An integrated approach for distributed energy resource short-term scheduling in smart grids considering realistic power system simulation

M. Silva, H. Morais, Z. Vale

GECAD – Knowledge Engineering and Decision Support Research Center – Polytechnic of Porto (IPP), R. Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal

ABSTRACT

The large increase of distributed energy resources, including distributed generation, storage systems and demand response, especially in distribution networks, makes the management of the available resources a more complex and crucial process. With wind based generation gaining relevance, in terms of the gen- eration mix, the fact that wind forecasting accuracy rapidly drops with the increase of the forecast anticipation time requires to undertake short-term and very short-term re-scheduling so the final imple- mented solution enables the lowest possible operation costs. This paper proposes a methodology for energy resource scheduling in smart grids, considering day ahead, hour ahead and five minutes ahead scheduling. The short-term scheduling, undertaken five minutes ahead, takes advantage of the high accuracy of the very-short term wind forecasting providing the user with more efficient scheduling solu-tions. The proposed method uses a Genetic Algorithm based approach for optimization that is able to cope with the hard execution time constraint of short-term scheduling. Realistic power system simula-
tion, based on PSCAD®, is used to validate the obtained solutions. The paper includes a case study with
a 33 bus distribution network with high penetration of distributed energy resources implemented in PSCAD®.

Keywords:
Distributed energy resources Genetic Algorithm, Network modelingPSCAD, Resource scheduling Simulation, Smart grid

1. Introduction

The large increase of Distributed Generation (DG) in Power Systems (PSs) and the introduction of liberalized markets in the electricity sector have caused significant changes in planning and operation of these systems.

A lot of small distributed generation units should be connected to the distribution network in the coming years and this will have significant consequences related to technological and economic matters.

Among DG technologies, especially wind power has already been largely applied but also other technologies are being used, such as hydro small units, photovoltaic units, fuel cell units, cogeneration units and biomass units. Future power systems will have to deal with large-scale integration of DG and other Distributed Energy Resources (DERs), such as storage units and demand response [1]. In the future, it is likely that consumers generate energy with micro generation systems and manage their consumption according to the electricity real-time price, the own generation or in response to the system operator solicitations.

One of the main constraints with renewable energy resources are the dispatchability and reliability problems associated with their operation. The output of some renewable generation, such as wind generators and photovoltaic systems, is determined by the weather conditions and operating patterns will therefore follow these natural conditions. The intermittent nature of these sources leads to an output which often does not suit the load demand profile. This generation intermittence makes network balance and reserve planning more complex than before due to the large number of power input nodes on all voltage levels and bidirectional energy flows between voltage levels.

Therefore, the most important basis for the design of new planning and operation methods is the recognition that distribution networks cannot still be seen as passive networks. Electricity generation and consumption must be measured separately.

The new constraints and the impossibility of accommodating intensive levels of distributed generation with the currently used power systems paradigms led to the smart grid concept. The smart grid can be seen as a digital upgrade of the existing electricity infrastructure to allow dynamic optimization of current operations as well as to incorporate dynamic gateways for alternative sources of energy generation [2,3].

The main characteristics of the smart grid include [2,3]:

- Self-healing – capability to recover from faults and restore the functionality and to operate in islanding mode.
- Fault tolerance – to resist attacks.

