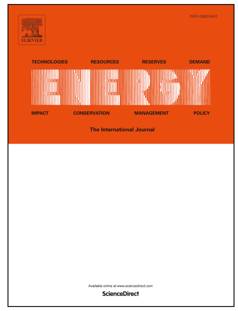

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An optimal versatile control approach for plug-in electric vehicles to integrate renewable energy sources and smart grids

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Highlights:

- Optimization problems are solved to size and site smart parking lots of electric vehicles.
- The effectiveness of the proposed algorithm is compared to other reported algorithms.
- An adaptive intelligent control strategy with V2G and G2V applicability is proposed.
- A global optimal solution is guaranteed with the proposed model.

Abstract

This study proposes a practical solution to deal with challenges of integrating renewable energy sources and electric vehicles into the electric grid, considering generation source intermittency and energy usage inconsistency, via a new adaptive intelligent controller. The present research describes a smart grid consisting of power plants and distributed generation, fueled via photovoltaic panels and wind turbines, and augmented with electric vehicles as power storage devices. Employing a parking lot to deal with challenges such as low penetration of the electric vehicles embedded with Vehicle-to-Grid functionalities encounters two difficulties: where they should be installed, and modeling of bi-directional power flow between electric vehicles, the grid, and the distributed generation system. In this regard, a nonlinear multi-objective problem is designed and solved via employing the Non-dominated Sorting Genetic Algorithm-II, and the forward and backward substitution method. In addition, Newton-Raphson Power Flow is adopted and modified to calculate the power flow of the distribution network. The results related to optimal placement and sizing of hybrid renewable energy systems show that bus 16 of the studied grid is the best place to integrate a parking lot – equipped with 117 photovoltaic and 10 wind turbine units - to the tested IEEE-26 buses. Furthermore, this study suggests that the aforementioned grid could employ a complex versatile control unit able to

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optimize the operating point, scheduling charging and discharging for a large number of electric vehicles while considering the technical aspects (total active power loss and voltage deviation). In this regard, a new hybrid control approach based on Particle Swarm Optimization-Adaptive Neuro-Fuzzy Inference System tuned via utilizing the optimal power flow problem is proposed. The controller's superiority to handle grid-to-vehicle and vehicle-to-grid services is discussed and compared to other studies.

Keywords: *Smart Grid; Electric Vehicle; Renewable energy sources; Distributed Generation; PSO-ANFIS controller;*

Acronyms

ANN	Artificial neural network	O&M	Operation and maintenance
ANFIS	Adaptive Neuro-Fuzzy Inference	PHEV	Plug-in Hybrid Electric Vehicle
ADN	Active distributed network	PSO	Particle Swarm Optimization
BEV	Battery Electric Vehicle	PS	Power system
DG	Distributed Generation	PV	Photovoltaic
DR	Demand response	PQ	Real and reactive power injections are fixed
ESS	Energy storage system	PV_b	Real power and voltage magnitude are fixed
EV	Electric vehicle	RG	Renewable generation
G2V	Grid-to-vehicle	RES	Renewable energy system
GV	Grid vehicle	SVD	Summation of voltage deviation
GHG	Greenhouse gas	SG	Smart Grid
HRES	Hybrid Renewable Energy System	SoC	State of charge
NN	Neural network	V2G	Vehicle-to-grid
OPF	Optimal power flow	WT	Wind turbine
OF	Objective function		

Nomenclature

P_{Loss}	Active power loss	$P_{DG,i}^{\min}$	Minimum power out of DG
$P_{DG-i,k}$	Active power of *i*th DG unit at kth time period	$P_{DG,i}^{\max}$	Maximum power out of DG
C_1 , C_2	Acceleration factor	R_{ij} , Z_{ij}	Resistance of line

τ	Average capacity coefficient	$C_{O\&M-i}$	Maintenance cost of ith DG unit
$P_{disch,t}$	Discharge power	n	Operational life of *i*th DG unit
$P_{ch,t}$	Charge power	δ_{ij}, δ_i, δ_j	Phase angles
$g_i(u,x)$	Equality constraints	Q_0	Population of offspring
r	Fixed annual interest rate	$V_i^{k,spec}$	Specified voltage magnitude
$h_i(u,x)$	Inequality constraints	f_1	Summation of voltage deviation objective
P_{I-i}	installation cost of *i*th DG unit	X	State variables
C_{I-i}	investment cost of ith DG	N_h	Total simulation hours
ij	Index of buses	f_2	Total active power loss objective
k	Index of time	f_3	Total annual investment and operation cost objective
$P_{Grid.t}$	Grid power at time *t*	$P_{PV,t}$	Total PV power
t_k	*k*th time segment	$P_{Wind,t}$	Total wind power
m	Number of DG units of a type	N_{DG}	Total number of DG units
N	Number of buses	V_i^k	Voltage magnitude
N_{DG}	Number of DG units	u, v	Vectors of control variables
$V_i^{k,\max}$	Maximum voltage limitation	$x_{1,t}, x_{N_{vehicles},t}$	Decision variables
$V_i^{k,\min}$	Minimum voltage limitation		

1. Introduction

Recent studies indicate that the world's energy demand will increase by 56% from 2010 to 2040 [1], with an expected increase in carbon dioxide annual emissions from 31.2 to 45.5 billion metric tons. Meanwhile, the energy market is confronted with greater challenges such as diminishing reserves of fossil fuels, lack of energy security, and economic and urbanization growth [2]. The existing circumstances and the future gap between energy demand and supply, as well as greenhouse gas emissions, compel scientists to follow two strategies, among others: substitution of using renewable energy sources for fossil-based power generating units, and improving energy efficiency [3]. The electrical power generation industry and the transportation sector – which were responsible for almost 27% of total energy consumption [4] and 33.7% of greenhouse gas (GHG) emissions in 2012 – are still excessively reliant on fossil fuels [5]. These concerns and the proliferation of electric vehicles (EVs) in recent years have led engineers to provide solution to challenges with EVs and create opportunities to the power industry. The former is undergoing a transformation from traditional power systems (PSs) to Smart Grids (SGs). Regarding increasing energy efficiency, efforts are concerned with the overall process of electricity production and use, from power plants to final users. Note that location and availability of energy resources, as well as having low cost and/or being renewable, play a prominent role in augmentation of energy efficiency. When concern is focused on electricity processes, aspects of efficiency to be accounted for include those related to generation, utilization and transmission; efforts include the introduction of highly efficient generators, motors, and drives to reduce losses [6].

A significant proportion of losses in electrical power systems (distribution, transmission and generation) is associated with the distribution system, where approximately 13% of the total power produced is lost [7]. Consequently, power loss reduction in the distribution section has been an important goal for researchers and engineers. A high proportion of the losses in the distribution section can be mitigated through the use of distributed generation (DG) units, which typically are small generators. Furthermore, EVs not only act as a load in the system of grid-to-vehicle (G2V), but also as a storage in the system of vehicle-to-grid (V2G); vehicles are parked roughly 95% of the time [8], allowing them to be used to feed PSs using their batteries. EVs and renewable energy systems (RESs) are categorized as distributed power storage and generation units to support the grid [9]. However, EVs and RESs face a number of difficulties; when the former are fed with the latter with poor regulation, the distribution infrastructure may be undermined and subject to severe stresses. This adversely affects power quality on a local scale and degrades system efficiency, especially when combined with the fact that power generation from RESs is directly linked to climatic and weather conditions. In this regard, integration of electric vehicles and RESs in power systems is an effective method to achieve peak shaving, voltage regulation, frequency regulation, load leveling, and other ancillary services [10]. But successful integration of RESs and EVs with PSs is unlikely without a more controllable system having good coordination of EVs (G2V, V2G), RESs and PSs relying on bi-directional smart grid communication infrastructure, which has the ability to handle the information that must be exchanged among different entities.

1.1. Literature review

In power systems, an effective mechanism for achieving energy efficiency is demand response (DR), in which demand for electricity is managed in response to severe times (e.g., when load exceeds generation, often during peak demand periods) or to market price in a smart grid environment. Progressive communication infrastructure provides two ways (power line communications and wireless sensor networks) for information on energy supply and demand to be used to enhance the DR capabilities of entire power systems. Indeed, employing communication techniques is the main purpose of introducing more intelligence in control for distributing electric energy from supplies to consumers. As addressed in [11], the backbone of a smart grid accentuates environmental protection, by using variable generation types (such as wind and solar), demand response, and distributed generation encompassing EV technology, in order to achieve better asset utilization while maintaining reliable system operation and recognizing the need for enhanced customer choice. Fig. 1 depicts these factors in relation to the new emerging smart grid paradigm, and illustrates the role of EV technology in the new era.

Figure 1. EVs in relation to the new emerging smart grids [11]

To explore the main technological challenges and to identify beneficial opportunities, Yu et al. [12] explored the main concepts of smart grids and concluded that advantages from those systems can be only attained in presence of integrated systems rather than standalone ones. The optimal integration of energy storage systems into the grid can offers opportunities for demand side management, load shifting, peak shaving and reducing power losses. Shaaban et al. [13] performed a multi-objective optimal sitting and sizing of renewable energy systems for a 33-bus grid by identifying optimal buses for installing renewable distributed generation; this was done to maximize the savings through allowing system upgrade investment deferrals, and reducing costs of annual energy losses and interruptions. Feruzzi et al. [14] examined a demand side management optimization technique and performed a sensitivity analysis for a micro-grid including a photovoltaic plant. They demonstrated the effectiveness of shifting the load from high energy price hours to low energy price hours and its economic benefits. EVs can not only contribute as energy storage systems for smart grids using vehicles integrated to grid infrastructures in support of appropriate demand response programs, but also can be used to overcome the vagaries of generation caused by inherent uncertainties of renewable energy. In this regard, Vasirani et al. [15] evaluated an agent-based approach to take the advantage of using EVs as storage systems to increase the profit and reliability of intermittent wind energy and also scheduling the supply to grid and storage in EVs via linear-programming. Integration of EVs into the grid requires appropriate management and control of EVs charging/discharging times, considering driving needs and simultaneous support of power services simultaneously [16]. By including vehicle-to-grid capability as an energy storage management technique, López et al. [17] utilized an optimization-based model in a smart grid environment for load shifting purposes. The study was performed on a 27-bus IEEE distribution grid considering load curve, mobility requirements of EVs, and hourly process configurations to allocate the demand more efficiently. Moreover, they reported that large fleets of EVs should be considered for attaining significant improvements in peak shaving and load flattening.

