune System structure for cogeneration scheduling. Tina and Passarello (2012) has developed a Matlab structure for short-term scheduling. However, for cogeneration scheduling, the most crucial data are the energy demand during the scheduling horizon. Without the demand forecast, it is inevitable to produce excess energy or endure shortages. Bhattacharyya (2011) classifies energy demand forecasting methods in nine: simple approaches, advanced techniques, econometric approaches, end-use methods, input-output models, scenario approaches, Artificial Neural Networks (ANNs) and hybrid approaches. Ediger and Akar (2007)

construct an Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) for annual energy demand prediction. However, for cogeneration scheduling, short term energy demand forecasts are convenient. Bhattacharyya (2011) states that for short term forecasting, ANNs are the most appropriate method. Becalli et al. (2008) implement an Elman Network with a sensitivity analysis. Nguyen and Nabney (2010) utilize three methods: ANNs with multi layer perceptrons, radial basis functions, linear regression and GARCH and find out that multi layer perceptrons yields the least error rate. Paudel et al. (2014) propose a dynamic ANN structure with orthogonal arrays and proves that the performance is more robust than static ANNs.

The implementation of metehauristic or the hybridization of ANNs are also common for demand forecasting. Ghabari et al. (2013) hybridize Ant Colony Optimization Algorithm with a Genetic Algorithm. However, the hybridizations are mostly applied to long term forecasting (Assareh et al. 2012). Another application area involves the forecasting of electricity demand where the back-propagated neural network is tuned by Particle Swarm Optimization (Jiang et al. 2013).

In this study, parameters of a Nonlinear autoregressive exogenous model (NARX) type of Neural Networks are tuned using Particle Swarm Optimization (PSO) for daily energy demand forecasting. The model is applied to a self-produced cogeneration system of a paper and pulp company. The results yield that the tuned NARX networks yields less error rates than standard NARX networks.

3 Methodology

In cogeneration systems, exogenous variables such as cost of electricity production, amount of previous imports from and exports to grid are influential for determining the demand of the following period. Recurrent structure of Nonlinear Autoregressive Exogenous type Neural Networks, which combine output to inputs, provide a time-series like approach together with exogenous variable inclusion and are appropriate methods for forecasting. Parameters of the NARX network can be tuned using metaheuristic algorithms. In this study, PSO algorithm is used to tune parameters of the NARX network.

3.1 Artificial Neural Networks (ANNs) and Backpropagation Algorithm

Artificial neural network (ANN) models imitate biological neural systems which are able to perform functional input-output mapping using electro-chemical structures (Haykin 2008). An ANN model consists of neurons which compute results by using

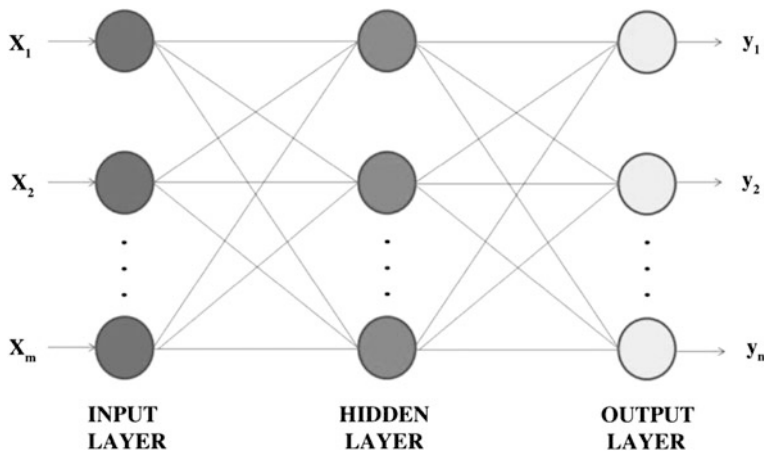


Fig. 1 A sample artificial neural network

input values throughout the network and transforming these inputs using transfer functions. The structure of an ANN is given in Fig. 1 (Altay et al. 2014).

