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Intelligent Scheduling of Hybrid and Electric Vehicle Storage Capacity in a Parking Lot for Profit Maximization in Grid Power Transactions

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Abstract *– This paper proposes an intelligent method for scheduling usage of available energy storage capacity from plug-in hybrid electric vehicles (PHEV) and electric vehicles (EV). The batteries on these vehicles can either provide power to the grid when parked, known as vehicle- to-grid (V2G) concept or take power from the grid to charge the batteries on the vehicles. A scalable parking lot model is developed with different parameters assigned to fleets of vehicles. The size of the parking lot is assumed to be large enough to accommodate the number of vehicles performing grid transactions. In order to figure out the appropriate charge and discharge times throughout the day, binary particle swarm optimization is applied. Price curves from the California ISO database are used in this study to have realistic price fluctuations. Finding optimal solutions that maximize profits to vehicle owners while satisfying system and vehicle owners' constraints is the objective of this study. Different fleets of vehicles are used to approximate varying customer base and demonstrate the scalability of parking lots for V2G. The results are compared for consistency and scalability. Discussions on how this technique can be applied to other grid issues such as peaking power are included at the end.*

I. INTRODUCTION

Upcoming deployment of plug-in hybrid electric vehicles (PHEVs) and fully electric vehicles (EVs) can integrate a huge amount of electrical storage into the electric utility grid. Current plans only allow for this storage to extract power from the grid through charging. With relatively small modifications in design of these vehicles, power could also be transferred into the grid from their batteries. Since PHEVs and EVs already have the necessary electronics to drive their electric motors, programming and wiring adjustments can be made to turn their power electronics into inverters suitable for grid interactions [1-2]. Alternatively, kits can be used to retrofit existing vehicles [3].

As the price of batteries decrease and the amount of personal distributed generation increases, consumers are likely to be interested in either selling power obtained from i) nightly charging at cheap prices or ii) their own generation such as photovoltaic (PV) or small wind turbines. Storage is especially beneficial for wind power, since its power generation fluctuates greatly throughout a given day [4-5]. If variable electric pricing is implemented, homes that produce extra wind power at night might want to store that power in their vehicles to either drive with or sell during peak pricing. Since these vehicles are likely to be parked in some type of parking lot during the day, a parking lot capable of selling this excess power would be needed.

In large parking lots with hundreds of vehicles, selling power in bulk could allow the parking lot operator to enter the peak power market where the best prices are available. The goal for the operator would then be to maximize profits by selling the excess power in these vehicles at the times when the market power price is highest. Due to the frequent turnover of vehicles in a parking lot, scheduling issues arise that make it difficult to determine the appropriate time for a given vehicle to buy or sell power. The optimal time to charge and discharge must be determined combined within the parking lot and vehicle owner's limitations and thus calls for an intelligent optimization algorithm capable of handling nonlinear and discontinuous variables.

Particle swarm optimization (PSO) is an iterative stochastic optimization algorithm based on the movement patters of flocks of birds or schools of fish [6-7]. The algorithm is able to search a multi-dimensional solution space by collectively searching with different particles and communicating the best solutions found to the other particles. This communication allows for an intelligent decision to be made on where each particle should move at each iteration to find the best possible solution. Random variations and weighting factors are also used in the algorithm to prevent early convergence where a local minimum is present. Binary particle swarm optimization (BPSO) applies the same stochastic search methodology as PSO except that it handles problems with discrete variables instead of the continuous variables [8-9].

In this paper, BPSO is applied to intelligently schedule whether each vehicle should buy, sell, or hold at every time step that it is in a parking lot. The typical results presented demonstrate the effectiveness of the BPSO algorithm to schedule optimal buying and selling times for a fleet of vehicles. Vehicle sets of 50, 500, and 5000, initialized within some given parameters, are tested and show the scalability of parking lots for V2G integration. The results are compared with buying or selling power only at the best corresponding price. The BPSO algorithm accurately finds near optimal solutions and significantly increases the potential profits for the vehicle owners.

II. SYSTEM DESIGN

The parking lot system is a scalable set of vehicles each with its own system parameters within the ranges defined in Table 1. Each parameter is determined by a uniformly distributed random number in each variable range. A given day is split up into hourly intervals to coincide with the hourly prices taken from the California Independent System Operators (CAISO) website [10]. The losses from charging and discharging limit the ability of a vehicle to charge when prices are low and sell when prices are high. Therefore only a certain number of power cycles are economical.