Sovacool and Hirsh [18] investigated the socio-technical barriers of transitioning to PHEVs and V2G systems, and focused on the technological, cultural, social, and political challenges. These need to be addressed to benefit from the services and revenues of such systems. Sovacool and Hirsh identified control strategies and battery improvements for widespread utilization of PHEVs and V2G technologies. Graditi et al. [19] investigated the economic viability of utilizing battery energy storage systems for load shifting at a consumer level for specific electricity tariffs, and suggested such systems as future competitive technologies. Graditi et al. stated that techno-economic analyses of such systems when integrated with renewable energy systems are merited. In an overview of battery management systems and their significance, Rahimi-Eichi [20] evaluated opportunities, needs and challenges of integrating renewable energy, smart grids and EVs via focusing on power delivery, lifetime, cost, reliability and SoC. They noted that SoC estimation techniques are an essential aspect, which needs research and development for satisfying the standards for smart grid and EV applications. In an optimization study, Silvestre et al. [21] considered the initial SoC and load consumption profile of EVs to minimize the power losses and energy costs via smart charging. It was noted that a majority of PEVs utilize lithium ion (Li-ion) batteries because of the environmental advantages, light weight, longer life span, and higher energy density [22]. Omar et al. [23] demonstrated that the energy efficiency of lithium-ion batteries is far superior to other rechargeable energy storage types, based on tests of dynamic discharging performance. Moreover, they showed that the performance of Li-ion batteries is highly dependent on temperature and depth of discharge [24]. In addition, it was indicated that the life cycle is reduced for higher charge current rate cases, and suggested that Li-ion batteries should not be subject to high charging rates.

Identifying the proper technical features and predicting realistic system behavior are required to control large scale deployment of V2G systems. Arrival and departure times, charging period and charging rates are significant aspects that should be managed and controlled for successful coordination of PHEVs, PS and HRESs in smart grids. To evaluate the potential challenges of smart grids, Waraich et al. [25] used an EV demand model combined with a power system simulation to examine the potential challenges and capacity of the network for particular penetration of EVs. Waraich et al. considered charging schemes and charging periods of the vehicles in various scenarios. Haidar et al. [26] reviewed technical challenges of grid-integrated electric vehicles and demonstrated that vehicle penetration, charging time, charging characteristics, driving patterns and transportation network are significant system-dependent factors for future practical utilization of grid-integrated electric vehicle systems. Little research has been reported on control aspects of EVs, PSs and RESs. To introduce a smart EV charging method for smart residences and buildings, an EV charging algorithm is proposed to determine the optimal schedules of EV charging based on anticipated RES output and electric consumption [27]. The results demonstrate the effectiveness of the proposed smart EV charging model. Similarly, intelligent workplace parking is proposed for EVs in [28] involving a smart power charging controller. Based on power requirements, a fuzzy logic power flow controller is designed in which charging rates are dependent on the predicted power generation of the PV output. The impacts of EV charging processes on the grid are compared with and without the developed smart charging technique. Researchers have analyzed the application of V2G systems as a power system regulator by utilizing aggregated EVs as a battery storage model in load frequency control simulations [29]. The model is applied for power system regulation for typical days with high and low wind energy in Denmark. The influence of EVs on PSs and their capabilities have been examined by using load flow technique [30]. However, previous work has not used smart control techniques to investigate charging or discharging of EVs energy in interaction with the grid. ANN and ANFIS controllers have been employed for examining the performance of those methods [31]. The results show that the controllers exhibit similar settling times but there is difference in the power allowed by the controller to the flow between the PSs and EVs. Moreover, as addressed in [32], two controllers based on fuzzy systems have been designed, one controlling the G2V concept of EVs and the other designed based on the V2G concept. In addition, controllers were tuned via knowledge and intuition of experts and the parameters associated with membership functions.

1.2. Motivation, objectives, and innovative contribution

The main attributes of an optimum on-grid renewable-powered parking lot can be categorized as follows:

- It is placed in an appropriate site in order to minimize the total active power loss as a distributed generation resource, and the summation of voltage deviation. It is grid-friendly and enhances power quality.
- It is a decentralized resource, and is integrated into an optimized renewable energy system. It is cost-effective and considers sustainable development.

Furthermore, the key attributes of PSO-ANFIS controller can be categorized as follows:

- It controls power flow and optimizes the system stability in PSs.
- It has a significant impact on the performance of unified power flow between components.

A precise estimation of the SoC is needed to determine the energy content of the battery and to prevent damage associated with excessive depth of discharge. In this study, the inputs of the proposed controller are designed using direct and indirect information regarding both grid and battery characteristics. Voltage deviations are defined as indirect signals and charging rates are defined as indirect signals. Also, SoC, which represents the percentage of the remaining capacity or energy of the battery, is introduced as a direct signal for all individual vehicles, to prevent batteries from excessive discharge. Throughout the analysis, battery chargers are assumed to be off-board.

Via considering the literature and looking into functionalities of conventional EV charging controllers, Table 1 presents that the previously used controllers have limited functionality, do not provide a simultaneous smart control to: a) meet user's needs in terms of satisfactory charging time and energy content, b) support active network operation, and c) prolong EV battery life compared to the objectives of the present study. Along this line and to cover the previously mentioned gaps, the present article proposes a new adaptive controller which not only is capable of overcoming the challenges of voltage profile regulation, but also considers reduction of charging cycle, discharging cycle and power loss.

Table 1. The capability of proposed control in comparison with other studies

Controller	**Objectives**		
	Network support	**User's requirements**	**Battery life extension**
Standard EV charger	-	✓	-
Centralized aggregator [32, 33]	Partially (not in real-time)	✓	-
Decentralized controller [34]	✓	-	-
Centralized control [35]	-	✓	-
Proposed centralized control	(Totally real-time)	✓	✓

This paper, by proposing two strategies, extends our previous work [4] to address the aforementioned problems. The first strategy is associated with an optimal power flow, which provides useful information on the tradeoff between energy demand such as load demand and G2V processes, and energy generation such as grid, DG, and V2G processes. The second strategy is to build a highly-sensitive controller by observing the voltage profile and power loss fluctuation. The main objectives of this paper are as follows:

- To determine appropriate locations of smart parking lots and sizing of hybrid renewable energy systems (HRESs) through reducing total active power losses and enhancing grid characteristics such as voltage profile, via an evolutionary algorithm.

- To introduce a new intelligent operation, based on a hybrid PSO-ANFIS, by optimizing the process of grid to vehicles, vehicles to grid consisting of hybrid renewable energy systems, and power systems.

2. Optimal siting and sizing of DG; formulation, constraints and algorithm

As mentioned earlier, the present study desires to perform a multi-objective optimal sizing and siting of smart parking lots in a power distribution network in order to develop an active distributed network (ADN). In this regard, different criteria are considered in the optimization process including voltage deviation, total active power loss and annual operation and maintenance (O&M) costs of DG. The first and second optimization objectives are to decrease the system voltage deviation and power losses. The third objective is to minimize the annual O&M cost of DG. These three objectives involve different perspectives based on DG power utilities and owners. For instance, adding more DGs to the distribution system can decrease power losses, but it increases the voltage variation and O&M cost.

2.1. Time sequence characteristic of load and DG

To consider the required regulation in different seasons of the year, time-dependent load curves on an hourly basis are considered for each season (see Fig. 2) in the present study.

Due to the fact that the output of photovoltaic (PV) or wind turbine (WT) electrical generators are significantly affected by geographical location and available natural wind and solar energy sources, the assumption of constant DG outputs in all seasons is far from being realistic. Hence, the average DG output capacity of 24 time periods in one day of each season is employed, and different types of DG considering PV and WT power generation are considered in this paper. Fig. 3 and Fig. 4 present one-year solar irradiation and wind velocity data for Tehran, Iran, obtained from Iran National Meteorological Organization. These data are utilized for the purpose of the present study.

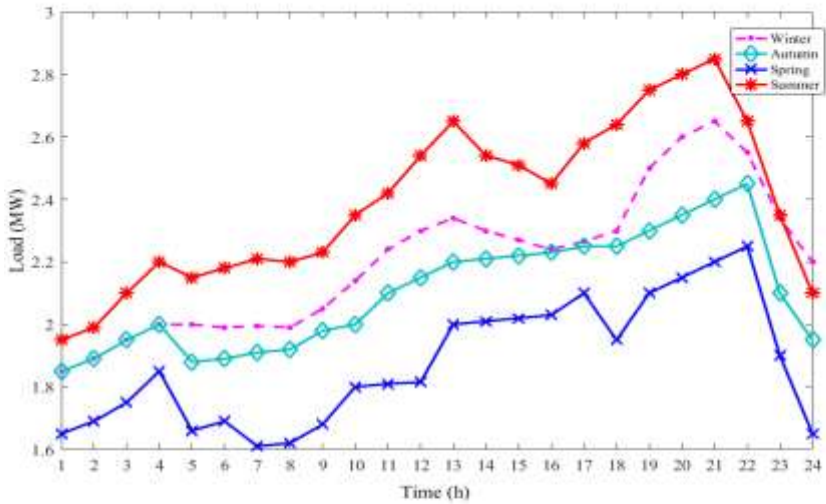

Figure 2. Time sequence characteristic curves of seasonal load types

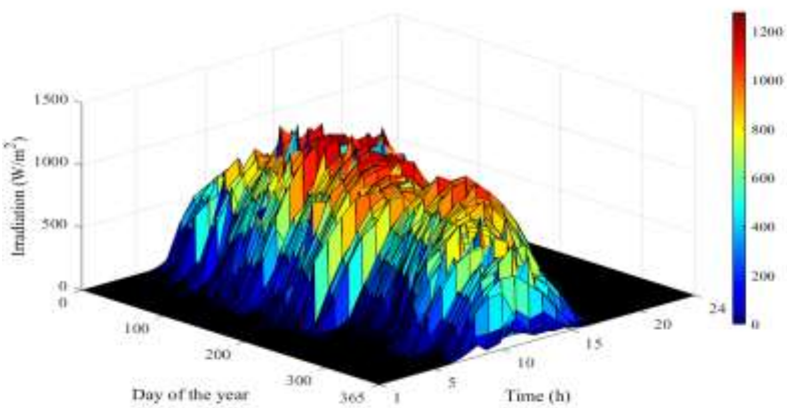

Figure 3. Hourly breakdown of annual solar radiation received on horizontal surface in Tehran, Iran

