Automating Virtual Power Plant Decision Making with Fuzzy Logic and Human Psychology

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***Abstract*—This paper presents a Virtual Power Plant (VPP) decision making approach which uses fuzzy logic and a novel "insecurity" metric, based on human psychology. The VPP approach is modelled as a multi-agent system, which aims to minimize carbon emissions and/or energy cost, using an aggregation structure similar to energy or carbon markets. The "insecurity factor" reflects the operational flexibility of micro-generators, translated to a numerical value through fuzzy logic. The system was able to create a functional internal VPP market, where the micro-generators were trading autonomously according to external price signals and taking into account their own needs and limitations, as well as short-term forecasts.**

Keywords— Virtual Power Plants, intelligent control, multi-agent system, distributed energy resources, aggregation, insecurity factor, fuzzy logic

I. Introduction

Decision-making in Virtual Power Plants (VPP) is a complex process, as it involves several players. Multi-agent systems are a common tool used in VPP for coordinating several entities, such as generators, microgrid operators, aggregators.

The concept of agency implies the property of autonomy. An agent would be able to act autonomously in its environment [1]. In order to implement autonomy, the agent developers often use Artificial Intelligence (AI) techniques. According to [2], an intelligent agent is defined as a physical of virtual entity which possesses a set of qualities. These qualities are summed up in [1] as (i) reactivity, (ii) proactiveness and (iii) social ability. Agents are characterised based on their representation of the environment as [2]:

(i) Cognitive, where "the agent has a symbolic and explicit representation of the world, on which it can reason." or

(ii) Reactive, where "its representation is situated at a sub-symbolic level, that is, integrated into its sensory-motor capacities."

The EU Emissions Trading Scheme (ETS) is designed with the prospect of reducing the overall carbon emissions from a set of organizations. For energy generators this translates to facilities with installed thermal input capacity over 20MW, regardless of their conversion efficiency. The operational principle of this scheme is based on the "cap and trade" concept. A cap is placed on the total emissions of an organization, e.g. 90%. The organization is then responsible for reducing its emissions by the remaining 10%. However, not all organizations can reduce their emissions by that amount, or at least not with a reasonable cost. The amount of allowed emissions is split into allowance units, called Carbon Credits. In the EU trading system, one Carbon Credit represents 1 tonne of CO_2 emissions, and can be traded freely. The ETS system allows the regulator to directly control the total emissions from the set of organizations that participate in the scheme, while leaving the organisations to agree upon themselves their individual emissions levels. On that basis, organisations within an ETS can be accurately simulated / represented by intelligent agents.

In [3], the authors use a LV network and a micro-grid control structure to investigate the benefits of DER participation in emissions markets. Significant benefits from DER participation in emissions markets were found. However, a centralised decision-making methodology was used as the control mechanism, where the MGCC was controlling the DER directly. In [4], agents are assigned to generators and consumers, which aim at optimising their own economical profit. A market is set up and auction protocols are implemented. The CO_2 emissions are taken into account in the auction process, creating a multi-objective trading environment. A multi-agent system is created that resembles the operation of energy markets, although the agents are not trading emissions credits. VPP interaction with emissions-related markets has been considered in the literature, albeit not as inherent components of the VPP operation [5].

Human psychology in conjunction with fuzzy logic has been used in the context of VPPs, by using a 'fuzzy satisfaction method' in scheduling optimisation of a VPP [6]. In [7], the authors present a similarly inspired method, which uses fuzzy satisfaction as a measure of 'confidence', which influences the VPP behaviour towards reliability risks.

This paper presents a VPP decision making approach which uses fuzzy logic and a novel 'insecurity' metric, based on human psychology. The VPP considered in this research aims to minimize carbon emissions and/or energy cost, using a structure similar to energy or carbon markets. It is using the concept of Carbon Credits, much like the EU Emissions Trading System (ETS). It is comprised of micro-generator agents, as well as aggregator agents. Decision making in the VPP is taking place over a number of operational time periods, e.g. every 5 minutes, to facilitate short-term forecasting.

