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Agent-Based System for Microgrid Power Real-Time Pricing with Client Preferences

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Abstract – *Microgrid technology is actually the most practical way for Distributed Energy Resources (DERs) deployment in urban and rural communities. The factors that motivate reliance to the microgrid technology include energy security, economy and environment. The economical sustainability of microgrids depends on the energy market within a community. This can be challenged by issues related to the scalability of the microgrid and the setting up of a pricing system. Various energy management systems and energy pricing methods developed so far offer little or no option to the end user/client to accept or reject the proposed price. Thus, this paper presents a client focused agent that automatically negotiates various available economical options in real-time pricing context within a microgrid. The proposed agent collects and analyses the prices as communicated by the microgrid network operator. Moreover, based on client predefined preferences, it regulates the client load demand in a predefined sequence with the aim of minimizing the power consumption during high price period. Therefore, the proposed system will reduce the client overall energy cost and contributes towards demand side management from the network operator perspective. The agent mathematical model and algorithm are simulated in MATLAB environment. The findings of the study demonstrate the effectiveness of the proposed agent approach in offering the client a real-time control over the energy cost control in a microgrid context.*

***Keywords**: Agent, Energy Trading, Demand Response, Distributed Energy Resources, Microgrid, P2P Energy Trading, Smart Grid*

I. Introduction

The structure of utility market around the world is changing, moving from the traditional top-down model to more Distributed Generation Resources (DER) and bottom-up model. The rationale behind this ongoing process is the need to reduce electricity costs, to increase the reliability and the resilience of the existing system on one hand and to address environmental concerns while providing low-cost electricity to non-electrified areas on the other hand. The ongoing increase in renewable energy penetration into the grid is also linked to the maturity of the associated technologies. The traditional power system structure had advantageous features such as reliability through the interconnection of sparse generating units, load diversification and reduced construction costs per kilowatt [1], [2]. Currently, DERs can provide the same advantages at a low cost and little impact on the environment. DERs offer advantages in terms of voltage control, reliability, power quality improvement, system losses reduction, demand reduction as well as energy production cost saving amongst others [3], [4]. Irrespective of the mentioned motivations behind the deployment of DERs that might vary from place to place, microgrids are found to be the best architecture platforms for DERs deployment in urban and rural communities. Though the term "microgrid" has various definitions, it can be defined as a conglomerate of interconnected loads and DER units within a defined electrical boundary [5]. The entire conglomerate is viewed as a single controllable entity by the grid, with the ability to operate in grid connected or off grid mode [6]. Therefore, microgrids are also viewed as separate entities from the main grid. The DERs within microgrids are locally controlled by the microgrids' controller and can operate independently from the grid [7]. Microgrids can be categorized according to the nature of the current flow, the mode of operation or application. Microgrids often consists of generation units from different technologies such as Photovoltaic (PV) panels, wind turbine and sometimes Energy Storage System (ESS) that require power electronics converters as means of integration. Power electronics converters are also used to interface microgrids for grid connected mode of operation. In the latter mode, the microgrids, through power electronics, can partake in black starts strategy and grid support in general [8]-[10]. The microgrid internal control deals mainly with fluctuation in power due to the intermittence nature of renewable resources [11]. The deployment of microgrids is motivated by three factors: energy security, economy and the green energy integration [12]. The control requirements of microgrid are operational mode oriented. Hence for the grid connected mode, controllers are required to interface the

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microgrid to the grid as a single self-controlled entity acting like a synchronous generator; while for the island mode the control is on the voltage, the frequency and the resource dispatch for supply-demand energy balance within microgrid [13]-[15]. Both types of control can be categorized as primary and secondary control while tertiary control oversees the optimal economic operation of the microgrid DER units [16]-[18]. The control coordination within microgrid is performed through the agents, which can be defined as goal oriented, physical or virtual entities with the ability to make decisions [19], [20]. Various studies have been conducted on agents or multi-agent concepts in microgrid protection, control, energy management and energy trading [21]. [22] has presented a multiagent based method for optimal power management for interconnected microgrids in distribution system. The method is a Supervised Multiagent Safe Policy Learning (SMAS-PL), unlike unconstrained reinforcement learning algorithms that might fail to meet the operational constraints of the grid.