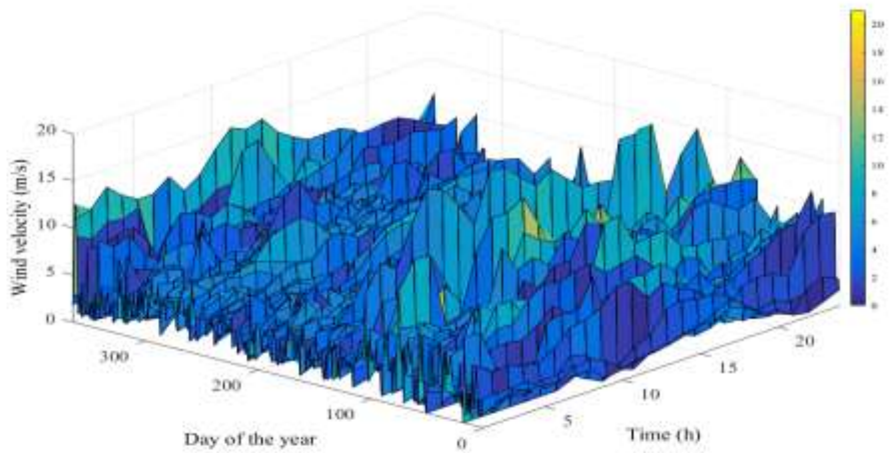

Figure 4. Hourly breakdown of annual wind velocity data for Tehran, Iran

2.2. Minimization of voltage deviation

The first objective is to minimize the voltage deviation between the nodal voltage and the specified voltage magnitude. The nodal voltage magnitude is a significant indicator for assessing power quality and system security. Lowering the voltage deviation can help provide a superior voltage level in the distribution system. This objective can be expressed as follows:

$$\min \ f_1(x) = \min \sum_{k=1}^{N_h} \left[\sum_{i=0}^{N} \left(\frac{V_i^k - V_i^{k,spec}}{V_i^{k,\max} - V_i^{k,\min}} \right)^2 \right] \tag{1}$$

where N_h, N, V_i^k and $V_i^{k,spec}$ are the total hours, the number of buses, the voltage magnitude at the *i*th bus of the *k*th time period and the specified voltage magnitude, respectively, while $V_i^{k,\max}$ and $V_i^{k,\min}$ are the upper and lower limits at the *i*th bus, respectively. The total hours N_h is equal to 24 h.

2.3. Minimize power losses

Power losses depend on two factors: current and line resistance. Line resistance is negligibly low [36]. Thus, the line loss is linked to the current, and the current line is related to the system topology and the loads. Note that decreasing the value of load demand, which is a function of time, is not feasible. Nevertheless, line currents can be reduced with proper placement of DGs. The total active power loss can be expressed as follows:

$$\min\ f_2(x) = \min \sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} R_{ij} \left(\frac{|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos\delta_{ij}}{|Z_{ij}|^2} \right) \tag{2}$$

Here, $P_{Loss}, R_{ij}, Z_{ij}, |V_i|$ and δ_{ij} are the total network active power loss, the resistance of the line between the nodes *i* and *j*, the voltage magnitude and difference between δ_i and δ_j which are the angles at bus *i* and *j*, respectively.

2.4. Minimize annual investment and operation cost

For HRESs, there are no significant pollutant emissions in power generation due to the use of renewable energy. In order to consider the time sequence characteristic of DG, working scenarios at various time periods are calculated. Assuming the DG power output in each time segment remains constant, the annual O&M cost can be determined as follows [36]:

$$\min\ f_3(x) = \min \sum_{i=1}^{N_{DG}} \left((C_{I-i} + C_{O\&M-i}) \sum_{k=1}^{N_h} P_{DG-i,k} t_k \right) \tag{3}$$

where $N_{DG}, C_{I-i}, C_{O\&M-i}, P_{DG-i,k}$ and t_k are the number of DG units, the investment cost, the maintenance cost of the *i*th DG unit, the active power of the *i*th DG unit at the *k*th time period and the duration of the *k*th time segment, which is set to 1 hour in this study. Again, N_h is equal to 24 hours.

The investment cost C_{I-i} is calculated as follows:

$$C_{I-i} = \frac{r(1+r)}{(1+n)-1} \times \frac{P_{I-i}}{N_h \times \tau} \tag{4}$$

where n, τ and r are the operational life of the *i*th DG unit, the average capacity coefficient, which is equals to the annual power production by the rated power in one year, and the fixed annual interest rate, respectively. Also, P_{I-i} is the installation cost of *i*th DG unit.

2.5. Constraints

In the optimization model, three constraints are considered relating to power flow, DG capacity, and nodal voltage.

(1) Power flow equation: when "Smart Parking" for electric vehicles is treated as a load, the backward and forward substitution method is adopted to calculate the power flow of the distribution network. But when they are treated as a power supply, the Newton-Raphson power flow calculation is employed, which is appropriate for power flow calculations in a multi-power-source network [37]. That is,

$$P_{PV,t}+P_{Wind,t}+P_{Grid.t}+P_{disch,t}-P_{ch,t}-\sum_{i=1}^{N}\sum_{\substack{j=1\\ i\neq j}}^{N}R_{ij}\left(\frac{\left|V_{i,t}\right|^2+\left|V_{j,t}\right|^2-2\left|V_{i,t}\right|\left|V_{j,t}\right|\cos\delta_{ij,t}}{\left|Z_{ij}\right|^2}\right)-P_{Load,t}=0 \tag{5}$$

where $P_{PV,t}, P_{Wind,t}$ and $P_{Grid.t}$ are the powers obtained from PVs, wind units and the main grid, respectively, at time *t*, while $P_{disch,t}$ and $P_{ch,t}$ are the EV batteries charge power and discharge power, respectively, at time *t*. Note that $P_{disch,t}$ and $P_{ch,t}$ are calculated based on the initial SoC, presented in Appendix A, and using data on the arrival and departure times of the electric vehicles.

(2) Generation limits: The following generation limits apply:

$$P_{DGi}^{\min}\le P_{DGi}\le P_{DGi}^{\max} \tag{6}$$

(3) Load bus voltage constraints: The load bus voltage is constrained as follows:

$$V_i^{\min}\le V_i\le V_i^{\max} \tag{7}$$

In the above two inequality constraints, $P_{DG,i}^{\min}$ and $P_{DG,i}^{\max}$ denote the minimum and the maximum power generation levels from DG *i*, $V_i^{\min}$ and $V_i^{\max}$ are the minimum and maximum voltages of bus *i*.

2.6. Overview of optimal sizing and siting formulation

The present model is developed considering minimal setup and maintenance costs for the PVs and wind turbines, and minimal total active power losses and voltage deviations. Integrating the objectives and constraints, the problem can be considered as a nonlinear multi-objective problem, and formulated as follows:

$$\begin{aligned}&\text{Minimize:} && f(x,u)=(f_1(x,u),\ldots,f_3(x,u)) &&\\ &\text{Subject to:} && g_i(u,x)=0 && i=1,\ldots,n_{eq}\end{aligned} \tag{8}$$

$$h_i(u,x) \leq 0 \qquad\qquad i = 1,\ldots,n_{ineq}$$

Here n_{eq} and n_{inqe} denote the number of equality constraints and inequality constraints, respectively, u is the vector, which contains the control variables, and x is the vector of the state variables. The assumption in this section is that DG can be considered as a PQ bus and includes a constant power factor. The controlling variables consist of type, sizing, and placement of DG units.

To have a realistic situation for DG integration, the unit capacity of the PV and WT units are 15 kW and 250 kW, respectively. Therefore, the total solar power and wind power generation coordinated with distribution network (DN) is $m_{PV}\times15$ kW or $m_{WT}\times250$ kW depending on the type of DG, where m denotes the number of DG units of a type. Integer coding is applied for the encoding the scheme, which is depicted as follows:

$$u = [Char_{DG_1}, PLC_{DG_1}, m_{DG_1}, \ldots, Char_{DG_{N-DG}}, PLC_{DG_{N-DG}}, m_{DG_{N-DG}}] \tag{9}$$

Here, $Char_{DG}$, PLC_{DG}, m_{DG}, and M-DG respectively denote the type, the location, the number of units of each DG unit and the maximum number of DG units, which are integrated into the distribution system.

2.7. NSGA-II algorithm

The NSGA-II, which evolved from Non-dominated Sorting Genetic Algorithm-II NSGA [38], is one of the first evolutionary algorithms and is used for optimal sizing and siting of the HRES in the present study. NGSA-II performs well and has proven useful for application in energy contexts. Recent applications in terms of electrical energy include the reconfiguration of a smart grid [39], the sizing of DG in a distribution system [36] and the optimization of the control of a doubly-fed induction generator for systems of wind energy [40]. The algorithm applies a fast non-dominating sorting procedure to find the optimal solution based on Pareto dominance [41]. The Pareto-optimal decision vectors create a Pareto-optimal front in the search region (or feasible area). Like other population-based algorithms, NSGA-II is initiated with the random generation of parent individuals, P_0, of latent solutions. The size of the parent population is N and it is controlled for domination of the Pareto and fitness values matching with a non-domination step allocated to every solution. Then, the algorithm applies the fitness value for ranking and assigning solutions to the varied fronts (i.e., each solution is related to varied fronts according to the domination level). The first front includes the solutions dominating the others.

The population of offspring, which is called Q_0 and whose size is as large as the parent's population, is produced according to tournament selection and mutation.

After producing the first generation, the method proceeds to combining the present population with the determined non-dominated solution. The entire method for the j_{th} generation is as follows:

1. parents and offspring populations are combined to produce R_j of size 2N;
2. non-dominated sorting for R_j is applied to determine the varied fronts F_i;
3. solutions of $(F_1,\ldots,F_n)$ are chosen to produce P_{j+1} of size N;
4. tournament selection is applied according to crossover, crowding-comparison, and mutation for P_{j+1} to produce Q_{j+1} of size N, and;
5. the aforementioned steps are repeated until the convergence conditions are satisfied.

To clarify, the flow chart of Fig. 5 illustrates the entire method.