In this study, it is assumed that each parking lot and the vehicles have an infinitely large connection to the grid to avoid possible current limitations. This assumption allows for observation of the maximum possible grid transactions. While transactions between two vehicles are possible, it is unlikely that circumstance would arise. Since power transactions are driven by price thresholds it would be costly to buy at the same time when it is economical for another vehicle to be selling. This situation can occur however if a vehicle is present for a very short period of time and needs to charge. With all vehicles being on the same bus, selling amongst vehicles simply results in a smaller grid power transfers. A typical parking lot setup is shown in Figure 1.

At each vehicle's departure time the battery state of charge (SoC) is expected to be at a certain desirable level. For the studies in this paper, every vehicle is assumed to have the same desired departure SoC of 60%. As an added limitation, once a vehicle reaches this desired departure SoC it can never be discharged below this level. This limitation or a similar discharge restriction would likely be implemented in a real system to account for situations where a vehicle unexpectedly leaves before its expected departure time. While PHEVs can make up for a lower SoC by using their alternative fuel sources, EVs cannot. Vehicle owners should be able to determine their minimum SoC in a real implementation, but this scenario is not considered in this study.

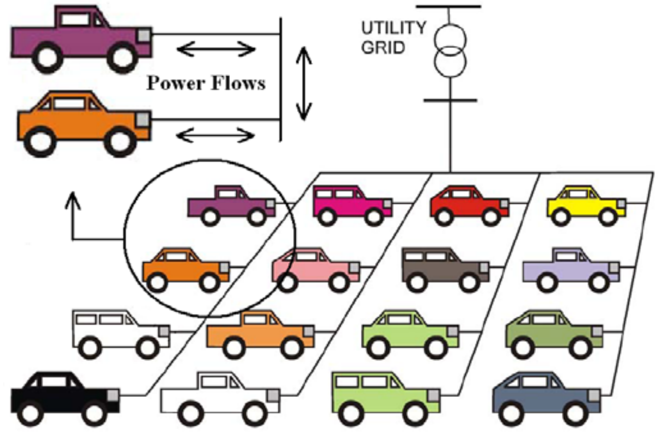

Fig. 1. – Example of a parking lot diagram

Table 1 – Vehicle Parameters

Parameter	Minimum	Maximum
Battery Capacity (kWh)	10	25
Available Capacity (%)	50	100
Arrive Time	1st hour	23rd hour
Departure Time	2nd hour	24th hour
Inverter Discharge Eff. (%)	80	95
Battery Charge Eff. (%)	80	95

III. PARTICLE SWARM OPTIMIZATION

PSO is an optimization algorithm suitable for finding potential solutions for multidimensional problems using real valued variables. The solution search is performed in a stochastic nature allowing the algorithm to overcome nonlinear, non-differentiable, and discontinuous problems. A set or population of potential solutions is known as a swarm. These potential solutions are referred to as particles and each one searches for the solution with a degree of independence from every other. In each iteration, the particles use their previous best solution as well as the swarm's best solution. In this way, the particles are guided collectively toward better and better solutions.

BPSO is a binary version of PSO where position updates correspond to bit changes. The difference between the versions is in how the positions are updated. The velocity is first calculated using (1), but a new normalized velocity term is also calculated by applying the sigmoid equation to the velocity as shown in (2). This new velocity term is constrained in the range [0-1]. The new position is then determined by (3) using the new velocity found from (2). The positions of the particles in BPSO can represent any of the three possible statuses of the vehicles. These statuses are namely – vehicle selling power, vehicle buying power and vehicle not buying nor selling. Two bits are used to define the three statuses of the vehicles that have been defined. The binary search is performed as described below.

1. Initialize a population of particles, each representing a possible solution, by assigning random solutions within the given solution space to the problem's variables.
2. Evaluate fitness function assigned to the problem. In this application equation (7) is used with better solutions having a higher result when the fitness function is evaluated.
3. For each particle, compare the fitness at the current iteration with the particle's best previous fitness. The best previous solution for a particle is known as its personal best or P_{best} solution.
4. Select the best solution of all the P_{best} solutions to be the global best or G_{best} solution.
5. Update of every particle velocity using (1) and (2), and position using (3).
6. Repeat steps 2-5 until a global solution is found within a predefined number of iterations. In this study the number of iterations is 100.

$$v_{ij}(k) = w * v_{ij}(k-1) + c_1 * rand_1 * (P_{best}(k) - X_{ij}(k-1)) \\ + c_2 * rand_2 * (G_{best}(k) - X_{ij}(k-1)) \quad (1)$$