This method uses gradient information during the learning process. Furthermore, it considers other operational constraints for an optimum control, safe and feasible decisions. In [23] a non-cooperative game algorithm in packet forwarding game in non-cooperative multidomain wireless sensor networks has been presented. The method proves to be efficient in packet delivery; it improves energy consumption in each domain and consequently the lifetime of the network. A multi-agent based Q-learning algorithm for revenue maximization has been presented in [24]. The approach is tested on a mid-market rate energy trading model. An automatic peer to peer trading algorithm based on Q-learning has been presented in [25]. It is adapted from stock trading algorithm and results show high profits and a reduction in losses due to over-generation. [26] has presented a multi-agent based protection technique that uses energy storage system to improve the resilience, while [27] has proposed a multi-agent system architecture for smart grid protection. A systematic review of application of multiagent system in smart grid has been also presented. Mostly, research about the use of agents in microgrids has focused on energy management and energy transaction within the microgrid, with the aim to optimize the dispatch of DERs or energy transaction price negotiation [28]. An agent algorithm for optimal energy management in a microgrid through optimal cost scheduling of DER, considering power losses has been presented in [29] and it simplifies the communication process. An autonomous management system with self-healing capabilities for application in green house or microgrids has been presented in [30]. It is a multi-agent based system controlled by a self-healing hierarchical algorithm and it offers a robust and stable control for microgrid. A multi agent based energy management system for an isolated photovoltaic (PV) microgrid has been presented in [31].

The system takes into account the voltage constraints and the load demand while maintaining the operational efficiency of the PV system at its maximum.

Furthermore, the proposed system reduces the chattering on energy storage system. In [32] an enhancement of system voltage stability through optimal placement of reactive compensators controlled by multi agents has been presented. Energy exchange or energy transaction as regards the microgrid can take place between the later and the grid or within the microgrid itself. Energy market within microgrid can be considered as peer-to-peer (P2P) if prosumers are involved. The P2P can be categorized either as a full P2P market where prosumers negotiate directly with the consumers or as a community based P2P where a central entity negotiate the price on behalf of all consumers. The full P2P market operation can be challenged by the scalability issue, the setting up, and the clearing of price. On the other hand a community based market relies on a central community coordinators as intermediate between resources, large DER or prosumers, which allows an easy setup of clearing price [33], [34]. In a community based P2P, many researchers have focused on the energy management and pricing through optimal dispatching of DER in the microgrid with a take-it- or-leave-it option to the client or the end user. [35] has presented a multi-agent based platform for energy trading that integrates an energy storage system into a microgrid energy management system that improves the supply and the demand balance in the microgrid. [36] has proposed an agent based platform running on a single board computer, for microgrid intelligent management in a peer to peer energy transaction context. A decentralized algorithm for local energy trading in microgrids with an integrated pricing mechanism and network voltage management has been presented in [37]. The proposed algorithm assures that the energy transactions within the network do affect the voltage constraints and it preserves the privacy of agents. A multi-agent transactive energy management systems for residential buildings to prevent the overloading of the grid and to optimize the energy cost of the building, has been presented in [38]. It consists of a multiagent system with a decentralized coordination; the system preserves the consumer's privacy. In that regard, [39] has explored the effects of an attack with false data on P2P energy trading platforms. A multiagent Q-learning based bidding strategy has been presented in [40]. The strategy has aimed to maximize the cumulative reward of the participants in energy auction and trading. This strategy considers the bidding renewable resource generators and end users as agents.

The latter use Q-tables to estimate and decide their best bidding prices. The method outperforms the existing comparable methods in terms of profit for renewable resource generators and energy satisfactory for end users.

An agent based forecast method with each users energy consumption prediction capability with a 1-hour lead has been presented in [41]. The method helps in the estimation of the energy required and in turn, in dispatching of multiple suppliers and in cost determination. In this paper, a client oriented agent that will automatically negotiate various economical option in event of dynamic pricing within the microgrid is presented.

The paper is organized as follows. Section II presents the pricing in microgrids. Section III presents the proposed agent, its mathematical model and algorithm.

Section IV discusses the simulation results. Section V presents the conclusions.