Each cell in ANNs is called a neuron and neurons are connected with links of different weights as can be seen in Fig. 1. Each set of neurons forms a layer. A network can have one or more hidden layers whereas input and output layers are essential. The input of each neuron is calculated by the weighted sum of the outputs of the previous layer and a bias term. Inputs of each neuron is exposed to a transfer or an activation function which form the output of the related neuron. The most commonly used activation functions are sigmoid (Eq. 1) and hyperbolic (Eq. 2) tangent functions (Haykin 2008; Altay et al. 2014).

$$f(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

$$f(x) = \frac{e^x + e^{-x}}{e^x - e^{-x}} \quad (2)$$

ANNs are known to be one of the most powerful approximation tools for modeling nonlinearity and revealing the black box structure of the real-world problems. Computations of an ANN are based on learning phases which make ANN models suitable especially in cases when complex mathematical formulations are not possible, nor convenient to implement (Rajpal et al. 2006). Practical implementations of the ANNs are vastly numerous and they are widely used at different fields such as mathematics, economics, medicine and others (Kalogirou 2001). Engineering applications of ANNs involve system identification, control, forecasting and classification (Cinar et al. 2010). Additionally, ANN models are convenient in cases where traditional approaches have complex constraints and countless limitations to be represented by analytical models (Sozen et al. 2005).

ANNs' mapping process emerges from learning by executing training and testing processes through patterns involving relations between inputs and outputs (Cam et al. 2005). In order to learn from system patterns, ANNs employ various learning algorithms. Backpropagation algorithm is undoubtedly the most commonly used and a very basic algorithm for learning in ANNs. In this chapter, ANNs are trained using the Backpropagation algorithm.

Backpropagation algorithm aims to minimize the error rate between actual (target) output and the output of the network. In order to achieve this objective, the weights between neurons are tuned using the following equation

$$w_{ji}^k(t+1) = -\eta \frac{\partial \epsilon}{\partial x_{ji}^k} + w_{ji}^k(t) \quad (3)$$

where $w_{ji}^k(t)$ is the weight between neuron i and neuron j at layer k and iteration t , η is the learning rate, $\frac{\partial \epsilon}{\partial x_{ji}^k}$ is the partial derivation of the error term of the input from neuron j to neuron i .

3.2 Nonlinear Autoregressive Exogenous Model Neural Networks

NARX networks are special types of recurrent neural networks (Lin and Horne 1996), which signify that the connections of the network form at least one directed cycle (Singh and Sahoo 2011). A generalized recurrent neural network is in the form of (4) and (5) (Lin and Horne 1996). In a sense, the outputs of the network becomes the input at a later stage.

$$x(t+1) = g(x(t), u(t); w) \quad (4)$$

$$y(t) = f(x(t)) \quad (5)$$

where x denotes the states, u denotes the inputs, y denotes the outputs, w denotes the weights of the network and f and g are network specific functions. In the NARX networks, Eq. (4) can be rewritten as

$$x(t) = [y(t-1) \cdots y(t-m) \ u(t-\theta-1) \cdots u(t-\theta-n)] \quad (6)$$

where $x(t)$ is the input at iteration t , y 's are outputs of previous m iterations, m is the number of past outputs, u 's are the exogenous variables and θ is the delay in the system. Hence, NARX networks both benefit from the previous outcomes and external variables (Bomberger and Seborg 1998). In this study, the number of hidden layers, the number of nodes in hidden layers and the number of delays of the

NARX network are three parameters that are tuned using Particle Swarm Optimization (PSO) algorithm.

3.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population based optimization technique invented by Kennedy and Eberhart (1995) influenced by the social behavior of fish schooling and bird flocking 1. It simulates the “collective behavior” of animals, which socio-cognitively share information among the swarms (Hassan et al. 2005). The flow of the algorithm is given in Fig. 2.

Let x_i be the position of the i th particle in the swarm which consists of N particles, and let each particle have n dimensions defined over a maximization objective function f . The steps of the algorithm is given below (Engelbrecht 2006):

Step 1. Particle velocities and positions of each particle are initiated as formulated in (7) and (8)

$$x_{ij} = x_{\min} + r(x_{\max} - x_{\min}) \quad i = 1, \dots, N, j = 1, \dots, n \quad (7)$$

$$v_{ij} = \alpha(x_{\min} + r(x_{\max} - x_{\min})) \quad i = 1, \dots, N, j = 1, \dots, n \quad (8)$$

where x_{ij} denotes the position of the i th particle at the j th dimension, v_{ij} denotes the velocity of the i th particle at the j th dimension, r is a uniformly distributed random number between $[0, 1]$ and α is constant in the range $[0, 1]$.