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II. Multi-Agent System Structure – Architecture

A. Structure – Architecture

The proposed system is designed using a hierarchical structure, as described in [8]. Two levels of aggregation are established: (i) at the micro-grid level and (ii) at the VPP level. The micro-generator agents are aggregated by the Micro-grid Aggregator agents, which in turn are aggregated by the VPP Aggregator agent. The Multi-Agent System was implemented in the JADE platform [9]. The role and main purpose of each agent is briefly described below:

a) The Virtual Power Plant (VPP) Aggregator agent is responsible for deciding upon the overall VPP behaviour, using a given policy. It issues the Carbon Credits to the micro-generators.

b) The Micro-grid Aggregator agent is acting as an intermediary between the micro-generators and the VPP Aggregator agent. No decision making is done at this level.

c) The Micro-generator agent is located in the micro-generator controller. It has a representation of the parameters affecting the micro-generator emissions, if there is any electrical or thermal storage capacity, and the local electrical and thermal demand. It has an individual strategy that defines its behaviour. Based on this strategy, it determines the amount of Carbon Credits to request from the VPP Aggregator agent, and/or trade with the other micro-generator agents.

B. Agent Internal Architecture

The main elements of the agents that contain executable code are called behaviours [9]. The JADE platform enables the agents to execute behaviours as lumps of code for a specific action. Behaviours can be timed to repeatedly execute at intervals, or can be executed once.

The agent functionality can be described with operational modules, which are responsible for a given function inside the agent. The internal structure of the three types of agents is shown in Fig. 1. Fuzzy logic techniques were applied for the decision-making processes of the agents. The agent functionality is different for each type of agent:

(i) The micro-generator agent communicates with (or is part of) the micro-generator controller.

(ii) The Micro-grid Aggregator agent has the aggregation functionalities of the VPP Aggregator agent, but it is not actively controlling the signals, it just transfers them from and to the VPP Aggregator agent.

(iii) The VPP Aggregator agent aggregates all the micro-generator information and sends the appropriate signals, following a specific control policy.

C. Agent Interaction

Agent interaction in the proposed VPP is framed according to the three aspects described in [2]:

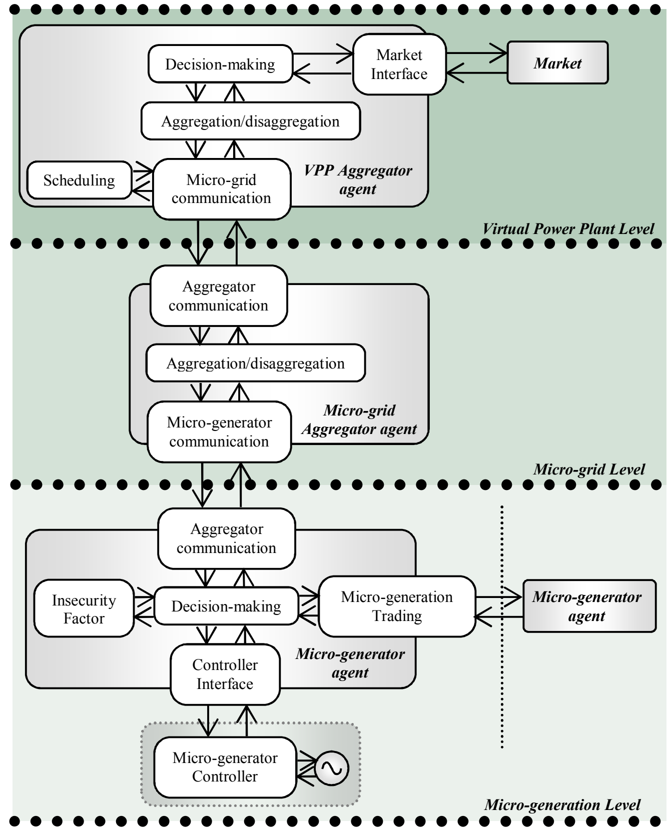

Fig. 1. Modular structure of the agents

(i) Goal compatibility: The goals of the different micro-generator agents are compatible. They aim at independently satisfying their own need for Carbon Credits, regardless of the other agents. The fact that one agent possesses enough Carbon Credits does not necessarily mean that another will not.

