Effect of Price Dynamics in the Design of Eco-Industrial Parks: An Agent-based Modelling Approach

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Abstract: Even though eco-industrial parks (EIP) models have proved to transform industrial areas by strengthen the emergence of sustainable EIP, there is a noticeable lack of research addressing the economic returns of the participating companies in the network which fluctuates according to prices offered for the resource exchange over time. In this paper, we develop an agent-based model sometimes refer to as bottom-up approach for the design of EIP in which price fluctuation and demand variability are emergent properties of the interaction among the agents. Agent-based modelling (ABM) is a computational methodology used in social science, biology, and other fields. It represents autonomous entities, each with dynamic behaviour. The agents within the eco-industrial park are the factories, market buyers and market sellers. The computational development was performed in Réseau.py, which was built in Python (a programmable modelling environment) from scratch. Based on the autonomy of each of the agents and their individual objectives, simulations were carried out on a bio-energy based EIP (BBEIP) system in order to study the influence of price fluctuation between the agents. The results show that variability in price is a factor for establishing symbiotic relationship among the symbiotic agents in the EIP.

1 INTRODUCTION

Eco-industrial parks (EIP) models have proved to transform industrial areas by strengthen the emergence of sustainable EIP. In the last two decades, more attention for eco-industrial park (EIP) development projects has grown enormously among national, regional governments and industries in many countries (Heeres et al., 2004).

Also, industrial ecologists have suggested the redesigning of industrial system using the natural ecosystem. Designing or redesigning an eco-industrial park is a complex undertaking, demanding integration across many fields of design and decision making. Industrial symbiosis are complex system (Cao et al., 2009) that are viewed as self-organizing (Chertow and Ehrenfeld, 2012, Yazan et al., 2016) systems whose evolution is a function of complex interactions among multiple organizations, each with its own objectives, which may have conflicting interests.

Since the emergence of industrial ecology in the 1950s and its take-off during the 1990s, much progress, in theory, policy and practice has been achieved for designing a fruitful and sustainable eco-industrial parks. Almost all research into EIP system involves either proposing a frame work (Martin et al., 2009) or mathematical model (Gonela and Zhang, 2014) to design of EIP. There are few works (Cao et al., 2009, Bichraoui et al., 2013) that focus on the simulation of EIP to understand its complexity. Therefore, there is still progress to be made in the area of computational modelling of the actions and interactions of the autonomous agents that formed the EIP. Major problems to unravel the complexity of EIP include but not limited to price, profit and supply-demand fluctuations. Agent-based model (ABM) has proved to be a promising tool to simulate (Cao et al., 2009, Ghali et al., 2017) the evolution of eco-industrial park.

The rest of the paper is organized as follows. Section 2 presents the previous related research and introduces the problem statement. In Section 3, the description and the overview, design concepts and details (ODD) (Grimm et al., 2006) of the model are discussed. Section 4 give description and simulation results of the case study used in this work while section 5 conclude the paper.

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2 RELATED WORKS

Eco-industrial Park (EIP) is viewed by many researchers as a self-organising complex system. According to (Chertow and Ehrenfeld, 2012), EIP is viewed as a dynamic systems comprises of companies with participants whose aims and goals are constantly changing with market conditions. In recent years, many researchers have studied the dynamic of an eco-industrial park (EIP) using different evolutionary approaches (Kim et al., 2012, Bichraoui et al., 2013, Ghali et al., 2017).

Agent-based modelling (ABM) is a computational simulation methodology (Kuhn et al., 2010) used in social science, biology, and other fields, which involves simulating the behaviour and interaction of many autonomous entities, or agents, over time (Chertow and Ehrenfeld, 2012, Ghali et al., 2017). Agent-based models, allow bottom-up (Fraccascia et al., 2017) simulations of organisations constituted by a large number of interacting parts. Thus, industrial ecosystems represent a field of application. This contribution explains what agent-based models are, reviews applications in the field of industrial ecosystems and focuses on a simulator of intra- and inter-firm communications.