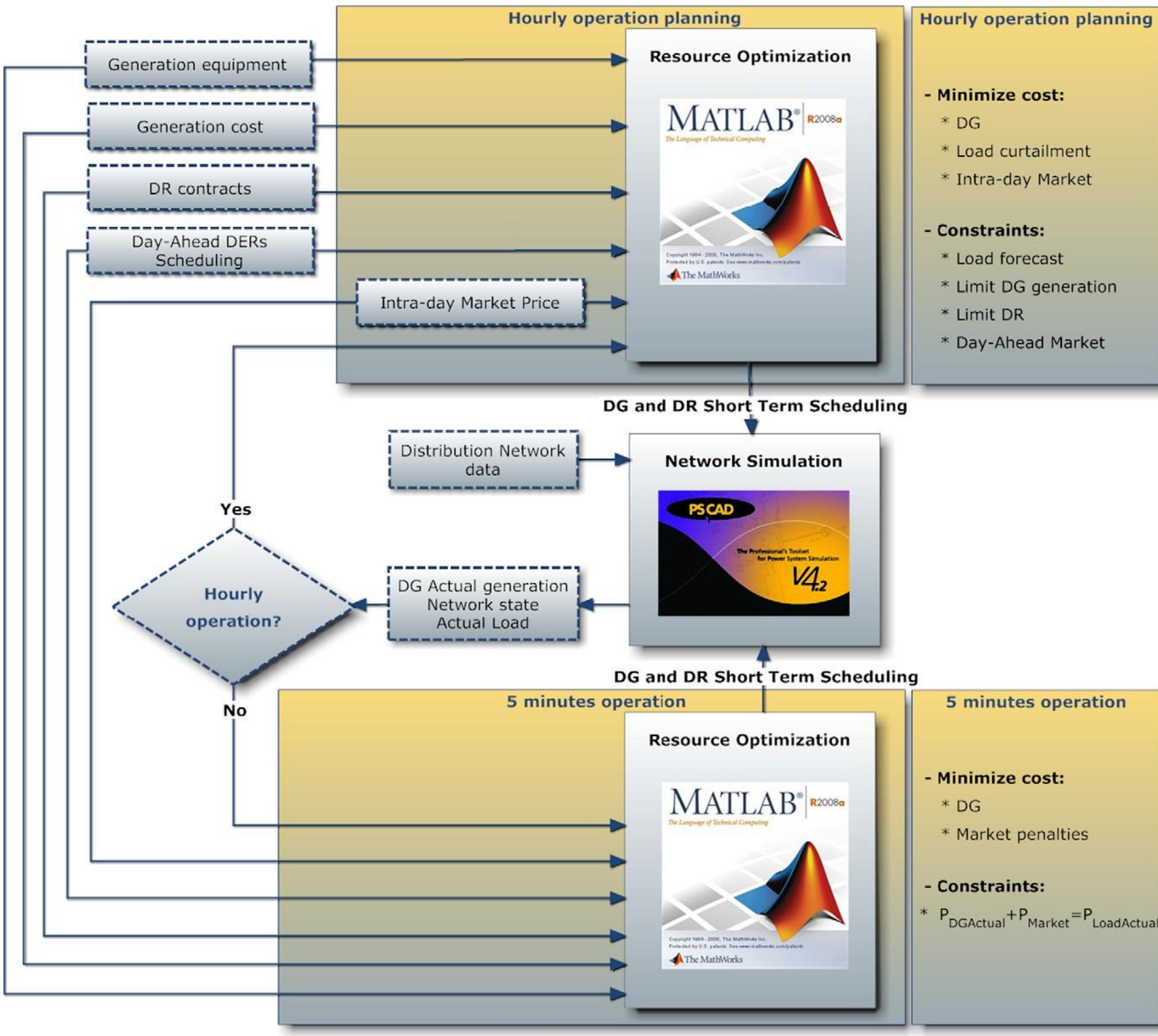

Fig. 1. Proposed methodology schematic diagram.

- Allow the integration of all forms of energy generation and storage options including plug-in vehicles and renewable distributed generation.
- Allow the dynamic optimization of grid operation and resources with full cybersecurity.
- Allow the incorporation of demand-response programs, demand-side resources and energy efficient resources.
- Allow electricity customers to actively participate in the grid operations by providing time information and control options.
- Improve reliability, power quality, security and efficiency of the electricity infrastructure.

Smart grids require a new management philosophy and new operation methods for adequately scheduling renewable based generation and all DER, including the available load curtailment opportunities [4].

In a smart grid context, the large number of players and the aimed distributed decision-making require new management methodologies based on a hierarchized but distributed philosophy. The Independent System Operator (ISO) is at the top level and the lowest levels can include customer control used by consumers to manage their installations according to their own strategy (considering their own generation, and contracts they may have with a Virtual Power Player (VPP)) [5].

Proper use of optimization techniques in the DER short-term scheduling is very relevant for smart grids, because with intensive penetration of DG, storage and load curtailment opportunities enabled by demand response programs, an adequate resource scheduling only can be achieved with little anticipation. This is mainly due to the lack of accuracy in wind forecasting when the forecasting anticipation is increased. In [6] the authors demonstrate that wind forecasting can be very accurate for very short-term forecasting, using the last 5 h of wind speed data to predict the next 5 min. This methodology can be used in this case to update 5 min ahead optimization input data. In [7] very short-term wind forecasting is also discussed for a real world application using data provided by Hydro Tasmania. A 2.5 min horizon is proposed in the used neuro-fuzzy methodology with less than 4% error. However, the forecast accuracy significantly drops when the time horizon is extended, with much higher errors when the prediction is made several hours ahead, namely for medium-term forecasting, with over 6 h of anticipation.

Short-term economic dispatch [8–15] is a very relevant function in modern energy systems. It consists in programming the electric generation correctly in order to reduce the operational cost. Recently, the use of wind power generation and photovoltaic units has significantly increased [16]. Additionally, demand response is currently recognized as a very relevant energy resource that should be considered along with generation and storage resources for cost optimization [1,17].

DER significantly increase the number of variables that must be considered in the economic dispatch problem. Therefore, it is necessary to develop new methodologies to improve the efficiency of economic dispatch methods able to cope with the new paradigms of power systems, namely aiming at obtaining fast response for optimization problems with many variables [18,19]. Deterministic optimization techniques require significant computer means and the execution times are not compatible with the short-term scheduling. Therefore, it is necessary to use alternative methodologies, to have fast response for optimization problems with many variables. Computational Intelligence techniques, namely metaheuristics inspired by biological processes, have advantages in terms of computational requirements compared with the traditional optimization techniques. Genetic Algorithms (GAs) are inspired by natural evolution and use concepts such as mutation, selection, and crossover. GA have been successfully used in many power systems problems [20–23].

The authors propose a new methodology to the short-term energy resource management that considers all the referred resources and aims at minimizing the operation costs. The inclusion of demand response events in the DER scheduling and the validation of the solution of the optimization process using a transient simulation tool are relevant contributes of this work. The developed methodology involves resource scheduling with different anticipation times: day-ahead, hour ahead and 5 min ahead. In this way, the most updated forecasted data is used to obtain the best scheduling for the actually available resources. Each resource scheduling considers the previously contracted resources and the new business opportunities.

The solutions that result from the optimization methods must be technically validated using an adequate transient simulation tool. This must be done with realistic models so that simulation results can be used for the real implementation of the scheduling solutions.

This paper focuses on the short-term energy resource scheduling in a smart grid, considering intensive penetration of DG and load curtailment opportunities enabled by demand response programs. The obtained solutions are validated in a simulator that uses PSCAD® for power system simulation.

After this introduction section, Section 2 presents the proposed methodology used to implement the short-term energy resource management. Section 3 describes the power system simulation module. Section 4 presents a case study with a 12.66 kV distribution network with 33 buses, 32 loads, 66 DG, with bus 0 connecting to the 60 kV network. Finally, Section 5 presents the most important conclusions of the paper.

2. Energy resource scheduling

The proposed DER scheduling method includes the optimization of the currently resources available with three different and successive anticipations: day ahead, hour ahead, and 5 min ahead. This paper focus on the short-term part of this methodology (hour ahead). Day ahead scheduling results are considered as input to the short-term described method which schematic diagram is presented in Fig. 1.

All the resources (generators, storage units, Demand Response (DR) programs, and the intra-day market) are considered by the hour ahead management. The 5 min ahead management only manages the connected generators (regulation up/down and spinning reserve), storage units, and DR with load reduction contracts, and considers eventual market penalties.

Power system simulation is undertaken using the model of the distribution network which has been implemented in PSCAD® [24]. In each period (5 min), the PSCAD® based network simulation module exports the instant measured data (bus voltages, generation, load consumptions, line power flows, etc.) to the MATLAB® based optimization developed module. The inputs to the optimization algorithms are the actual data of generation and consumption, equipment characteristics, DR contracts, all the previously contracted resources, and electricity market information.