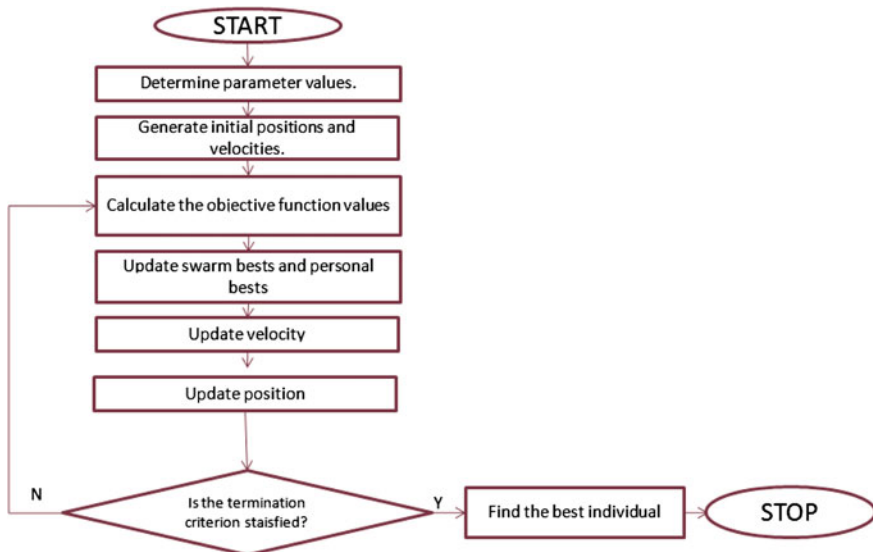


Fig. 2 The particle swarm optimization algorithm

Step 2. The objective value of each particle is calculated as $f(x_i)$.

Step 3. The best position for each particle and the global best position for the swarm is updated. For a minimization problem

$$\text{If } f(x_i) < f(x_i^{pb}) \text{ then } x_i^{pb} \leftarrow x_i \quad (9)$$

$$\text{If } f(x_i) < f(x^{sb}) \text{ then } x^{sb} \leftarrow x_i \quad (10)$$

where pb denotes the particle best and sb denotes the swarm best.

Step 4. Particle velocity and particle position are updated, that is, the new velocities and positions are calculated for each particle.

$$v_{ij} \leftarrow wv_{ij} + c_1r_1(x_i^{pb} - x_i) + c_2r_2(x^{sb} - x_i) \quad (11)$$

$$x_{ij} \leftarrow x_{ij} + v_{ij} \quad (12)$$

where w is the inertia rate between $[0, 1]$, and r_1 and r_2 are uniformly distributed random numbers between $[0, 1]$. c_1 and c_2 are the cognitive and social coefficient of the algorithm, respectively. The cognitive coefficient denotes the weight of confidence of the particle in its own best value and the social coefficient is the weight of confidence of the particle in the swarm.

Step 5. Step 2 is returned to until a termination criterion is satisfied. Various termination criteria include iteration number, convergence of the result, convergence of error in results, etc.

4 Application and Results

4.1 Application

The application of forecasting energy demand in a self-produced cogeneration system is made in a leading FMCG company operating in Turkey. The company offers various brands in several categories such as home-care category, sanitary pads category, baby diapers category, and adult diapers category and produces most of its products at an “Integrated Production Facility Campus”. A cogeneration facility within that campus which consists of four gas turbines and boilers meets the electricity, thermal and steam energy demand. Excess energy generated from this cogeneration facility is exported to the regional electricity network grids. Likely, in case of shortages, the shortcoming amount of electricity is purchased from the regional network. The structure of the energy flow is provided in Fig. 3.