II. Pricing in Microgrids

The purpose of pricing in electricity market is to recover the production cost throughout the supply chain down to the end users [42]. This supply chain can be broken down into wholesale, which looks at buying and selling from generators and the retailing, which deals with end users. The wholesale price is linked to the economic dispatching of generation resources. The aim is to supply electricity at low cost, through scheduling of the resources according to their respective operational cost in regards to the power demand. The levelized cost of energy allows a comparative analysis of the cost of electricity produced by different generators with varied capital cost, fuel cost and lifetime. The Levelized Cost Of Energy (LCOE) is the basis in determination of energy tariffs/price in order to recover the cost. Equation (1) gives the LCOE for an individual generating unity:

$$\alpha = \frac{(I + F) + (C_F + V)}{E} \tag{1}$$

where I is the total investment cost, F is the fixed operation and maintenance cost and variable, C_F is the total generation cost of the unit over its lifetime, V is the variable operational and maintenance (O&M) costs, E is the energy produced. In a microgrid with multiple integrated DERs, the overall LCOE is given by the aggregate of individual LCOEs (α_i) as in Equation (2) and the individual cost can be expressed using the LCOE:

$$C_i = \alpha_i \times E_i \tag{2}$$

$$\alpha_{tot} = \frac{\sum_{i=1}^{k} C_I}{\sum_{i=1}^{k} E_i} \tag{3}$$

In order to recover the cost and make profit and to some extent to reshape the demand response, different pricing strategies are used. In electricity retailing, pricing strategies can be classified into static or dynamic pricing.

In static pricing strategies, additionally to the fixed price, the retail price might as well vary according to a pre-set period of the day, which is referred to as Time of Use (TOU) prices. On the other hand, with the dynamic pricing strategy, prices are allowed changing more often during a day and on short notice in line with dynamics in wholesale prices and the supply-demand balance.

Dynamic pricing can be Real-Time Pricing (RTP), which is subject to the hourly changes, or it can be a Critical Peak Pricing (CPP) that allows high retail price for a limited period, i.e. few hours. In this paper, dynamic real-time pricing has been considered.

III. Proposed Agent Algorithm

The dynamic pricing consists of adjusting the retail price to the wholesale price of electricity in order for the retailer to balance the real time cost. Fig. 1 shows a microgrid distribution system with the proposed agent for price decision making on the behalf of the client. The agent scans the prices as they are continuously published by the microgrid operator and based on preset preference by the client or end users, the agent can accept, accept for a fixed period or adjust the client demand to keep to consumption cost in line with the budget. The agent purpose is to adapt the client demand and budget to the actual price, by setting up constraint or criteria upon which the agent will base its decision in the context of dynamic pricing. The agent will act according to the client price preferences, by connecting and disconnecting the load. Initially the agent subdivides the load into N number of small loads, which can be connected depending on the active price and its duration. The agent can decide to connect a N number of loads (full load), N-1 loads, N-2 and so on. The decision of the agent depends on both the active price P_i, its duration T_i and client criteria price P_{ci} and its duration T_{ci}. The agent action can be expressed by Equation (4):

$$Y_{agent} = \begin{cases} N \text{ for } P_i \le P_{c1} \text{ and } T_i \le T_{c1} \\ N-1 \text{ for } P_{c1} < P_i \le P_{c2} \text{ and } T_i \le T_{c2} \\ N-2 \text{ for } P_{c2} < P_i \le P_{c3} \text{ and } T_i \le T_{c3} \\ N-3 \text{ for } P_{c3} < P_i \le P_{c4} \text{ and } T_i \le T_{c4} \end{cases} \tag{4}$$

where $P_{c1} < P_{c2} < P_{c3} < P_{c4} < \cdots < P_{cN}$. Fig. 2 shows the agent algorithm that flows in the following sequence:

- The agent starts by scanning the active or the actual price P_i and the estimated period T_i that price is valid;
- The scanned values are compared to the sequential client price preferences from P_{c1} to P_{cN} and to the various client acceptable per price commitment time T_{c1} to T_{cN};
- The determination of the client price and the time duration preferences are beyond the scope of this paper;
- Depending on the number of subdivisions of the load, the agent will perform N number of iterations;
- For the first iteration the input price P_i and time duration T_i are compared to the client's preference; if they match, the corresponding number of loads will be connected;
- On the other hand, if there is a mismatch with the client first preference, the agent will move on to the second or third until nth preference until a match is found and corresponding loads are connected; otherwise it stops;
- After connecting loads, the agent will keep up monitoring the change in price and repeat the process.