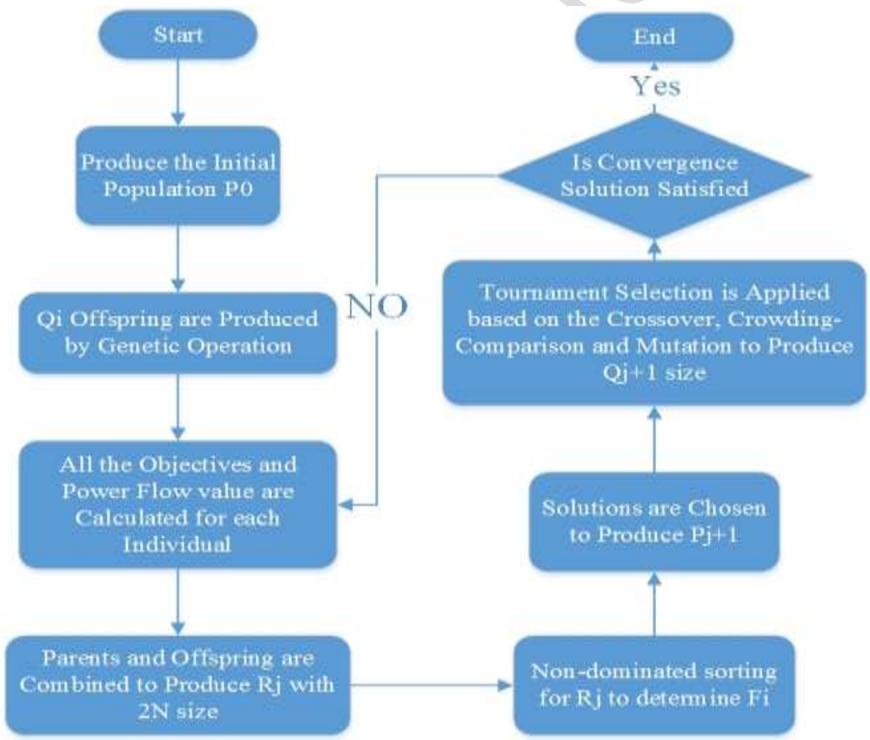

Figure 5. Flow chart of NSGA-II solving process.

3. Adaptive control; formulation, constraints and algorithm

Without properly controlling the supply and demand, it is difficult to achieve the desired task for the PSs, due to the inability of a conventional controller such as PID or PI types under a wide range of operations. Providing optimal coordination between EVs, PSs and HRESs requires a new controller that can conform to the ideal situation in which the grid can be stable and power losses can be reduced. In this regard, an adaptive charging and discharging controller is described in this section, along with its formulations, algorithms and constraints.

3.1. Constraints and formulation of optimal charging and discharging control

As mentioned earlier, no less than 90% of the cars are parked during the day, providing an opportunity to shift the electricity consumption from EV to times with lower demand, referred to as G2V. This situation may also be employed for injecting power to the grid in order to flatten the peak demand and to help regulate the grid frequency, referred to as V2G operation. It is important to take into account energy requirements, which battery electric vehicle (BEV) owners should meet, and which can be implemented in several ways by limiting the energy allowed for use in V2G operation. In this way, it is guaranteed that the battery will not be completely depleted. Nevertheless, based on the assumption for the BEV in this study, the missing energy in the V2G condition could prevent the owners from making a trip, which is clearly not desirable. Further, it has been demonstrated that the average distance traveled per day is approximately 40 km, which typically requires 8 kWh of electricity; this can be provided in 200 min at a rate of 2.4 kW [42]. Therefore, it is assumed that vehicles are not allowed to discharge to less than 8 kWh, which is defined as "deep discharge" in this article. Providing exactly the same amount of power to each (plug-in) electric vehicle is the most obvious and simple way to share the available active power among EVs. Being adapted in a domestic charging scenario, it may be too complex and unfair to allow higher or lower charging rates to some individual vehicles. Consequently, EVs are considered to be charged or discharged at similar rates.

However, how frequently and at what times customers charge their vehicles determine whether EVs help or harm the electricity infrastructure. Electrical energy storage for EVs can play a prominent role in the electricity infrastructure with anticipated benefits encompassing ancillary services, integrating renewable energy, and increasing the utility of the end user. Accomplishing these objectives requires optimal coordination of EVs (charging and discharging), PSs, and HRESs. The coordination of charging and discharging of EVs – which is a demand response or demand side management application – illustrates the two pertinent categories. Demand response is the underlying philosophy of these applications, as it aims to adapt the power demand to the power generation applied to maintain the normal operation of the electrical grid. One category is focused on charging and discharging decisions based on the information of the state of the PS, and a second lies in forecasted estimation of the future power demand and the future state of the PS while making decisions about charging and discharging.

An objective function is utilized to provide a dataset that can be employed to minimize the total active power loss and to reduce the summation of voltage deviation. The objective function is expressed as follows:

$$
\begin{aligned}
&\min f = \min(P_{Loss}(u,v), V_{Deviation}(u,v)) \\
&g_i(u,v) = 0 \\
&h_i(u,v) \le 0 \\
&u = \left[x_1, \ldots, x_{N_{vehicles}} \right] \\
&g_1 = P_{DER}(t) + P_{Grid}(t) + \sum_{j=1}^{N_V} x_i(t) R - P_{Load}(t) - P_{Loss}(t) \\
&E_{StorageLimit-vehicle-i} \le E_{Storage}(t) \\
&E_{StorageLimit-vehicle-i} = 8kWh \\
&V_{i-\min} \le V(t) \le V_{i-\max} \\
&x_i(t) \in \{-1, 0, 1\}
\end{aligned}
\tag{10}
$$

Here, the vector $g_1(u,v) = 0$ represents equality constraints and is the load flow equation; the vector $h_1(u,v) \le 0$ represents inequality constraints, such as the 8 kWh electric vehicle discharge threshold mentioned earlier; u is the controlling variables vector, which will be the output of the learning algorithm; and v is the vector of state variables.

3.2. Controller learning algorithms and system tuning configurations

Artificial intelligence-based controllers are widely used in industry, e.g., fuzzy, ANN, and ANFIS controllers. One problem with the conventional fuzzy controller is that its operation rules depend broadly on the knowledge and intuition of experts and the parameters associated with the membership functions. To overcome this problem, an adaptive neuro-fuzzy controller is proposed, which has advantages compared to conventional PI and PID controls and their adaptive versions. Due to the nonlinear and complicated nature of modern PSs, conventional control methods are not perfectly suitable for designing controllers which can cover a wide range of areas.

Neuro fuzzy techniques have emerged from the fusion of Artificial Neural Network (ANN) and Fuzzy Inference Systems (FIS) and have become popular for solving real-world problems. A neuro fuzzy system is based on a fuzzy system, which is trained by a learning algorithm. Indeed, an ANFIS-based controller can be trained without significant expert knowledge.

The adaptive controller in the present study is designed based on optimal power flow and utilizes the Adoptive Neuro-Fuzzy inference System, which has exhibited well-known advantages in the modeling and control of highly nonlinear systems [43].

Tuning the ANFIS structure involves adjusting all the modifiable parameters like values of ANFIS rules and Gaussian membership function variables, which are generally $\{c_i, b_i, C_i, B_i\}$ and $\{p_m, q_m, r_m\}$. Because of the random initial values for the controller, the procedures require updating of the parameters, which may result in overestimations or underestimations. In this regard, PSO as an evolutionary computational method is employed to tune the neuro fuzzy system as derived from neural network theory.

The adaptive error PSO method updates the weights of the system for fast convergence of the controller. The proposed controller, illustrated in Fig. 6, requires a set of data including inputs and outputs to minimize the output error. Therefore, the optimal power flow (OPF) problem, which was defined in the early 1960s to determine the optimal setting for control variables while satisfying various constraints [44], is used here to provide the dataset of the optimal control variables setting. The included control variables are $u = \left[x_1, \ldots, x_{N_{vehicles}}\right]$ where x indicates whether the BEV or PHEV must be charged, discharged or not exchange power by applying +1, -1 and 0 values, respectively. The variable decisions are used for tuning the rules in the ANFIS structures. Another most notable feature of the OPF problem is its applicability over a wide time horizon. From the system operator perspective, the problem needs to be executed every 5 minutes, which is fixed in this study, to determine the optimal dispatch and to control the action to be taken.

Training the ANFIS considering the data obtained, the system adjusts the parameters based on the submitted inputs/outputs. The process of training continues only if the designated number of times or the objective of the training error is reached. Moreover, a N-dimension vector is created, where N represents the number of membership functions, which is optimized via the PSO algorithm. The fitness function is defined as the mean square error.

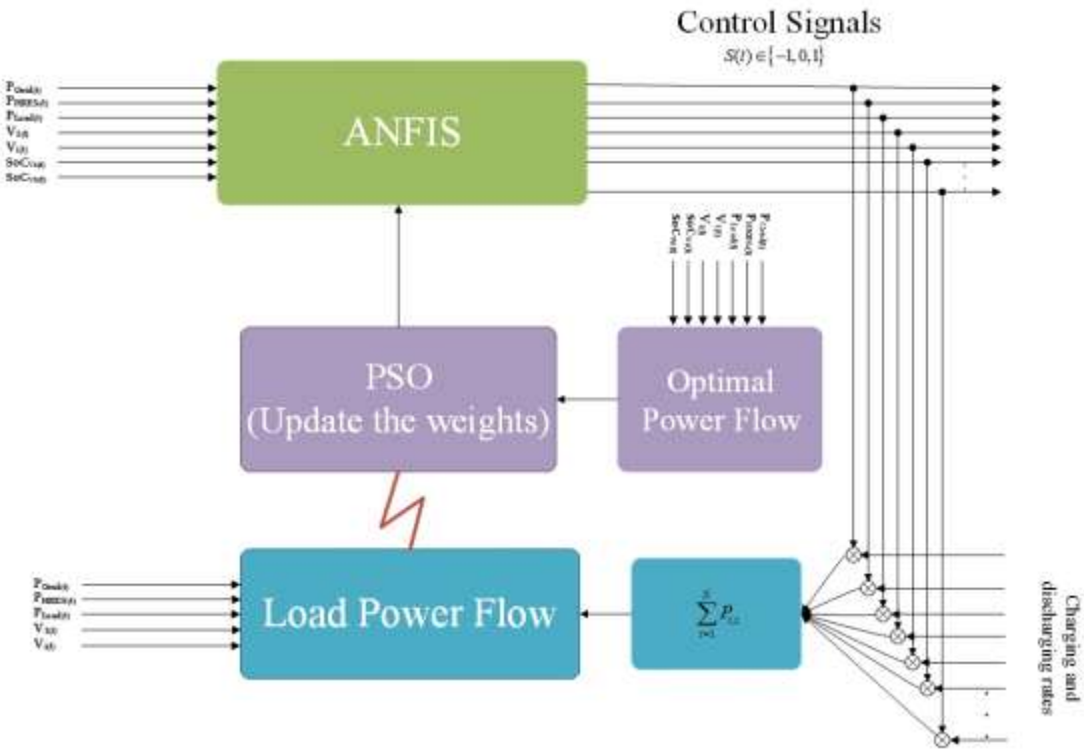

Figure 6. Proposed controller

In order to solve the single objective OPF problem, the objective functions presented earlier are applied as a single objective in the optimization process on an IEEE-26 bus system.