Gas turbines are the basic and essential components of the cogeneration units. The electricity produced is spent in three ways. First, the cogeneration units should provide themselves necessary energy to operate. Secondly, the rest of the electricity

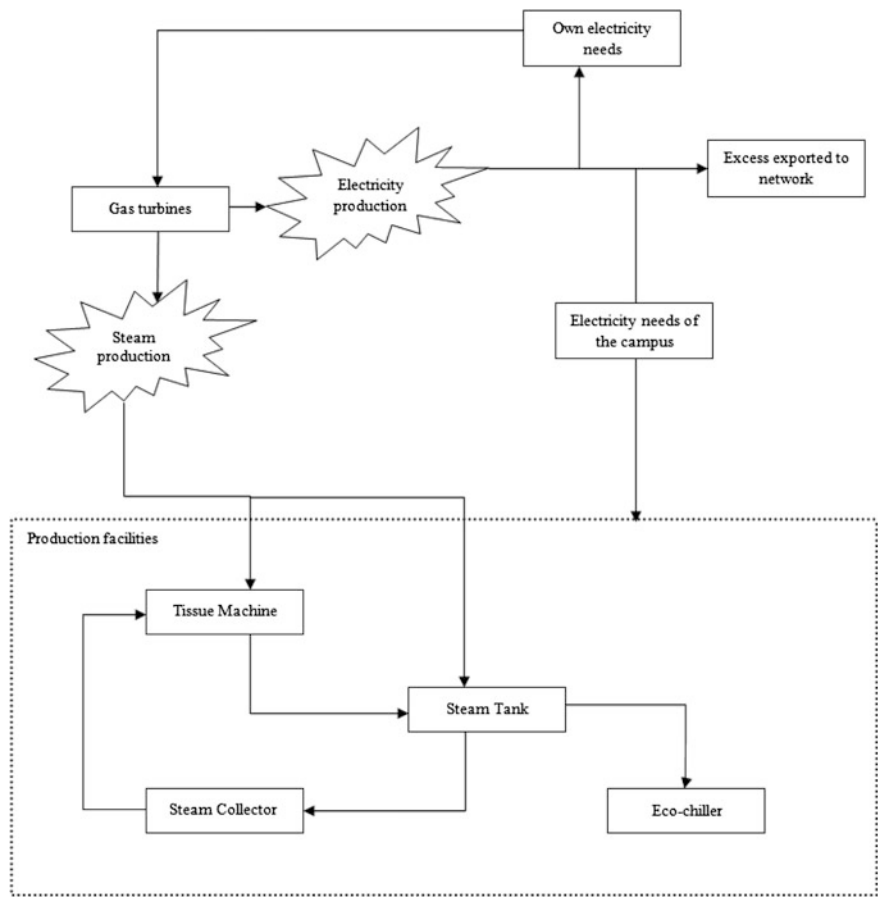


Fig. 3 Energy structure of the company

is sent to the production facilities for their operations. Lastly, if any excess electricity is produced, it is sold to the regional electricity network. On the other hand, the steam produced is only sent to production facilities; yet, follows a more complicated path. Four gas boilers (GB1, GB2, GB3, GB4) produce exhaust gas. GT1 is connected to a 16-bar steam tank, and rest of the each turbine has two steam tank sets that consist of a 3-bar and a 16-bar steam tanks. 16 bar steam tanks are used for production processes and 3-bar tanks are used for comfort-only processes like central heating, hot water etc. Two tissue machines (TM1 and TM2) involve wet or dry manufacturing processes. Exhaust gas from GT1 and GT2 is used for wet phases of the TM1 and exhaust gas from GT3 and GT4 is used for dry and wet phases of the TM2. After drying phases in TTM1 and TM2, exhaust gas is transmitted to steam tank to produce steam. Steam tanks are also directly connected to cogeneration units. The steam collector also reuses the generated and stored steam

in tissue machines. After steam generation, the process is ended with the exhaust gas being sent to the chiller and air conditioning units of the facility during the summer season.

In the light of literature survey, 38 exogenous criteria that affect the energy demand in such cogeneration systems are determined as listed in Table 1 with their resources. However, this excess number of criteria has resulted in 38 exogenous inputs which have made the computationally unaffordable given that the NARX network uses a number of previous outputs together with given exogenous variables. In order to obtain reasonable computational time values, various criteria are eliminated in accordance with their frequency of observations in literature, that is, the frequency of each criterion in articles has been counted and then, converted into a “frequency percentage” by being divided into the total number of observations. 17 criteria that are mentioned at least in two studies (with a higher frequency ratio than 9 %) are selected. During this process, some of the criteria are eliminated due to the lack of information such as data related with total energy savings, pollution levels, previous investment cost, payback period of the investment and total income come from electricity sales. then reduced to 11 in order only subject to convenient criteria to optimization study for existed cogeneration power plant.