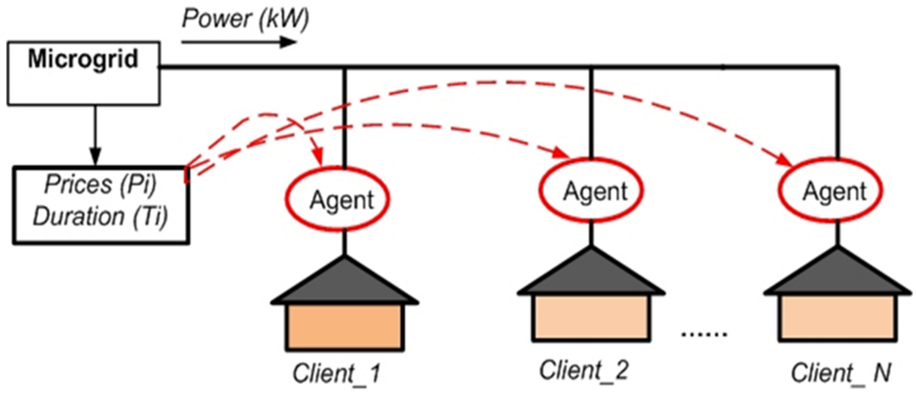

Fig. 1. Agent in microgrid distribution network system

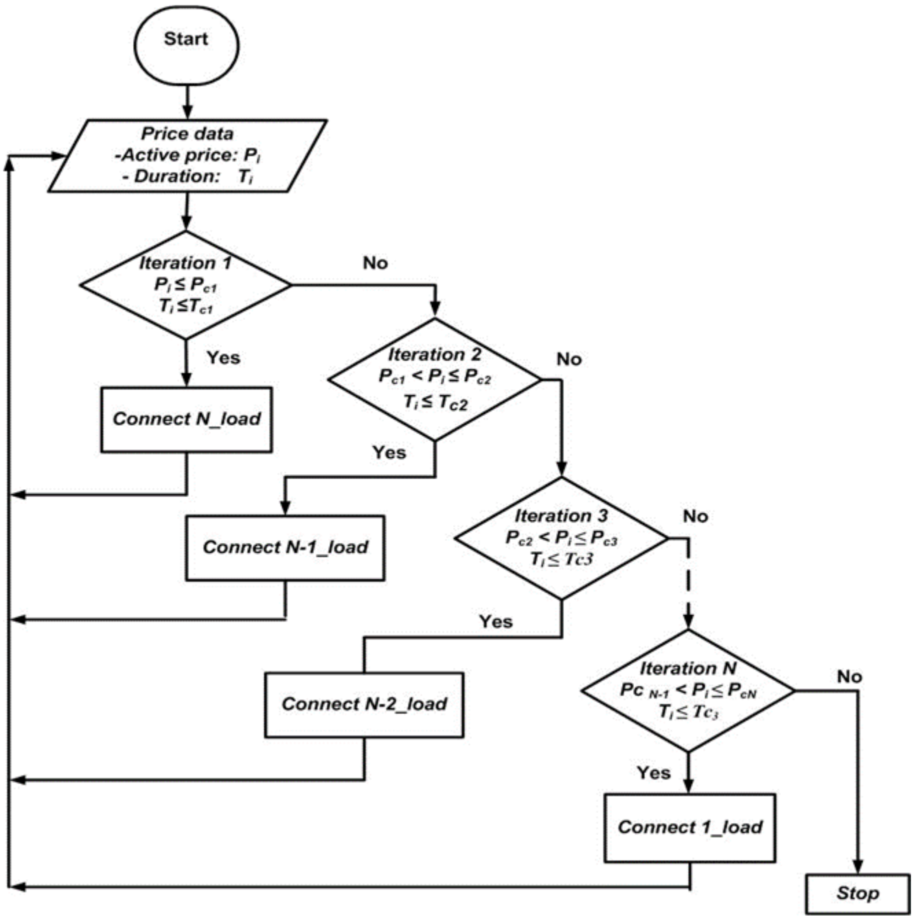

Fig. 2. Proposed agent algorithm

IV. Simulation and Results

The proposed Agent is applied on a case study of a client connected to a local microgrid with a dynamic pricing scheme. MATLAB Simulink environment is used for simulation. The agent is expected to check the price as broadcasted by the microgrid operator and to manage the load according to the preset criteria in line with the client budget. Table I shows the simulated dynamic prices, their respective expected duration and occurrence period. It should be noted that assumptions are made on the value of the prices. However, the logic of high price during peak hours is observed. In Table II, the real-time prices and their occurrence time over 24 hrs are shown.

