ELECTRIC VEHICLE-INTELLIGENT ENERGY MANAGEMENT SYSTEM FOR FREQUENCY REGULATION APPLICATION USING A DISTRIBUTED, PROSUMER-BASED GRID CONTROL ARCHITECTURE

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ELECTRIC VEHICLE-INTELLIGENT ENERGY MANAGEMENT SYSTEM FOR FREQUENCY REGULATION APPLICATION USING A DISTRIBUTED, PROSUMER-BASED GRID CONTROL ARCHITECTURE

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To my parents for their undying love and sacrifice. They have taught me to face adversity without losing dignity or fail in the attempt. They have inspired everything I have: my values, my principles, my perseverance and my commitment, all with a great deal of love and never asking for anything in return. They have been my example, and wherever I go I will take them in my heart.

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SUMMARY

The world faces the unprecedented challenge of the need change to a new energy era. The introduction of distributed renewable energy and storage together with transportation electrification and deployment of electric and hybrid vehicles, allows traditional consumers to not only consume, but also to produce, or store energy.

The active participation of these so called "prosumers", and their interactions may have a significant impact on the operations of the emerging smart grid. However, how these capabilities should be integrated with the overall system operation is unclear.

Intelligent energy management systems give users the insight they need to make informed decisions about energy consumption. Properly implemented, intelligent energy management systems can help cut energy use, spending, and emissions.

This thesis aims to develop a consumer point of view, user-friendly, intelligent energy management system that enables vehicle drivers to plan their trips, manage their battery pack and under specific circumstances, inject electricity from their plug-in vehicles to power the grid, contributing to frequency regulation.

CHAPTER 1

INTRODUCTION

As energy costs and electricity demand continues to rise, and as more renewable energy sources are installed, it becomes necessary to revisit the electricity control paradigms. Under the presence of these emerging devices, the present electricity grid is not capable of efficiently balancing supply and demand, resulting in frequency oscillations, requirements for higher fossil fueled reserve, and risk of blackouts. The development of a two-way communication smart grid promises to address electricity control problems in the long-term [1].

Plug-in electric vehicles (PEV) provide an opportunity for small-scale distributed electric-energy storage while they are plugged-in. With large numbers of PEV and the communications and sensing associated with the smart grid, PEVs could provide ancillary services for the grid. Frequency regulation is an ideal service for PEV because the duration of supply is short and it is the highest priced ancillary service on the market offering greater financial returns for vehicle owners [2].

These new operation paradigms change the traditional control architecture of power systems and make necessary to identify a new approach that can be used to overcome the current system limitations. The inclusion of distributed energy generation in the form of solar panels, wind turbines, or even fuel cells makes the traditional consumer become a new entity that can also produce, store, or transport electricity: the prosumer [3]. The electric vehicle is the perfect prosumer because it consumes, produces, stores, and transports electricity. Therefore the distributed control architecture encompassed by the network of prosumers can be used to address frequency regulation, which has traditionally been performed by fast large-scale generating units, and now can be assisted by the collectively massive, distributed power electronic sources in PEVs [4].

Particularly some questions arise related to the incorporation of plug-in electric vehicles as a source of frequency regulation: Without knowledge of the entire system, what local operating parameters should be used to determine what the PEVs should supply? How can the vehicle owners effectively and economically implement solutions for managing their energy consumption and costs? How can an electric vehicle system maximize its own function while interacting with other owners and the power grid? This thesis addresses these questions with the implementation of a simulation software prototype that incorporates a reliable, prosumer-based and scalable electric vehicle-intelligent energy management system simulator for frequency regulation applications.

CHAPTER 2

THE VEHICLE TO GRID CONCEPT

There are two main types of plug-in electric vehicles: hybrids and battery electric vehicles. These vehicles contain power electronics which could generate 60 Hz AC power, at power levels from 10kW (for the Honda Insight) to 100kW (for GM's EV1) [5]. The concept of "Vehicle-to-Grid" power or V2G refers to the case when vehicle power is fed from the vehicle into the electric grid.

Recent research has been conducted to demonstrate that the three types of PEVs have potential roles to play as utility resources, and that ancillary services are the most lucrative use for vehicle power. Actually, some studies predict that power from electric drive vehicles could reduce the global requirement for central station generation capacity by up to twenty percent by the year 2050 [6].

The following conclusions can be made regarding the use of plug-in electric vehicles as a distributed energy resource based on the power and energy characteristics [2]:

- Not suitable for base load power supply,
- Ideal for short duration services such as frequency regulation, load following, or spinning reserve, and
- Ideal for household scale services such as load smoothing or peak reduction.

However, realizing this potential will require some minor design modifications to current vehicles and some coordination of vehicle and infrastructure planning. Three elements are required for V2G [5]:

- Power connection for electrical energy flow from vehicle to grid,

- Control or logical connection, needed for the grid operator to determine available capacity, request ancillary services or power from the vehicle, and to meter the result,
- Precision certified metering on board the vehicle.

The first V2G requirement is the power connection. PEVs by definition must be connected to the grid in order to recharge their batteries; to add V2G capability requires slight modifications to the charging station and no modification to the cables or connectors, but on-board power electronics must be designed for this purpose.

The second requirement for V2G is control, for the utility or system operator to request vehicle power exactly when needed. This is essential because vehicle power has value greater than the cost to produce it only if the buyer can determine the precise timing of dispatch.

The third element of precision, certified, tamper-resistant metering, measures exactly how much power or ancillary services a vehicle did provide, and at which times [5]. Figure 2.1 shows the vehicle to grid basic scheme.

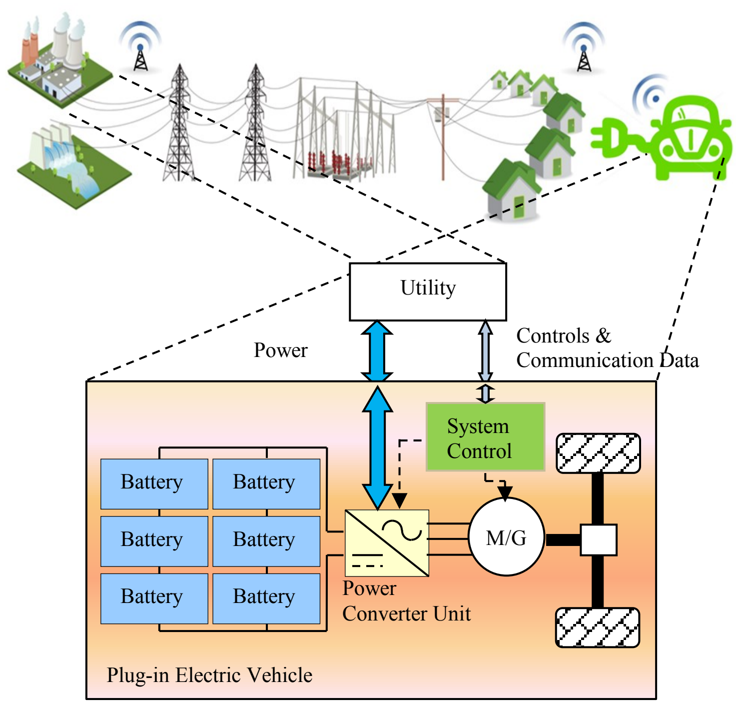


Figure 2.1: Vehicle to Grid Basic Scheme

2.1 Vehicle-to-Grid Market Overview and technology drivers

The key to realizing economic value from V2G is making the power available without compromising the driving requirements of a single vehicle owner, yet meeting the time- critical "dispatch" needed by the electric distribution system. The research and consulting group Zpryme [7] has estimated that by 2020 the V2G market will exhibit the following behavior in their various functional areas:

2.1.1 V2G Units

The global V2G vehicle unit sales are projected to grow from 103900 (year 2015) to 1.06 million (year 2020). This growth is projected to have a 59 percent compound annual growth rate (CAGR) from 2015 to 2020. Some of the drivers behind this trend are gas price volatility, increase in mass production, and improvements in battery technology, that will ultimately drive electric vehicles' prices down. It can be highlighted that the US and Japan are attractive markets where V2G related technologies and infrastructure will be required at the same increasing rate.

2.1.2 V2G Technology Market Value

The global V2G technology market is projected to grow from $1.5 billion (year 2015) to $10.5 billion (year 2020). This growth is projected to have a 46.8 percent compound annual growth rate (CAGR) from 2015 to 2020. V2G technology is comprised of the key components an automobile manufacture must place into a vehicle to produce a V2G vehicle. These consist on:

- Equipment: computers, networking equipment, cabling, processors, and circuits that allow for the management, reporting, and processing of V2G tasks.
- Software and communication systems: systems that enable the two-way communication between the grid and the vehicle, and that allow monitoring,

scheduling, and analysis of charge times and demand response programs associated with the vehicles.

- Power electronics unit: the drive system is the most expensive component among the key V2G technology components. The drive system operates as a DC-AC inverter and enables bi-directional power to flow from the vehicle to the grid.

2.1.3 V2G Vehicle Market Value

The global V2G vehicle market value is projected to grow from $3.2 billion (year 2015) to $26.6 billion (year 2020). This growth is projected to have a 53.1 percent compound annual growth rate (CAGR) from 2015 to 2020. V2G vehicle market value is the aggregate of expected annual revenues received by automobile manufactures for the sale of V2G vehicles. The United States will lead the way in 2015 with a market value around $1.1B followed by Japan at $.5B. In 2020, however, the US market will grow to $8.1B with China now in second place at a market value of $6.5B.

2.1.4 V2G Total Market Size

The global V2G grid revenues are projected to grow from $284.4 million (year 2015) to $2.9 billion (year 2020). This growth is projected to have a 46.8 percent compound annual growth rate (CAGR) from 2015 to 2020. Table I shows the Global V2G Market Forecast in year 2020 according to Zprime [7].

TABLE 1.1
V2G Total Market Size [7]

Country	Units	Market	Infrastructure	Technology	Revenue
	Thousands	US billions	US Billions	US Billions	US Billions
Global	1056	$26.6	$6.7	$10.5	$2.9
US	296	$8.1	$1.8	$2.8	$.654
China	294	$6.5	$1.8	$2.8	$.521
Japan	188	$4.4	$1.2	$1.8	$.735
Germany	62	$1.6	$.377	$.587	$.587
UK	45	$1.3	$.277	$.432	$.323
South Korea	30	$.72	$.175	$.283	$.053

CHAPTER 3

THE PROSUMER ARCHITECTURE

The prosumer concept abstracts the electricity infrastructure as a network of intelligent agents (the prosumers) and allows a control paradigm based on networked control theory [4]. Prosumers are entities that own or operate an electric power system of any scale and may:

- Consume
- Produce
- Store, and
- Transport electricity.

The prosumer conceptualizes a natural progression from centralized control to distributed capability (see communications, data processing industries, banking, etc).

The electric vehicle is the perfect prosumer because it consumes, produces, stores, and transports electricity. As a vehicle–to-grid prosumer, the electric vehicle controls its internal processes to maximize its satisfaction function while it interacts with the external world. Each prosumer also contributes to the overall system reliability.

Frequency control is the most important service that can be achieved in a distributed way because each electric vehicle can locally detect changes in the system; internal electric vehicle controllers can regulate frequency by adjusting generation, load or storage.

The multi-layered prosumer model that implements the control and interactions has been adapted from [3] for the PEV case and is illustrated in Figure 3.1.

