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Investigation of an Optimized Energy Resource Allocation Algorithm for a Community Based Virtual Power Plant

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***Abstract*—Recently, significant advances in renewable energy generation have made it possible to consider consumers as prosumers. However, with increase in embedded generation, storage of electrical energy in batteries, flywheels and supercapacitors has become important so as to better utilize the existing grid by helping smooth the peaks and troughs of renewable electricity generation, and also of demand. This has led to the possibility of controlling the times when stored energy from these storage units is fed back to the grid. In this paper we look at how energy resource sharing is achieved if these storage units are part of a virtual power plant. In a virtual power plant, these storage units become energy resources that need to be optimally scheduled over time so as to benefit both prosumer and the grid supplier. In this paper, a smart energy resources allocation algorithm is presented for a virtual power plants using genetic algorithms. It is also proposed that the cause of battery depreciation be accounted for in the allocation of discharge rates. The algorithm was tested under various pricing scenarios, depreciation cost, as well as constraint. The results are presented and discussed. Conclusions were drawn, and suggestion for further work was made.**

***Keywords*—Prosumers; Battery; Virtual Power Plant (VPP); Genetic Algorithm (GA); Smart Grid.**

I. INTRODUCTION

The driving goals for the use of energy storage in the electricity grid is to promote the usage of renewable energy, improve grid reliability through the provision of peak and off-peak services etc. and also to provide a cost effective means for grid operation [1], [2], [3], [4].

There is an ongoing global restructuring of electric power utilities [5], [6]. This is changing the electric power utilities from its usual vertically integrated form to a form with a much liberalized market [5], [6], [7]. Therefore, opportunities are created in the electric power market for the energy consumer. With these emerging market opportunities, it is envisaged that the consumer role could change to that of a prosumer. The prosumer role involves both energy consumption and energy production. As the consumer role changes to that of a prosumer, energy storage becomes an important part of the prosumer. With energy storage, a prosumer can buy energy from the grid at a lower cost during off-peak period, and then sell the energy back to the grid at high prices during peak period.

In Africa, countries are adopting renewable energy into their energy mix. In some countries such as Nigeria, Liberia, etc. there are large number of standby gasoline or diesel generators that provide electricity when the grid is unable to provide. Battery storage may be a way forward for African countries that are keen to adopt the use of renewable energy. The UK government has made energy storage a key strategy in its aim to move towards decarbonizing its energy supply. Renewables play a key part in this. In this paper we propose an environment in the future in which domestic consumers have batteries embedded in their houses, together with renewables. For such systems, it is essential to know when to utilize the batteries. With differential pricing within the day ahead power market, it is important to control the energy transactions. This paper proposes the use of genetic algorithms to optimize the energy transactions in a local community, where a virtual power plant is based.

Prosumer participation in the power market is done through a third part agent called the virtual power plant (VPP). This is because the energy required by the bulk power system when it purchases energy is large, and cannot be provided by a single prosumer. A VPP is an aggregator and a business entity that aggregates large numbers of small unit of prosumer's energy resource like battery storage, photovoltaics, micro combine heat and power etc. VPP uses the aggregated unit to participate in the power market of the bulk power system on behalf of the prosumer. The financial reward for both the VPP and the prosumer is important, if both entity are to remain participant in the power market. A proper pricing scheme and coordination of the prosumer's energy resource are required to achieve maximum reward for both entities.

The concept of domestic energy consumer using battery energy storage to participate in the power market was proposed by Kempton et al [8]. Work on different energy management strategy for dealing with battery electric vehicle has been done by these authors [9] [10] [11], [12]. These strategies are also applicable to virtual power plants, and could be used by a prosumer who wishes to have his battery embedded in his house.

There are four main power markets in which domestic energy consumer could participate using battery storage. These includes; baseload power market, peak power market, regulation service power market, and spinning reserve. Base load power market requires the provision of energy round the clock to meet grid's minimum energy demand. Peak power market requires the provision of energy to the grid during peak period. Regulation service power market is a frequency control support service required by the grid. Spinning reserve market requires keeping an extra energy capacity for the grid. This extra capacity can be dispatch within 10 minute when there is grid capacity loss.