Where,

X_{ij} = particle position
w = inertia weight
c_1 = cognitive acceleration constant
c_2 = social acceleration constant
i = particle number
j = dimension
k = iteration

$$v'_{ij}(k) = sig(v_{ij}(k)) = \frac{1}{1+e^{-v_{ij}(k)}} \quad (2)$$

$$X_{ij}(k) = \begin{cases} 1 & if \quad rand < v'_{ij}(k) \\ 0 & otherwise \end{cases} \quad (3)$$

IV. CASE STUDIES

In this paper, the two following case studies show different methods for determining how a vehicle should buy and sell power throughout a given day. The decisions are based upon the market prices given by CAISO for different days. The day selected for the majority of the study was arbitrarily determined and is August 07, 2008. The other two dates chosen for use as a comparison of different price curves are December 07, 2007 and April 07, 2008. By spreading out the dates, different seasonal conditions are considered and examined. Figure 2 shows the hourly average clearing price for August 07, 2008 and Table 2 lists the prices for all three days mentioned above. The prices are read from the graphs and therefore are estimated prices. For the purposes of these studies they are accurate enough to generalize how the scheduling would be performed on the given days.

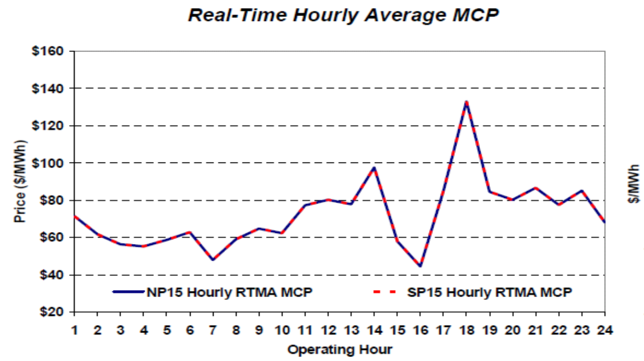

Fig. 2. – Price curve from CAISO [10] on 08/07/2008

Table 2 – Market Clearing Price Each Day in $/kWH

Hour	Dec. 07, 2007	Apr. 07, 2008	Aug. 07, 2008
1	$ 0.052	$ 0.071	$ 0.071
2	$ 0.051	$ 0.060	$ 0.060
3	$ 0.046	$ 0.058	$ 0.056
4	$ 0.055	$ 0.042	$ 0.056
5	$ 0.069	$ 0.059	$ 0.059
6	$ 0.060	$ 0.056	$ 0.061
7	$ 0.094	$ 0.075	$ 0.045
8	$ 0.066	$ 0.099	$ 0.060
9	$ 0.062	$ 0.084	$ 0.066
10	$ 0.058	$ 0.089	$ 0.062
11	$ 0.067	$ 0.095	$ 0.076
12	$ 0.060	$ 0.096	$ 0.080
13	$ 0.061	$ 0.095	$ 0.078
14	$ 0.071	$ 0.094	$ 0.098
15	$ 0.044	$ 0.090	$ 0.049
16	$ 0.044	$ 0.100	$ 0.043
17	$ 0.040	$ 0.109	$ 0.076
18	$ 0.107	$ 0.078	$ 0.134
19	$ 0.063	$ 0.068	$ 0.082
20	$ 0.061	$ 0.211	$ 0.080
21	$ 0.072	$ 0.282	$ 0.085
22	$ 0.072	$ 0.161	$ 0.079
23	$ 0.105	$ 0.105	$ 0.086
24	$ 0.073	$ 0.157	$ 0.070

A. *Case Study 1 – Sell at Maximum Price or Purchase at Minimum Price*

This first case study takes the price curve and finds the best (maximum) selling price for each vehicle over the desired departure SoC of 60% and the best (minimum) buying price for each vehicle under the desired departure SoC. With this strategy, a single transaction occurs for each vehicle in a given day. This limitation results in lower profit potential but the schedule is very easy to determine.