Section 2.1 presents the mathematical formulation of the considered energy resource management problem aiming at minimizing the VPP operation costs. The problem formulation is similar for both used optimization approaches and considers the equipment technical characteristics, envisaged load management actions, and VPP goals.

Section 2.2 presents a Genetic Algorithm (GA) based methodology to obtain the optimal solution for short-term energy resource management.

2.1. Mathematical formulation

This sub-section presents the mathematical formulation considering one hour periods, corresponding to the hourly operation planning modeling referred in Fig. 1.

This problem is classified as mixed-integer non-linear. The implementation of this algorithm has been performed on GAMS optimization software. The objective function (1) is formulated with the aim of finding the minimum operation costs in each period (t), usually 1 h, of supplying the demand. Eqs. (2)–(5) refer to the considered constraints that are considered.

$$\textit{Minimize}\, f = \mathit{Min}\left[\begin{array}{l} \sum_{W=1}^{N_W} P_{Wind(W,t)} \times c_{Wind(W,t)} \\ + \sum_{Pv=1}^{N_{PV}} P_{Photovoltaic(Pv,t)} \times c_{Photovoltaic(Pv,t)} \\ + \sum_{Fc=1}^{N_{FC}} P_{FuelCell(Fc,t)} \times c_{FuelCell(Fc,t)} \\ + \sum_{LC=1}^{N_{LC}} P_{LoadCurtailment(LC,t)} \times c_{LoadCurtailment(LC,t)} \end{array}\right]$$

$$\forall t \in \{1, \ldots, T\} \qquad (1)$$

where $c_{FuelCell(Fc,t)}$ is the generation cost of fuel cell unit Fc in period t, $c_{LoadCurtailment(LC,t)}$ the energy cost of load curtailment LC in period t, $c_{Photovoltaic(Pv,t)}$ the generation cost of photovoltaic unit Pv in period t, $c_{Wind(W,t)}$ the generation cost of wind unit in period t, N_{FC} the number of fuel cells, N_{LC} the number of curtailable loads, N_{PV} the number of photovoltaic panels, N_W the number of wind turbines, $P_{FuelCell(Fc,t)}$ the active power generation of fuel cell unit Fc in period t, $P_{LoadCurtailment(LC,t)}$ the load curtailment of load LC in period t, $P_{Photovoltaic(Pv,t)}$ the active power generation of photovoltaic unit Pv in period t, $P_{Wind(W,t)}$ the active power generation of wind unit W in period t, t the period, and T is the simulation time horizon

subjected to the following constraints:

- Power balance in each period t

$$\sum_{W=1}^{N_W} P_{Wind(W,t)} + \sum_{Pv=1}^{N_{PV}} P_{Photovoltaic(Pv,t)} + \sum_{Fc=1}^{N_{FC}} P_{FuelCell(Fc,t)} + \sum_{LC=1}^{N_{LC}} P_{LoadCurtailment(LC,t)} = \sum_{L=1}^{N_L} Load_{(L,t)} + Ploss; \quad \forall t \in \{1,\ldots,T\} \tag{2}$$

where $Load_{(L,t)}$ is the Active power demand of load L in period t, $Ploss$ the total power losses in distribution lines – calculated through $5\% \times \sum_{L=1}^{N_L} Load_{(L,t)}$, and N_L is the number of loads

- Wind generation limits in each period t

$$P_{Wind(W,t)} \le P_{WindLimit(W,t)}; \quad t \in \{1,\ldots,T\}; \; w \in \{1,\ldots,N_W\} \tag{3}$$

where $P_{WindLimit(W,t)}$ is the maximum active power generation of wind unit W in period t.

- Photovoltaic generation limits in each period t

$$P_{Photovoltaic(Pv,t)} \le P_{PhotovoltaicLimit(Pv,t)}; \quad t \in \{1,\ldots,T\}; \; Pv \in \{1,\ldots,N_{PV}\} \tag{4}$$

where $P_{PhotovoltaicLimit(Pv,t)}$ is the maximum active power generation of photovoltaic unit Pv in period t

- Fuel cell generation limits in each period t

$$P_{FueCell(Fc,t)} \le P_{FuelCellLimit(Fc,t)}; \quad t \in \{1,\ldots,T\}; \; Fc \in \{1,\ldots,N_{FC}\} \tag{5}$$

where $P_{FuelCellLimit(Fc,t)}$ is the maximum active power generation of fuel cell unit Fc in period t

2.2. Genetic Algorithm approach

The use of meta-heuristics to address optimization problems has several advantages, namely in what concerns the lower processing time when compared with deterministic approaches for solving large dimension complex problems. The authors have already undertaken a comparison study of MINLP and GA approaches to address the energy resource scheduling problem [25]. The GA approach proved to be able to find solutions with costs that are not more than 5% higher than those found by the MINLP approach. The GA approach presents processing times as lower as 10% of the ones required by the MINLP approach. This advantage is very relevant to address the short-term scheduling problem considered in the present paper.

Genetic Algorithms (GAs) are inspired on genetic biological processes, with the goal of finding the best solution of combinatorial problems. In fact, this type of algorithm cannot guarantee to find the optimal solution but has advantages as it requires less computational resources than traditional approaches [26,27].

The functioning of GAs is broken down into steps of initialization, evaluation, selection, crossover, mutation, update and finalization [28]. Basically, a GA creates a population of possible responses to the problem being treated (initialization) and then submits it to the evolution process constituted by the following steps:

- Evaluation – evaluates the fitness of solutions (individuals of the population) which are analyzed in order to establish how well they respond to the proposed problem.
- Selection – individuals of the population are selected for reproduction. The probability of a given solution being selected is proportional to its fitness.
- Crossover – characteristics of the selected solutions are recombined, generating new individuals.
- Mutation: characteristics of individuals resulting from the process of reproduction are altered, thus adding variety to the population;
- Update: individuals created in this generation are inserted in the population.
- Finalization: checks if the convergence criteria have been achieved. In this case, the execution ends; otherwise it returns to the evaluation stage.

The adequate parameterization of the proposed methodology, such as size of population, number of generations, probability of crossover and type of crossover and mutation, allows finding a balance between the convergence speed and the probability of the process being stuck in local optima.