The process of training can employ off- and on-line approaches. With the off-line approach, the dataset does not include the full range of operating conditions, which may entail external disturbances. Also, due to the uncertain behavior of PSs and BEVs, there are many unknown conditions that may occur. To overcome these problems, a combination of on-line and off-line training approaches is used. In many studies on SoC estimation, ANN and extended Kalman filter approaches have been utilized [45]. These efforts demonstrate acceptable results once a root mean square error of about 3% is achieved by the neural networks (NNs). The accuracy of the NN model increases over time due to its adaptive and learning features. In addition, with increasing in deployment of EVs, the availability of different types of data will increase and, therefore, the model performance can improve. The modified PSO algorithm has been employed to solve the single objective OPF problem. The modified PSO algorithm flowchart is presented in Fig. 7.

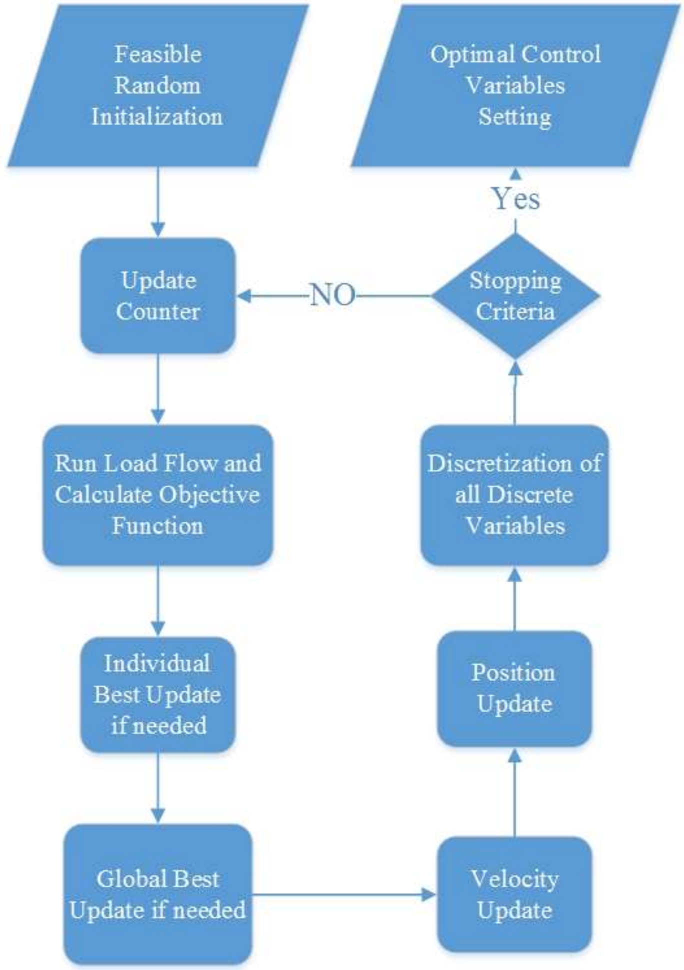

Figure 7. Single objective OPF algorithm using PSO algorithm

The PSO algorithm begins in an off-line mode to optimize the modifiable parameters of ANFIS based on the dataset. The proposed PSO initialization procedure is as follows:

Step 1: Initialize the PSO operators, the swarm size and the maximum number of iterations.

Step 2: Generate the initial swarm randomly, within certain bounds while each swarm contains the ANFIS controller's parameters such as Gaussian membership functions and rules $\{c_i, b_i, q_i\}$.

Step 3: Set the ANFIS initial parameter values $\{c_i, b_i, q_i\}$ for the PSO; they are used to calculate the mean square error.

Step 4: For each particle, update the P_{best} and G_{best} according to the cost value, which is the mean square error, and update each particle's velocity and position.

Step 5: Stop if the maximum number of generations is reached, otherwise increment the generations counter by one and go to step 3.

In total, the four aforementioned algorithms are integrated to develop the proposed controller encompassing PSO, the modified OPF problem, the load flow and ANFIS, as shown in Fig. 7.

4. Case study features

Devices which are able to store electricity like BEVs can help the system to smooth the intermittent behavior of renewable sources enabling easier integration. The non-deterministic output is the main difference of parking lots as DGs and conventional DGs. The algorithm was developed to provide net results for optimal placement and sizing of DGs. The peak loading dataset of the test system is employed as typical load data.

In the implementation of the NSGA-II algorithm, the population number is 150, the maximum iteration number is 250, and the crossover and mutation factors are both set to 1.5. The costs for the PV and WT units are set to 2220 \$/kW and 720 \$/kW, respectively. The unit cost for maintenance and operation of PVs and WTs is set to 0.015 \$/kWh. These values can be adjusted according to the system and local distribution company under consideration.

The examined IEEE 26-bus system is depicted as a single line diagram in Fig. 8. The possible candidate nodes for integrating parking lots as a DG system are nodes 6 to 25. Moreover, the rated unit power is set to 15 kW for PV and 250 kW for WT, used to solve the OPF objective function in the PSO algorithm.

5. Results and discussion

The results (see Table 2) demonstrate that the system s improves in terms of power loss and voltage deviation reductions after integration of the optimally sized DGs into the studied grid. The optimal multi-objective solution obtained out of sizing and siting problem considers voltage profile, power losses and load characteristics of the busses besides V2G and G2V loads through the grid to search for optimal location and number of units needed as summarized in Table 3. PV and WT with 50 and 7 units, PV and WT with 117 and 10 units, PV and WT with 103 and 8 units located at node 14, 16 and 24, respectively. To consider the challenges of available load near parking lots and to install WTs in real-world cases, besides the suitability of parking lot structural issues, the maximum possible number of WT units can be restricted in the algorithm (e.i. 10).

Table 2. System improvement after implementation of the optimally sized DGs into the system

System	Total active power load (MW)		Results before and after optimization		
			Annual DG I&O cost ($)	Voltage deviation	Total active power losses (MW)
26-bus	1263	Before	0	17.6×10^{2}	14.337
		After	950×10^{5}	9.8×10^{2}	13.586

Table 3. Optimal sizing and sitting results

Node No.	No. of PV units	No. of WT units
14	50	7
16	117	10
24	103	8

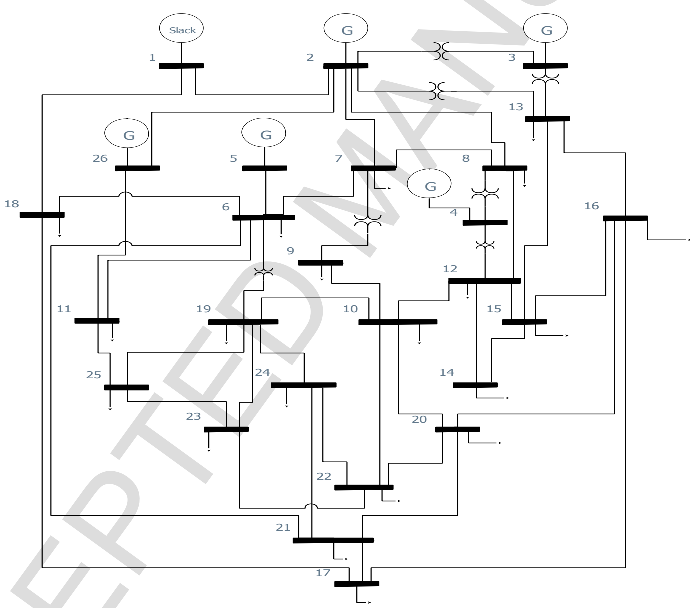

Figure 8. Single line diagram of the test system

To verify the effectiveness and performance of the proposed PSO algorithm for solving the optimal power flow problem, and to assess the optimal values of PV buses over the time required in the next stage, objective functions were introduced to minimize a) the total active power loss, and b) the voltage deviation. As shown in Fig. 6 the optimal control values of $u=\left[P_{g1},\ldots,P_{g_n}\right]$ can be determined via the PSO algorithm, so it is used to solve the objective OPF problem. The following parameters are used to enhance the algorithm's performance. The number of particles is set to 20, the acceleration factor including C_1 and C_2 are assumed to be 1.5, the inertia factor is presumed to decrease linearly throughout each run, and the number of intervals N determining the maximum velocity V_k^{max} is selected to be 8. The values of the objective function, P_{loss}, and the voltage deviation, for a standard 26-bus power system are listed in Table 4 and compared with Ref. [46]. Note in Table 4 that GSA refers to gravitational search algorithm.