From a technical network perspective, ABM seems to be useful to model complex system, by feeding the system with rules corresponding to the assumptions of what is most relevant regarding the situation within the industrial eco-park and then watch the emerging behaviour from the agents' interactions.

(Cao et al., 2009) applied agent-based modelling to simulate the emergence of EIP. They also developed a new concept, the internal-flow energy, is use to indicate the direction of an eco-industrial system. However, their model was limited to the simulation of profit and inventory fluctuations within the EIP. (Kim et al., 2012) proposed an agent-based modelling method for by-product exchange network between by-product buyers and sellers in an industrial park. The proposed method is limited because price setting is not captured. (Yazan et al., 2016) adopted an enterprise input-output approach for the design of a perfect industrial symbiosis but the output of their work is static.

Therefore, in this work, we focus on the application of agent-based model to the design of EIP in which price fluctuation is the emergent property of the interaction among the agents. We simulate the effect of price fluctuations to express the dynamic of BBEIP system.

3 RÉSEAU-EIP AGENT-BASED MODEL

In this work, a computer modelling method namely agent-based model (ABM) is adopted and the proposed model is named réseau-EIP. The model name réseau-EIP is an allusion to “network of industries”. It was developed through the Python programming language. From literature, several works (Zheng and Jia, 2017, Mantese and Amaral, 2018) on dynamic modelling of EIP have used many of the known ABM toolkits; NetLogo (Wilensky and Evanston, 1999). From our perspective, all the EIP ABM model share a key weakness: they do not use Python. The model description was done using ODD (Overview, Design Concepts, and Details) protocol by (Grimm et al., 2006). The ODD for réseau-EIP is discussed next.

3.1 Model Description

Following the Overview, Design concepts and Details (ODD) protocol developed by (Grimm et al., 2006) for describing individual- based and agent-based models, this section describes all the seven elements of ODD as related to réseau-EIP ABM. The first three elements provide an overview, the fourth element explains general concepts underlying the model’s design and the remaining three elements provide details.

3.2 Overview

The overview of the ODD consist of three elements, the model purpose, state variables and scales, and process overview and scheduling. These are explain further.

3.2.1 Model Purpose

The réseau-EIP ABM is constructed as a decision-making tool for understanding the emergence behaviour that favours the design of eco-industrial parks. The model is intended to be used in assessing the sustainability of EIP and by improving the economic, environmental and social performance of the industrial park. The model is used to simulate the effect of price, demand and supply fluctuations to express the dynamic of EIP system. In the future, the model will be improve to estimate the impact of energy storage system inclusion in the design of EIP a “what-if” scenarios” incorporated, generate hypothesis and test policy ideas related to EIP development policy.

3.2.2 Entities, State Variables and Scales

The model consists of two core entities called market and factory agents. The factory agents represented here as industrial plants within a network and links, which represent the exchange of resources, while the market agents on the other hand does not produce anything but only buy finished goods or sell raw materials. As indicated earlier, EIP involved sustainable exchange of resources among partners within the park. Therefore, a raw material to a plant can be an output of another plant.

The factory agents are characterized by the state variables: factory agent identification number (ID), raw materials type, raw materials stock, raw materials usage, products (finished, by-product and waste) name, product price, price variance, output capacity of a product type (product target), net worth and the location (x and y co-ordinate) of the factory agent within the EIP network. The market agent is divided into two; the selling agent and buying agent. The selling agent is characterized by the state variables: selling agent ID, products (goods) name, selling price, price variance product type (product target), net worth balance and location. The buying agent is characterized by the state variables: buying agent ID, raw materials type, demand quantity, net worth and location.

In the model, all the agents (factory, selling and buying) interact with each other. The factory agents at a time step fulfil its input requirement (based on product demand) by initiating a contract with a selling agent. After getting the input materials, the factory agents begin to produce, determine product prices and sell to the buying agents. Since the factory agents buy raw material and sell its output, it can also compete with the market agents.