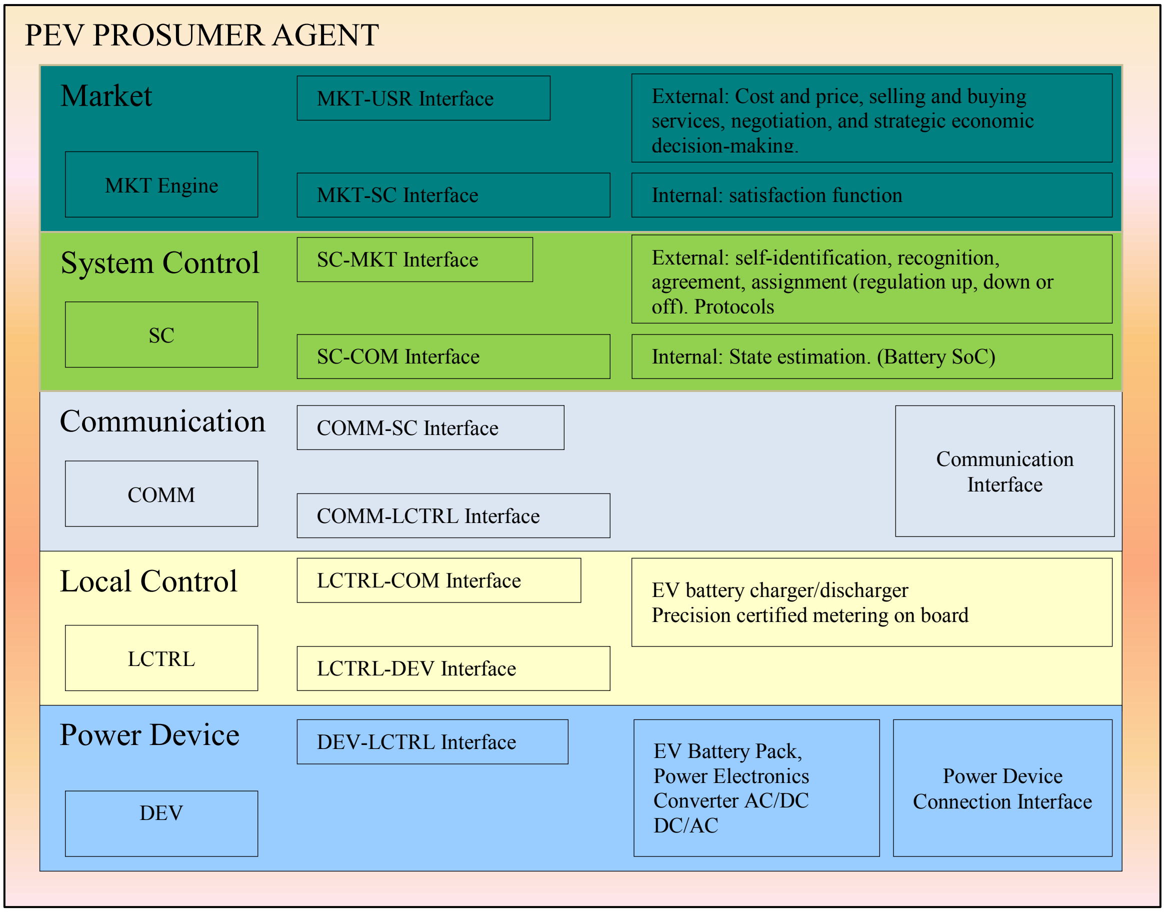


Figure 3.1: PEV Prosumer-Based Layered Architecture

3.1 The Device Layer

The device layer corresponds to the electric battery pack. In this analysis a 25 kWh lithium-ion battery pack has been selected. However, the EV-IEMS allows for different values. Thermal models and multiple time constant models have been developed for lithium-ion battery packs [8]. This allows estimating the battery state of charge (SoC) and the battery life time according to system usage. However, these models are not considered in the present analysis and the SoC is updated according to power transactions.

3.2 The Local Control Layer

The local control layer corresponds to the hardware and software used for controlling stand-alone device actions. In this case the local layer corresponds to the EV battery charger/discharger. The EV-IEMS allows setting the charging and discharging efficiencies of the system. The default values are set to 90% for both: charging and discharging efficiency.

3.3 The Systems Control & Communication Layers

The systems control contains two components, internal and external control. The internal system control corresponds to Energy Management System (EMS) -like algorithms such as state estimation, and optimization. The external system control addresses interactions with the surrounding world, including self-identification, recognition, agreement, assignment, and formation protocols.

A small number of plug-in electric vehicle (PEV) use cases for connection of PEV to accept energy from the grid, and customer enrollment in a demand response program were released in 2008 by the Southern California Edison (SCE) [9]. In addition a frequency regulation case is being developed for PEVs. A full repository for smart grid use cases is being managed by the Electric Power Research Institute (EPRI) and includes the previously discussed SCE studies along with several other PEV use-cases [10].

This framework has been considered as a preliminary point in the development of this project. Particularly, the system control layer assumes that the electric vehicle owner is enrolled in a frequency regulation program that involves PEV-Utility Communication & Authentication. In this way it is possible to implement a one level-prosumer interaction between the utility and the PEV. The EV-IEMS simulates the frequency communication session as shown in Figure 3.2.

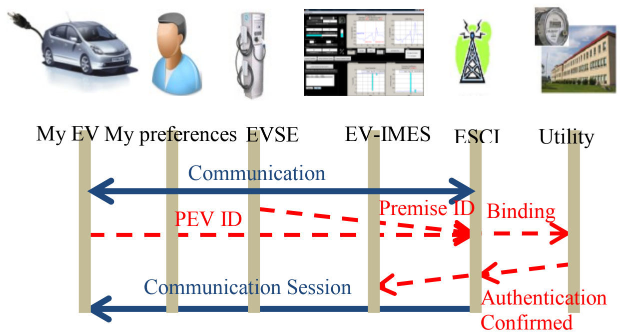


Figure 3.2: Initial communication Session Diagram [5].

The communication session is established as follows: after the customer has enrolled his PEV with the home utility, the customer plugs in the PEV using either an electric vehicle supply equipment (EVSE) cordset or home EVSE for charging or discharging [10].

The PEV and Energy Services Communications Interface (ESCI) establish a communication connection between the vehicle and the utility (binding) and authentication processes. The PEV provides an indicator to the customer that binding has been successful and that the PEV will receive an incentive rate upon charging, or discharging according to the regulation needed (if such a rate is available). At that time the PEV sends an energy request or offer (amount and rate) and schedule. The Utility compares request with its available energy or required energy and confirms or adjusts and sends a message back to PEV. The Utility sends the message containing information about the energy available or required (amount and rate) and schedule (according to the frequency regulation needed). The PEV prepares for charging or discharging. Then PEV begins charging or discharging based on Customer-selected preferences and the response from the utility. Charging may be delayed based upon Customer preferences or grid reliability and frequency regulation (up-down) criteria. Also the EV-IEMS records charging information and energy supplied to the PEV for each charge/discharge session. The information includes PEV ID, charging/discharging place ID, energy usage, and time stamp for each metering interval. The EV-IEMS communicates to the Energy Services Communication Interface the energy supplied to PEV for each charge/discharge session. The Energy Services Communication Interface communicates to the Utility the energy supplied to PEV for each charging session. The ESCI transmits the date, time, duration and energy delivered to utility or to the Vehicle. Finally the utility records each PEV charging/discharging regulation for bill generation and reporting to the customer account associated with the charging place and PEV ID [10].

As described in the diagram the customer is attempting to charge or discharge a PEV under a selected PEV rate tariff that may provide an incentive to charge or discharge according to the frequency regulation program. This also means that the price superimposes the frequency regulation needed. Therefore, a lower electricity price will mean that no power is needed from the vehicle (incentive to buy electricity, charging state) and a higher price will mean that power is needed for frequency regulation (incentive to sell electricity, discharge state).

The internal communication from the controlled device (battery pack) is provided by the EV-IEMS. The external communications may occur through dedicated protocols and network infrastructure or through the internet.

3.3 The Market Layer

The market layer consists of two components: the internal portion addresses the economics of the internal world, such as production, storage, demand shift and the satisfaction function associated with the objectives of economics, security, and sustainability along with the objectives and constraints of consumer preferences and comfort. The external function addresses interactions concerning cost and price, such as interpretation of price signals, selling and buying services, negotiation, and strategic economic decision-making [3]. The functionality of these layers is described in the following section.

CHAPTER 4

SYSTEM DESIGN

In particular, the EV-IEMS:

a) Automates energy management: Based on owner preferences, battery state and power system requirements, the system will automatically set charging/discharging/hold modes. Also the system allows scalability to incorporate for example solar sources and extra battery packs.

b) Allows economic energy management: The system will create economic benefit by powering the grid during peak times and shifting charging to off-peak hours. This will be allowed by the price forecast download that gives hourly prices of electricity. This is essential because vehicle power has value greater than its production cost only if the precise timing of dispatch is determined.

c) Predicts energy use and measures results: Based on the information about next trip mileage and state of charge of the battery the system is able to communicate to the user what will be the state of the battery and the percentage charge consumed. Also the system has a precision, metering, that measures how much power for ancillary services a vehicle did provide, and at which times.

Depending on the connection location four different cases can occur:

- Owner’s Home
- Another's Home: Inside the utility’s service territory
- Another's Home: Outside the utility’s service territory
- Public: Building parking lot inside the utility’s service territory

After enrolling in the frequency regulation program and independently of the connection location the EV prosumer objective would be to maximize profits by selling the excess power at the times when the market rate is the highest and buying power when the market rate is the lowest. This assumes that the price corresponds to the incentive to participate in frequency regulation. In this project only the cases when the connection location is inside the utility's service territory are considered. The optimal time to charge and discharge must be determined combined within vehicle owner's preferences and hence an intelligent optimization algorithm is needed to handle nonlinear and discontinuous variables.

4.1 The Internal Systems Control

4.1.1 Particle Swarm Optimization

Particle swarm optimization (PSO) is an iterative stochastic optimization algorithm based on the movement patters of flocks of birds or schools of fish [11]. 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 where each particle should move at each iteration to find the global best possible solution. Random variations and weighting factors are also used in the algorithm to prevent early convergence where a local minimum is present.

Following the analysis in [12] the electric vehicle system parameters are defined in Table 4.1. Each parameter is defined by the user in the EV-IEMS. 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]. 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.

Assuming an efficiency of 1kWh per mile the miles needed for next trip equal the desired battery state of charge (SoC) after the transaction. The default value is set to be

50 miles or 50 % of the SoC. Once the vehicle reaches this desired departure SoC it can never be discharged below this level.

TABLE 4.1
Vehicle Parameters [7]

Parameter	Minimun	Maximun
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
Next trip miles	1	100

4.1.2 PSO Initialization

1. Objective: Find the optimal hour to sell or to buy power from the grid.

2. Topology: The star configuration of a swarm is used where all particles communicate with all other particles.

3. Particle Definition: In this case the particles can be defined as follows:

$$X_i = [h] \tag{1}$$

where h represents the optimal hour to sell or to buy.