Table 3. Simulation results using GSA and PSO (26-bus system – after minimisation of voltage deviation and power loss)

Objective	Minimization of voltage deviation [46]	Minimization of power loss [46]	Minimization of power loss and voltage deviation without considering DGs and parking lot	Minimization of power loss and voltage deviation considering DGs and parking lot (off peak)	Minimization of power loss and voltage deviation considering DGs and parking lot (on peak)
	GSA	GSA	PSO	PSO	PSO
P_{g1}	494.0021	451.7632	479.9778	100	426.4658
P_{g2}	199.6346	199.8991	200	50	164.7030
P_{g3}	171.7571	206.3199	180.2400	64.0185	2100
P_{g4}	147.7545	150	140	50	1600
P_{g5}	194.2034	180.7755	193	50	190.4443
P_{g14}	-	-	-	2.5	2.5000
P_{g16}	-	-	-	4.2300	4.2300
P_{g24}	-	-	-	3.5	3.5000
P_{g26}	69.6752	85.7769	80.8493	50	81.5117
V_1	1.0228	1.0500	1.0250	1.0250	1.0250
V_2	1.0225	1.0494	1.0200	1.0300	1.0200
V_3	1	1.0469	1.0350	1.0450	1.0350
V_4	1	1.0214	1.0600	1.0800	1.0600
V_5	1.0499	1.0499	1.0450	1.0550	1.0450
V_{14}	-	-	-	1.0300	1.0100
V_{16}	-	-	-	1.0300	0.9900
V_{24}	-	-	-	1.0300	0.9900
V_{26}	1.0069	1.0497	1.0150	1.0550	1.0150
OF	0.2534	0.1058	0.5858	0.1766	0.3105
P_{loss}	13.2551	10.5873	11.7460	2.6440	11.1070
SVD,	0.2534	0.6910	0.4684	0.15	0.3000
P_{dt}	1263	1263	1263	378.9000	1263

It can be observed from the Table 4 that, when the voltage deviation is considered as an objective function (OF) in the minimization mode, the power loss increases to 13.25 MW, and the summation of voltage deviation (SVD), which is a destructive characteristic of power quality, decreases to 0.25 (see columns 2 and 3). Nevertheless, as shown in column 3 where the power loss is considered as an OF, the inverse of the prior result is observed. The power loss decreased to 10.59 MW and the summation of the voltage deviation increased to 0.69. In addition, in columns 2, 3, 4 the effect of considering both of the OFs including power loss and voltage deviation can be identified. When the total active power loss is reduced to 11.75 MW from 13.25 MW, the total active power loss is increased to 11.75 from 10.59, as can be seen in column 2, because both voltage deviation and active power loss are considered as the objective. Moreover, the summation of the voltage deviation is increased to 0.47 from 0.25; but it is reduced to 0.47 from 0.69 when both the power loss and voltage deviation are identified as the objective.

Consequently, combining the power loss and the voltage deviation as the OFs in an optimization process demonstrates that the proposed OPF algorithm is able to manage both values in a positive way. With the assumption of constant power generation by a HRES at off-peak and on peak periods, the problem is resolved. Accordingly, the results indicate that the power loss and the summation of the voltage deviation for on peak periods are reduced to 11.11 MW from 11.75 MW and to 0.30 from 0.47, respectively. Nonetheless, the intermittent behavior of an HRES is worth considering; therefore, the output of the PV and WT units is subject to the achievable power patterns of irradiation and wind velocity data, which were illustrated in Figs. 4 and 5. The transition from verification and obtaining the variable decisions, the control vector of the optimal power flow problem is rewritten as $u=\left[x_{1,t},...,x_{N_{vehicles},t}\right]$ and the state of charge of the electric vehicles arrived at for the previous time is obtained from the state of the vector, which is formulated as $v=[SoC_{1,t},...,SoC_{N,t}]$. Notably, the objective of the OPF problem is to determine the setting of the control variables with broad aims, such as reactive power output of different reactive power sources, the active and reactive power generation at power plants, the on-load tap charging transformer tap position, etc. [46].

The arrival and departure times are created randomly. The former are generated between 6:00 AM to 11:59 PM, and the minimum departure times of BEVs are considered to be 30 minutes. The OPF introduced previously has been run on a core i-7 computer with 4G DRR3 RAM and CPU 1.73 GHz in MATLAB®. Further, the parameters of the PSO algorithm in this step are the same as previously given. The design capacity of the parking lot located on bus 16 is 300 electric vehicles. Moreover, the capacity of EV batteries generally ranges from 20 to 85 kWh in this study, therefore, the capacity of EVs for simulation is considered to be 50 kWh, 100 Ah. Note that the battery parameters and associated characteristics vary with respect to the type of the battery and its manufacturer.

The modified OPF problem begins using random data regarding the EV departure and arrival times from 6 AM to 11:59 PM, with run time intervals set to five minutes. The power generation from the power plants encompassing P_1 to P_5 and P_{26} are fixed from the previous step and remain constant during the estimation of the modified controlling vector related to the EVs. As shown in Appendix A, during the time interval 6 AM-7 AM, 37 EVs arrive at the parking lot, and approximately 23 of them have energy contents between 2 kWh to 30 kWh. On the supply side, the power generation by the HRES is 1.97 MW on bus 16. The results related to this interval indicate that 18, 19 and 0 EVs are charged, kept on standby and discharged when the irradiation and wind velocity are 100 W/m^2 and 4 m/s, respectively. In addition, during this interval, the status of the five EVs that were on standby in the previous step changed their status to charging. The energy stored from 6 AM-7 AM is increased to 0.92 MWh from 0.85 MWh. As the power generation increases to 3.26 MW from 1.97 MW and simultaneously the load demand steadily increases to 36 MW, and the number of EVs increases to 75, Among these, 38 EVs are plugged in between 7 AM-8 AM such that 20, 15 and 3 of them are charged, held on standby and discharged. The number of EVs remaining in the charged and standby statuses from the prior interval are 28 and 9, respectively. The EVs with IDs 64, 65, and 66 discharge in 20 minutes. In third time interval from 8 AM to 9 AM, 9 EVs with IDs 3, 4, 31, 33, 39, 40, 62, 63, and 92 departed from parking with their energy increased to 23.8, 9.8, 21.8, 32, 27.8, 8.8, 15.8, 14.8, and 30 kWh, while EVs with IDs 3, 4, 40, and 63 were plugged in all the time.

Fig. 9 illustrates the power generated by the components sized for the HRES of bus 16 over 24 h. As can be seen, the PV modules supply electricity to the grid at 6 AM-4 PM and most of the electricity via the generic WTs is supplied between 2 PM-8 PM and 1 AM-4 AM owing to higher presence of the wind energy density and the received solar radiation in these time ranges. Also, the lowest solar generation occurs between 5 PM-11.59 PM and 1 AM-5 AM.

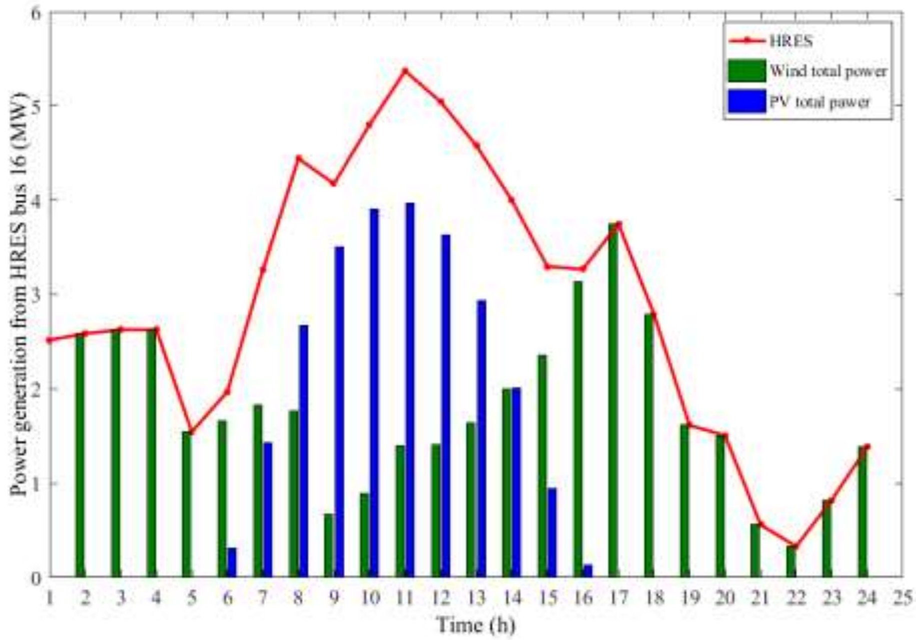

Figure 9. Simulation of optimal result of HRES bus 16

The results of the modified OPF problem control vector are depicted as a contour plot, which is a graphical technique to represent a 3 dimensional surface while the data do not form a regular grid, that indicates the state of the EVs as a function of time. According to Fig. 10, the X and Y axes are related to the EVs' ID and time, and the three color spectrums of red, white, and blue represent the charging, standby or not connected and discharging states, i.e., 1, 0, -1, respectively.

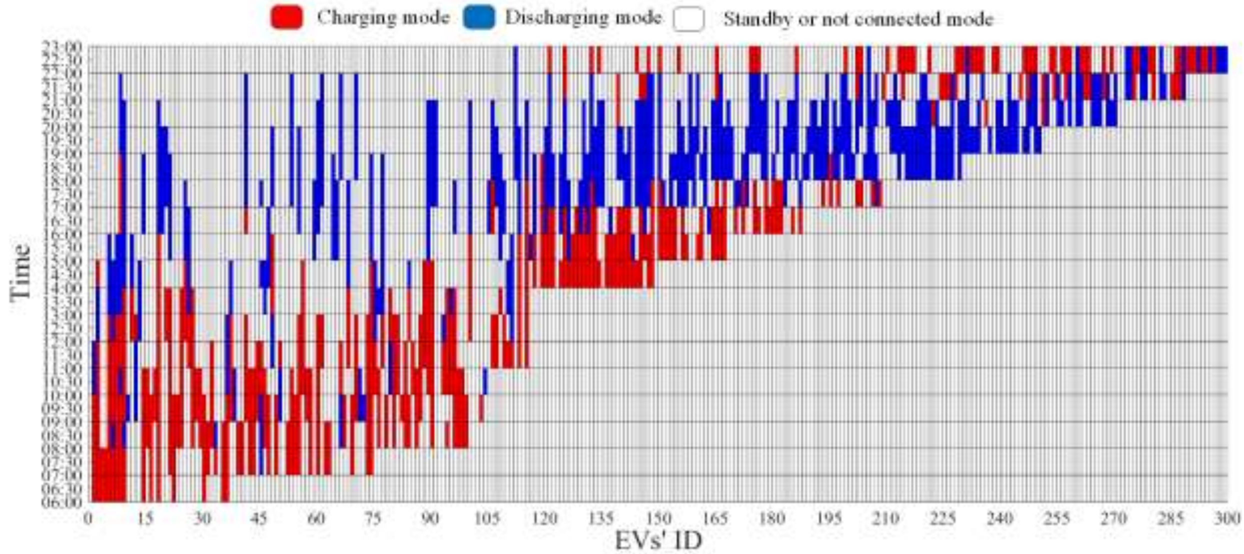

Figure 10. Charging and discharging results for the OPF problem

The plot in Fig. 10 is divided into two areas. The first between 6 AM-4 PM when the electricity generation via renewable energy is high and the load demand is low; therefore, a high portion of EVs are charged in this period. Nevertheless, owing to the fluctuation of renewable energy resources, some of the EVs are discharged in this time. The second area occurs from 4 PM-10 PM when load demand is a maximum. Hence, as peak demand and the HRES power generation reduction occur in this period, a high number of EVs are discharged in this time. The minimum and maximum energy storages of EVs (14 kWh and 49 kWh) demonstrate that all vehicles satisfy the formerly stated constraints.