II. ARCHITECTURE OF VIRTUAL POWER PLANT INVESTIGATED

Fig. 1 is a diagram describing the VPP model developed in this work.

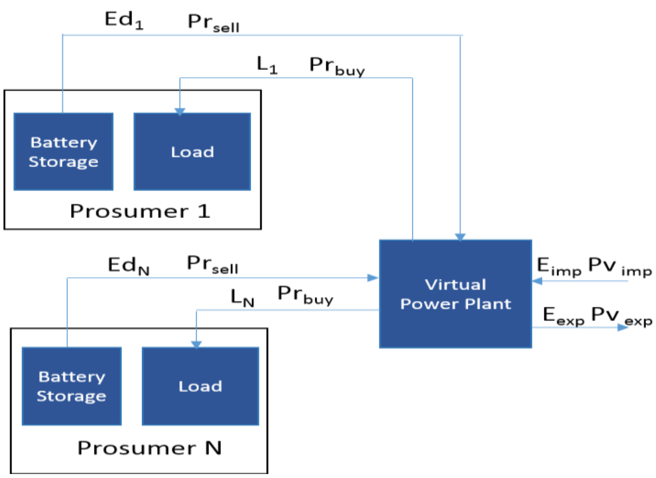

Fig. 1. Framework for the VPP model.

From Fig 1, N is the total number of prosumers within the community aggregated as a VPP. Ed_1 to Ed_N is the discharge energy from prosumer 1 to N battery respectively. Pr_{sell} is the prosumer sell price of energy from battery, or the price at which the VPP buys energy from the prosumer's battery. L_1 to L_N is the load demand of prosumer 1 to N respectively. Pr_{buy} is the price at which the prosumer buy energy from the VPP to meet its load, or the price at which VPP sells energy to the prosumer to meet load demand. E_{imp} and E_{exp} are the amount of energy imported from the grid, and exported to grid by the VPP. Pv_{imp} and Pv_{exp} are the VPP import and export price of energy to the grid respectively.

A. Virtual power plant

In Fig. 1. The VPP can buy energy from the grid (E_{imp}) at price Pv_{imp} and from the prosumers (Ed_1 to Ed_N from prosumer 1 to prosumer N) at price Pr_{sell} respectively. The energy bought from the grid is use to meet the prosumer's energy demand (L_1 to L_N) respectively. The VPP buys power in bulk from the power market to meet its prosumer's load demand, as would be expected. In this model the VPP can combine both energy from the grid and the prosumer's battery to meet the load demand of each prosumer respectively. (L_1 to L_N). The energy bought from each prosumer's battery (Ed_1 to Ed_N from prosumer 1 to prosumer N) are aggregated by the VPP. The aggregated energy is first use within the community to meet each prosumer's load demand respectively before it can be traded in the power market (exported to the external grid) by the VPP on behalf of the prosumers.

This model considered a VPP which has a day ahead forecast of each prosumer hourly load profile respectively, as well as the day ahead agreed prosumer's sell price and buy price of energy. The VPP also has a day ahead forecast of the price at which the external grid would buy energy from the VPP (Pvexp) and sells energy to the VPP (Pv_{imp}). Based on these forecast (assume no error band), the VPP prepare its day ahead schedule of its energy resource by optimally allocating its energy resources so as to maximize profit in the day ahead power market. The energy resource allocation is done by determining the amount of energy that would be discharge from each prosumer's battery. Based on the amount of energy to be discharged from the prosumer battery, the amount of energy to be imported from the external grid to meet the prosumer's load demand, and the amount of energy to be exported to the external grid is then determine. VPP can only export energy after the load demand of the prosumers are first met by the energy discharge from the prosumers battery.

B. Prosumer

A community consisting of three prosumers (N=3) was considered in this model. Each prosumer was considered as having a fully charged battery energy storage embedded inside their home respectively. The battery energy capacity was considered to be the same for all the prosumers. The day ahead hourly load profile of each prosumer is shown in Fig. 2.