Total energy demand of company is used as target data that represent the facility’s total amount of energy that is produced by heat energy and is required in order to maintain manufacturing and other related processes of the campus. Input data are determined as follows:

- Unit cost of energy production (\$/MW): This input refers to production cost of electricity from cogeneration units which contribute competitiveness level of the CHP unit with existing separate production systems.
- Heat Energy Production (MW): Heat energy is mainly used to generate electricity required throughout the campus. This input refers to daily amount of heat energy generation.
- Steam Energy Production (MW): Steam energy is directly used for the manufacturing processes of the paper including products. Cogeneration facility also produces steam to meet demand for unconverted steam energy.
- Daily Imported Amount of Electricity from Network (MW): If any electricity shortage occurs during the cogeneration process, the required electricity is purchased from grids. This input refers to daily electricity amount of buy decisions from grid.
- Daily Exported Amount of Electricity to Network (MW): This input represent to amount of excess electricity sold to the network.
- Daily Electricity Unit Sales Prices to Network (\$/MW): This input refers to daily electricity purchasing price of the network which is determined by external regulators considering electricity market conditions. The selling price of excess electricity might be lower than the cost of production.
- Daily Electricity Unit Import Cost (\$/MW): The daily electricity purchasing price from network which is determined by grid regulators in case of electricity shortages are referred in this input.

Table 1 Criteria that affect energy demand

Criteria	Resources	Frequency among papers (%)
Pre-used electricity cost	Aralavagan et al. (1995) and Cardona et al. (2012)	9
Unit cost of electricity	Aralavagan et al. (1995), Kralj and Glavic (2009) and Cardona et al. (2012)	14
Operating hours of the plant	Cardona et al. (2012)	5
Annual plant operating cost	Cortes and Rivera (2010)	5
Operating hours and capacity usage of the equipment	Cakemberg-Mas et al. (2010), Popli et al. (2011) and Buoro et al. (2012)	14
Amount of exported electricity to the network	Kralj and Glavic (2009), Cakemberg-Mas et al. (2010), Popli et al. (2011) and Buoro et al. (2012)	18
Thermal flows of district heating network	Buoro et al. (2012)	5
Type of used energy system	Bettocchi et al. (2009)	5
Exergoeconomic cost	Cortes and Rivera (2010) and Bohorquez et al. (2012)	9
Exergetic efficiency percent	Wang et al. (2011) and Bohorquez et al. (2012)	9
Transformation of alternative sources into fuel	Bettocchi et al. (2009)	5
PES Index	Bettocchi et al. (2009), Wang et al. (2011), Hong et al. (2011) and Torchio (2013)	23
Profitability of the plant	Benelmir and Feidt (1998), Streckiene et al. (2009), Bettocchi et al. (2009), Marshman et al. (2010) and Gabrielli and Zanmori (2012)	27
Type of biomass used	Bettocchi et al. (2009)	5
Thermal energy capacity of the plant and CHP units	Streckiene et al. (2009) and Buoro et al. (2012)	
Incentives	Gabrielli and Zanmori (2012)	5
Pollution (emission level of generation, air pollution or solid waste)	Bloemhof-Ruwaard et al. (1996), Mancarella and Chicco (2008), Wang et al. (2011), Hong et al. (2011), Cakir et al. (2012) and Ashar et al. (2012)	27
Maintenance cost	Gabrielli and Zanmori (2012)	5
Investment cost of the plant	Benelmir and Feidt (1998) and Gabrielli and Zanmori (2012)	9
Payback period of the investment	Dotzauer and Holmström (1997) and Benelmir and Feidt (1998)	9
Thermal temperature limits for operational cost	Marshman et al. (2010)	5

(continued)

Table 1 (continued)