TABLE I
DYNAMIC PRICES AND THEIR RESPECTIVE EXPECTED DURATION

No.	Price (Pi) ($/kWh)	Duration (Ti) in Hrs.	Occurrence period
1	1.5	7	00:00 – 07:00
2	2.1	2	07:00 – 09:00
3	1.9	3	09:00 – 12:00
4	1.5	4	12:00 – 16:00
5	2.3	2	16:00 – 18:00
6	3	2	18:00 – 20:00
7	2.5	2	20:00 – 22:00
8	1.9	2	22:00 – 00:00

TABLE II
CLIENT PRICE PREFERENCES AND CORRESPONDING AFFORDABLE LOAD CAPACITY

Client price preference categories P_{ck}, K=1,2,3..n	Criteria versus active Price P_i ($/kWh)	Preferred Duration (T_i) in Hrs	Affordable Load capacity
1	$P_i \leq 2$	n.a	Full - load
2	$2 < P_i \leq 2.3$	≤ 3	¾ Full- load
3	$2.3 < P_i \leq 2.5$	≤ 2.5	½ Full-load
4	$2.5 < P_i \leq 3$	≤ 2.5	Critical loads

The client preferences are shown in Table II. The load is subdivided into 4 categories where for a certain range of prices corresponds a portion of the total load that the client would be able to afford the cost. Those categories are the full load, the three quarter of the load, the half load and the critical load. The client power demand is adjusted according to the active price P_i, where the full load might be connected for the price less or equal to 2 $/kWh for any duration, three quarter of the load for price between 2 and 2.3 $/kWh for a period not exceeding three hours, half load for a price greater than 2.3 $/kWh but lower than 2.5 $/kWh for a period of time that not exceeds 2.5 hours. For a price high than 2.5 $/kWh and less than or equal to 3 $/kWh and valid for a period not exceeding 2.5 hours, only critical loads are connected. The simulation is run for 24 seconds representing 24 hours of a complete day. Midnight is set as the starting point. Figure 3 shows the simulation's results of the prices and their respective duration as communicated by the microgrid operator. The peak price 3 $/kWh appears between 18:00 and 20:00, corresponding to the peak demand as usually seen by the generation side. The price gradually decreases and reaches the lower price, 1.5 $/kWh, from midnight to 7:00 am and from 12:00 to 16:00. In the latter case, it can be explained by the availability of PV plant production while in the former case the lower price can be explained by the low power demand from microgrid clients. The agent is expected to react to the changes in price and regulate the consumption through the switching in and out portions of the total load. As developed in Section III, the load is subdivided into 4 portions: full- load, three quarter of the full- load, half- load and critical load which should correspond to the lowest consumption. It should be noted that the prices are broadcasted to the client through communication system, which is beyond the scope of this paper. Fig. 4 shows the simulation results of the agent output logic control signals in response to the change in price and according to the client preferences as presented in Table II. Since the price is at its lowest value at the beginning of the simulation at midnight, the agent connects the full load for the duration of the price according the client preferences. Therefore, the full load is connected from midnight to 7 a.m., when the price goes up to 2.1 $/kWh.

The agent responds to that increase in price by reducing the full-load to its three quarter, from 7 am to 9 am.

Thus, the agent output logic signal for three quarter is valid for the duration of the price. Similarly, the three quarter status will be active again from 16:00 to 18:00.

From 18:00 to 20:00 corresponds to peak price, 3 $/kWh, upon which the agent react by only connecting critical loads for the duration of the price. From 20:00 to 22:00 the price drops to 2.5 $/kWh making the agent to generate the logical signal to connect only half of the total load, followed by the reconnection of the full load from midnight. From the results discussed the agent is responding as the per client preferences.

The role of the agent is to control and manage the client power consumption and therefore the cost in the context of dynamic pricing. The effect of the agent action on the client power consumption as well as on the cost is shown in Fig. 5. From midnight to 7:00 am, i.e. for 7 hours duration, the price is at its lowest point, 1.5 $/kWh.