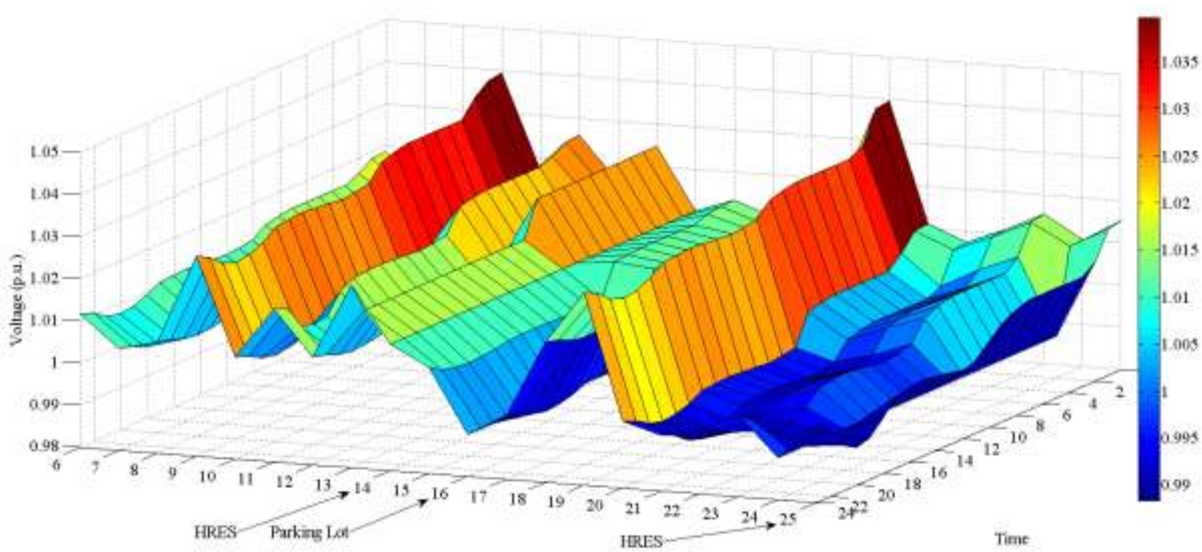

Figure 11. Time-based Voltage profile through the buses

Fig. 11 shows the voltage profile for buses, which demonstrates the stability of the system within the desired per unit defined range. The obtained results are utilized to tune the real time controller (PSO-ANFIS), and the main advantage of the proposed controller as mentioned earlier is being adaptive and making the system responsible for different contingencies.

Model verification is based on the data in Appendix A. Reference [47] presents arrival and departure times of vehicles and initial energy contents. In addition, the wind velocity and irradiation data used to calculate power generation are obtained for the date, February 2nd as design data. Note that the total active power loss and voltage deviation are considered throughout the entire charging and discharging. If at any time the load flow and the voltage deviation violate a constraint (e.g. voltage out of limits) at any node, the load flow algorithm sets zero values in the controller outputs, which indicates a standby status; the controller will be tuned again by the data collected and provided via a modified OPF. The reason for using the proposed controller instead of a modified OPF is its real-time functionality for EVs. The modified OPF is run at 5 minute steps; therefore, it is unlikely to be used instead of the proposed controller.

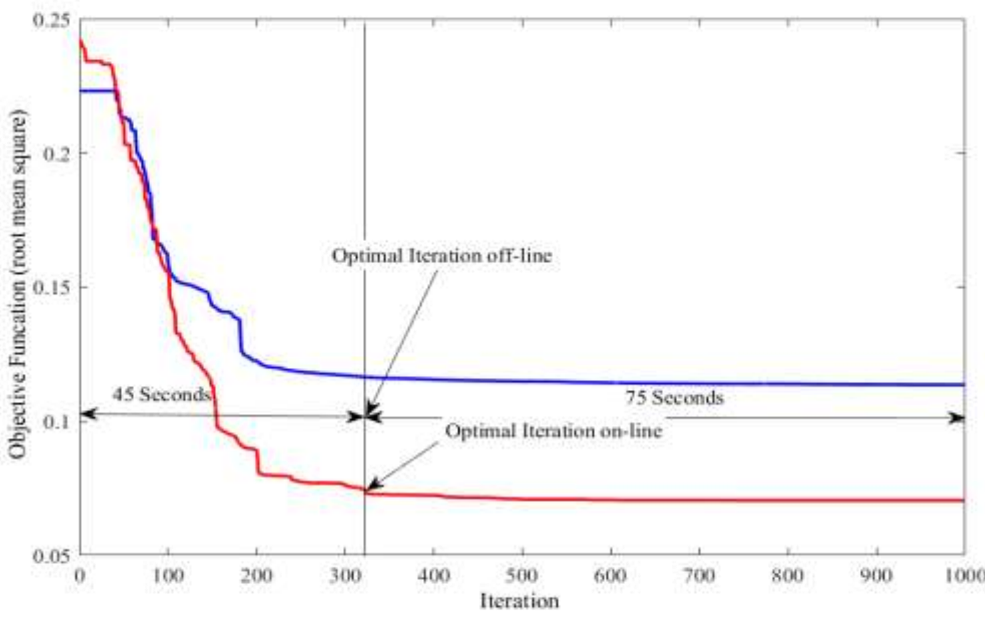

Figure 12. Number of iterations for convergence of controller

Fig. 12 shows the number of required iterations for achieving convergence, which is obtained via trial and error. Tuning modifiable ANFIS parameters takes 45 seconds for the off-line and on-line methods.

Despite the differences between the objective functions of the present study and [47], there are some structural similarities between the two studies. In reference [47], the proposed model optimally charges and discharges the EVs based on avoiding overload in the distribution system and the technical and economic preferences of owners. EVs are charged during time periods of low electricity prices and they are discharged at high price time periods; charging and discharging prices are associated with off-peak and on-peak periods, respectively. Therefore, the net results of the present study with the aforementioned reference are compared.

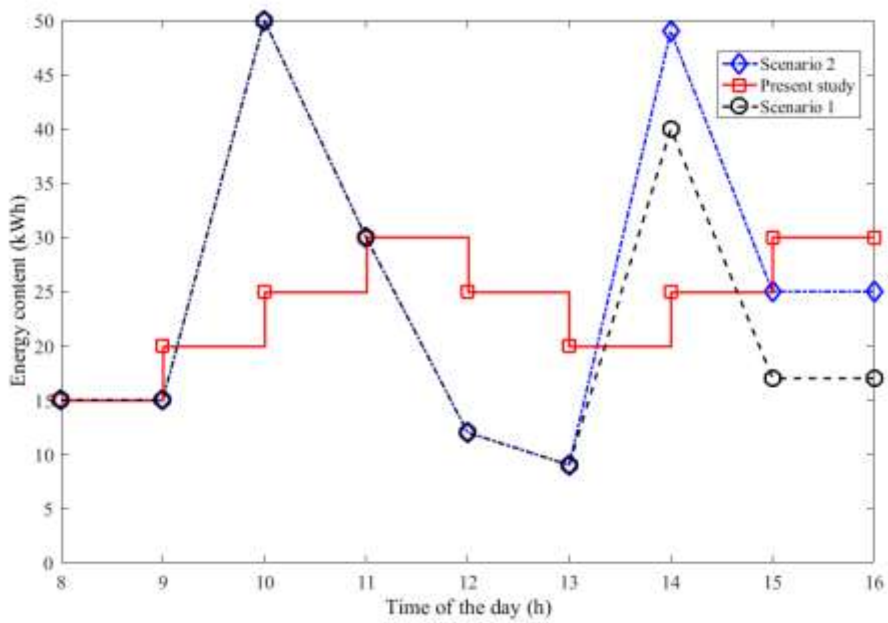

Figure 13. Comparison of the 75th EV's Energy content in reference 59 and the present study

With regard to [47], the charging and discharging of the 75th vehicle are marked with stars and circle symbols in Fig. 13. As can be seen, from 9-10 AM, the energy content is increased from 15 kWh to 50 kWh, showing that the battery was charged at the maximum charging rate and that, after 3 hours, the energy level is dramatically decreased by 41 kWh from 50 kWh to 9 kWh which is not favorable from battery life point of view. Hence, the battery experiences a significant deep discharge rate in scenarios taken from the literature compared to the present study which exhibits a steadier trend. In addition, at the end of the whole charging and discharging processes, the proposed controller charged the vehicle by 30 kWh and outperformed compared to scenarios 1 and 2 which charged the same vehicle to 17 and 25 kWh, respectively. Based on the time-energy content plot for the present study in the first cycle, the battery was charged 30 kWh because of considering the state of the grid, the HRES, and the 75th vehicle's

SoC. Then, the controller will discharge to around 20 kWh, demonstrating that the controller prevented the vehicle from reaching the point which were defined as deep discharge state in the proposed algorithm. It should be taken into consideration that the energy flow exchanged via scenarios 1 and 2 are higher compared to the present study.

6. Conclusions

This study not only used an intelligent NSGA optimization approach for optimal sizing and siting of distribution generation systems, but also presented a real-time PSO-based controller with an adaptive neuro-fuzzy inference system toward optimal integrating of renewable energy sources (wind and solar) and EVs into a smart grid infrastructure.