4. Fitness Function: the equations to be minimized- maximized are the cost and revenue incurred because of the power transaction, respectively:

$$C = \frac{P(h)*(SoC*kWH_{Max}-kWH_{Available})}{Eff_{charge}} \tag{2}$$

$$R = P(h) * (kWH_{Available} - SoC * kWH_{Max}) * Eff_{discharge} \tag{3}$$

where,

C = the resulting cost of charging that vehicle

R = the revenue made by selling from that vehicle

$P(h)$= the price at instant h

h = the optimal buy/sell time instant

$kWH_{Available}$ = killowatt*Hrs in the battery

kWH_{Max} = maximum battery capacity

SoC = desired departure battery state of charge

Eff_{charge} = charging efficiency

$Eff_{discharge}$ = inverter discharge efficiency

5. Search space (constraints): The constraint for this problem is that the hour must be strictly a positive real number which is limited by the arriving and departure time.

$$Arrive\ Time < h < Departure\ Time \quad (4)$$

6. PSO Parameters. - The tested PSO parameters are shown on Table 4.2.

TABLE 4.2
Tested PSO Parameters

Parameters	Tested Maximun
Number of Particles	{10,20,40}
Number of Iterations	{10,50,100}
Inertia weight	{0.3,1,1.5}
Individual Acceleration Constant	{0.1,1.5,2.5,4}
Social Acceleration Constant	{0.1,2.5,4}

4.1.3 PSO Implementation

The PSO was implemented using a Graphical User Interface (GUI) in MATLAB. The PSO algorithm implemented by the program is described by the following steps:

1. Particle initialization: The first step was to initialize a population of particles, each representing a possible solution, by assigning random solutions within the given solution space to the problem's variable. To make the optimization converge faster, a random value inside the range [Arriving time, Departing Time] is chosen

$$X_i(0) = ArriveTime + (DepartureTime - ArriveTime) * rand(1,1) \quad (5)$$

2. Swarm definition: In this step the swarm is defined as a set of particles according to the number of particles specified.

$$Swarm(0) = [X_1(0)\ X_2(0) \cdots X_n(0)\ ]^T \quad (6)$$

3. Fitness function evaluation: The fitness function assigned to the problem is evaluated for each particle. Therefore the set J of fitness functions is:

$$J(0) = [J_1(0)\, J_2(0) \cdots J_n(0)\,]^T \tag{7}$$

where the fitness function for each particle every iteration is:

$$J_i(t) = \begin{cases} C & if\ SoC < KWH_{Available} \\ R & if\ SoC > kWH_{Available} \end{cases} \tag{8}$$

4. Feasibility check: Also, the constraint for this problem is checked to see if the random hour values are strictly positive real numbers inside the grid connection interval. $Arrive\ Time \leq X_i(0) < Departure\ Time\ for\ i = 1{:}n$ where n is the number of particles.

If this doesn't hold then

$$J_i(iteration) = \infty \tag{9}$$

5. Calculate initial best particle positions Pbest and Gbest: For each particle, the fitness at the current iteration is compared with the particle's best previous fitness. The best previous solution for a particle is known as its personal best or Pbest solution. At the first iteration, the randomly initialized particles are assigned as the respectively particle's best positions. Therefore

$$P_I(0) = [X_1(0)\, X_2(0) \cdots X_n(0)\,]^T \tag{10}$$

Also the best solution of all the Pbest solutions is selected to be the global best or Gbest solution. This global best position is chosen between the particles, according to the smallest Fitness value J:

$$P_g(0) = min(J(0)) = min([J_1(0)\, J_2(0) \cdots J_n(0)\,]^T) \tag{11}$$

6. Update each particle's velocity and position. Since each individual possible solution can be modeled as a particle that moves through the problem hyperspace. The position of each particle is determined by the vector $x_i \in \mathbb{R}^n$and its movement by the velocity of the particle $v_i \in \mathbb{R}^n$, as shown in (12).

$$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t) \tag{12}$$

The information available for each individual is based on its own experience (the decisions that it has made so far and the success of each decision) and the knowledge of the performance of other individuals in its neighborhood [11]. Since the relative importance of these two factors can vary from one decision to another, it is reasonable to apply random weights to each particle, and therefore the velocity will be determined by

$$\vec{v}_i(t) = \varphi_{ic} \cdot \vec{v}_i(t-1) + \varphi_1 \cdot rand_1 \cdot (\vec{p}_{Ii}\vec{x}_i(t-1)) + \varphi_2 \cdot rand_2 \cdot (\vec{p}_g - \vec{x}_i(t-1)) \qquad (13)$$

where $\varphi_1, \varphi_2 \cdot$ are two positive numbers and $rand_1$, $rand_2$ are two random numbers with uniform distribution in the range of [0.0, 1.0].

7. Calculate new values for the fitness function and Update individual and global best positions: For each particle the following is applied:

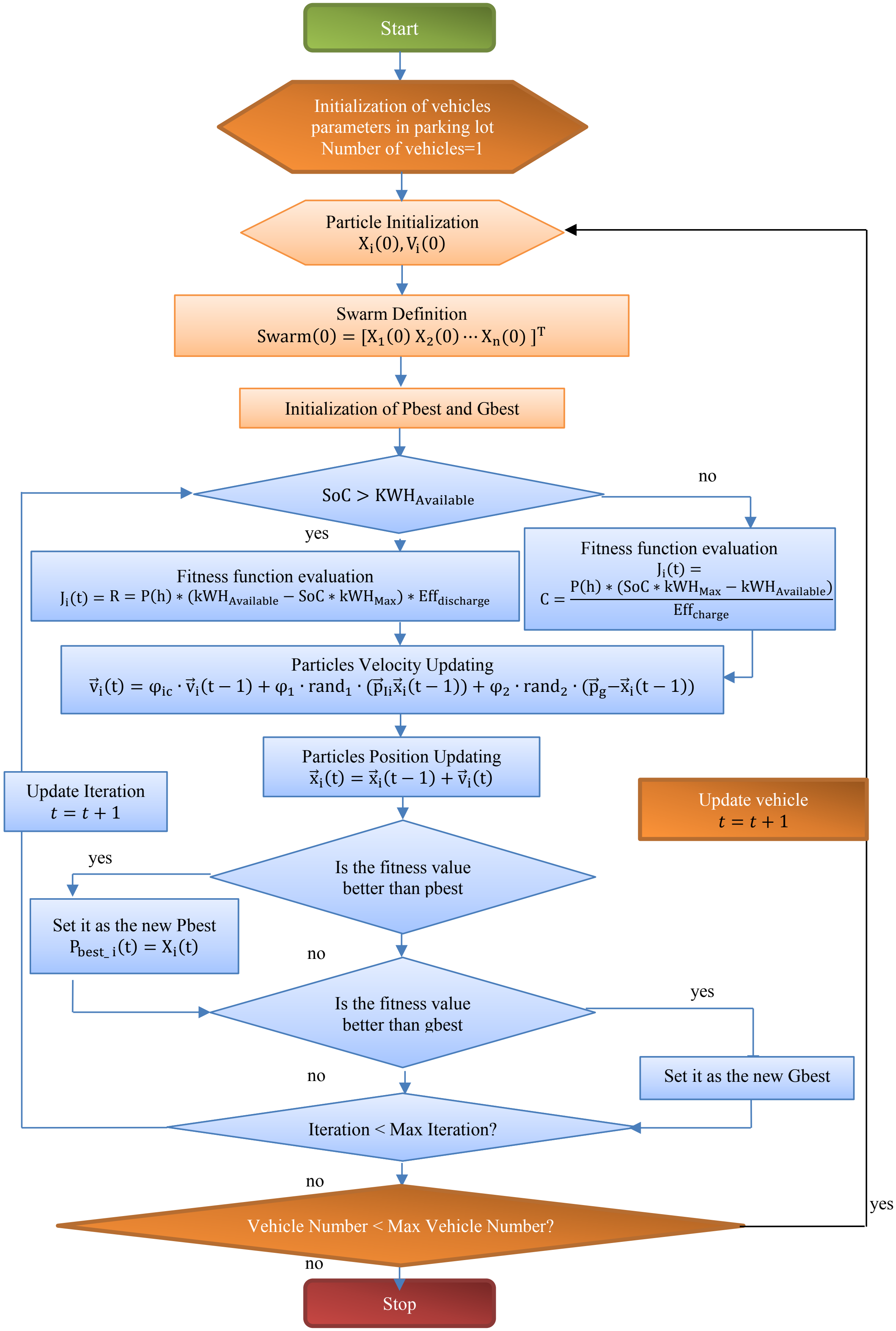
$if\ \ J_i(t) > J_i(t-1)$ then $P_{Ii}(t) = P_{Ii}(t-1)$

$if\ \ J_i(t) < J_i(t-1)$ then $P_{Ii}(t) = X_i(t)$

$$P_g(t) = min(J(t)) = min([J_1(t)\, J_2(t) \cdots J_n(t)\ ]^T) \qquad (14)$$

Finally this procedure is repeated from step (5), until the stopping criterion is accomplished. In this analysis the PSO continued until the maximum number of iterations was reached. This means that a global solution was found within a predefined number of iterations. The program produces a set of plots showing the optimal time to sell or to buy based on the PEV parameters.

4.1.4 PSO Flowchart



4.2 The External Systems Control

4.2.1 Distributed Power Agreement Protocol

The decentralized control is based on the model developed in [14]. The model has been adapted to the plug-in electric vehicle case. The model defines each electric vehicle prosumer's desired power need ($\hat{p}_i$) and agreed upon power need ($\tilde{p}_i$), and actual power need (p_i). In this case, it is assumed that due automation actual and agreed upon power will be the same. The power need can also be power imbalance as it is the difference between generated power and load. Figure 4.1 shows the basic relationships between the model parameters.

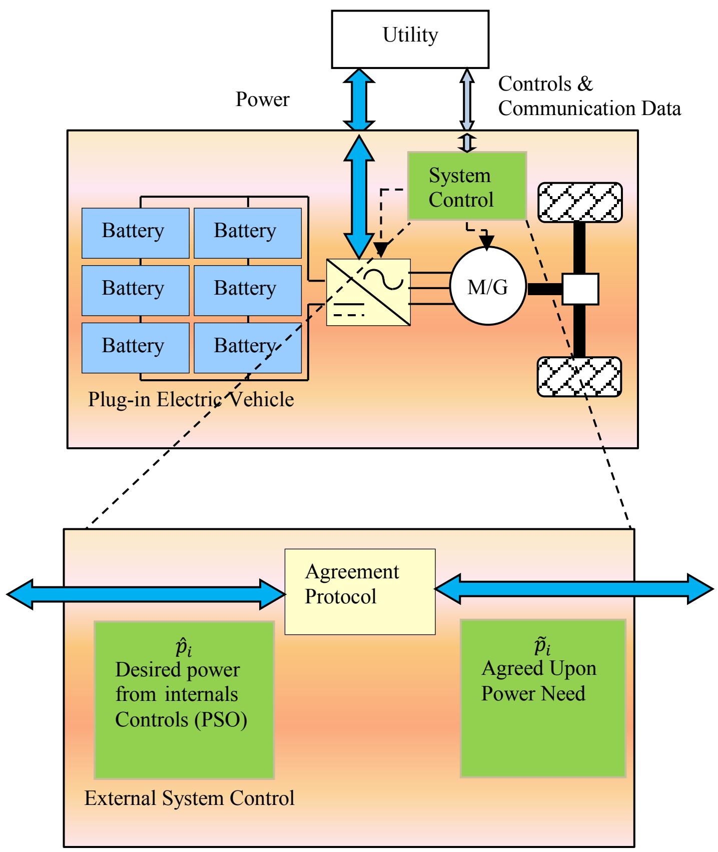


Figure 4.1: External Controls Basic Scheme

Equation (15) shows the distributed agreement protocol where ϖ represents a desired weigh that determines the “importance” of each prosumer.

$$\min_{\tilde{p}} \sum_{i=1}^{N} \varpi_i \|\tilde{p}_i - \hat{p}_i\|^2 \tag{15}$$

A variable load profile was determined for 24 hours. Then the agreement protocol was run in Matlab and the resulted solution was displayed in PowerWorld. Figure 4.2 shows the time-step implementation of the agreement protocol in PowerWorld for the case of 50 generators (that can be considered as the EV’S) divided in 10 prosumers. The simulation shows a contour of the line congestion for the specific agreed power. It is possible to see that while some areas have higher power congestion, the agreed upon power does not overload the lines.