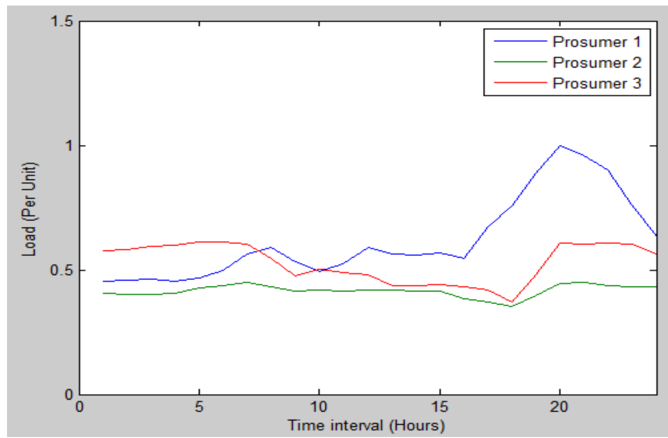

Fig.2 Forecasted hourly load profile of each prosumer.

Fig. 2, is a typical hourly load profile of three different class of domestic energy consumers within residential community in the United State. This data was obtained from Xcel energy [13]. This hourly load profile was assumed to be each prosumer's day ahead hourly load profile in this work. As shown in Fig. 2, each of the prosumers have got a different hourly load profile.

III. MATHEMATICAL FORMULATION

A. VPP Energy Balance

The VPP energy balance during import and export of energy at time interval *t* is represented in (1) & (2) as follows.

$$E_{imp_t} = \sum_{i=1}^{N} \left(L_{i,t} - Ed_{i,t} \right) \tag{1}$$

$$E_{\exp_t} = \sum_{i=1}^{N} \left(Ed_{i,t} - L_{i,t} \right) \tag{2}$$

i is an integer. *N* is the total numbers of prosumers connected to the VPP. E_{imp_t} and E_{exp_t} are the amount of energy imported from the grid by the VPP, and the amount of energy exported to the grid by the VPP respectively during the time interval *t*. $Ed_{i,t}$ and $L_{i,t}$ are the energy discharge from prosumer *i* battery, and the load of prosumer *i* respectively during the time interval *t*.

B. VPP Profit

The VPP profit Vpp_{profit}, at each time interval t over the day's total number of time interval (T) is calculated as follows.

$$\sum_{t=1}^{T} Vpp_{profit_t} = \sum_{t=1}^{T} \left(Vpp_{revenue_t} - Vpp_{cost_t} \right) \qquad (3)$$

Where $Vpp_{revenue_t}$ and Vpp_{cost_t} are the VPP revenue and cost during time interval t respectively. T is the day's total number of time interval. Both VPP revenue and cost are calculated respectively as follows.

$$\sum_{t=1}^{T} Vpp_{revenue_t} = \sum_{i=1}^{N}\sum_{t=1}^{T} \left(\Pr_{buy_t} .L_{i,t} + Pv_{\exp_t} .E_{\exp_t} \right) \qquad (4)$$

$$\sum_{t=1}^{T} Vpp_{cost_t} = \sum_{i=1}^{N}\sum_{t=1}^{T} \left(\Pr_{sell_t} .Ed_{i,t} + Pv_{imp_t} .E_{imp_t} \right) \qquad (5)$$

Where Pr_{sell_t}, Pr_{buy_t}, Pv_{imp_t}, and Pv_{exp_t} are the prosumer selling price of energy to the VPP, prosumer buy price of energy from the VPP, the VPP import price of energy, and the VPP export price of energy respectively during the time interval t.

C. Prosumer Net Cost

The prosumer's net cost $\Pr_{cost}$, at each time interval t over the day's total number of time interval T is calculated as follows.

$$\sum_{t=1}^{T} \Pr_{cost_t} = \sum_{i=1}^{N}\sum_{t=1}^{T} \left(\Pr_{buy_t} .L_{i,t} - \Pr_{sell_t} .Ed_{i,t} \right) \qquad (6)$$

D. Battery Constraints

$$Ed_{\min i} \le Ed_{i,t} \le Ed_{\max i} \qquad (7)$$

$$\sum_{i=1}^{N}\sum_{t=1}^{T} Ed_{i,t} \le E_{batt_i} \qquad (8)$$

Where Ed_{min_i} and Ed_{max_i} are the bound constraint, which are the minimum and maximum energy that can be discharge from prosumer i battery. $Ebatt_i$ is prosumer i initial battery energy level. Since each prosumer was assumed to have a fully charged battery, the initial battery energy level is the same with the battery capacity. From (8), the total energy discharge from each prosumer's battery over T must be less than or equal to their respective initial battery energy level.