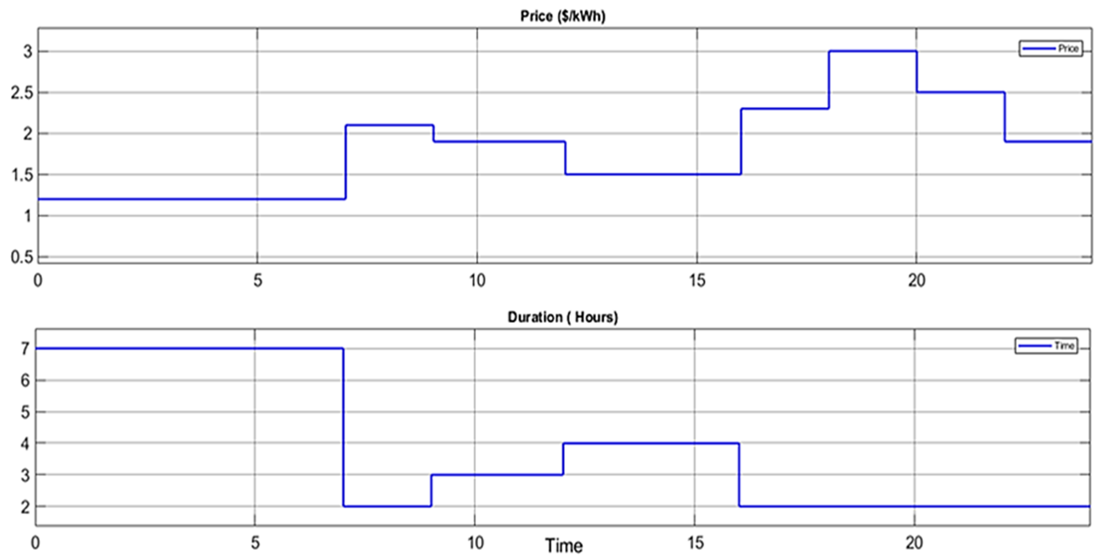

Fig. 3. Prices set and the expected duration

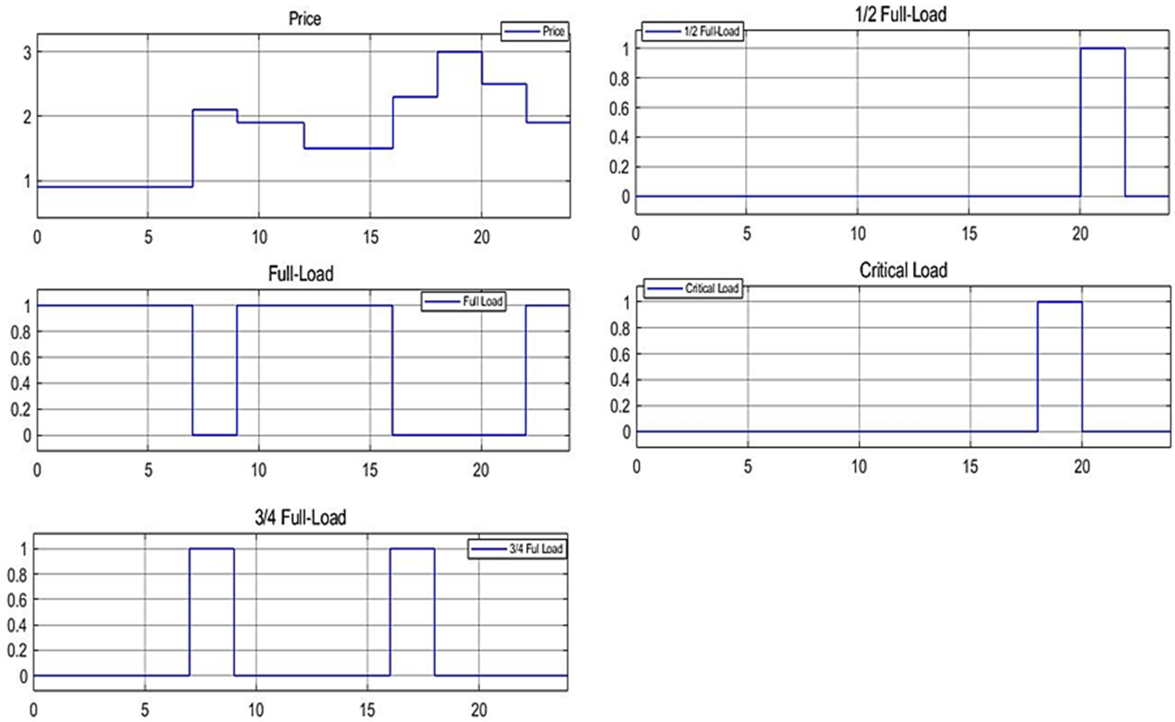

Fig. 4. Agent output logic control signal versus price

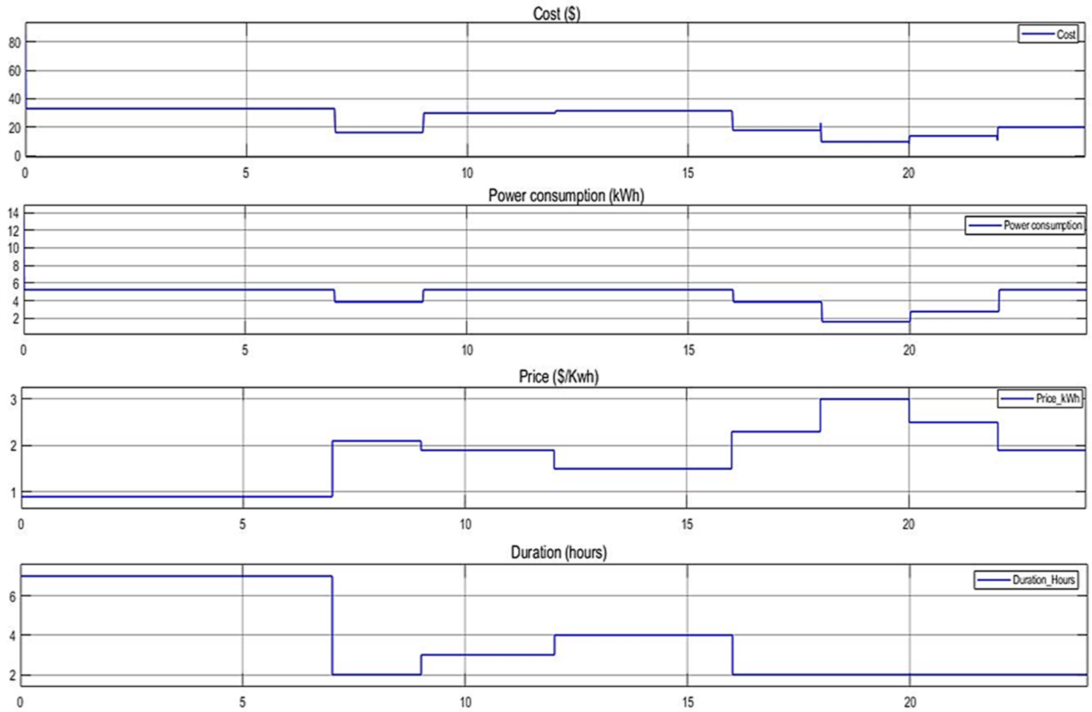

Fig. 5. Agent action effect on client power consumption and energy cost

Thus the agent connects the full load and for that duration, the power consumed is 5.2 kW, and the cost energy for that duration is around 38 $/kWh. For the following period of 2 h, from 7:00 to 9:00, the price hikes up to 2.1 $/kWh. The action of the agent can be observed through the reduction in power consumption as it drops from 5.2 kW, the full load, to 4 kW, which corresponds to the third quarter of the full load. Consequently the cost of energy for that period drops from 38 $/kWh to 16 $/kWh. From 9:00 and for a period of 3 hours, the energy price goes down to 1.9 $/kWh which satisfies the agent criteria to operate the full load.

For that period, the cost of energy goes up to 30 $/kWh which is still in the client preference range.