A monthly time step is chosen for this work but any time step (daily, weekly etc.) can be chosen. The model is a grid base and there is no specific dimension used. Each agents has its x and y axes to indicate its location on the grid. The grid served as the réseau-EIP boundary. No interface or visualization is built in with the model and all output of the simulation are exported to excel file and necessary analysis is performed thereafter.

3.2.3 Process Overview and Scheduling

As shown in Figure 1, the réseau–EIP ABM runs with a monthly time steps. Within each month or time step, six different submodels run in succession. Each of these submodel is discussed briefly here and a full discussion of each submodels can be seen in the Detail section. At the beginning of the simulation and for each time step, the factory, buying and selling modules load their variables and parameters from an external file, predict production (factory agent) and determine price. While the interaction of all the three agents from these modules ongoing in a time step, the transaction module begin and handles the contract between the buyers and sellers. The history module run next and record the history of each of the agents. The reporting module runs last and report all the outputs of all the agents in external file.

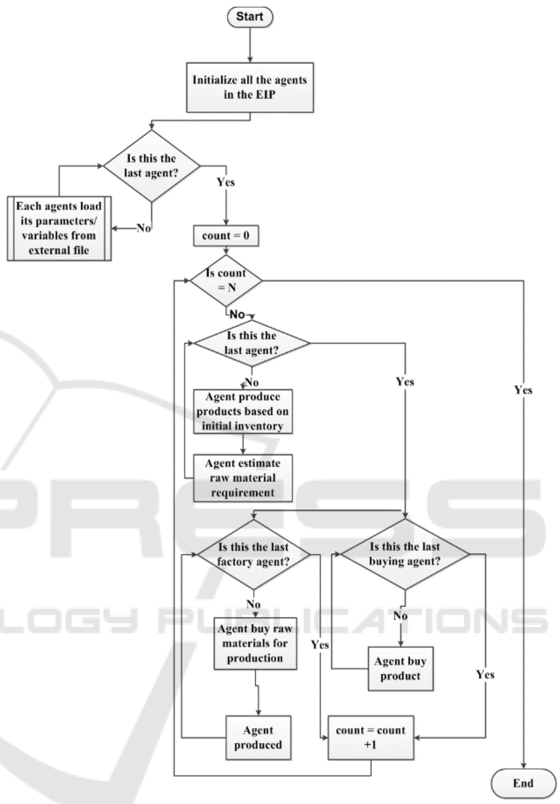

Figure 1: Réseau-EIP Model Logic Flow.

3.3 Design Concepts

3.3.1 Interactions

Factory agents interact with each other and with the market agents (buy input materials, and sell output goods). The primary interaction between agents is the exchange of resources. In the buying and selling submodels, a buyer (factory or market buying agents) establish contract with sellers (factory or market selling agent) through transaction submodel. In the transaction submodel, based on the quantity of goods available and price, the buyer enter a contract with the sellers and purchase its raw materials from the best seller (cheapest price). The agents also interact by also imitating each other's attribute.

3.3.2 Sensing

All agents are assumed to know their own attributes. It is also assumed that agents are also aware of their environment. This information informs factory, buying and selling agents to make decisions at any point in time.

3.3.3 Emergence

The dynamics of the park and resources exchange demonstrates emergence based on the lower level interactions and decisions of factory and market (buying and selling). Therefore, the important thing from the model is the emergence of net worth value of each agent based on the individual agent interaction with other agents.

3.3.4 Adaptation

Adaptation are modelled explicitly in réseau–EIP ABM model. Agents adapt with supply and demand request by finding a new partner to exchange goods with. Each factory agent always look for raw materials to purchase either from another factory agents or from market selling agents to produce its output and sell to waiting buyers (factory or market buying agents).

3.3.5 Learning

Each agent in the core entities of this model learn from their history by using the learning procedure to make decision at every time steps. An example is the history of the prices of goods in the market. All agents always check the previous price and based on Weibull distribution function make a decision either to change (increase or reduce) or maintain the price for the next time step.