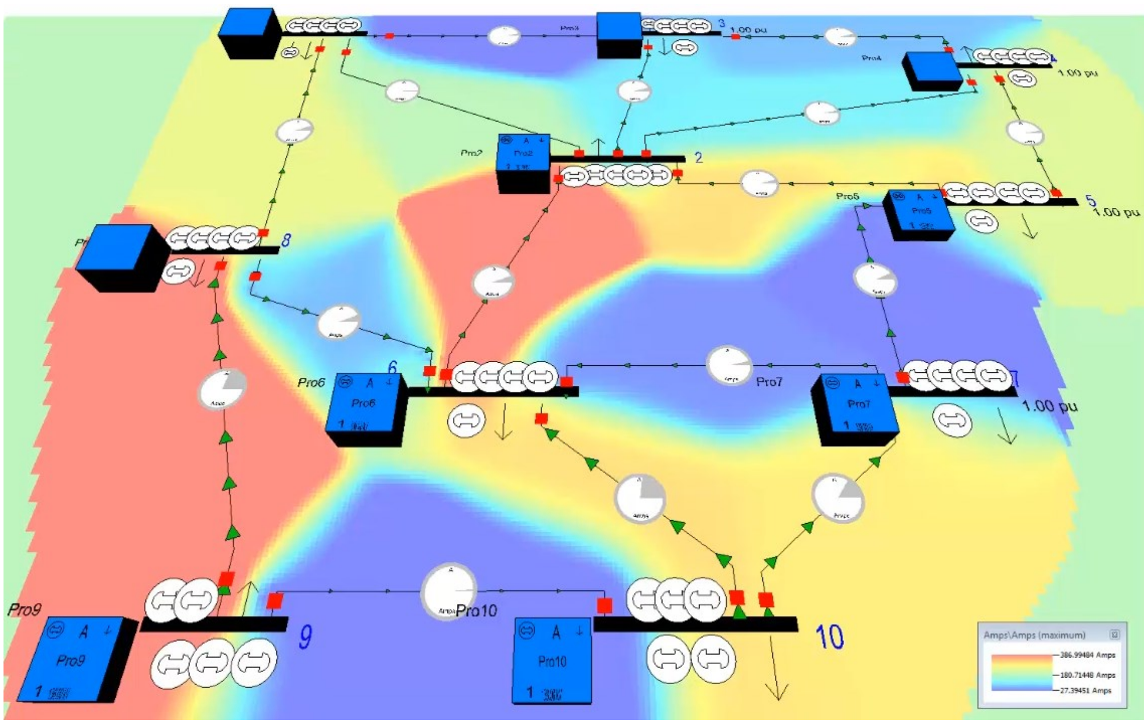


Figure 4.2: PowerWorld Simulation of the Agreement Protocol

CHAPTER 5

SIMULATIONS

When implementing the particle swarm algorithm, several considerations must be taken into account to facilitate the convergence and prevent an “explosion” of the swarm. These considerations include selecting acceleration constants, the number of particles, the number of iterations and the inertia constant. First, the best-selling/buying hour for one vehicle was analyzed. In order to have consistency in the results all the trials were run based on the same parameters. The battery capacity was chosen to be 25 KWh, the available capacity was 80%, the arriving time was at 7 am and the departure time was at 5 pm. The charge and discharge efficiencies were selected to be 90 %.The best parameters were determined after various sets of simulations and are summarized at the end of the following section.

5.1 Effect of the number of iterations on the PSO.

5.1.1 Results with inertia = 1, individual acceleration constant = 1.5, social acceleration constant=2.5, number of particles = 10, number of iterations=10.

First in order to see the effect of the number of iterations, the PSO was implemented using 10 particles and 10 iterations. Figure 5.1 shows the position of the particles for different times. The optimal hour to sell is the 14th hour. Figure 5.2 shows the car revenue vs hours, the maximum revenue in the time interval is 0.44 $.

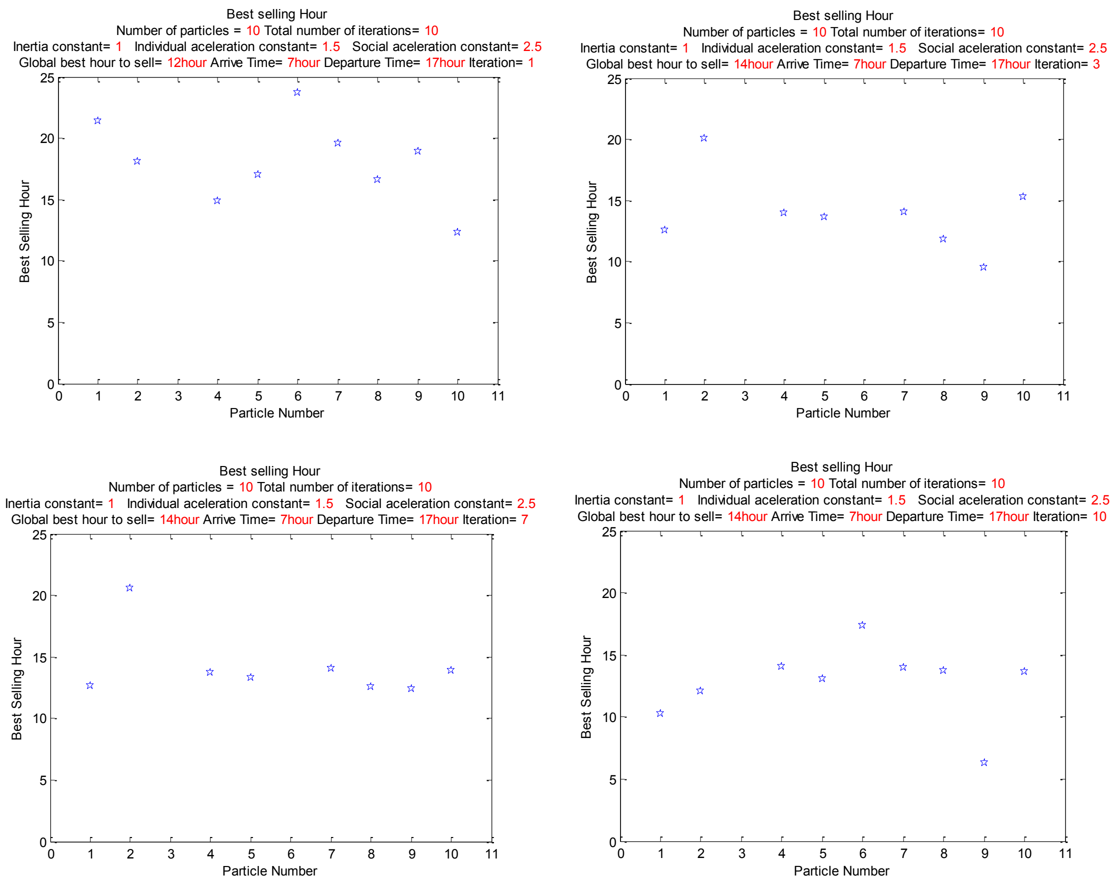


Figure 5.1: Positions of the particles for different times

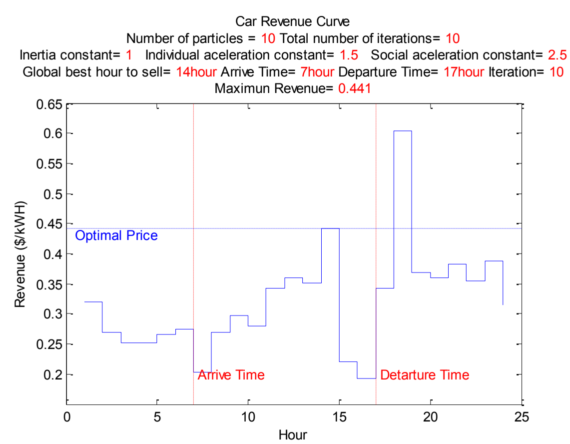


Figure 5.2: Car Revenue Curve vs Number of Hours

5.1.2 Results with inertia = 1, individual acceleration constant = 1.5, social acceleration constant=2.5, number of particles = 10, number of iterations=50.

In this case the number of iterations was increased to 50. Figure 5.3 shows the position of the particles for different times. The optimal hour to sell is the 14th hour. Figure 5.4 shows the car revenue vs hours, the maximum revenue in the time interval is 0.44 $.

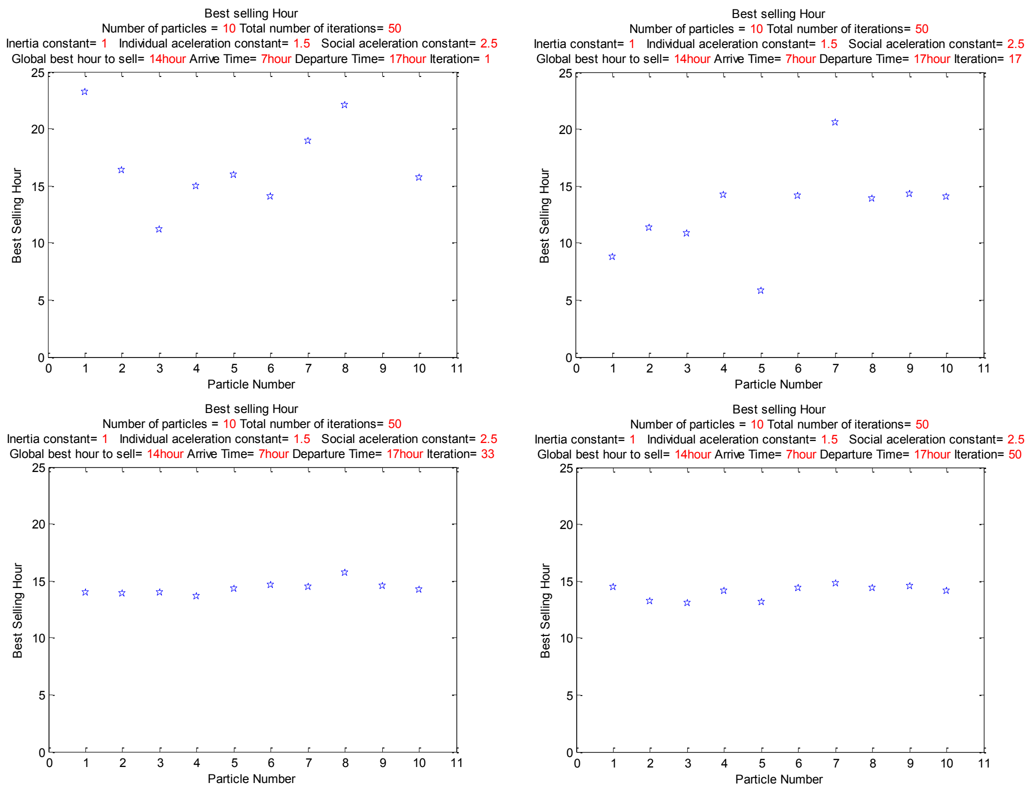


Figure 5.3: Positions of the particles for different times

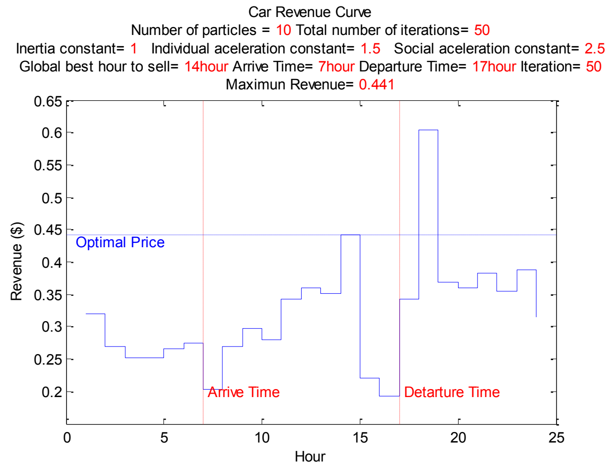


Figure 5.4: Car Revenue Curve vs Number of Hours

5.1.3 Results with inertia = 1, individual acceleration constant = 1.5, social acceleration constant=2.5, number of particles = 10, number of iterations=100.