In this paper, the first step of the optimization process is the input of data concerning the number of the available resources, such as wind turbines, PV panels, fuel cells, and curtailable loads. The operation limit (for instance the maximum active power generation) and cost for these resources are also inputs of the algorithm.

In order to address the problem considered in this paper, the genes (G_{R_i}) of each GA individual can be of four different types, corresponding to: wind generation, photovoltaic generation, fuel cell generation, and load curtailment. Each individual has 99 genes, corresponding to the 66 DG units, 32 controlled loads, and the supplier from the 60 kV network:

$$[G_{W_1};\ldots;G_{W_{N_W}};G_{PV_1};\ldots;G_{PV_{N_{PV}}};G_{FC_1};\ldots;G_{FC_{N_{FC}}};G_{LC_1};\ldots;G_{LC_{N_{LC}}}]$$

The initial population is obtained through a heuristic method illustrated in Fig. 2 [29]. The method to determine the initial solution consists in choosing the generators that will be connected with the lower costs and the loads that will be cut or reduced. For this purpose let us consider Fig. 2, in which the lines corresponding to the ascending cost of the production generators and to the descending cost of the load curtailment are shown. The method chooses the initial population corresponding to point A which corresponds to cost C. The chosen point corresponds to a value for the production and load. Using generation and load curtailment merit orders, the scheduled generation units and the curtailed load are determined. The initial population is selected to the minimum cost, and the variables that are associated with this cost are set equal to 1 and the others are initialized as zero.

After setting the initial population, the simulation is performed to reach the final configuration according to the proposed methodology. GA will automatically select the best chromosome at every generation. Thus, at the end of generation the chromosome with the lowest cost is obtained.

To choose the best parameter set, the proposed method has been run 100 times with each considered set of parameters. The choice of the parameters has taken into account the following

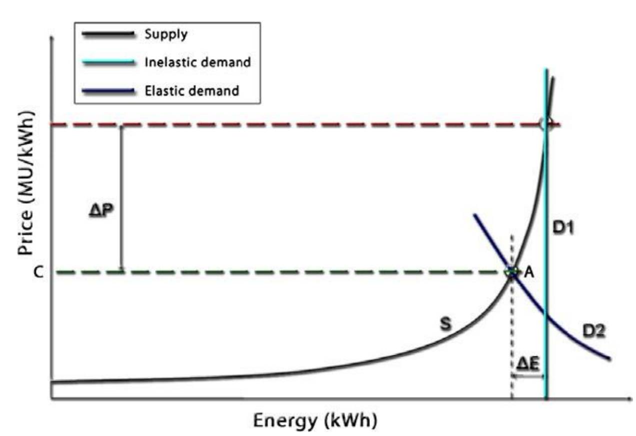

Fig. 2. Chose initial population for each hour based on (adapted from [29]).

factors: average fitness, maximum fitness, minimum fitness and execution time. Table 1 presents the results for the choice of the GA parameters. More details concerning MATLAB® optimization toolbox parameters can be found in [30].

Each run stopping depends on two criteria: maximum number of generations and maximum time over which the changes in the fitness function are negligible (StallTimeLimit). Fig. 3 shows the fitness function evolution concerning to the case of the set of parameters with the fastest time presented in Table 1.

After a problem sensitivity analysis, the GA parameters used to solve the envisaged short-term scheduling problem are the following:

• Size of population:	30
• Number of generations:	80
• Fitness scaling:	Proportional
• Probability of crossover:	0.95
• Crossover function:	Heuristic
• Mutation function:	Gaussian
• Elitism:	2 chromosomes

3. Short-term scheduling simulator

In order to improve the efficiency of the use of DER in power systems, it is necessary to create adequate models in simulation tools so that scheduling solutions can be tested before their actual implementation. The work presented in this paper includes the development of a distribution network model, considering intensive penetration of DG units, and the use of a Genetic Algorithm (GA) approach for the short-term energy resources management. MATLAB® is used as the programming environment that supports the developed application which uses PSCAD® as the network simulation tool.

The choice of these two software packages fulfilled the requirements, providing us with powerful mathematical resources of MATLAB® and with the advantage of an efficient connection with the PSCAD® power system simulator through its FORTRAN interface [31–33]. PSCAD®/EMTDC™ has been widely used in the study of distributed energy resources [34–39].

To simulate the distribution network for the hourly operation planning, the authors had to implement the network in PSCAD® and to create models of distributed generation units, loads, lines and substation. During the simulation, PSCAD® receives information concerning distribution network data, network state, DG and DR short-term scheduling resulting from the optimization process. The optimization process, executed in MATLAB®, needs the following data: generation data, generation costs, DR contracts, day-ahead DER scheduling and the intra-day market price, with the objective to minimize the cost of the DG, load curtailment and the intra-day market.

3.1. PSCAD® model

As explained above, it is possible to build custom models using PSCAD® Design Editor. Figs. 4–7 show the models used to represent the electricity network, the loads and the distributed generators. The different technologies of production lead to different interfaces with the power system. The interface with the power system plays an important role when considering the operational aspects related to DG. The interfaces considered in this sub-section for the DER models were based on [40,41]. Each component has been modeled and tested independently in PSCAD®, considering the direct connection to an infinite bus. The obtained results were compared with the real equipment is same cases (wind unit and photovoltaic unit), and with theoretical models (small hydro unit, cogeneration unit, waste to energy unit, fuel cell unit and the biomass unit).

Fig. 4 shows the substation model implemented in PSCAD®.

The substation model is represented by an infinite bus, the 60 kV transmission line and the substation transformer, which reduces voltage magnitude to the distribution network level.

Loads are modeled in PSCAD® as shown in Fig. 5, by using a resistance and an inductance that are adjusted, taking into account the maximum power demand provided for the simulation period, through the variable control fck shown in Fig. 8.

Fig. 6 shows the distributed generation models implemented in PSCAD®.

For the models that represent the small hydro units, the wind units, the cogeneration units, the waste to energy units, and the biomass units, a rotor synchronous machine with torque control has been used. For each PSCAD® component that represents the mentioned technologies, a characteristic curve of torque versus electric power is determined. A block that adjusts the torque of the machine has been created to simulate this curve, according to the variable control fgn provided for the simulation period. The subjacent models consider the generator model and its role for the efficiency of the conversion process; the turbine model is not considered for this work although it can be easily integrated, when available. The characteristic curves are different for each one of these generation technologies.