Since each vehicle has a defined charging and discharging efficiency, an extra factor is needed in the profit and cost equations. The cost and revenue resulting from the transactions at each vehicle's optimal hour of buying or selling are found using (4) and (5). Table 3 shows the results for this case study and is compared to those of case study 2.

$$C = \frac{P(k) * (SoC * kWH_{Max} - kWH_{Available})}{Eff_{Charge}} \quad (4)$$

$$R = P(k) * (kWH_{Available} - SoC * kWH_{Max}) * Eff_{Discharge} \quad (5)$$

Where,

C = the resulting cost of charging that vehicle
R = the revenue made by selling from that vehicle
$P(k)$ = the price at instant k
k = the optimal buy/sell time instant
$kWH_{Available}$ = Kilowatt*Hrs in the battery
kWH_{Max} = maximum battery capacity
SoC = desired departure battery state of charge
Eff_{Charge} = charging efficiency
$Eff_{Discharge}$ = inverter efficiency

B. *Case Study 2 – Multiple Purchases and Sells*

This second case study allows for multiple transactions to occur for each vehicle throughout the day. Multiple transactions allow for higher profits but greatly increase the scheduling difficulty. Higher profits are achieved by buying power when the price is low then selling it at a higher price later in the day. BPSO is used to find the solution for each vehicle individually. Since there are no common constraints between vehicles in this study, it is much easier to schedule buy and sell times on a per vehicle basis. Two bits are used to represent buy, sell, and hold. Specifically, buying is represented by '11', selling by '00', and hold by '10' or '01.' Since priority should not be given to either buying or selling, holding is allowed to be represented by the extra state. There are 24 sets of these bits, one for each hour, but not each set is used for a given vehicle. The arrival and departure times define the time window that transactions are allowed. Therefore the buying and selling information outside of the determined time window is disregarded.

The BPSO algorithm evaluates the fitness of each particle in a very similar manner as the first case study. Instead of finding the best time to buy or sell, the algorithm finds the best combination of times to buy and then sell later. With buying, selling, and holding at each time step defined for each particle, (4) and (5) are used again except at more than once if possible. Also after every transaction the available kWh ($kWH_{Available}$) of each vehicle is updated according to (6) to keep track of the batteries' SoC. Since the schedules of each vehicle are independent of each other, the BPSO algorithm only needs to find the appropriate schedule for one vehicle at a time. This separation of the problem greatly reduces the dimensionality of the problem and allows the parking lot operator to quickly find a good schedule.

$$kWH_{Available} = \begin{cases} kWH_{Max} & if\,(A) \\ SoC * kWH_{Max} & if\,(B \,\|\, C) \end{cases} \quad (6)$$

Where,

A = buying more than once
B = selling
C = buying only once

$$Fitness_i = \sum_{j=1}^{Hours} (R_{ij} - C_{ij}) \quad (7)$$

Where,

$Fitness_i$ = the fitness for a given vehicle, i
C_{ij} = (4) for different vehicles and times
R_{ij} = (5) for different vehicles and times

V. RESULTS

The results section is divided into three sections with each section comparing case studies 1 and 2. The first section shows the scalability of the parking lot system by showing the scheduled magnitude of power transactions, monetary transactions, and number of vehicles involved in the V2G transactions per hour. The second section focuses on how a different price curves affect the V2G transactions results. The same 500 vehicle parking lot is used with the three different price curves form Table 2. The last section shows the consistency of results for a given parking lot with 10 different vehicle settings and then for 10 different parking lots.

A. *Results Comparing Parking Lots of 50, 500, and 5000 Vehicles*

The results shown in Table 3 indicate that case study 2 not only significantly increases the profits of a given parking lot but also significantly decreases the net power out to the grid. The reason for the smaller net power is the efficiency drops. Every time a vehicle buys power from the grid and sells later there are two efficiency drops, one for the charger and one for the inverter. Given that the only goal of these case studies is profit maximization the results are still very good. Figures 3 to 8 show a clear pattern in the grid power transactions. All three cases look very similar except scaled up from 50 to 500 to 5000.

Table 3 – Results of the Three Different Sized Sets of Vehicles on August 07, 2008

# of Vehicles	Case Study	Power into Lot (MWh)	Power out of Lot (MWh)	Net Power Out (MW)	Profit
50	CS1	0.0089	0.1131	0.1042	$11.41
	CS2	0.3492	0.3421	-0.0072	$19.09
500	CS1	0.0984	1.2533	1.1549	$128.42
	CS2	3.5167	3.8271	0.3104	$234.22
5000	CS1	1.0359	12.1769	11.1401	$1223.49
	CS2	31.9632	35.2408	3.2777	$2200.40