In this case the number of iterations was increased to 100. Figure 5.5 shows the position of the particles for different times. It is possible to see that the optimal hour to sell is the 14 hour which is exactly the same value obtained in the previous section. Figure 5.6 shows the revenue vs hours in the day, the maximum revenue achieved is 0.44 $. Therefore, better results are achieved if a higher number of iterations is used. However, this increases the amount of computation.

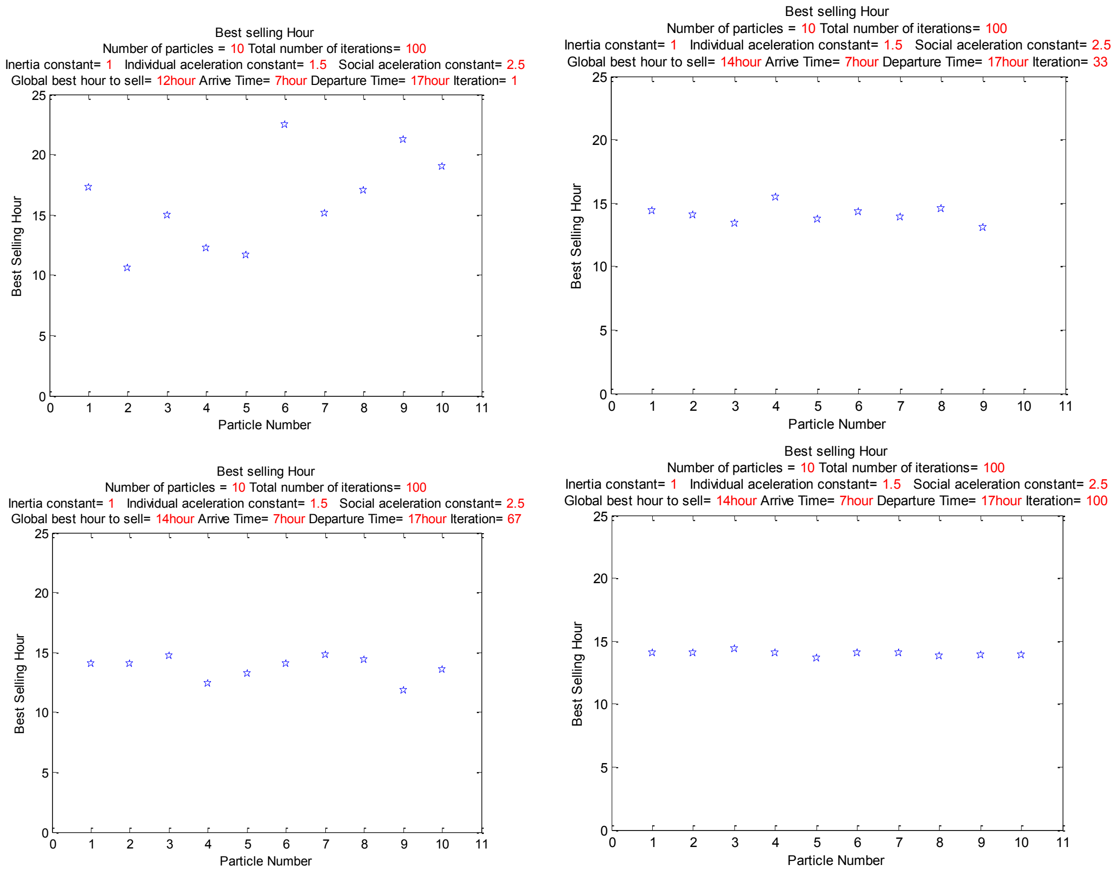


Figure 5.5: Positions of the particles for different times

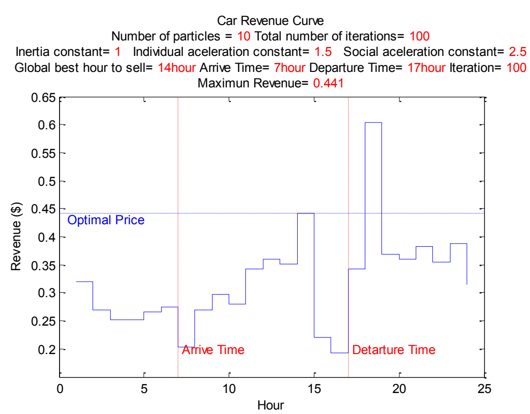


Figure 5.6: Car Revenue Curve vs Number of Hours

5.2 Effect of the number of particles on the PSO.

5.2.1 Results with inertia = 1, individual acceleration constant = 1.5, social acceleration constant=2.5, number of particles = 20, number of iterations=100.

In this case the number of particles was increased to 20. Figure 5.7 shows the position of the particles for different number of iterations, where it is possible to see that the initial random values converge to 14 which is exactly the same value obtained as in the previous section. Figure 5.8 shows the revenue vs the number of hours, the maximum revenue achieved is 0.44$.

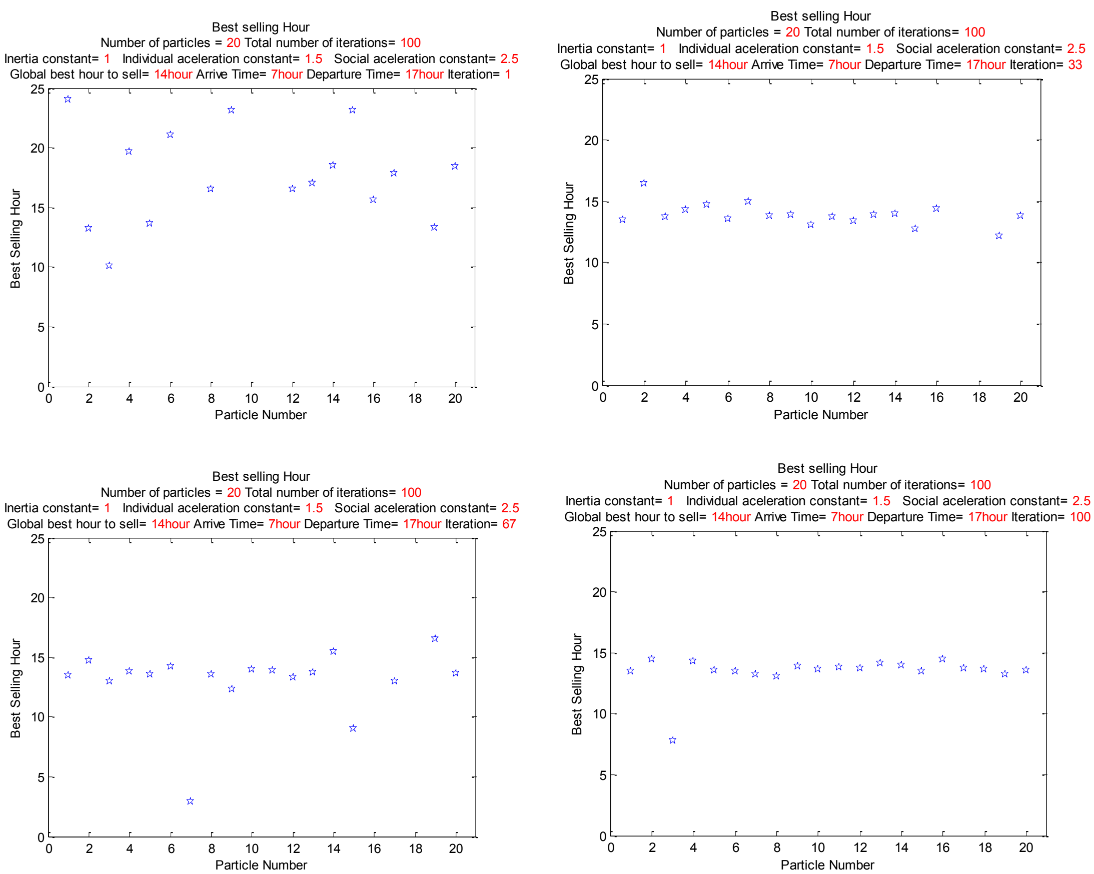


Figure 5.7: Positions of the particles for different times

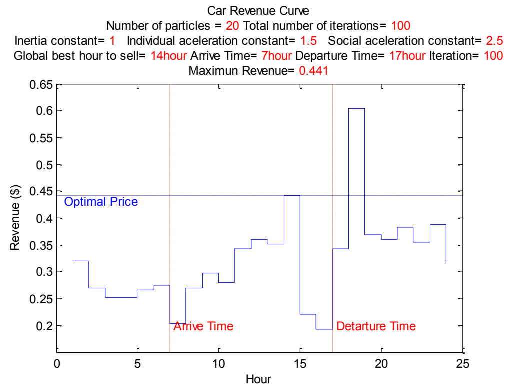


Figure 5.8: Car Revenue Curve vs Number of Hours

5.2.2 Results with inertia = 1, individual acceleration constant = 1.5, social acceleration constant=2.5, number of particles = 40, number of iterations=100.

In this case the number of particles was increased to 40. Figure 5.9 shows the position of the particles for different number of iterations, where it is possible to see that all the initial random values converge to 14 which is exactly the same value obtained in the previous sections. Figure 5.10 shows the revenue vs the number of hours, the maximum revenue achieved is 0.44$. It is possible to see that the oscillations stop after 33 iterations.