The distributed generators models remaining, namely for photovoltaic units and fuel cell units, use a controllable current source and a voltage divider. The voltage divider allows the power control, by the measured DC-link voltage, (Uc in Fig. 6), and calculates the magnitude of the controlled current source. These distributed generators are connected to the network through the DC–AC power conversion model represented in Fig. 6.

Fig. 7 shows the distribution line model implemented in PSCAD®.

The line model is defined as a line for which the capacitive current effect of capacitive current can be despised. The line is characterized by the resistance and inductive reactance.

Table 1
Choice of GA parameters.

Parameters GA					Results			
Population	Generations	% Crossover	Mutation	Crossover	Time	Mean	Min	Max
30	80	0.95	Heuristic	Gaussian	48.36	39,282	39,261	39,346
35	100	0.93	Heuristic	Gaussian	50.32	39,278	39,269	39,262
30	80	0.80	Heuristic	Gaussian	52.07	39,285	39,161	39,417
35	100	0.93	Two point	Uniform	60.15	39,373	39,351	39,394
35	100	0.93	Arithmetic	Uniform	62.33	39,374	39,370	39,377
35	100	0.93	Arithmetic	Adapt feasible	65.40	39,375	39,369	39,382
35	100	0.93	Two point	Gaussian	71.58	39,288	39,264	39,362
100	300	0.80	Two point	Uniform	157.48	39,373	39,363	39,380

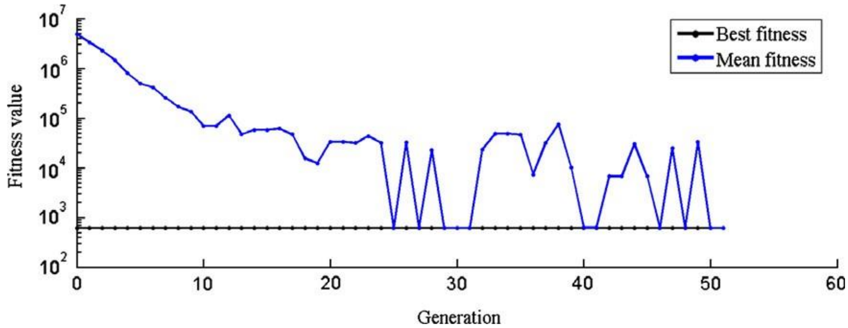

Fig. 3. Fitness function evolution of the proposed methodology in the best value of the period 2.

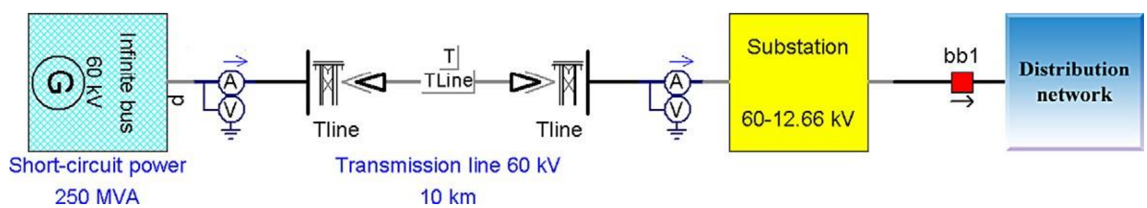

Fig. 4. The distribution substation model implemented in PSCAD®.

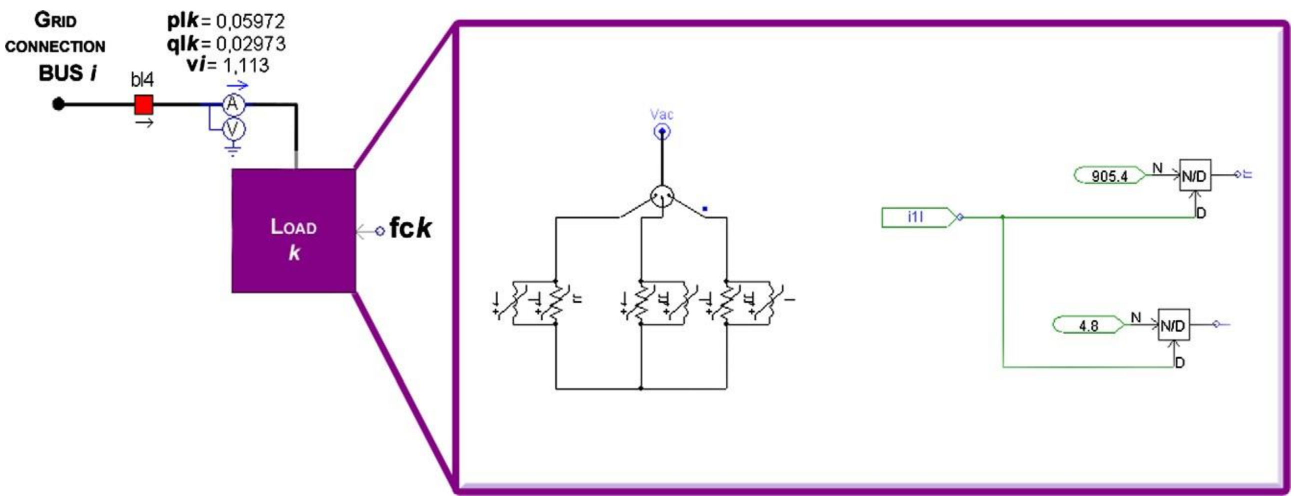

Fig. 5. The load model implemented in PSCAD®.

3.2. PSCAD®–MATLAB® interface

PSCAD® has the capability of interfacing with MATLAB® commands and toolboxes through a special interface. MATLAB® programs or block-sets that are to be interfaced with PSCAD® must be designed and saved as a MATLAB® program file. Then, a user-defined block must be provided in PSCAD®, with the necessary inputs and outputs, to interface the MATLAB® file. In this paper, the case study distribution network has been modeled in the PSCAD®/EMTDC™ environment. An interfacing block has been created in PSCAD®/EMTDC™ to link the MATLAB® files through FORTRAN scripts defined within the block.