IV. IMPLEMENTATION

To understand the optimization problem, the number of households chosen to participate in the VPP was kept at three. The optimization function is the VPP profit which would be expected to be given by (3). However, (3) does not account for the fact that the battery depreciates. Typically, the higher the discharge energy the shorter the life time of the battery. As such depreciation was reflected in the optimizing function in (9) as follows.

$$[Max]F = \sum_{t=1}^{T} Vpp_{profit_t} - Dep * \sum_{t=1}^{T} \left(Ed_{i,t} \right)^2 \qquad (9)$$

F is the VPP profit, and is the objective function to be maximize. Dep is the depreciation cost. The energy discharge (Ed) is squared to give an indication that the battery would degrade much faster when it is subjected to higher discharge. In this work, both $Ed_{\min}$ and $Ed_{\max}$ values were chosen to be 0 and 1 per unit respectively for each and every prosumers. *Ebatt* (initial battery energy level) for each prosumer was chosen to be 18 per unit respectively. Only discharging of battery has been considered in this work. Genetic Algorithm (GA) was used to determine the optimum day ahead energy discharge pattern from the battery given the day ahead pricing regimes and prosumer's load profile to the VPP. To implement GA, an initial population of one thousand chromosome was randomly generated considering battery constraints. These chromosome represents the initial candidate solutions to the optimization problem F. Each chromosome is composed of three genes. Each gene represent the energy discharge variable from each of the three prosumers battery respectively. Each gene is composed of 24 DNA which represents the prosumer's battery energy discharge at each time interval of t (an hour) over the day's total number of time interval T (24 hours). Fitness function (F in equation (9)) was used to calculate the fitness value of each chromosome. Selection, based on fitness value was used to eliminate half of the chromosome population that has the least fitness value. Random crossover points, and random pairs where used to generate a new population. The cycle is then repeated in order to reach an optimum solution.

V. RESULTS & DISCUSSION

Fig. 3 shows the price profile used by the VPP. These values are based on percentages above the import price, which is considered as the lowest price. The values at the two peaks reflect the prices that would be charged to reduce load demand or increase battery discharge. Dep was set at 0.6 pence.

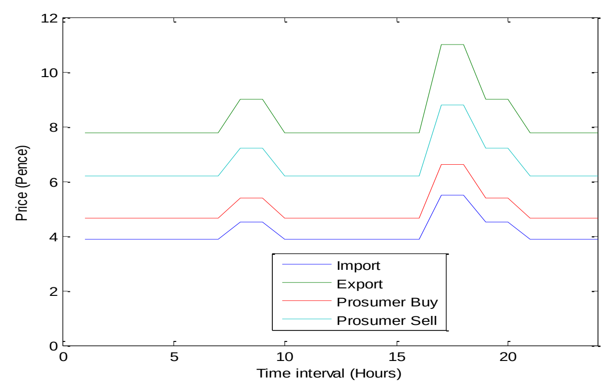

Fig. 3. Price based on percentages, and stepped base value.

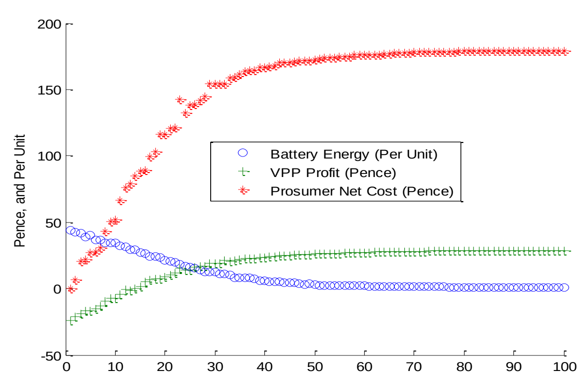

Fig. 4. Effect of Percentage Pricing on Community.