(ii) Access to resources: Their access to resources (Carbon Credits) is usually limited by the VPP Aggregator agent, since it regulates the supply of Carbon Credits. Most of the time, this leads to insufficient resources. Thus, the agents need to collaborate (trade) in order to satisfy the goals of each individual.

(iii) Agent skills: The skills of the agents for satisfying their goals are usually insufficient, in the sense that they cannot always match their emissions with their Carbon Credits, without trading Carbon Credits with other agents.

The above characteristics (compatible goals – insufficient resources – insufficient skills) lead the agent interaction to be described as Coordinated Collaboration [2]. The agents collaborate in order to exploit the advantages of working together both for the common (VPP) as well as their individual (micro-generator) goals.

The above description resembles human society and the individual's need for sufficient resources (e.g. food). While most humans are able to secure these resources by collaborating with others, this behaviour is driven to an extent by insecurity.

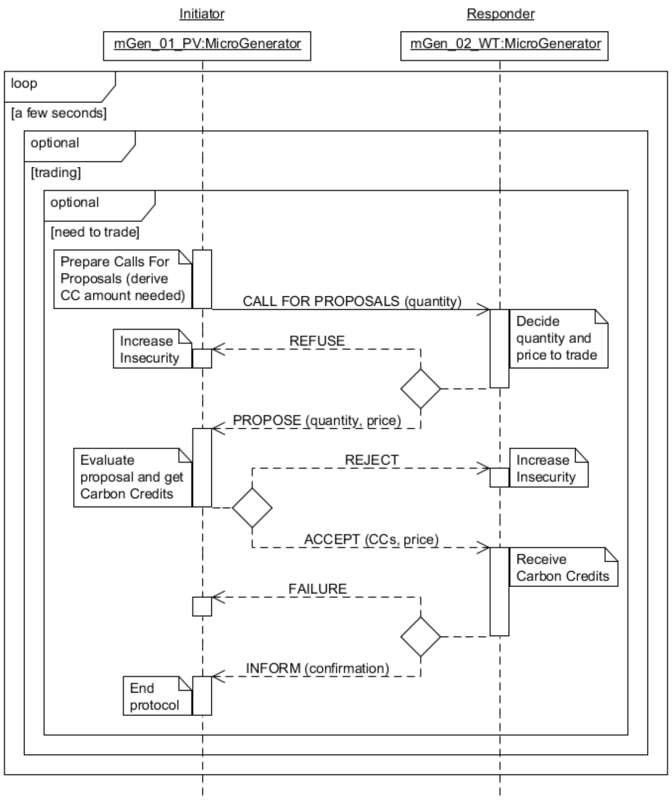

Fig. 2. UML sequence diagram showing the trading interaction between micro-generator agents

The developed trading procedure is an auction process, chosen due to its simplicity. According to the classification in [1], it is described as First-Price Sealed-Bid auction. In this type of auction, the agents bid according to their valuation of the commodity (Carbon Credit), which is finally sold to the highest bidder, at the price of this bid. Contrary to other types of auction, there is only one bidding round, and the agents do not know the bids of other agents. This can be implemented with FIPA protocols in JADE. The interaction sequence between the micro-generators and the aggregators is illustrated in Fig. 2.

Once the micro-generator agents have received the Carbon Credits from the Micro-grid Aggregator agents, they calculate the difference between the emissions justified by the Carbon Credits and their projected emissions. Then, if they find a discrepancy, they start trading Carbon Credits with other agents, in order to match their projected emissions. They do this by using the Contract Net agent interaction protocol [2], [9]. This interaction is drawn in a Unified Modelling Language (UML) sequence diagram in Fig. 3.

III. INSECURITY FACTOR

The insecurity factor is the core of the decision making in the micro-generator agent. It reflects the operational flexibility of the micro-generator. This factor is calculated by the agent and is used in conjunction with fuzzy logic functions (see Section IV) for the following purposes:

- To forecast the amount of energy that the micro-generator aims to generate during the next operational period.