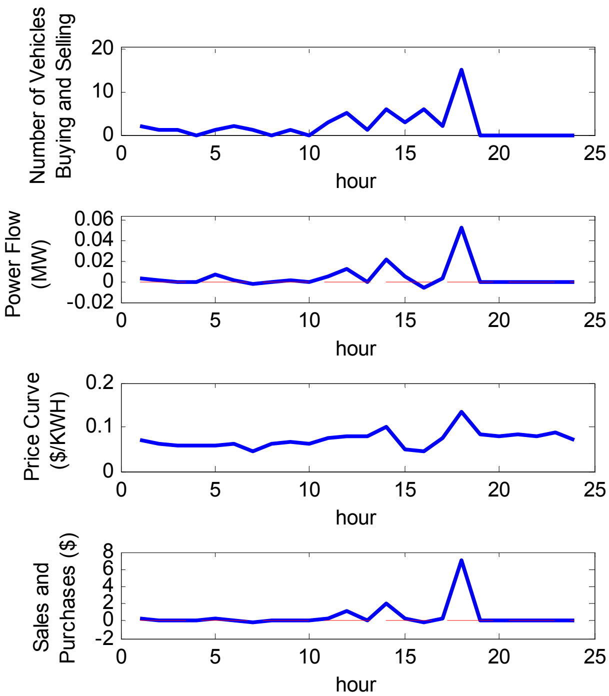

Fig. 3. CS1 - 50 Vehicle Set on Aug. 07, 2008

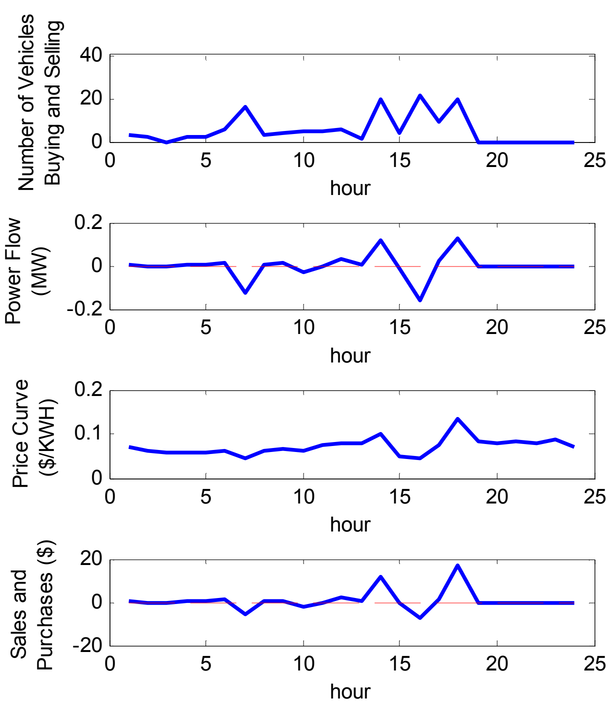

Fig. 4. CS2 - 50 Vehicle Set on Aug. 07, 2008

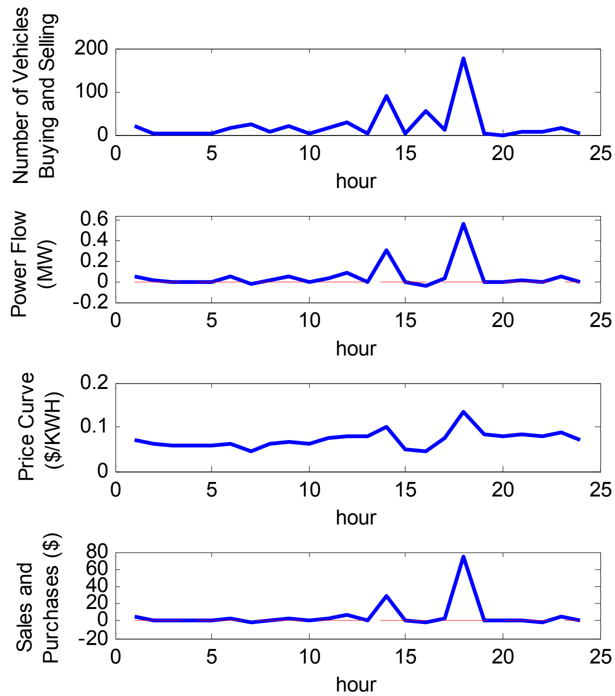

Fig. 5. CS1 - 500 Vehicle Set on Aug. 07, 2008

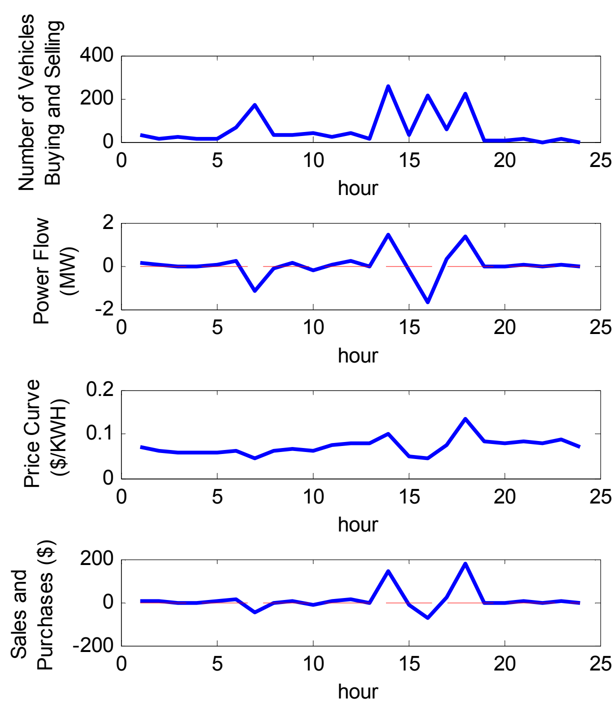

Fig. 6. CS2 - 500 Vehicle Set on Aug. 07, 2008

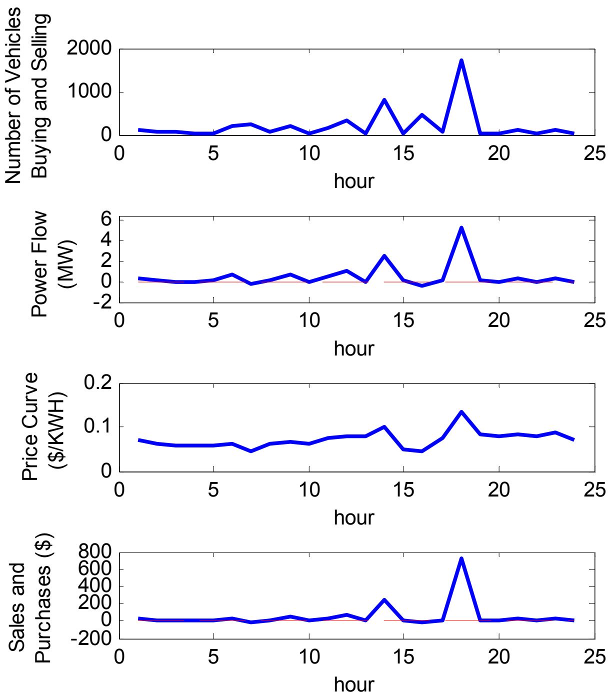

Fig. 7. CS1 - 5000 Vehicle Set on Aug. 07, 2008

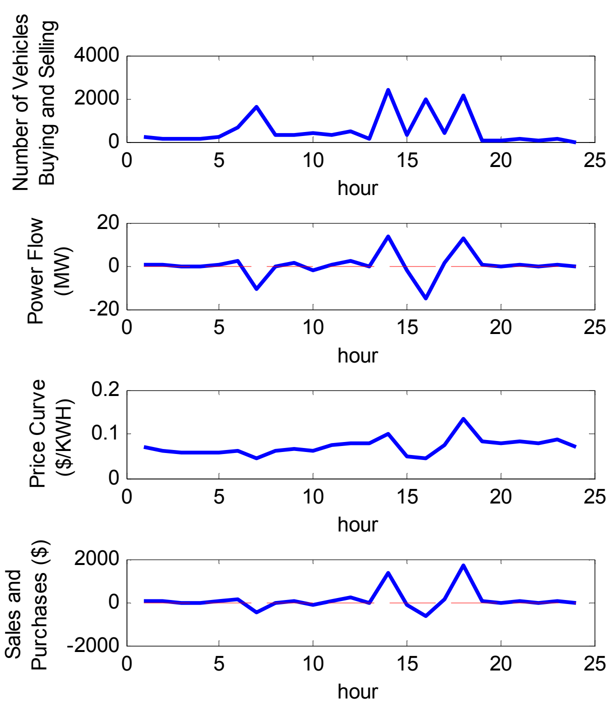

Fig. 8. CS2 - 5000 Vehicle Set on Aug. 07, 2008

B. Three Different Price Curves on the Same 500 Vehicle Set

When comparing the results for the three different price curves in Figure 9, it is evident that prices can very greatly at different times of the year as well as within one day. Every day sees a large increase in profit when using the intelligent algorithm to find the appropriate buy and sell times. As expected the net power for CS1 is exactly the same on each day. Table 4 shows that the same amount of power is used to charge and discharge the vehicles since the vehicle parameters are identical. The differences in power in and out of the lot for CS1 are attributed to overlap where buying and selling is done internal to the parking lot. For this vehicle set there is 1.2533 MW of power available to sell and 0.0984 MW of power needing to be purchased resulting in the net power output to the grid equaling 1.1549 MW.