Figure 4, shows how the VPPs profit changes and finally converges as the algorithm optimizes. It can be seen that this is at the cost of the prosumer. Also, as the algorithm optimizes to maximize VPP profit, the battery energy (total energy used from all prosumers battery) changes and finally converges to zero. Further investigation reveals that the price setting is unrealistic. Fig. 5 shows the proposed pricing that would enable the market to work better. This pricing setting is based on the energy need of the grid. This is what is reflected in the peaks and off-peaks period. During off-peak period, the grid is not interested in buying energy from the prosumer. Ideally, the Prosumers should be charging their batteries during off-peak period. The results of the optimization are given in Fig. 6 and Fig. 7. Fig. 6 shows that the cost to the prosumers has actually gone down compared to Fig.4. The VPP profit has also gone up. This profit is at the expense of the prosumer whom is not able to sell energy during peak period as a result of the low price margin between the VPP export price and the prosumer sell price, as well as the high battery depreciation cost. Fig. 7 shows the actual discharge from each prosumers battery. The results are not as one would expect. The batteries are meant to discharge at the peak periods. This would have resulted in supporting the grid as would be expected in peak hours from energy storage. The battery actually discharges at the off-peak hours and avoids the peaks hours completely. This is because of the optimization which favors the VPP. Since the VPP would be paying out to prosumer more than he would be gaining from selling the same to the grid, his decision would be not to purchase energy from the prosumer.

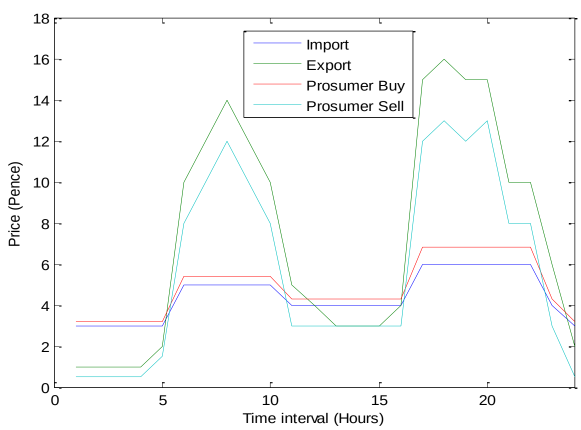

Fig.5. Proposed pricing.

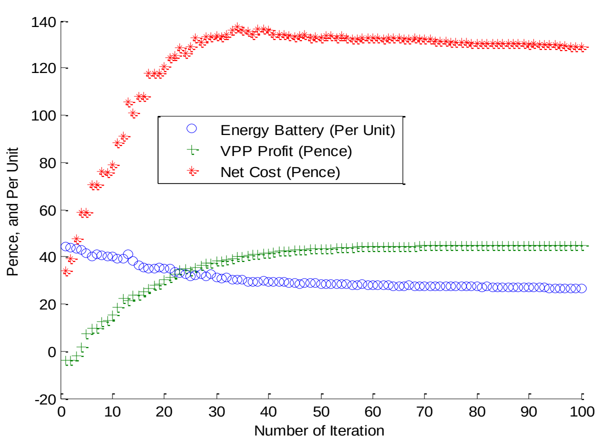

Fig.6. Effect of Proposed Pricing on Community.

The effect of the depreciation cost is tested by changing *Dep* to 0.06 pence. This allows the battery to discharge at higher currents. Fig.8 shows the new discharging levels. It is noticeable that they are higher than that of Fig. 7. In Fig. 9 we also notice that both the VPP profit and the prosumer's net cost improved slightly because of the higher discharge. However, the peak times are still low. In order to make sure that the storage is used at peak time, the margin between the import and export price is modified during the peak as shown in Fig. 10. A key change is noticed in the prosumer discharging profile in Fig. 12, where discharging occurs during peak periods. From Fig. 11, the net cost to prosumers is also significantly lowering as the VPP seeks to purchase much energy from the battery storage.