Fig. 8 shows components connected to a bus implemented in PSCAD®.

The network values obtained for period t and with load forecast and generation forecast for period $t + 1$, are important data for optimization process. The obtained optimized solution is sent to PSCAD®, through the following variables: the load control variable in each load, the maximum instantaneous active power in each distributed generation unit, and the generator control variable in each distributed generation unit. These variables will set the new state of the generators and loads.

4. Case study

This case study shows the simulation of a distribution network with high DER penetration using PSCAD® simulation tool and MATLAB® to optimize the energy resources usage. The simulator will iterate with the optimization of the Distributed Energy Resources (DERs) short-term scheduling, in terms of the hourly operation planning for a 24 h scenario. The case study was implemented on the distribution network with 33 buses, from [42,43], as seen in Fig. 9, with load and Distributed Generation (DG) evolution prediction for the year 2040 [44]. This network is connected in bus

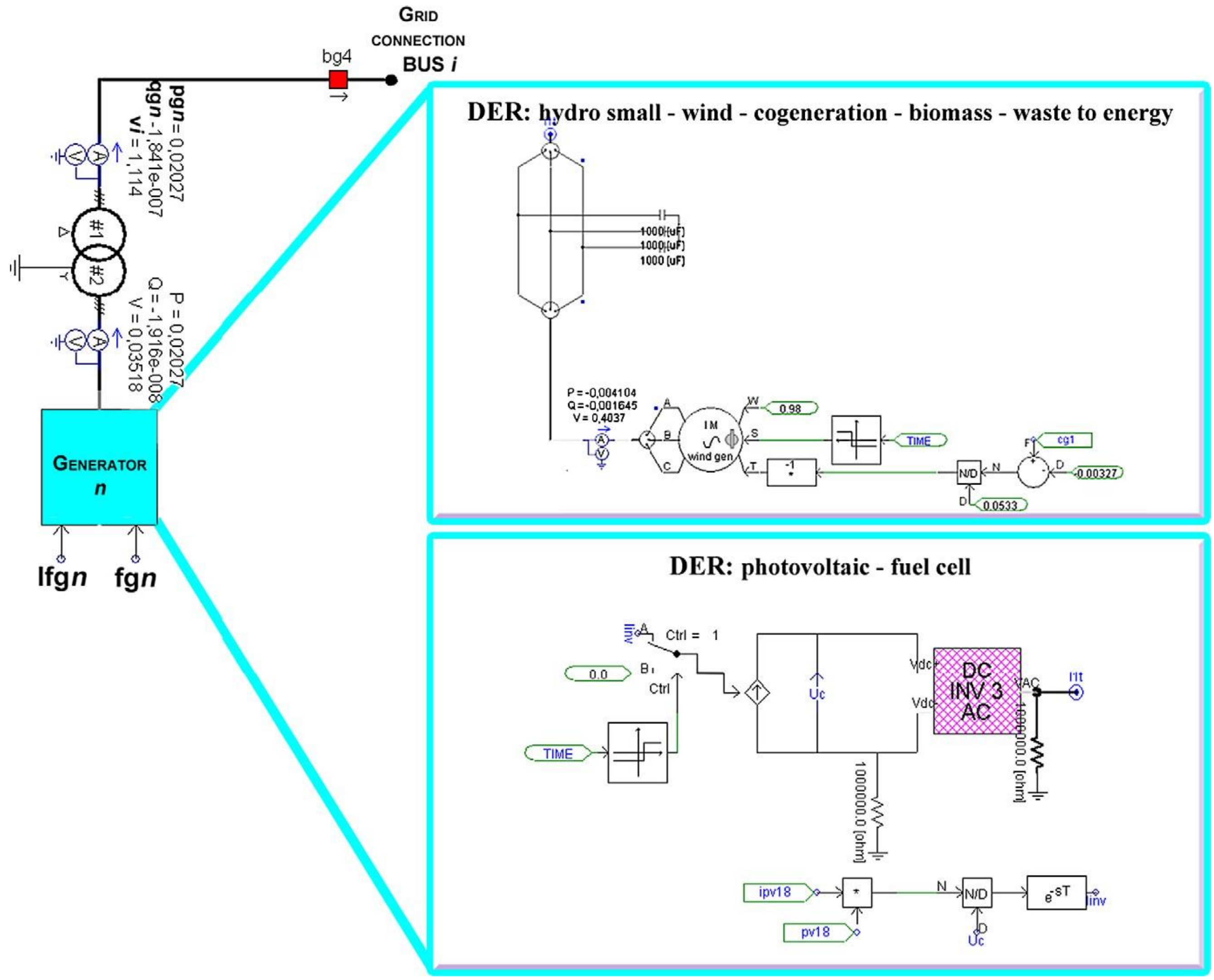

Fig. 6. The distributed generation models implemented in PSCAD®.

0 to the 60 kV network (represented in Fig. 3 with infinite bus and distribution substation).

Table 2 summarizes the considered energy resources costs for the case study and the number of DG units.

The results of evolution prediction of loads consumption and the DG can be seen in Fig. 10.

The Mixed-Integer Non-Linear Programming (MINLP) approach and Genetic Algorithm (GA) based optimization approach described in Section 2 have been used for determining the distributed generation and demand response short-term scheduling for this case study. The method that had the best result (cost vs. runtime) has been simulated in PSCAD®. It is important to note that all 24 optimizations, each one undertaken for one hour, are independent from each other. DER scheduling for period t is undertaken in period $t-1$, considering the operation state resulting from the schedule already used for the previous periods. An important input to the hour ahead problem is the energy resources status and the consumption and generation very-short term forecast. In the present case study, the information about energy resources status are sent by PSCAD® and the forecast of consumption and generation is determined by a specific algorithm presented in [6]. Only with this information and with the information about the day ahead scheduling is possible to do the hour ahead scheduling to period t.

The methodology used to simulate the power system of this case study has been tested on a PC compatible with one Intel Xeon W5450 3.00 GHz processor, with 8 Cores, 12 GB of random-access-memory (RAM) and Windows Sever Enterprise.

Table 3 shows the results of the DERs scheduling from MINLP.