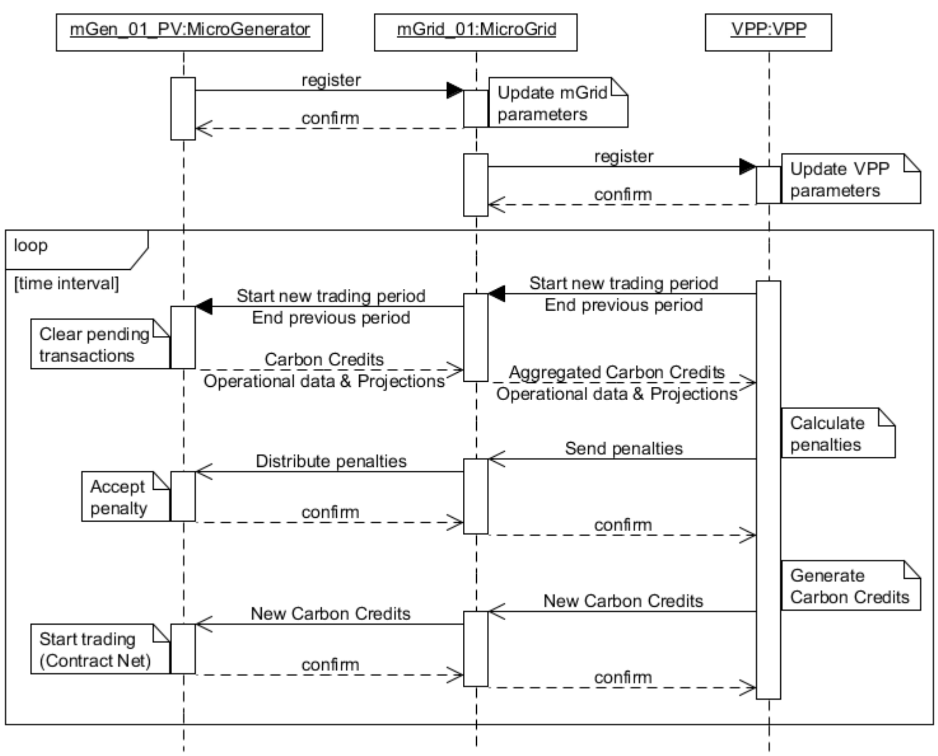

Fig. 3. Unified Modelling Language (UML) sequence diagram showing the interaction between aggregator and micro-generator agents

- To derive a Carbon Credit price, when the micro-generator agent needs to provide a price in a trading proposal.
- To evaluate a Carbon Credit price, when the micro-generator agent receives a trading proposal, thus determining how many Carbon Credits to trade at this price.

A. Micro-CHP Insecurity Factor

For the micro-CHP (Combined Heat and Power) units, the insecurity factor I is calculated using fuzzy inference rules between I_G and I_S (see Section IV), assuming that some form of thermal storage / buffer is available, typically a hot water tank:

$$I_G = \frac{G_{min}}{G_{max}} \tag{1}$$

s.t. $$0 < I_G < 1 \tag{2}$$

$$I_S = \frac{S_{th} - E_P}{S_{th}} \tag{3}$$

s.t. $$E_P \geq U \tag{4}$$

where: I_G is the generation insecurity factor.

I_S is the thermal storage insecurity factor.

G_{min} is the minimum generation limit coefficient.

G_{max} is the maximum generation limit coefficient.

S_{th} is the thermal storage / buffer capacity (kWh).

E_P is the stored heat forecast for the next time step (kWh).

U is the unserveable thermal demand in kWh.

G_{min} and G_{max} represent the operational limits of the micro-generator based on the availability of storage. They are determined as follows:

$$G_{min} = \frac{D_P - E_P}{G_{rated}} \tag{5}$$

s.t. $$E_P \geq U \quad and \quad G_{min} > 0 \tag{6}$$

$$G_{max} = \frac{D_P + (S_{th} - E_P)}{G_{rated}} \tag{7}$$

s.t. $$E_P \geq U \quad and \quad G_{max} < 1 \tag{8}$$

where: D_P is the forecasted thermal demand (kWh).