In order to integrate EVs and reduce the fluctuation of renewable DG outputs, a robust control method was introduced and developed to tackle efficiently an optimal power flow problem allowing G2V and V2G functionalities and addressing deep discharging challenges. This method was compared to others reported in the literature. In addition, the proposed approach could exhibit techno-economic capabilities in offering ancillary services such as power leveraging, voltage regulation, and power system operating cost reduction to the studied PS while having EVs as a system component. Hence the study offered a real-time and intelligent control approach to provide beneficial options and opportunities for grid-friendly deployment of EVs in smart grid systems. Nevertheless, the following limitations need to be addressed in future studies:

1- As the great proportion of objectives of such studies focus on economic aspects, further investigations are merited on other technical aspects (e.g. frequency deviation and harmonic distortions).

2- Since a reduction in the voltage deviation generally leads to an increase in the total harmonic distortion of voltage, such factors should be considered as targets in weighted multi-objective functions.

3- In addition to the proposed multi-objective problem for improving the grid stability, the influence of EV discharging and charging rates, which are fixed in this study, need to be assessed.

4- Although battery state of health plays a prominent role in V2G concepts, it is not considered in the present study due to the inherent complexity of doing so, but this value should be considered as a direct signal in future work, leading to further computational cost and inputs. The present authors are starting to address this issue by data fusion processes. However, it was predicted that by considering these parameters, EVs are not capable to provide desirable energy for V2G services because of the high battery degradation costs corresponding to V2G cycling.

5- EVs chargers are based on assumption of off-board placement, which raise concerns about battery heating management and their capability with other charging stations, and further information about this is required.

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Appendix A

Table A.1

Data on electric vehicles

Vehicle no.	Arrival time	Departure time	Initial SoC	Vehicle no.	Arrival time	Departure time	Initial SoC	Vehicle no.	Arrival time	Departure time	Initial SoC
1	6:00	12:00	26	101	9:00	9:30	30	201	17:33	19:54	28
2	6:00	15:00	9	102	9:05	10:50	30	202	17:36	22:47	21
3	6:00	8:00	19	103	9:10	12:50	32	203	17:39	22:33	21
4	6:00	8:00	5	104	10:00	11:00	38	204	17:42	18:30	48
5	6:00	16:00	10	105	10:05	17:30	43	205	17:45	23:27	50
6	6:05	15:00	44	106	11:00	20:30	26	206	17:48	22:00	33
7	6:05	15:50	8	107	11:05	19:45	36	207	17:51	21:20	47
8	6:05	21:05	19	108	11:10	18:30	43	208	17:54	20:23	25
9	6:05	20:10	44	109	11:10	17:50	33	209	17:57	21:20	14
10	6:10	9:10	43	110	11:15	14:50	41	210	18:00	23:00	17
11	6:10	15:35	35	111	11:15	16:00	42	211	18:03	21:45	34
12	6:10	12:25	44	112	11:20	23:05	45	212	18:06	22:00	37
13	6:15	14:20	44	113	11:30	19:40	23	213	18:09	22:30	37
14	6:15	18:45	24	114	11:30	15:30	30	214	18:12	22:36	10
15	6:20	12:55	23	115	11:35	20:40	1	215	18:15	23:55	30
16	6:20	9:35	18	116	11:40	16:05	30	216	18:18	23:47	17
17	6:20	10:15	28	117	12:00	18:35	30	217	18:21	22:30	38
18	6:20	20:30	2	118	12:10	15:25	27	218	18:24	21:00	48
19	6:25	19:45	47	119	14:00	21:20	3	219	18:27	23:55	42
20	6:25	19:05	33	120	14:00	19:35	30	220	18:30	22:41	50
21	6:30	18:30	7	121	14:05	23:15	24	221	18:33	23:55	30
22	6:30	13:00	12	122	14:05	18:30	9	222	18:36	20:35	12
23	6:30	12:35	26	123	14:25	15:30	20	223	18:39	21:00	48
24	6:30	16:15	6	124	14:25	19:00	47	224	18:42	21:50	20
25	6:35	15:30	30	125	14:30	22:18	13	225	18:45	21:55	25
26	6:35	17:25	40	126	14:30	16:10	41	226	18:48	22:00	25
27	6:35	14:00	6	127	14:30	15:55	10	227	18:51	22:05	47
28	6:35	11:30	35	128	14:30	16:35	10	228	18:54	22:10	15
29	6:40	10:55	9	129	14:30	18:00	21	229	18:57	22:15	27
30	6:45	9:40	9	130	14:30	20:35	23	230	19:00	22:45	29
31	6:45	8:50	17	131	14:30	18:40	37	231	19:03	22:41	50
32	6:45	13:30	14	132	14:30	22:40	13	232	19:06	20:20	24
33	6:50	8:10	32	133	14:30	19:35	18	233	19:09	22:30	18
34	6:50	9:20	31	134	14:30	23:10	44	234	19:12	23:17	26
35	6:55	10:15	15	135	14:30	21:00	35	235	19:15	23:38	16
36	6:55	13:00	18	136	14:30	15:30	7	236	19:18	20:50	12
37	6:55	16:15	21	137	14:30	17:00	19	237	19:21	19:34	34

38	7:00	10:55	38	138	14:30	16:00	8	238	19:24	23:55	19
39	7:00	8:50	23	139	14:30	22:10	5	239	19:27	22:42	31
40	7:00	8:10	4	140	14:30	19:15	2	240	19:30	21:30	38
41	7:00	21:10	20	141	14:35	16:53	18	241	19:33	21:35	29
42	7:05	12:20	5	142	14:35	19:40	30	242	19:36	21:40	40
43	7:05	11:15	6	143	14:40	15:50	33	243	19:39	21:45	40
44	7:05	13:30	21	144	14:40	22:12	43	244	19:42	21:50	43
45	7:10	17:25	38	145	14:45	21:35	21	245	19:45	21:55	11
46	7:10	14:35	20	146	14:48	21:37	45	246	19:48	23:34	13
47	7:10	16:05	26	147	14:51	23:47	35	247	19:51	23:00	29
48	7:15	19:40	35	148	14:54	21:50	26	248	19:54	23:00	27
49	7:15	9:55	11	149	14:57	16:40	30	249	19:57	23:30	47
50	7:20	13:45	31	150	15:00	22:32	27	250	20:00	20:45	33
51	7:20	11:05	32	151	15:03	17:40	21	251	20:03	22:00	14
52	7:25	11:10	22	152	15:06	16:42	19	252	20:06	21:50	40
53	7:25	21:40	26	153	15:09	18:20	26	253	20:09	23:55	13
54	7:25	9:10	11	154	15:12	18:21	11	254	20:12	22:18	13
55	7:25	19:40	15	155	15:15	23:46	32	255	20:15	22:49	38
56	7:30	14:50	3	156	15:18	19:34	22	256	20:18	22:30	36
57	7:30	10:15	21	157	15:21	18:11	25	257	20:21	22:35	16
58	7:30	10:20	1	158	15:24	22:39	50	258	20:24	22:40	31
59	7:35	17:30	39	159	15:27	19:25	48	259	20:27	22:45	28
60	7:35	20:40	15	160	15:30	21:30	45	260	20:30	22:50	40
61	7:00	21:20	36	161	15:33	18:49	12	261	20:33	22:55	32
62	7:40	8:55	11	162	15:36	19:11	47	262	20:36	23:00	13
63	7:45	8:45	10	163	15:39	16:55	29	263	20:39	23:50	11
64	7:45	18:55	45	164	15:42	20:49	36	264	20:42	22:00	49
65	7:45	17:20	44	165	15:45	23:14	17	265	20:45	23:55	28
66	7:45	21:10	46	166	15:48	21:32	38	266	20:48	23:00	47
67	7:45	10:00	21	167	15:51	19:50	15	267	20:51	23:10	15
68	7:50	17:30	34	168	15:54	20:12	47	268	20:54	22:30	40
69	7:50	9:30	10	169	15:57	19:26	33	269	20:57	23:43	18
70	7:50	23:00	27	170	16:00	17:34	27	270	21:00	23:55	38
71	7:50	10:20	37	171	16:03	19:20	36	271	21:03	21:45	19
72	7:55	9:30	40	172	16:06	18:40	24	272	21:06	22:00	29
73	7:55	12:52	2	173	16:09	19:10	46	273	21:09	22:30	49
74	7:55	18:30	8	174	16:12	23:25	31	274	21:12	23:10	50
75	7:55	14:15	40	175	16:15	23:25	25	275	21:15	23:08	10
76	8:00	13:30	18	176	16:18	23:34	25	276	21:18	23:55	20
77	8:00	18:40	44	177	16:21	23:55	35	277	21:21	22:40	49
78	8:00	9:45	10	178	16:24	22:50	34	278	21:24	22:45	48
79	8:00	15:28	33	179	16:27	17:30	21	279	21:27	23:50	21
80	8:00	14:25	9	180	16:30	18:35	17	280	21:30	23:55	12

81	8:00	12:20	12	181	16:33	22:24	20	281	21:33	23:55	26
82	8:00	9:10	18	182	16:36	17:40	18	282	21:36	22:40	43
83	8:00	12:03	12	183	16:39	19:20	41	283	21:39	23:11	45
84	8:00	14:20	19	184	16:42	21:30	47	284	21:42	23:55	30
85	8:00	12:20	18	185	16:45	20:47	24	285	21:45	23:55	21
86	8:00	10:50	11	186	16:48	22:41	41	286	21:48	23:55	12
87	8:00	12:10	8	187	16:51	18:00	27	287	21:51	23:55	13
88	8:00	16:25	14	188	16:54	19:05	26	288	21:54	23:55	45
89	8:00	20:15	25	189	16:57	19:30	25	289	21:57	23:55	14
90	8:00	20:45	5	190	17:00	21:00	35	290	22:00	23:55	17
91	8:00	20:40	45	191	17:03	22:00	34	291	22:03	23:55	17
92	8:00	9:00	30	192	17:06	19:25	28	292	22:06	23:55	36
93	8:00	12:10	32	193	17:09	21:00	33	293	22:09	23:55	11
94	8:00	15:40	3	194	17:12	21:28	50	294	22:12	23:55	11
95	8:00	13:40	22	195	17:15	18:30	17	295	22:15	23:55	35
96	8:05	17:20	4	196	17:18	20:21	35	296	22:18	23:55	12
97	8:05	19:20	14	197	17:21	19:45	31	297	22:21	23:55	49
98	8:05	10:25	18	198	17:24	21:46	45	298	22:24	23:55	49
99	8:10	10:00	11	199	17:27	23:55	35	299	22:27	23:55	44
100	8:10	20:25	25	200	17:30	20:39	35	300	22:30	23:55	41