Table 4 presents the energy total power loss, mean voltage, GA execution time and costs resulting from GA and PSCAD®.

The results of the costs described in Tables 3 and 4 are based on Eq. (1) and the cost per kWh for each generator and load varies according to each period. The minimum and maximum values of the cost (m.u.) are shown in Table 2.

Comparing the results of the proposed methodology based on the GA heuristic, presented in Table 4, with the results of the MINLP approach, presented in Table 3, it is possible to conclude that the difference of operation cost obtained with both methods is less than 10%. On the other hand, processing time is substantially different, with the GA methodology being about 90% faster than the MINLP methodology. The proposed methodology performance has already been analyzed in [25] for 3 distinct load diagrams scenarios. The GA approach is considered for the methodology proposed in the present paper for realistic power system simulation because the processing time is crucial for short-term scheduling, which is the focus of this paper.

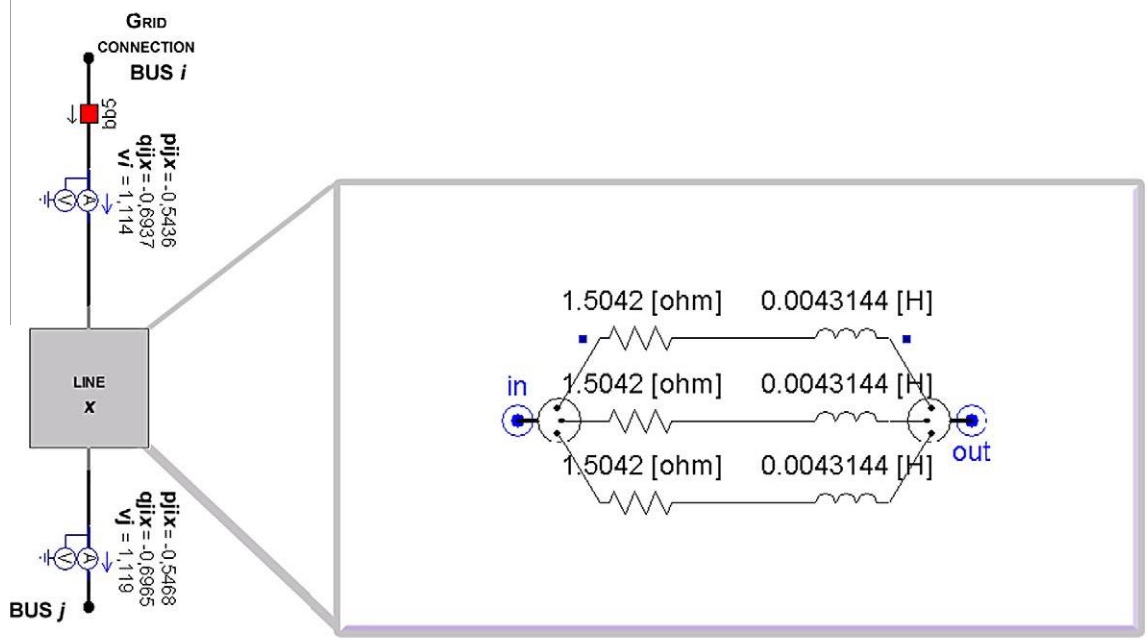

Fig. 7. The distribution line model implemented in PSCAD®.

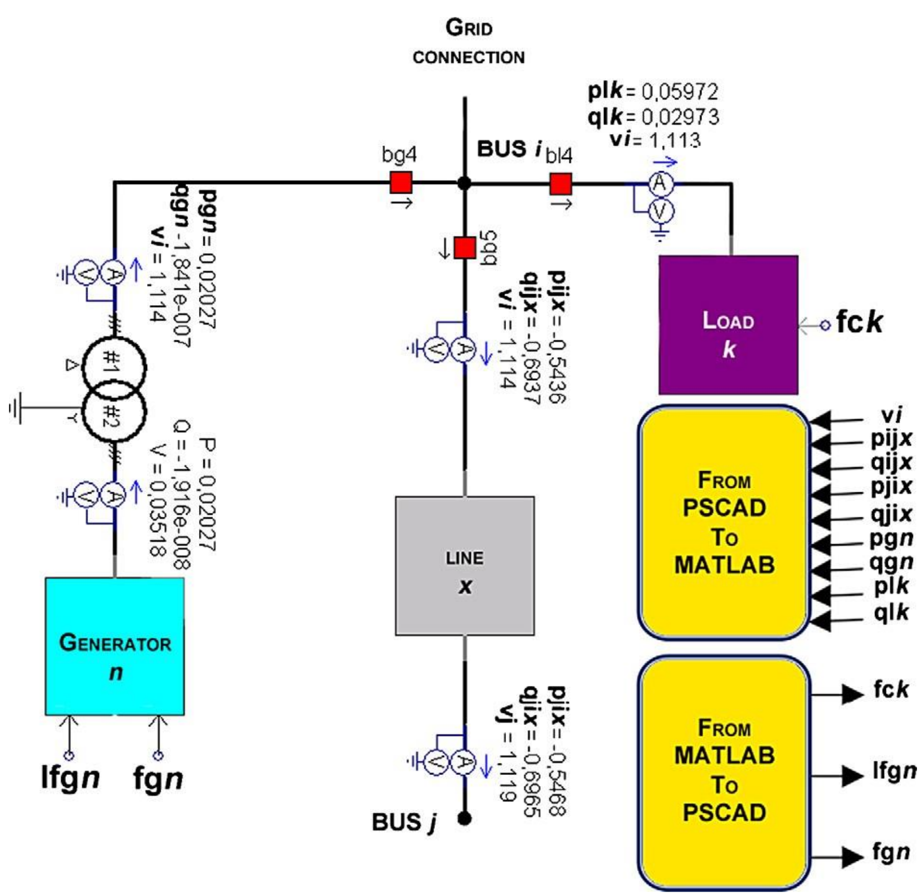

Fig. 8. The simulator model to one bus implemented in PSCAD®. pg*n* – Active power of distributed generation unit *n* in BUS *i*. qg*n* – Reactive power of distributed generation unit *n* in BUS *i*. v*i* – Voltage magnitude in BUS *i*. v*j* – Voltage magnitude in BUS *j*. pl*k* – Active power demand of load *k* in BUS *i*. ql*k* – Reactive power demand of load k in BUS *i*. pij*x* – Active power in line *x* from BUS *i* to BUS *j*. qij*x* – Reactive power in line *x* from BUS *i* to BUS *j*. pji*x* – Active power in line *x* from BUS *j* to BUS *i*. qji*x* – Reactive power in line *x* from BUS *j* to BUS *i*. fc*k* – Load control variable of load *k*. lfg*n* – Maximum instantaneous active power generator power of distributed generation unit *n*. fg*n* – Generator control variable of distributed generation unit *n*.