3.3.6 Prediction

Presently agents in the réseau–EIP ABM model do not use any prediction models to make decisions.

3.3.7 Stochasticity

Stochasticity plays a vital role in the réseau–EIP ABM model. At the beginning, each agents load their parameters from an input file and based on some level of random distributions which adds an element of stochasticity into all subsequent runs.

3.3.8 Objectives

All agents in this model do not only seek to collectively maximize their ”purpose”, but instead make decision to buy, sell, produce goods and determine price as an autonomous agents. At each decision period, agents make decision in accordance with the sensed data and with a set of random techniques.

3.4 Details

3.4.1 Initialization

The réseau–EIP ABM model is initialised by using data obtained from the literature which related to this research area. There are three different agents (Factory, buying and selling) as mentioned earlier. The variables with their parameters for each agents are organized an external excel file and the agents pre-load their data. Based on this, users can therefore run different scenario by varying input parameters and observing their impact on their output.

3.4.2 Input Data

The input data are excel based and are specific for each of the agents (factory, market buying and selling agents). Apart from the initialization data no other data is required to run the model. The input file is user friendly and users can easily change the parameter to suit the problem in question.

3.4.3 Submodels

Parameter Loading: Each agent load its parameters from an input file. The parameters are agent specific with a unique identifier.

Requirement Prediction: This method is used by all the agents to predict their needed requirement at every time step. The method is modelled based on Gaussian distribution with mean and standard deviation. The market agent demand is equivalent to the requirement predicted while factory agent have two variables to determine at the beginning of each time step. These are the sales quantity and price. These two variables are modelled using Gaussian distribution also. The market selling agents only predict the selling price of all its goods.

Production Step: Since the market buying and selling agents do not produce anything, so nothing is associated to this agents except for the selling agents where the goods to be sold are readily available. In contrary, the factory agent produce goods, therefore, a production method is included in the factory class as an input-output ratio formulation.

Purchasing Method: Only the buying agents (Factory and Market agent) buy goods/raw material. Therefore, this method is only associated to these two agents. For each time step, each buyer check all the prospective sellers and make contract with all the sellers that have the quantity of goods to purchase. The sellers are appended in a list and the buyers buys from the cheapest seller until its requirements are fulfilled.

3.5 Decision Making

The price of product that agent buys is based on the best price in the EIP at any time. The price is randomly generated using Gaussian distribution (normally distributed). In the future work, we intend to extend the decision making of the agent via some rule e.g. price setting, price versus quality and quality alone.

4 CASE STUDY

A case study is conducted for only one input-output factory type in order to demonstrate the effectiveness of the proposed methodology and gain some managerial insight in the emergence of EIP. It is believe that if the model works for a single input-output system, it will definitely works for multiple input-out EIP system. To build our simulation we used data referring to real case study concerning two-stage bioenergy based eco-industrial park (BBEIP) discussed in (Gonela and Zhang, 2014). Figure 2 shows the potential structure of the proposed EIP system. The system include six factories with their possible connection. Each of the factories can also make possible connection between the different external markets if the price of the external markets agent over shadow the factory agents. Three of the factories are combined heat and power plant (CHP) differentiated by their unique identifier, CHP1, CHP2, CHP3. The CHP's use biogas as main input raw material apart from other input which are not included in this simulation to fulfil the single input-output scenario to produce electricity.

The other three factories are, anaerobic digestion (AD), represented as AD1, AD2 and AD3. The AD plants use electricity as one of its input to generate biogas. The main input material for the AD system is the waste from cattle and food and bio-solid wastes but is not being consider in this work. Apart from the factories, the EIP also contains three infinite sink agents (market buyers B1, B2 and B3) that willing to buy from the source agents at a considerable price and also infinite source agents (market sellers, S1, S2 and S3). The infinite market agent either buys or sells directly from/to the factory agents.