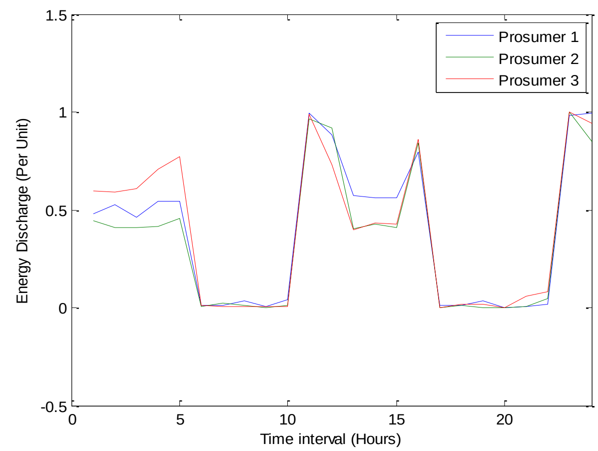

Fig.7. Prosumer battery discharge at *Dep* = 0.6 pence.

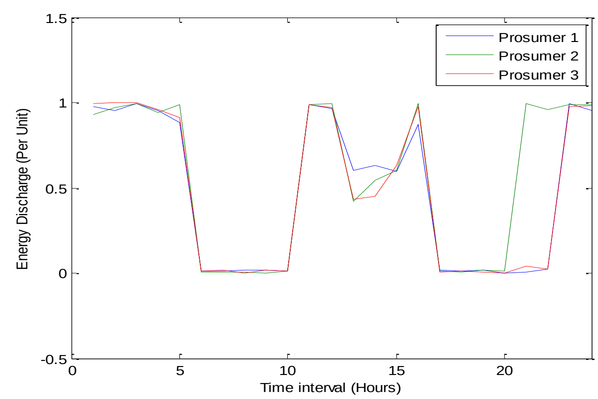

Fig.8. Prosumer battery discharge at *Dep* = 0.06 pence.

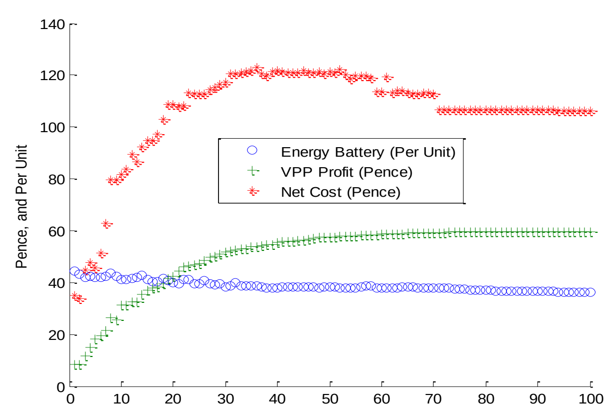

Fig.9. Effect of depreciation lowering on Community.

The above experiments show that pricing is very important. Any algorithm will optimize but may not meet the objectives of introducing the VPP technology. Furthermore, for storage it is important to account for the actual discharge and its effect on the life-time of the battery. Economic models will attach a price based on life time. This may not be suitable for real-time optimization of energy resources.

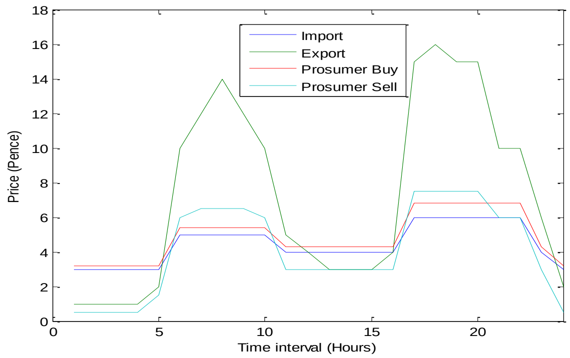

Fig.10. Modified pricing scheme.

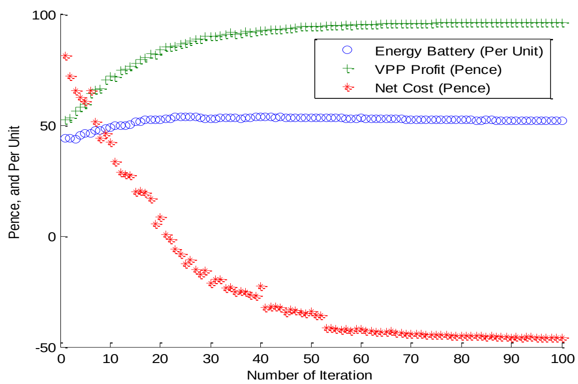

Fig.11. Effect of modified pricing scheme on Community.