Criteria	Resources	Frequency among papers (%)
Total power generation (MWh)	Marshman et al. (2010)	5
Total fuel cost	Aralavagan et al. (1995), Mancarella and Chicco (2008), Marshman et al. (2010), Cakembergh-Mas et al. (2010) and Ashar et al. (2012)	23
Purification of H ₂	Kralj and Glavic (2009)	5
Product flow rate	Dotzauer and Holmström (1997) and Hong et al. (2011)	9
Energy saving	Popli et al. (2011), Hong et al. (2011), Gabrielli and Zanmori (2012), Cakir et al. (2012) and Torchio (2013)	23
Energy and heat loss of generation system	Hong et al. (2011)	5
Pressure levels of generators	Cakembergh-Mas et al. (2010)	5
Reduction of waste heat	Cortes and Rivera (2010)	5
Toxicity level	Bloemhof-Ruwaard et al. (1996)	5
Energetic efficiency percent	Wang et al. (2011), Cakir et al. (2012) and Bohorquez et al. (2012)	14
Photovoltaic oxidation level	Bloemhof-Ruwaard et al. (1996)	5
Different manufacturing technologies (i.e. pulping)	Bloemhof-Ruwaard et al. (1996)	5
A geographical distribution of utilities	Bloemhof-Ruwaard et al. (1996)	5
Equivalent cogeneration ratios	Mancarella and Chicco (2008)	5
A thermal multiplication factor (TMF),	Mancarella and Chicco (2008)	5
Technical characteristics of heat pump	Mancarella and Chicco (2008)	5

- **Energetic Efficiency Percentage:** There are several technical parameters that are used for evaluating overall performance of cogeneration systems. This input aims to refer to the efficiency rate of energy parameters of the designed system.
- **Thermal Energy Capacity and Efficiency of Facility:** Technical capacity of plants describes the maximum power generation rates of the related facility.
- **Natural Gas Unit Purchasing Cost (\$/cm³):** The cogeneration facility needs to use natural gas as raw material to generate energy. This input refers to unit purchasing cost of natural gas for electricity generation.

Daily data of the year 2013 is used for training, testing and validation. The prediction is achieved in one-day hence.

4.2 Method Adaptation

In the method adaptation phase, the NARX method inputs and outputs are determined, as well as the PSO algorithm particle coding scheme. The inputs of the algorithm are derived through a thorough literature survey and interviews with experts and stakeholders. The 65 % of the data are assigned for training, 15 % are assigned for testing and the rest are assigned for validation. As aforementioned, three parameters of the NARX network are tuned using PSO: the number of hidden layers, the number of nodes in hidden layers and the number of delays. Binary encoding is used for constructing particles. The minimum number of hidden layers are determined as 1 and the maximum number of hidden layers are determined as 16. As for the number of neurons in the hidden layer, the minimum number is determined as 1 and the maximum is determined as 32. In terms of the number of delays, the minimum number is determined as 1 and the maximum is determined as 16. Further validation is achieved through the results of the PSO algorithm. A sample particle is given in Fig. 4.

As can be seen in Fig. 1, the first five binary digits of the particle are constructed in order to set the number of neurons in the hidden layer. The second four binary digits are set for the number of hidden layers and the last four digits are set for the number of delays. These three parameters are crucial inputs for the NARX network; yet, before feeding these parameters into the NARX network, a particle has to be decoded. For the sample particle in Fig. 1, the decoding of the first five digits are $1 \cdot 2^0 + 1 \cdot 2^1 + 0 \cdot 2^2 + 1 \cdot 2^3 + 0 \cdot 2^4 = 11$. However, in this scheme, the minimum number of neurons in the hidden layer can be 0 and the maximum number can be 31. Hence, after decoding, 1 is added to the decoded number; making the number of neurons in the hidden layer 12 in the given sample. Adding 1 to the decoded number also stands in cases of the number of hidden layers and the delay. The second four digits in the sample indicate $0 \cdot 2^0 + 1 \cdot 2^1 + 0 \cdot 2^2 + 1 \cdot 2^3 + 1 = 11$ hidden layers and the last four digits indicate $1 \cdot 2^0 + 1 \cdot 2^1 + 0 \cdot 2^2 + 0 \cdot 2^3 + 1 = 4$ delays between inputs and outputs.