Table 4 – Results Comparing 3 Price Curves

Date	Case Study	Power into Lot (MWh)	Power out of Lot (MWh)	Net Power Out (MW)	Profit
12/07/07	CS1	0.0863	1.2412	1.1549	$112.45
	CS2	3.1902	3.6094	0.4191	$190.74
04/07/08	CS1	0.0830	1.2379	1.1549	$190.65
	CS2	2.8958	3.3845	0.4886	$334.51
08/07/08	CS1	0.0984	1.2533	1.1549	$128.42
	CS2	3.5167	3.8271	0.3104	$234.22

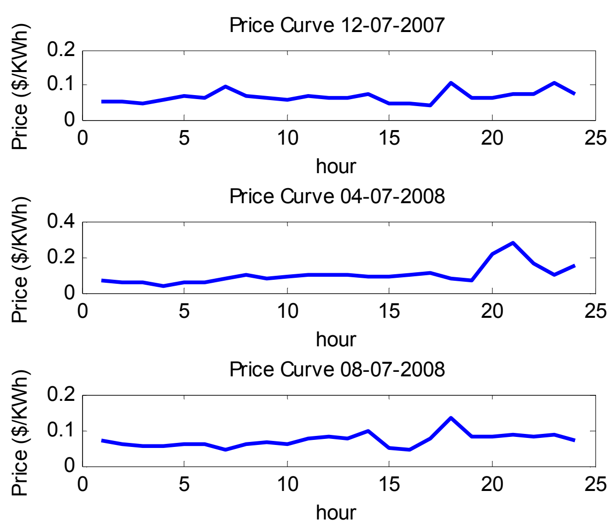

Fig. 9. – Daily Price Curves for the 3 Test Days

C. Consistency of Solutions

The results of running the BPSO algorithm on the same 500 vehicle set 10 times are shown in Table 5. Since the BPSO algorithm is stochastic and the maximum number of internal BPSO iterations is limited to 100, the same solution is not found each time. With a standard deviation of less than \$1.00 or 0.045% of the average, the solutions in each case were very close to each other. Implementation of an improved BPSO algorithm or an increase in the number of internal BPSO iterations would increase the consistency and accuracy, but the results are still very good.

The study of 10 different vehicle sets with the same price curve as in Table 6 shows that as the number of vehicles in each set increases, the differences between vehicles begin to average out. With 10 different randomly initialized vehicle sets defined within the constraints of Table 1, the standard deviation in profit is only \$22.22 or 0.01% of the average. This conclusion suggests that with an accurate market price curve and estimate of the number of incoming vehicles, the profit made in a given day can be predicted with a small margin of error. Data over the course of a parking lot's lifetime can aid the operator in determining average vehicle parameters. Tables 7 and 8 show the best schedules found by the BPSO algorithm on August 07, 2008 for the 50 vehicle parking lot.

Table 5 – Results Over 10 Trials, Same 500 Vehicles on August 07, 2008

Run	Power into Lot (MWh)	Power out of Lot (MWh)	Net Power Out (MW)	Profit
1	31.9632	35.2408	3.2777	\$2200.44
2	31.9970	35.2534	3.2564	\$2203.67
3	32.0993	35.3389	3.2395	\$2201.88
4	31.9690	35.1875	3.2185	\$2200.59
5	32.1034	35.3485	3.2450	\$2200.27
6	31.9942	35.2482	3.2540	\$2200.37
7	32.0954	35.3311	3.2358	\$2201.96
8	32.1325	35.3531	3.2205	\$2201.10
9	32.0281	35.2952	3.2672	\$2201.59
10	32.1526	35.3788	3.2262	\$2201.04
Avg	32.05±0.067	35.30±0.059	3.24±0.019	\$2201.29±0.99