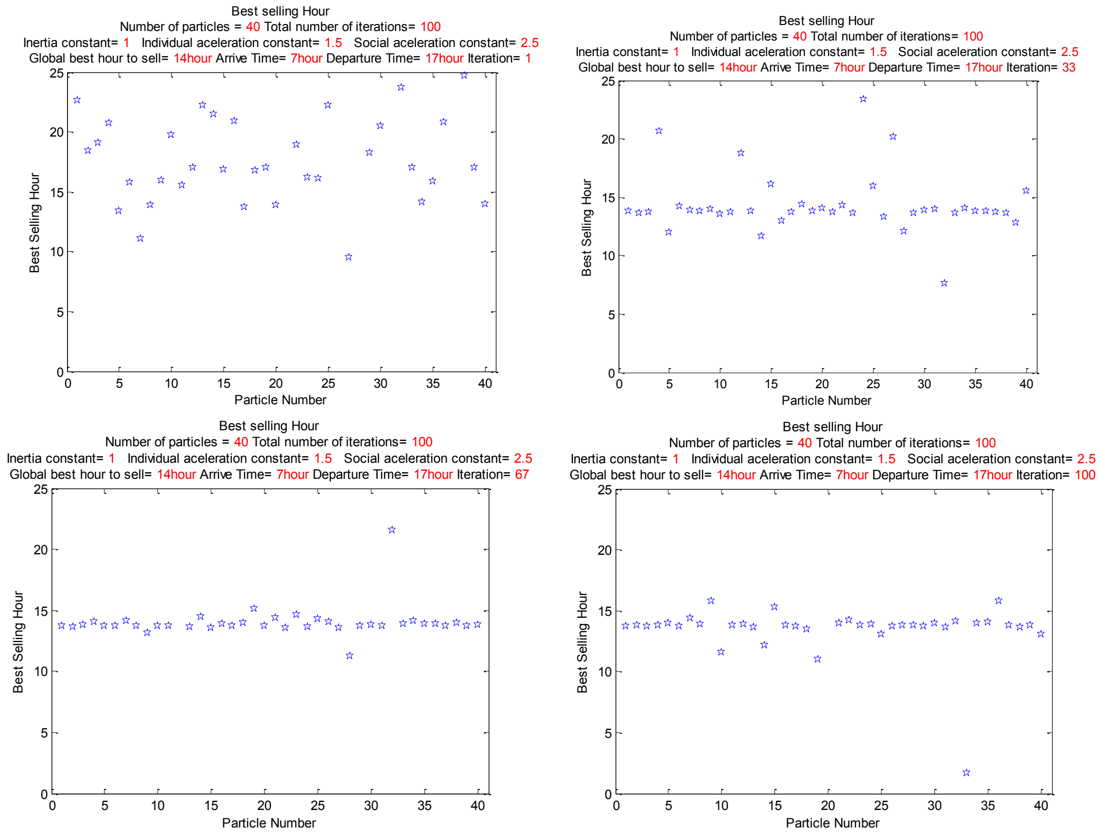


Figure 5.9: Positions of the particles for different times

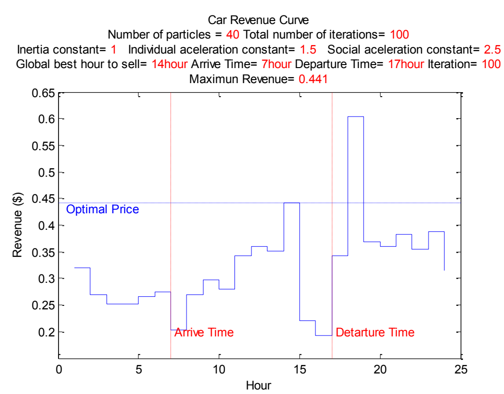


Figure 5.10: Car Revenue Curve vs Number of Hours

5.3 Effect of the selection of acceleration constants.

5.3.1 Results with inertia = 1, individual acceleration constant = 0.1, social acceleration constant=2.5, number of particles = 40, number of iterations=100.

In this case a small number of individual acceleration constant was used. Figure 5.11 shows the position of the particles for different number of iterations, where it is possible to see that the initial random values converge to 14 which is exactly the same value obtained in the previous section. Figure 5.12 shows the revenue vs the number of hours, the maximum revenue achieved is 0.44$. It is possible to see that there are not oscillations. With a very low value of individual acceleration the convergence was faster, in less than 33 iterations the surface area didn't oscillate like in the previous examples

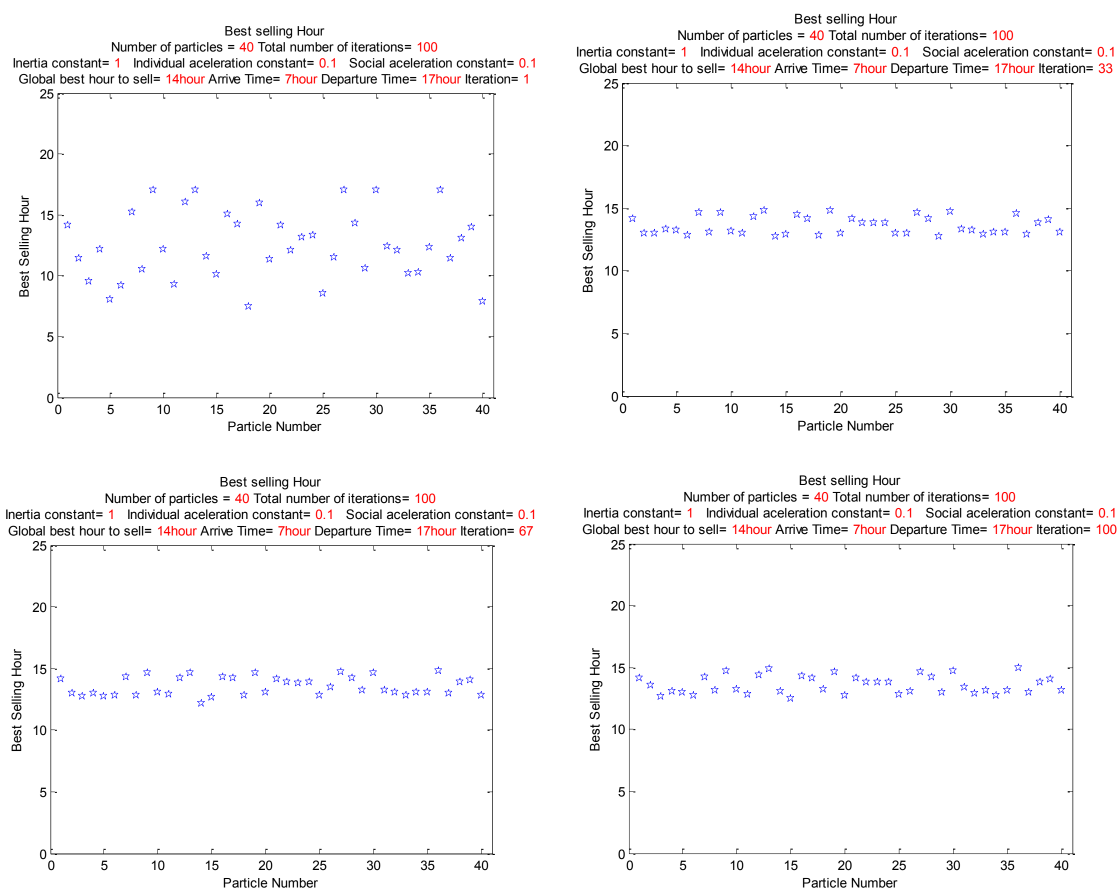


Figure 5.11: Positions of the particles for different times

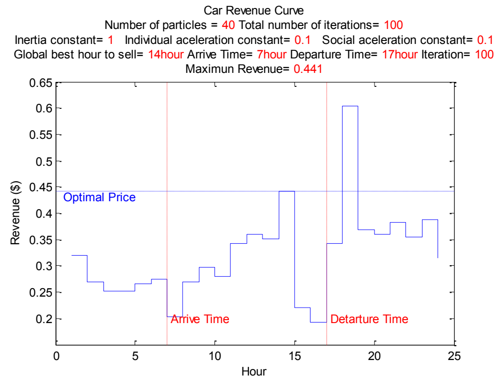


Figure 5.12: Car Revenue Curve vs Number of Hours

5.3.2 Results with inertia = 1, individual acceleration constant = 0.1, social acceleration constant=0.1, number of particles = 40, number of iterations=100.

In this case a small number of individual and social acceleration constants were used. Figure 5.13 shows the position of the particles for different times, where it is possible to see that the particles oscillate around the optimal value 14. Figure 5.14 shows the shows the revenue vs the number of hours, the maximum revenue achieved is 0.44$. Therefore, for smaller values of acceleration constants then the particles oscillate around the optimal value.

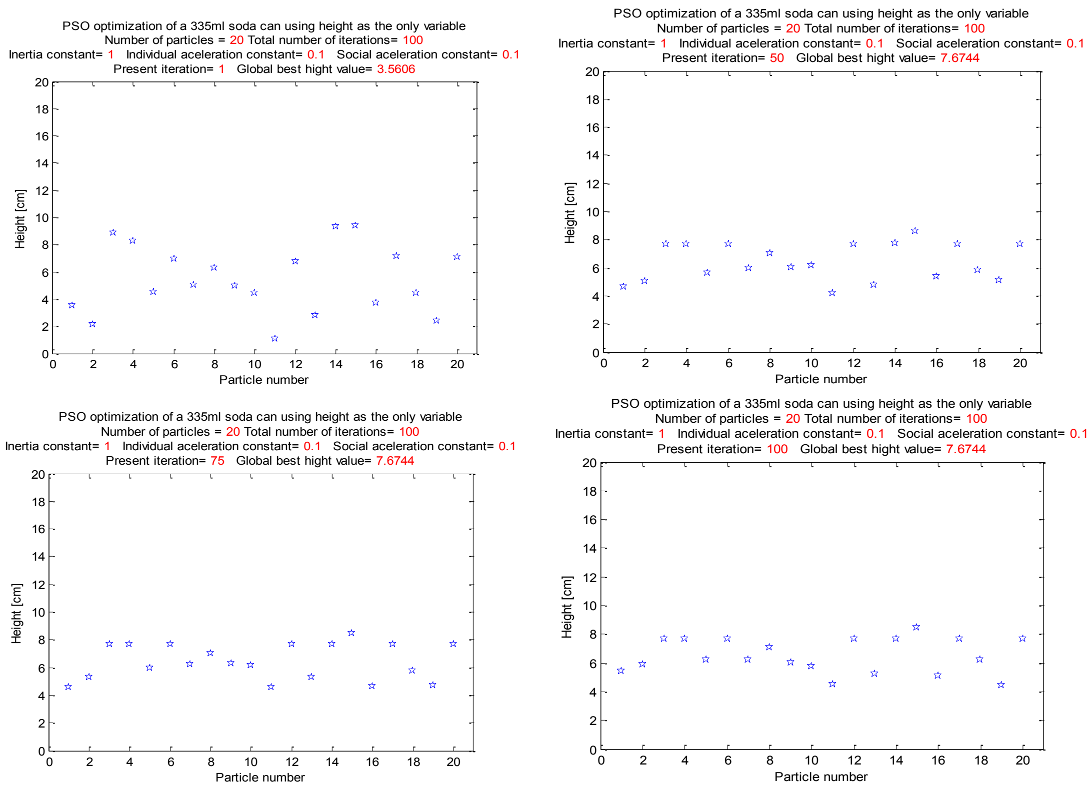


Figure 5.13: Positions of the particles for different times

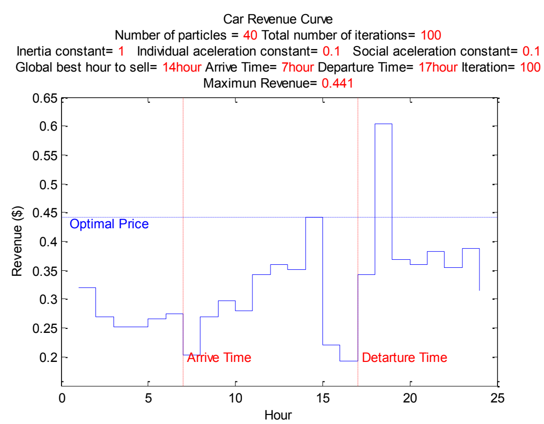


Figure 5.14: Car Revenue Curve vs Number of Hours

5.3.3 Results with inertia = 1, individual acceleration constant = 2.5, social acceleration constant=0.1, number of particles = 40, number of iterations=100.

In this case a small number of social acceleration constant was used. It is possible to see in Figure 5.15 that the positions of the particles for different times oscillate around the optimal value 14. Also it is possible to see in Figure 5.16 shows the shows the revenue vs the number of hours, the maximum revenue achieved is 0.44$.