G_{rated} is the generator rated energy (heat rating * time step duration).

The unserveable demand U is the proportion of the demand that exceeded the capacity of the micro-generator during the previous n time-steps (e.g. 24 hours):

$$U = \sum_{i=-n}^{0} (D_i - G_{rated}) \tag{9}$$

s.t. $$D_i - G_{rated} \geq 0 \tag{10}$$

where: D_i is the thermal demand at time-step i.

B. Renewables Insecurity Factor

For the renewables (wind turbines, photovoltaics), the insecurity factor I_G is calculated as follows, assuming that some form of electrical storage is available alongside the generator:

$$I_G = \begin{cases} \dfrac{\left(\frac{E_P}{S_e} - E_T\right)}{E_T}, & if \ \dfrac{E_P}{S_e} > E_T \\ \dfrac{\left(\frac{S_e - E_P}{S_e} - E_T\right)}{E_T}, & if \ \dfrac{E_P}{S_e} < E_T \end{cases} \tag{11}$$

where: E_P is the battery level projection for the next time step.

S_e is the electrical storage / buffer capacity.

E_T is the target battery level, defined by the micro-generator strategy.

C. Collective Insecurity Factor (CIF)

The micro-generator agent insecurity factor is also sent to the VPP Aggregator. The VPP Aggregator calculates the average agent collective insecurity factor for the whole VPP, and sends it back to the micro-generators. Therefore the micro-generator agents are aware of the overall average level of insecurity in the whole population, and take it into account when deciding upon prices using fuzzy inference rules (Section IV).

When the VPP Aggregator agent creates the Carbon Credits, it evaluates the current grid emission factor. It uses this evaluation together with the collective insecurity, to infer the amount of Carbon Credits that will be fed into the internal agent market. The Carbon Credits are distributed to the micro-generators proportionally to the amount they requested (forecasted/desired emissions).

IV. Fuzzy Logic

A. Fuzzy sets

Fuzzy logic techniques were applied during agent development, to implement the agent intelligence processes. Fuzzy sets were derived for the insecurity factor, in a relatively simplified, uniform manner, as shown in Fig. 4. This enabled the utilisation of fuzzy inference rules for the decision-making of the agent. This process can be described as learning, since it is adaptable to new data and the meaning of characterisations such as "high price" adjusts to the environment. The agent records the inputs from its environment (e.g. trading price) and plans its future actions according to this input, in order to achieve its design objectives.

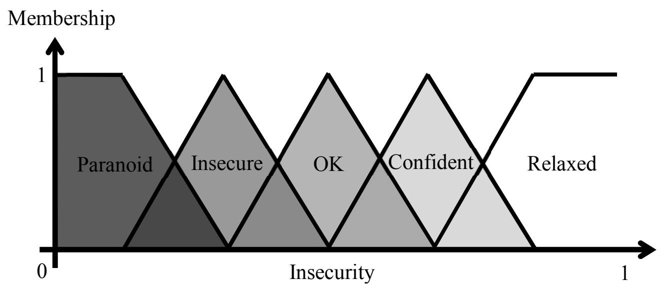

Fig. 4. Fuzzy sets for the insecurity factor

B. *Fuzzy Clustering*

The Fuzzy c-Means clustering algorithm is used by the agents to create fuzzy sets out of the following data [10]:

- Grid real-time emission factor (VPP Aggregator agent).
- Electricity market price (VPP Aggregator agent).
- Carbon Credit trading price (micro-generator agent).

These fuzzy sets are used for the decision-making. The fuzzy clustering algorithm runs every time new data points are added to the respective database:

- In the VPP Aggregator agent, this occurs every time period (e.g. 5 minutes), when it receives data on the grid emission factor and/or the electricity market price.
- In the micro-generator agent, this occurs every time it receives a trading proposal with a Carbon Credit price from another agent.

This method enables the agent to retain a form of approximate "memory" of the data which can be used along with a fuzzy inference method for adaptive decision-making.