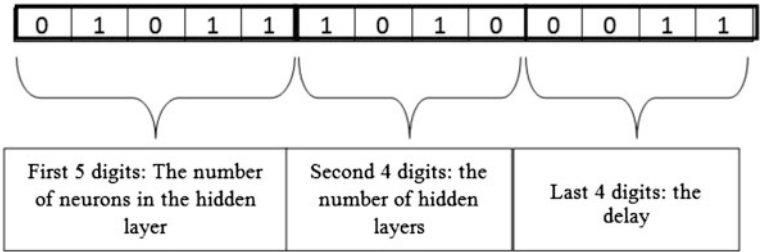


Fig. 4 A sample particle

4.3 Application Results

In the application, the results PSO-NARX algorithm is compared with the NARX algorithm itself with predetermined parameters. NARX algorithm alone and PSO-NARX algorithm are run 50 times. The comparison of the algorithms are achieved over Minimum Absolute Percentage Errors (MAPE). The parameters of the PSO algorithm are given in Table 2 and the NARX algorithm parameters (in cases that are not tuned with PSO) are given in Table 3. The NARX parameters are selected by asking NARX experts to assign generic parameters.

The tuned NARX algorithm parameters calculated by the PSO algorithm are presented in Table 4. The mean, standard division, best and worst MAPE values of both algorithms are given in Table 5.

In order to prove the statistical significance of the results, a t-test is applied with the following hypotheses.

$$H_0 = \mu_{NARX} \leq \mu_{PSO-NARX}$$

$$H_1 = \mu_{NARX} > \mu_{PSO-NARX}$$

by

$$t_{score} = \frac{\bar{X}_{NARX} - \bar{X}_{PSO-NARX}}{s_{\bar{X}_{NARX} - \bar{X}_{PSO-NARX}}} \quad (13)$$

$$s_{\bar{X}_{NARX} - \bar{X}_{PSO-NARX}} = \sqrt{\frac{s_{NARX}^2}{n_{NARX}} + \frac{s_{PSO-NARX}^2}{n_{PSO-NARX}}} \quad (14)$$

Table 2 PSO algorithm parameters

Parameter	Value
Number of particles	20
w	0.9
c_1	2
c_2	2
Termination condition	50 iterations

Table 3 NARX algorithm parameters

Parameter	Value
Number of hidden layers	2
Number of neurons in the hidden layer	10
Delay	2

Table 4 NARX algorithm parameters tuned by PSO algorithm

Parameter	Value
Number of hidden layers	8
Number of neurons in the hidden layer	26
Delay	7

Table 5 Application results

Parameter	NARX	PSO-NARX
Mean result	2.1068	0.9862
Standard deviation	0.1628	0.0031
Best result	1.8087	0.9771
Worst result	2.5216	0.9973

$$dof = \frac{(s_{NARX}^2/n_{NARX} + s_{PSO-NARX}^2/n_{PSO-NARX})^2}{(s_{NARX}^2/n_{NARX})^2/(n_{NARX} - 1) + (s_{PSO-NARX}^2/n_{PSO-NARX})^2/(n_{PSO-NARX} - 1)} \quad (15)$$

where $\bar{x}$ is the sample mean, s is the standard deviation, n is the sample size and dof is the degree of freedom. Using Eq. 15, the degree of freedom is calculated as 49. $s_{\bar{X}_{NARX} - \bar{X}_{PSO-NARX}}$ is calculated as 0.1627. Hence, the t value is calculated as $1.0206/0.1627 = 48.6648$. For the one-tailed t test, with a confidence interval of 99 %, the t statistic value is 2.33. Hence, $t_{score} > t$. In this one-tailed test, there is not significant evidence to reject H_1 and thus, H_1 is accepted; meaning that NARX algorithms results are significantly greater than the results of PSO-NARX results. With this t -test, it is proven that tuning algorithm parameters have yielded less error rates than NARX itself.

5 Conclusions

The need for energy is bigger than ever and is growing progressively. Hence, greener and more efficient ways of generating energy has become crucial. Cogeneration methods have brought a more effective means of generating more than one type of energy simultaneously. In this chapter, a Neuro-PSO approach has been developed for forecasting energy demand in a self-produced cogeneration system. Recurrent Neural Networks have been recognized to be appropriate tools for prediction. NARX Network is a special type of Recurrent Neural Networks that use external criterion as inputs. Inputs for the neural network are derived and selected from a literature survey. However, the performance of Neural Networks are highly dependent on system parameters. Hence, a Particle Swarm Optimization algorithm is used for tuning NARX Network parameters. Results indicate that PSO

tuned NARX algorithm results are significantly better than NARX algorithm itself. Further studies include different hybridizations of metaheuristic and Artificial Intelligence based algorithms.

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