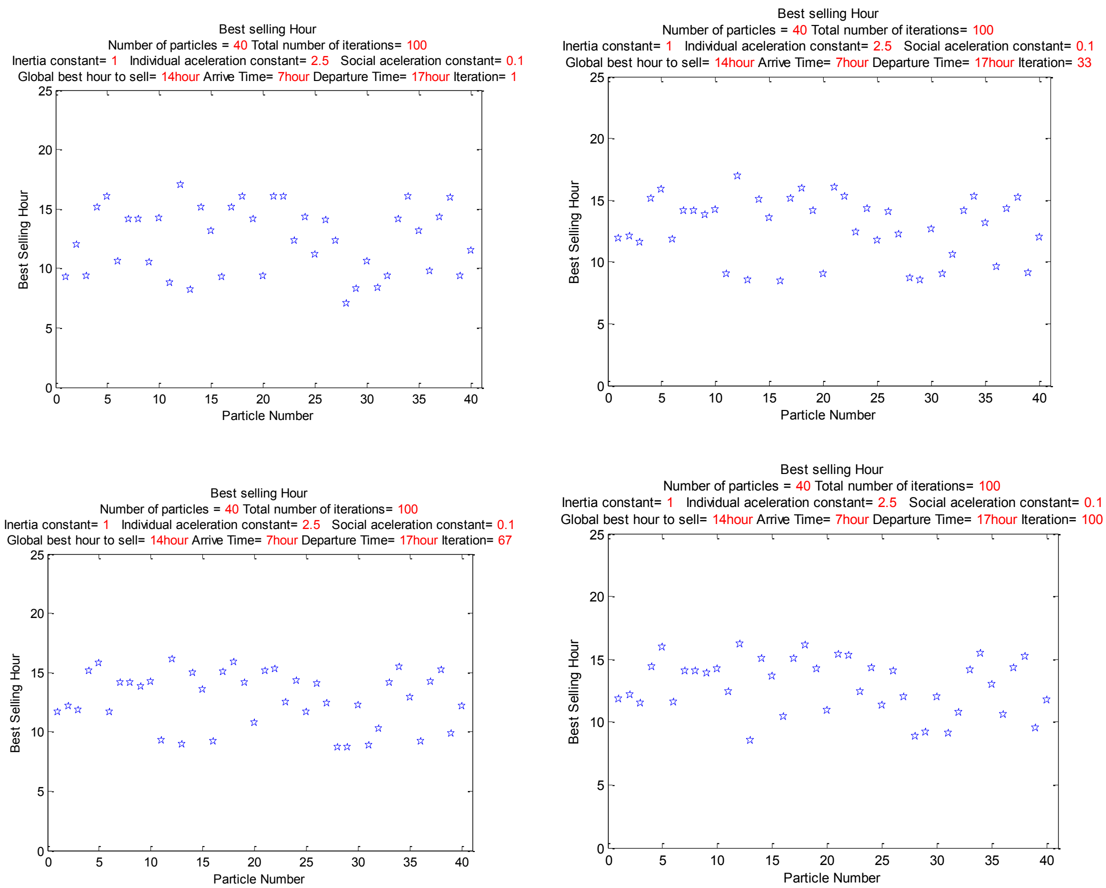


Figure 5.15: Positions of the particles for different times

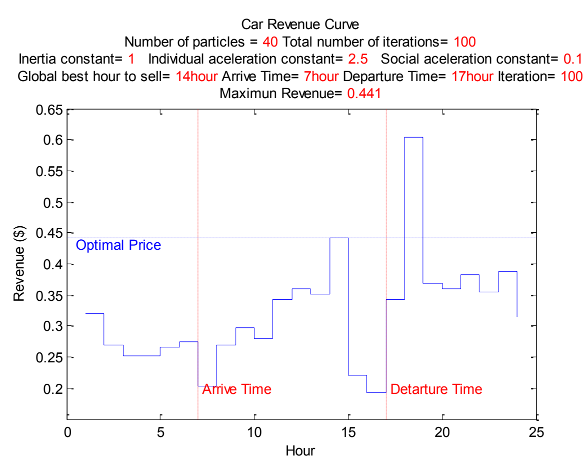


Figure 5.16: Car Revenue Curve vs Number of Hours

5.3.4 Results with inertia = 1, individual acceleration constant = 4, social acceleration constant=4, number of particles = 40, number of iterations=100.

In this case each of the acceleration constants was increased to 4. Figure 5.17 shows that the response diverges for these values. In fact for different sets of acceleration constant it was possible to find that the results diverge if the addition of the acceleration constants is greater than 4.

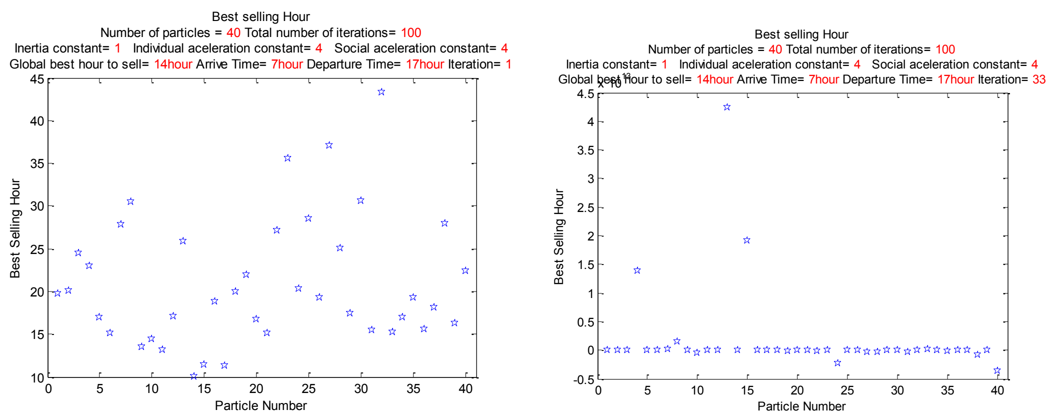


Figure 5.17: Positions of the particles for different times

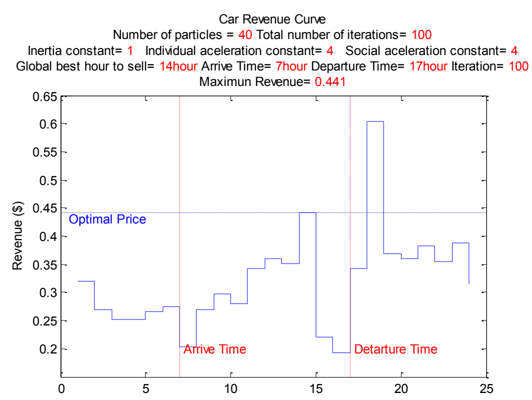


Figure 5.18: Car Revenue Curve vs Number of Hours

5.4 Effect of the selection of inertia constant.

5.4.1 Results with inertia = 0.3, individual acceleration constant = 1.5, social acceleration constant=2.5, number of particles = 20, number of iterations=100.

In this case a small number of inertia was used. Figure 5.19 shows the position of the particles for different times, where it is possible to see that the initial random values converge to 14. Figure 5.20 shows the revenue vs number of hours. It is possible to see that there are some oscillations. Therefore it is possible to conclude that if the inertia weight is small the search is narrowed, this means that the mode is basically exploitative.

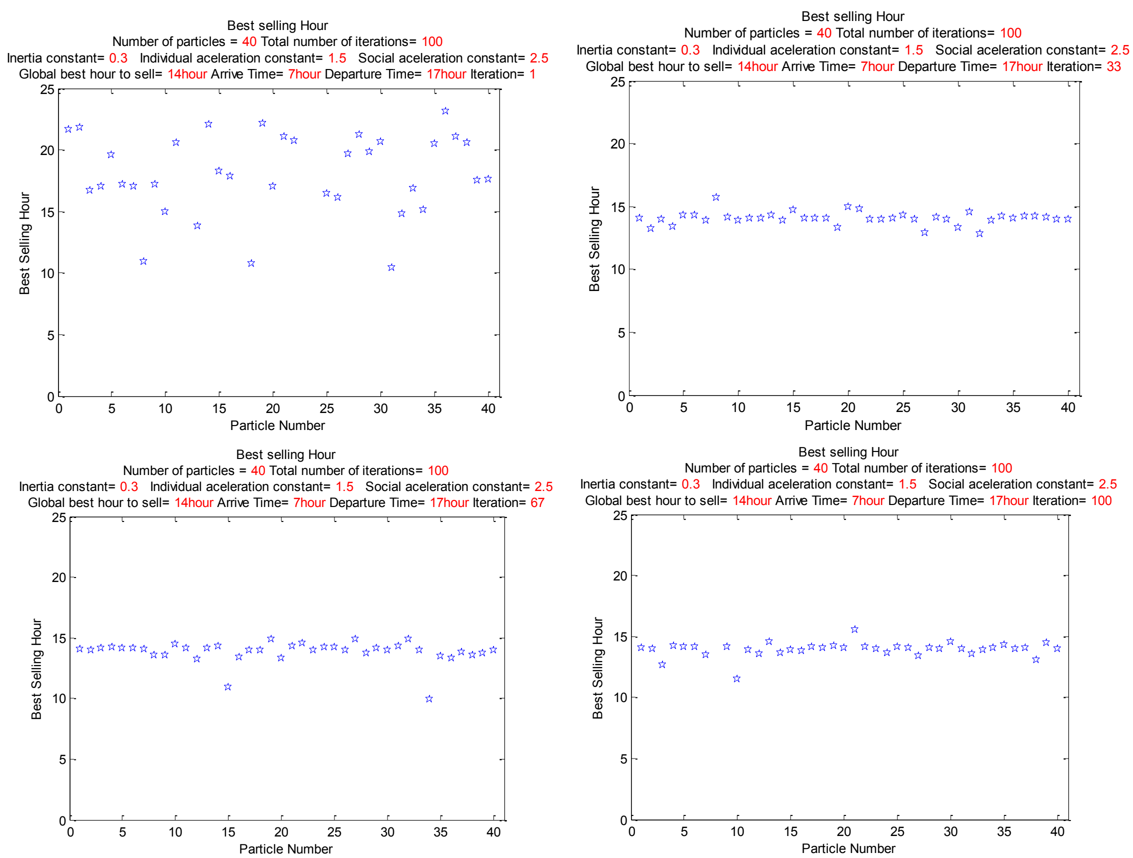


Figure 5.19: Positions of the particles for different times

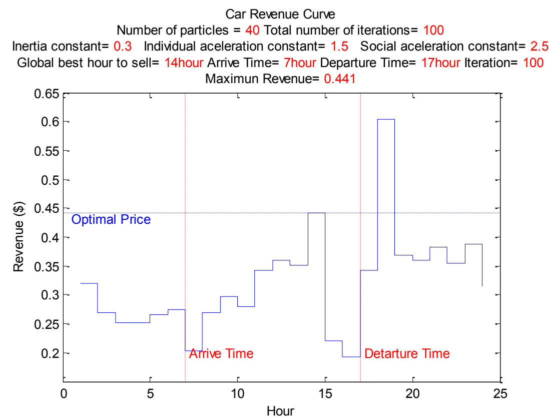


Figure 5.20: Car Revenue Curve vs Number of Hours

5.4.2 Results with inertia = 1.5, individual acceleration constant = 1.5, social acceleration constant=2.5, number of particles = 40, number of iterations=100.

In this case the inertia constant was increased to 1.5. Figure 5.21 shows the position of the particles for different times, where it is possible to see that the initial random values converge to 14. Figure 5.22 shows the revenue vs number of hours. It is possible to see that there are more oscillations than the previous case. Therefore it is possible to conclude that if the inertia weight is big the search is expanded, this means that the mode is basically explorative.