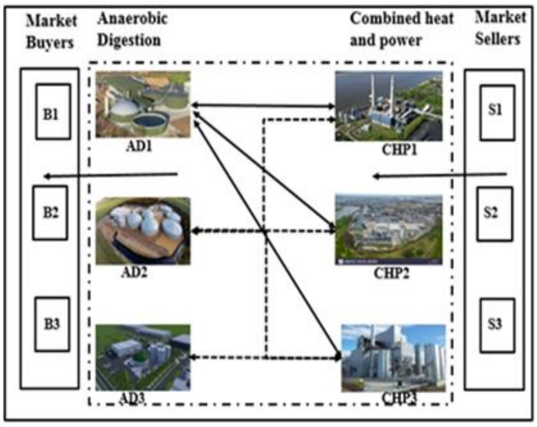

Figure 2: Bio-energy based Eco-industrial Park (BBEIP) System.

The initial data for the anaerobic digestion and combined heat and power plants were obtained from (Gonela and Zhang, 2014). The three CHP plants separately have demand capacity for biogas (methane) ranging from 80,000 – 500,000 cubic meter per month while the AD plants utilizes food and bio-solid wastes in the range of 0.3 million tons and required energy within 30 – 65 megawatt.

4.1 Simulation Results and Discussion

The results of a single simulation run are shown in figures 4 – 5. Figure 3 show the demand evolution of the three combined heat and power plant (CHP) while figure 5 shows the demand evolution of the three anaerobic digestion plants AD1, AD2 and AD3 in the EIP. Note that one simulation cycle stands for a time period of one month. This was found to be enough to give a stable final configuration. It can be seen that CHP2 has a higher demand evolution with average value around 480,000 cubic meter per month. CHP3 demand for biogas is the lowest while CHP1 has a demand in between the value of CHP2 and CHP3. This is understandable based on the demand capacity of each of the three combined heat and power plant. However, Figure 4 shows the electricity demand on monthly basis by the AD plants. AD2 has the highest demand per month while AD1 has the lowest. The demand by each plants is basically based on their demand capacity. Variation in the demand for electricity or biogas by each of the respective process plant is based on the price variation in the market.

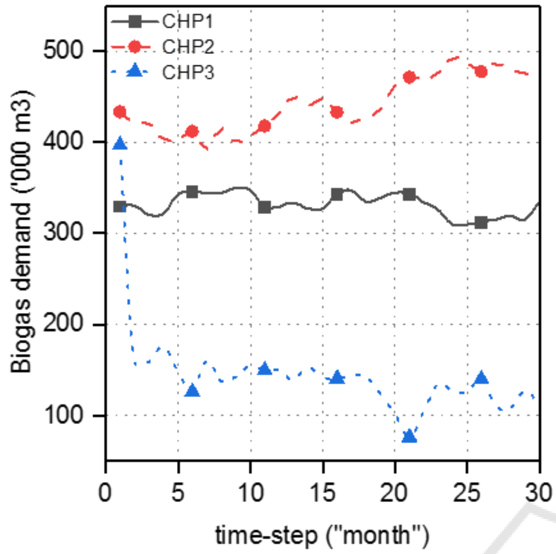

Figure 3: Biogas demand per month by combined heat and power (CHP) plants.

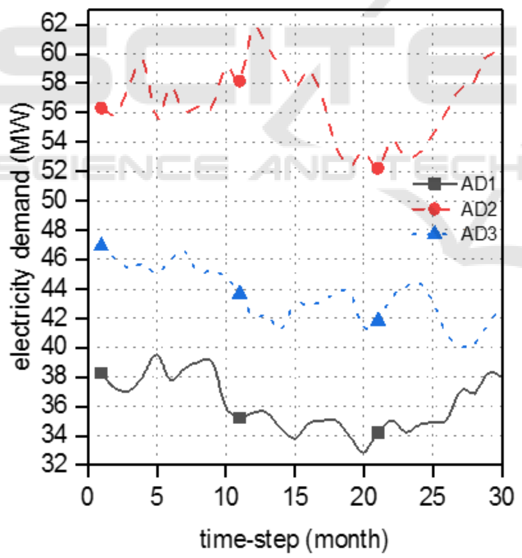

Figure 4: Electricity demand per month by CHP plants.