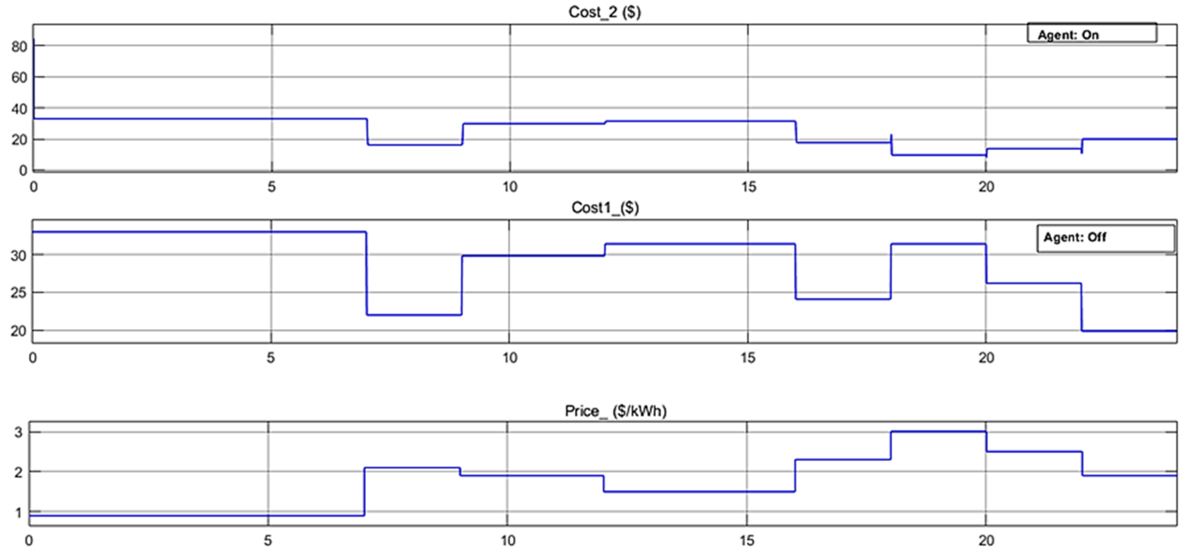

Fig. 6. Client energy cost comparison with and without use the agent

As the price further goes down to 1.5$/kWh from midday to 16:00, the agent keeps the full-load according to the criteria.

The cost is slightly higher compared to the previous one, due to the duration, 4 hours. It can be noted that the cost is calculated as the product of the active price, duration and power consumption. Further analysis of Fig. 5 shows a change in price from 1.5 $/kWh to 2.3 $/kWh, from 16:00 to 18:00. The agent reacts with reference to the client preference as described in Table II, thus reducing the load to its half and consequently the cost to $18. The highest price or the peak occurs from 18:00 to 20:00. During that period, the agent will only operate critical loads. Minimum power consumption and cost, 1.5 kW and $10 respectively, are achieved while maintaining supply for critical loads. From 20:00 to 22:00 the price goes down to 2.5 $/kWh making the agent to supply the half of the load. Thus, there is an increase in power consumption and the cost with 2,5 kW and $9.7 respectively. From 22:00 to midnight, the price goes further down to 1.9 $/kWh which is considered by the agent as affordable price for full-load supply. The cost for that period and for full-load of 5.2 kW is around $ 20. The economic benefit for the client in using the agent is the reduced cost of energy in the context of dynamic pricing. A cost comparison for the same client when using the agent (Agent: On) and when not using the agent (Agent: Off) has been simulated for 24 hours as well. For case of the client not using the agent, the full load is used throughout, that is the load is constant for the 24 hours. In Fig. 6, the results of the cost comparison of both cases are shown. It shows that during the low price period, in either case the cost is the same. This is because in both case full load is applied. On the other hand, the difference in cost rise as the price increases and in the case with agent application, the latter will reduce the load according to the preset preference, thus regulating the consumption and consequently the cost.

Thus from 7:00- 9:00, the energy cost without the agent (cost_2) is $ 22 versus $ 16 when an agent is used for (cost_1), corresponding to 27% higher than cost_1.

From 16:00 to 18:00, cost_2 is $ 24 versus $ 17, 6 for cost_1, an average of 27% difference in cost. During peak hour period 18:00 to 20:00, cost_1 is $ 31.4 while for cost_2 is $ 9.6, thus a 69.4% of difference. As the price goes down from 20:00 to 22:00 the cost_1 is $ 26.1 versus $ 13.72 for cost_2, thus making a cost difference of 47.4%. From 22:00 to midnight as the price drops to the lower value, both the cost_1 and cost_2 equal to $ 20, as full load is connected in case agent application.

V. Conclusion

This paper presents a microgrid client focused agent that automatically negotiates economical options, as well manages client loads in the context of dynamic pricing. The agent decision making is based on the pre-set client preferences on one hand and on the active price and duration as broadcasted by the microgrid operator, on the other hand. The mathematical model and the emanating algorithm are presented. The results of the algorithm simulation performed show the efficacy of the agent in tracking price change and taking action accordingly. The energy efficiency and the economic benefits associated with the use of the agent are also presented through an energy cost comparison. It shows that the use of the proposed agent improves energy efficiency and consequently the cost. The microgrid operator can benefit from the agent, as it can be included in the demand side management. Moreover, the agent contributes to the sustainability of the microgrids through management of the client ability to afford the energy cost. The agent offers the possibility for various functionality to be added including the integration of client owner energy resources, such as energy storage system or generator set and their economic dispatching. Future work will also explore the extension the agent functionality to dynamic evaluation of client preference using real time demand and price.

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