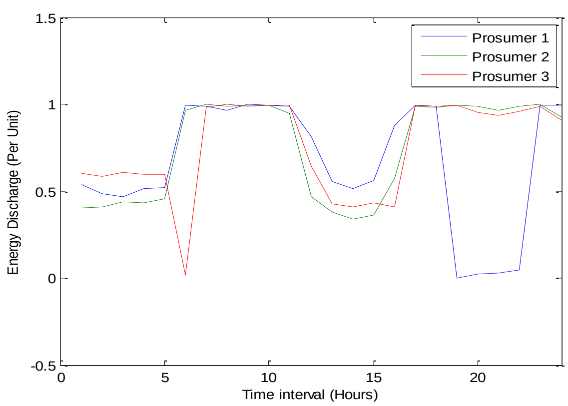

Fig.12. Effect of modified pricing scheme on discharge.

Further work on this project will investigate types of communities with representative energy patterns based on national demographics. It is envisaged that VPP could be used for large African cities. However, tariff schemes need to be carefully addressed.

VI. CONCLUSIONS

In this paper, it has been demonstrated that it is possible to have a virtual power plant that is involved in embedded energy storage at the residential level. It has been shown that pricing plays a key role. However, whilst daily optimization may be possible to seek daily optimum, it is essential to include an element of the degradation effect as a result of high discharge rates from the prosumer batteries. This factor should be accounted for in any optimization. In this paper GA algorithm has been used to optimize a local community. It is feasible that adjustment of the loads is possible if scheduling is also used.

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REFERENCES

[1] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, and Y. Ding, "Progress in electrical energy storage system: A critical review," *Progress in Natural Science*, vol. 19, no. 3, pp. 291-312, 2009.

[2] H. L. Ferreira, R. Garde, G. Fulli, W. Kling, and J. P. Lopes, "Characterisation of electrical energy storage technologies," *Energy*, vol. 53, no. pp. 288-298, 2013.

[3] V. A. Boicea, "Energy Storage Technologies: The Past and the Present," *Proceedings of the IEEE*, vol. 102, no. 11, pp. 1777-1794, 2014.

[4] IEA, "Technology roadmap: energy storage," Paris 2014.

[5] X. Vallvé, A. Graillot, S. Gual, and H. Colin, "Micro storage and demand side management in distributed PV grid-connected installations," in *Electrical Power Quality and Utilisation, 2007. EPQU 2007. 9th International Conference on*, 2007, pp. 1-6.

[6] A. Ihbal, H. Rajamani, R. Abd-Alhameed, M. Jalboub, A. Elmeshregi, and M. Aljaddal, "Development of Electricity Pricing Criteria at Residential Community Level," *Universal Journal of Electrical and Electronic Engineering*, vol. 2, no. 2, pp. 81-89, 2014.

[7] E. Veldman, M. Gibescu, J. Slootweg, and W. Kling, "Technical benefits of distributed storage and load management in distribution grids," in *PowerTech, 2009 IEEE Bucharest*, 2009, pp. 1-8.

[8] W. Kempton and S. E. Letendre, "Electric vehicles as a new power source for electric utilities," *Transportation Research Part D: Transport and Environment*, vol. 2, no. 3, pp. 157-175, 1997.

[9] D. Wu, D. C. Aliprantis, and L. Ying, "Load scheduling and dispatch for aggregators of plug-in electric vehicles," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 368-376, 2012.

[10] C. Pang, V. Aravinthan, and X. Wang, "Electric vehicles as configurable distributed energy storage in the smart grid," in *Power Systems Conference (PSC), 2014 Clemson University*, 2014, pp. 1-5.

[11] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl, "Demand dispatch," *Power and Energy Magazine, IEEE*, vol. 8, no. 3, pp. 20-29, 2010.

[12] R. J. Bessa and M. A. Matos, "Forecasting issues for managing a portfolio of electric vehicles under a smart grid paradigm," in *Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on*, 2012, pp. 1-8.

[13] Xcel Energy, “Hourly Load Profile” 2012. https://www.xcelenergy.com/staticfiles/xe/Corporate/Corporate%20PDFs/AppendixD-Hourly_Load_Profiles.pdf