An example of fuzzy clustering is illustrated in Fig. 5 and Fig. 6. In Fig. 5, a typical domestic load profile is shown [11]. This set of data is then clustered in fuzzy sets by the Fuzzy c-Means algorithm. The resulting sets are shown in Fig. 6.

C. *Fuzzy Inference*

The implication matrix for inference between the agent individual insecurity factor and the collective VPP insecurity factor is shown in Table I. This inference procedure produces a combined micro-generator insecurity value, which also encompasses the Collective Insecurity Factor.

TABLE I. INDIVIDUAL INSECURITY – COLLECTIVE INSECURITY FACTOR (CIF) IMPLICATION MATRIX

Individual \ CIF	Paranoid	Insecure	OK	Confident	Relaxed
Paranoid	Paranoid	Paranoid	Insecure	Insecure	OK
Insecure	Paranoid	Insecure	Insecure	OK	Confident
OK	Insecure	Insecure	OK	Confident	Relaxed
Confident	Insecure	OK	Confident	Confident	Relaxed
Relaxed	OK	Confident	Relaxed	Relaxed	Relaxed

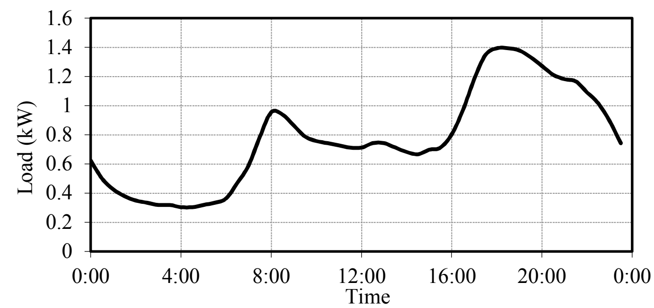

Fig. 5. Domestic load profile

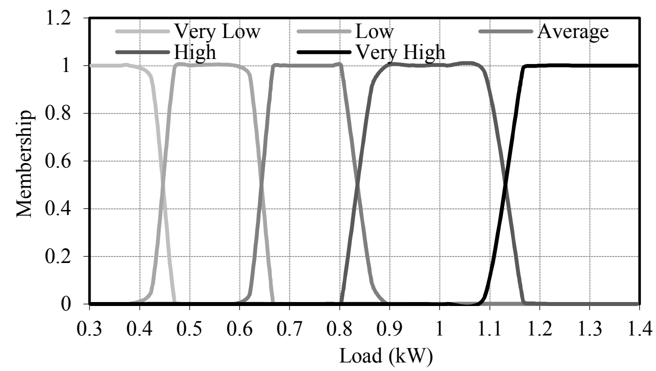

Fig. 6. Fuzzy clusters for the domestic load profile

When a trading proposal is received, this combined insecurity factor is used together with the proposal price to infer the percentage of Carbon Credits that the agent will trade. The percentage of Carbon Credits is relative to the trading quantity proposed by the other agent. Different implication matrices were used for different proposal types. The implication matrix that was used in response to a proposal to sell Carbon Credits is shown in Table II. The output from this inference procedure is a percentage of Carbon Credits, while 100% being the original requested amount received in the sell proposal. The agent then decides to accept to sell only that proportion of Carbon Credits.

TABLE II. INSECURITY – PRICE IMPLICATION MATRIX FOR A PROPOSAL TO SELL

Insecurity \ Price	Very Low	Low	Fair	High	Very High
Paranoid	0%	0%	25%	50%	75%
Insecure	0%	25%	50%	75%	100%
OK	25%	50%	75%	100%	100%
Confident	50%	75%	100%	100%	100%
Relaxed	75%	100%	100%	100%	100%

D. *Defuzzification*

The method of interpolation was used to find the inference result. However, the result is a fuzzy number, which cannot be used directly by the agent. Instead, a single real number is required, which is obtained by a defuzzification method.

Two defuzzification methods were used in this study, the Centre of Gravity and the Mean of Maxima [10]. The values were normally defuzzified with the Centre of Gravity, except when the result was close to the limits 0 and 1. For these boundary values, the Centre of Gravity method was found to be inaccurate, so the Mean of Maxima method was used instead.