It is generally accepted that single realization of a stochastic process usually generates illustrative information that is not representative of the general system behaviour. So the simulation was run fifty times to generate average demand and the error over 30 step. Some statistical characteristics, such as average, standard deviation and correlation coefficient, can be obtained from these random variables. The result of the average demand and the error margin for each agents in the EIP per period is shown in Figure 6 – 9. 50 simulation runs were carried out to assess the effect of the initial conditions for all the agent. Figure 5 and 7 show the average demand of electricity by AD And AD2.

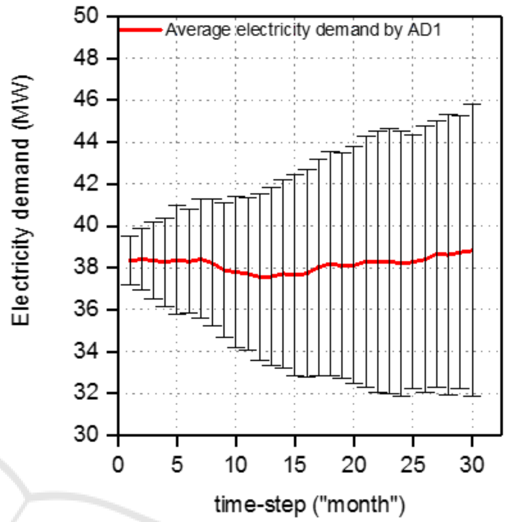

Figure 5: Average electricity demand by AD1.

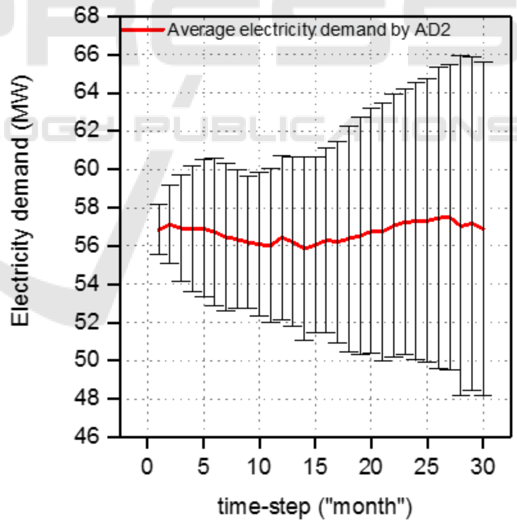

Figure 6: Average electricity demand by AD2.

Figure 7 and 9 show the average biogas demand. It can be seen that the demand for biogas by CHP1 with a mean of 340,000 cubic meter and standard deviation (SD) of 40 while CHP2 has an average demand of 440,000 cubic meter and SD of 50.

The result of a single run for the price evolution are shown in Figure 9– 11. Figure 10 show the sales price of electricity per month for each of the combined heat and power plant. In the figure, it can be seen that CHP2 has the lowest average price per step and has overshadow effect on the remaining two CHP's.

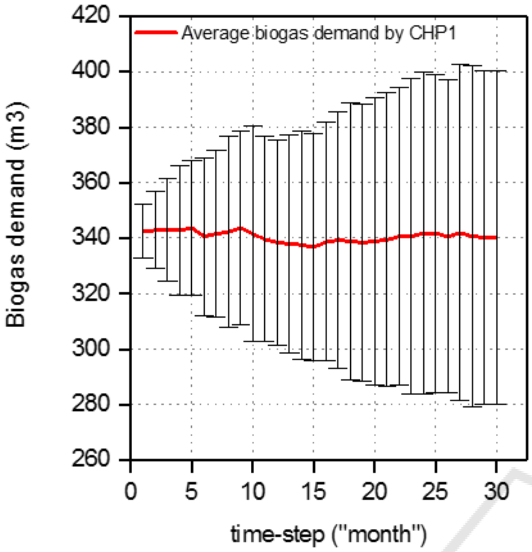

Figure 7: Average biogas demand by CHP1.