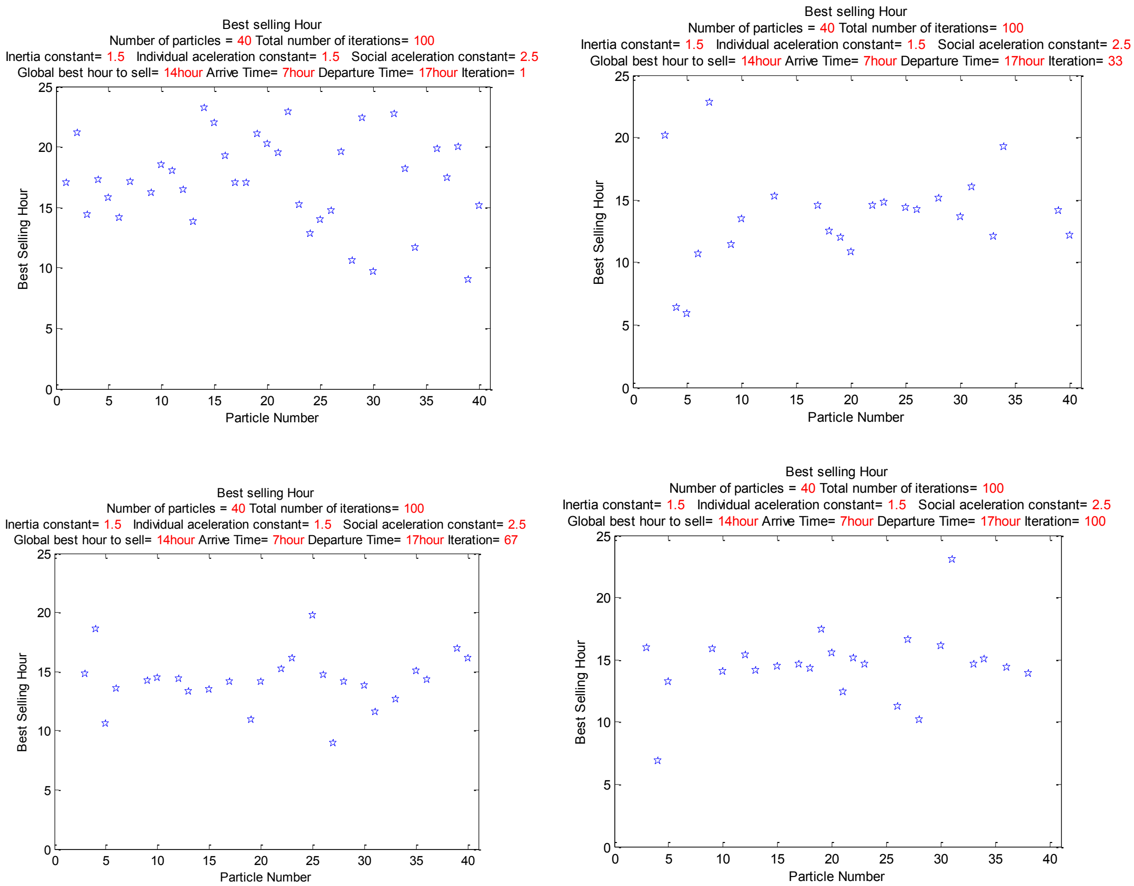


Figure 5.21: Positions of the particles for different times

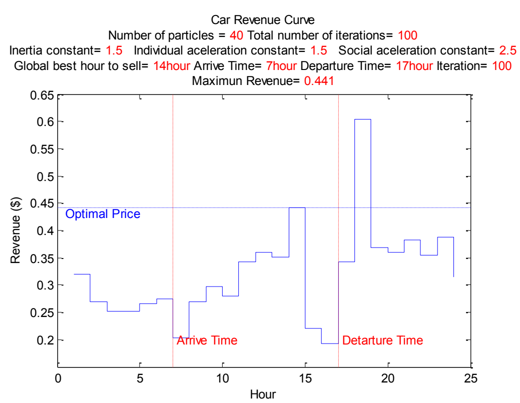


Figure 5.22: Car Revenue Curve vs Number of Hours

Table 5.1
PSO parameters

Parameter	Tested Values	Best Values
Number of particles	{10, 20, 40}	40
Number of Iterations	{10, 50, 100}	100
Inertia weight	0.3, 1, 1.5	1
Individual acceleration constant	{0.1, 1.5, 2.5,4}	1.5
Social acceleration constant	{0.1, 2.5,4}	2.5
Optimal Hour to sell (arrive time =7, departure time=17)		14
Maximun Revenue		0.44 $

Table 5.1 shows the Best Values determined for the PSO parameters. The results show that better results are achieved if a bigger number of iterations is used. However this increases the amount of computation. Also, increasing the number of particles makes the PSO converge faster. However, the results show that when a very big number of particles is used, there are more oscillations of the particles around the optimal value. If small numbers are used for both acceleration constants then the solutions oscillate around the optimal value. On the other side, if the acceleration constants are too big then the PSO diverges. In fact, for different sets of acceleration constant it was possible to find that the results diverge if the addition of the acceleration constants is greater than 4. This corresponds to general results where it is stated that the trajectory goes to infinity for values of acceleration constants whose addition is greater than 4.0. In the case where each particle was selected to have two variables when a small individual acceleration was selected, the solutions converged faster. In this case, the minimum of the function is also a global minimum. However when a small social acceleration constant was selected, the solutions oscillated and the solutions hardly converged.

A higher value of inertia constant allows the particles to move freely in order to find the global optimum neighborhood. On the other side, when a small inertia constant was used (0.1) the search was narrowed and therefore the mode was exploitative which actually made the convergence to be faster. Therefore it is possible to conclude that if the inertia weight is small the search is narrowed, this means that the mode is basically exploitative and if the inertia weight is big the search is expanded, this means that the mode is basically explorative. In general the performance of the PSO with one-variable particles was better in terms of convergence.

The proposed PSO algorithm to determining buying and selling times throughout a day successfully found very profitable solutions.

5.4 Graphical user Interphase

Particle swarm optimization (PSO) results are shown in Figure 5.23. It is possible to see that the optimal hour is determined correctly according to the user preferences.

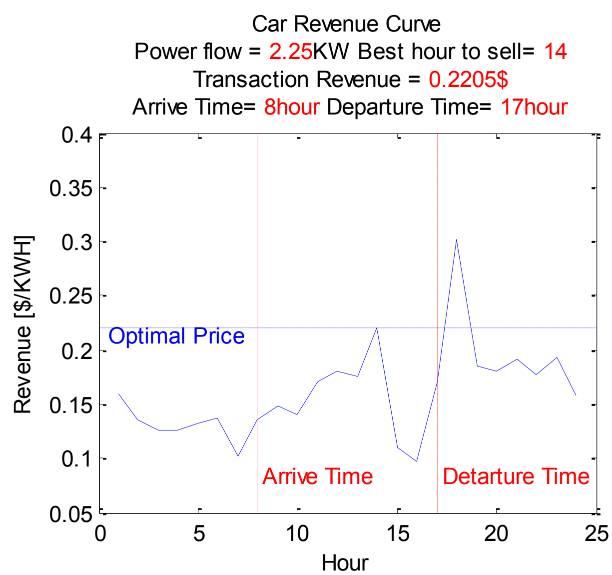


Figure 5.23: Car Revenue Curve

The system User Interface is shown in Figure 5.24 It is constituted by the transaction preview section, the controls section and the function selection section. The different EV-IEMS functions allow to: start the frequency communication session; accept the transaction; estimate the system state and overview the behavior of a parking lot.

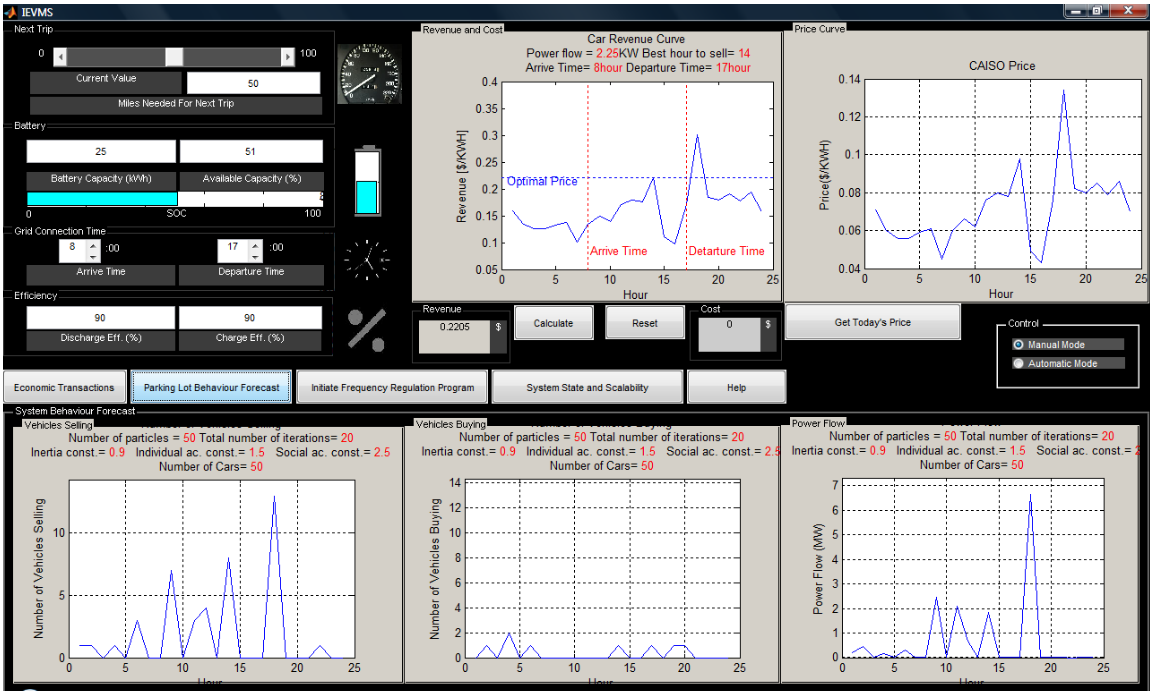


Figure 5.24: EV-IEMS Graphical User Interphase

While the purpose of this thesis has not been to evaluate the performance of a specific computer–intelligence algorithm related to Electric Vehicle Management Systems, some "best" PSO parameters for finding the optimal time to sell/buy electricity using Particle Swarm optimization have been recommended. The objective has been to offer a perspective about the integration of different resources that could advance the implementation of Vehicle-to-Grid programs for frequency regulation applications based on the prosumer architecture. The topic of Intelligent Energy Management System and Genetic algorithm has been addressed in prior literature. For details about other optimization algorithms and comparisons, the reader is referred to [11].

CHAPTER 6

CONCLUSIONS

An electric vehicle intelligent energy management system for frequency regulation application has been proposed. The system is designed based on the prosumer-architecture that allows implementing the scheme as a one-level interaction between the utility and the PEV owner.

Based on the owner preferences about next trip mileage, the system is able to automate the energy management of the battery pack. Also the system uses particle swarm optimization to create economic benefit by powering the grid during peak times and shifting charging to off-peak hours.

The results show that the prosumer based architecture provides the adequate framework to address this difficult distributed control problem.

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VITA

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SANDOVAL was born in Quito, Ecuador. He graduated as the best student in Sebastian de Benalcazar High School and won the third place in the Albert Einstein National Physics Competition in Ecuador which granted him the Maxwell Scholarship at Universidad San Francisco de Quito. He graduated as Magna Cum Laude in Electrical Engineering from Universidad San Francisco de Quito, Quito, Ecuador in 2010. Before coming to Georgia Tech as Fulbright Scholar to pursue a Master of Science in Electrical and Computer Engineering, he worked as a research assistant and laboratory instructor in Universidad San Francisco de Quito (2010) and as a research engineer at ABB Corporate Research Center in Krakow, Poland (2011). He also participated in internships at the Solar Business Division of Eaton Corporation (2012), the Control Research Group at Queen's University of Belfast (2009) and in The Advanced Power Applications Laboratory at the University of Illinois at Urbana Champaign (2008). He has been offered a Controls Internship in Intel Corporation (2013). Currently, he is a PhD student completing his fourth semester in the School of Electrical and Computer Engineering, and is an active member of the Advanced Computational Electricity Systems (ACES) Laboratory. His current research interests lie at the interface of power systems theory and control theory, with special emphasis on sustainable and renewable energy systems. When he is not working on his research, Mr. Sandoval enjoys the small things that give life meaning like learning new things, reading, dancing, traveling, painting, and trying to make this a better world.