V. Results – Case Study

A. Simulated VPP

The number of agents that were simulated is based on the case described in [12]. In total, 48 micro-generators were simulated. Two micro-grids were simulated, each of them containing 4 Wind Turbines, 2 Photovoltaics, 2 Microturbines, 3 Fuel Cells and 13 Stirling Engines. Although the wind turbines and photovoltaics are renewable energy sources and are considered carbon-free, their life-cycle carbon emissions were also considered, as described in [12]. Electrical storage capacity of $20kWh_e$ was considered for the wind turbines and photovoltaics and 500L ($20kWh_{th}$) thermal storage for the micro-CHPs. One Carbon Credit was equal to 1 gCO_2-e.

B. VPP output deviation from Carbon Credits

The amount of Carbon Credits supplied by the VPP Aggregator is compared with the actual emissions output in Fig. 7. A very close match can be observed, except for small inconsistencies such as the one depicted with the dotted circle. In some trading sessions, the micro-generators were not able to acquire enough Carbon Credits to match their emissions, even after trading, because the other agents also needed Carbon Credits. This is evident in Fig. 8, where the deviation between the Carbon Credits (set-point) and the actual emissions output is compared with the thermal demand. It was observed that most of the deviation occurrences were under two circumstances:

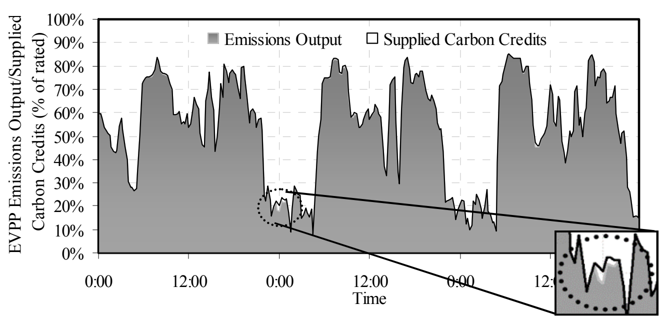

Fig. 7. VPP emissions desired (Carbon Credits) and actual output

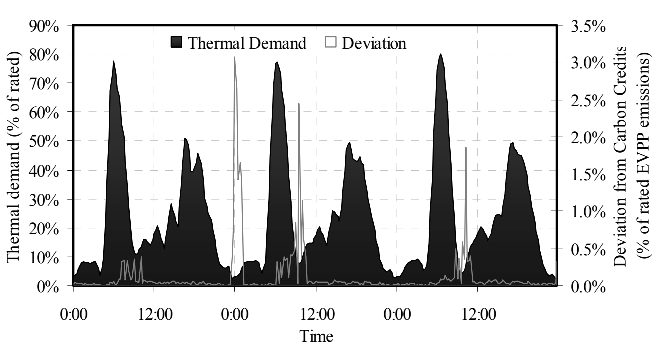

Fig. 8. VPP emissions output deviation from Carbon Credits and total thermal demand

- **Immediately after a peak in thermal demand**, when the micro-CHP thermal storage level is normally low (see Fig. 8). Some micro-CHPs cannot reduce their production to meet their Carbon Credits, or they would fail to supply the domestic thermal load. The Carbon Credit availability is also low. Thus, they cannot buy Carbon Credits either, and a deviation occurs.
- **At times when the thermal demand is very low** and the thermal storage level is high. When the micro-CHP storage levels are high and the VPP supplies a lot of Carbon Credits, some micro-CHPs cannot increase their production to match their Carbon Credits. If they do, they would waste recovered heat, or overheat their storage tank. They cannot sell their Carbon Credits either, since the availability is high and the other agents are not interested in buying.

VI. Conclusions

In this work, a VPP decision-making mechanism was presented, which is based on a modelled version of human insecurity. The insecurity factor was modelled using fuzzy logic. Fuzzy inference methods were used to get useful operational actions. An internal emissions market was modelled inside a VPP and it was shown that the agents can self-regulate their emissions, while satisfying their individual constraints / goals.

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