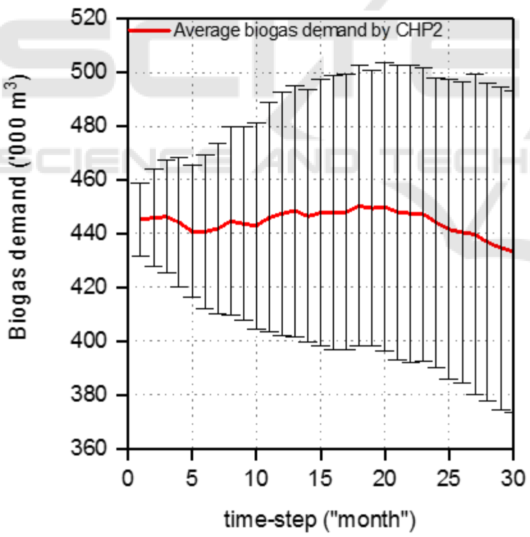

Figure 8: Average biogas demand by CHP2.

Figure 10 show the sales price of biogas per month for each of anaerobic digestion plant. In the same vein, AD2 has the best price and that dictates why it dominates the transaction in the EIP. It can be concluded that price variation is a factor that needs to be consider in the dynamic simulation of eco-industrial Park.

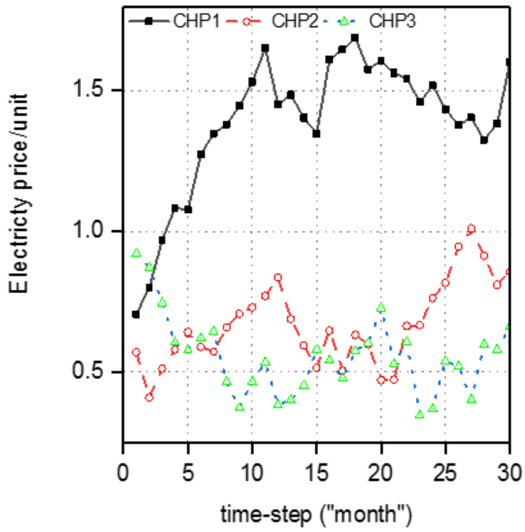

Figure 9: Electricity price/unit.

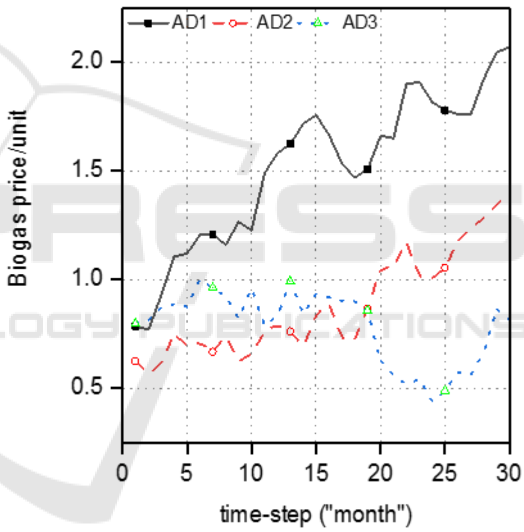

Figure 10: Biogas price/unit.

5 CONCLUSION

In this paper, agent-based modelling has been used to simulate eco-industrial parks in order gain insight on their behaviour to internal and external decision criteria. An EIP system consisting of six different process plants and infinite source and sinks (market buyers and sellers) were developed. The sink agents buy from the source agents based on the lowest price at any period. In conclusion, this study shows that the ABM is a useful tool that can be used in simulating periodic demand and supply. The study also show price variation is a factor to be consider in the model of eco-industrial Park. As future work, we will investigate how price setting by each of the agent will have effect over the configuration of the EIP. We intend to investigate the effect energy storage system will have in the supply/demand mismatch that can occur in the EIP system.

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