Table 6 – Results for 10 Different Sets of 500 Vehicles on August 07, 2008

Run	Power into Lot (MWh)	Power out of Lot (MWh)	Net Power Out (MW)	Profit
1	32.0520	35.3283	3.2763	\$2221.74
2	32.6428	35.8169	3.1741	\$2220.27
3	32.3628	35.5204	3.1576	\$2228.07
4	32.0382	35.2211	3.1829	\$2207.05
5	32.0490	35.5350	3.4860	\$2207.83
6	31.6423	34.8533	3.2110	\$2180.61
7	31.5704	35.3345	3.7641	\$2219.38
8	31.3600	34.8054	3.4454	\$2174.77
9	31.9023	35.2629	3.3606	\$2194.69
10	32.4391	35.9618	3.5227	\$2253.98
Avg	32.01±0.384	35.36±0.350	3.36±0.187	\$2210.84±22.22

VI. CONCLUSIONS

The proposed intelligent BPSO algorithm based approach to determining buying and selling times throughout a day successfully found very profitable solutions. In every test, comparing case studies 1 and 2, the results proved that multiple power transactions in a day resulted in much higher profits. The results also show that if profit is the only goal of the hybrid parking lot then the net power into the grid is greatly reduced. If a different fitness functions is defined such as replacing the price curves with power demand curves to offset peak power, different grid issues can be solved.

Table 7 –Parking Lot Owner's Schedule for the 50 Vehicle Set on August 07, 2008

Hour	Buying Vehicle ID	Purchases	Selling Vehicle ID	Sale
1	-	0	7, 10, 47	3
2	8	1	39	1
3	25	1	-	0
4	1	1	8	1
5	14	1	22	1
6	34	1	1, 6, 9, 25, 49	5
7	1, 6, 8, 9, 10, 21, 23, 24, 27, 30, 33, 36, 41, 45, 47, 48, 49	17	-	0
8	40	1	9, 47	2
9	15, 31	2	43, 49	2
10	12, 17, 37, 43, 44	5		0
11	26, 46	2	21, 23, 28	3
12	-	0	10, 16, 24, 27, 30, 41	6
13	-	0	45	1
14	-	0	1, 6, 8, 11, 12, 14, 15, 17, 26, 29, 31, 33, 34, 36, 37, 40, 43, 44, 46, 48	20
15	12, 33	2	2, 32	2
16	1, 4, 5, 8, 14, 15, 17, 19, 20, 29, 31, 34, 36, 37, 38, 40, 41, 43, 45, 46, 50	21	-	0
17	13, 35, 42	3	1, 4, 5, 37, 38, 46	6
18	-	0	8, 12, 13, 14, 15, 17, 19, 20, 29, 31, 33, 34, 35, 36, 40, 41, 42, 43, 45, 50	20
19	-	0	-	0
20	-	0	-	0
21	-	0	-	0
22	-	0	-	0
23	-	0	-	0
24	-	0	-	0

VII. FUTURE WORK

Now that a preliminary parking lot power transaction scheduling technique has been explored different additional problems can be included. The next step is to implement a vehicle set with proportional buying and selling to account for system and vehicle current limits as well as setting unique thresholds for charging and discharging each vehicle. In a real implementation these limitations are present and affect the overall scheduling of the parking lot. Once these steps are complete it is possible to expand further and consider other markets such as regulation, spinning reserves, and peak power offsetting which add another dimension of complexity to the scheduling algorithm with multiple sources of income and new time limitations on when each activity can be performed.

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[10] CAISO, California Independent System Operator, Daily Market Watch, www.caiso.com.

Table 8 – Sample Vehicle Owner’s Schedules from Same Vehicle Set as Table 7 on August 07, 2008

Vehicle ID	Buying Hours	Selling Hours
1	4, 7, 16	6, 14, 17
2	-	15
3	13	-
4	16	17
5	16	17
6	7	6, 14
7	-	1
8	2, 7, 16	4, 14, 18
9	7	68
10	7	1, 12
11	-	14
12	10, 15	14, 18
13	17	18
14	5, 16	14, 18
15	9, 16	14, 18
16	-	12
17	10, 16	14, 18
18	3	-
19	16	18
20	16	18
21	-	11
22	-	5
23	7	11
24	7	12
25	-	6
26	11	14
27	7	12
28	-	11
29	16	14, 18
30	7	12
31	9, 16	14, 18
32	-	15
33	7, 15	14, 18
34	6, 16	14, 18
35	17	18
36	7, 16	14, 18
37	10, 16	14, 17
38	16	17
39	-	2
40	8, 16	14, 18
41	7, 16	12, 18
42	17	18
43	10, 16	9, 14, 18
44	10	14
45	7, 16	13, 18
46	11, 16	14, 17
47	7	18
48	7	14
49	7	69
50	16	18