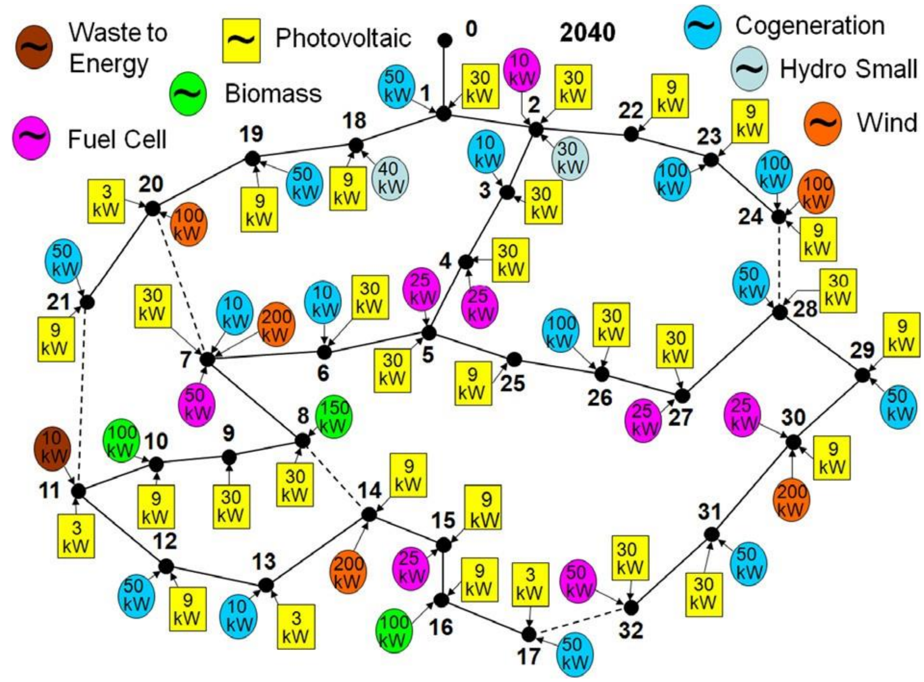

Fig. 9. Bus distribution network configuration in 2040 scenario [44].

Table 2
Case study energy resource data.

Energy resources	Number of units	Maximum/minimum price Case study (m.u./kW h)
Biomass	3	0.30–0.50
Cogeneration	15	0.30–1.00
Fuel cell	8	0.40–1.00
Hydro small	2	0.30–0.50
Photovoltaic	32	0.30–0.50
Waste to energy	1	0.30–1.00
Wind	5	0.30–1.00
Load	32	1.00–3.00
Energy supply	1	1.50–3.00

Analyzing the obtained results presented in Table 4, it is possible to conclude that the difference between the results of GA optimization process and PSCAD® simulation is low. Other important aspect is the processing time of the proposed methodology. The advantage of low run-time will allow reading DER units in real time and implementing the methodology "5 min ahead" in order to ensure the system balance and stability.

In the presented scenarios the generation is insufficient to supply all the demand, even using the available DR contracts. In this situation, some loads without DR contracts have to be shed, what implies the payment of the corresponding penalties. The obtained results are sent to PSCAD® where it is possible to analyze the transient effects and the system balance before and after the optimization process.

Let us consider the optimization results for periods 2 and 3 (i.e. hours 2 and 3 of the day considered in this case study) to analyze the transient effects after the optimization process, between two periods. Table 5 shows the results of the DERs scheduling for periods 2 and 3. Table 6 presents the results for the voltage magnitude in distribution network buses, confirming the voltage stability in the system.

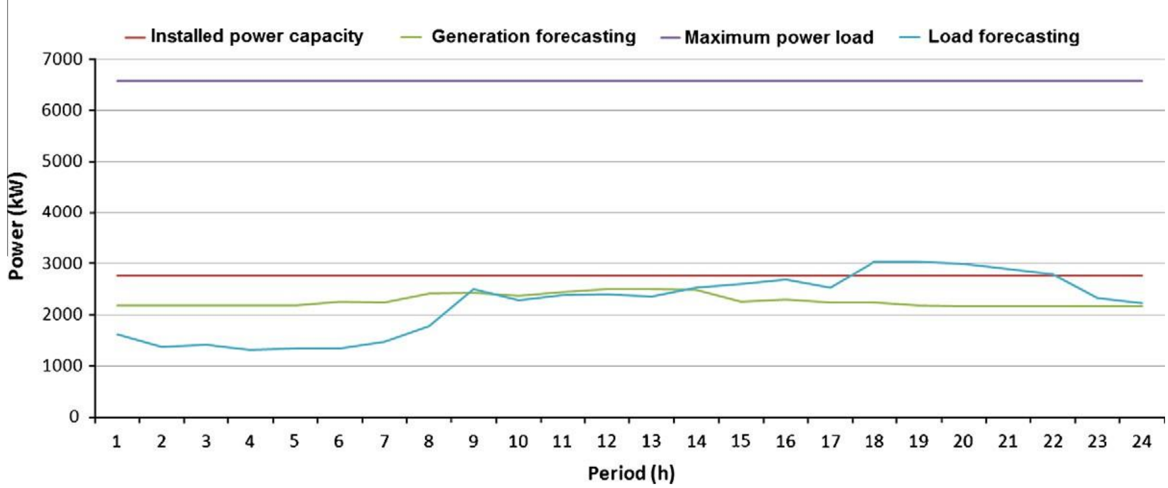

Fig. 10. Load forecasting and the generation forecasting in period $T = 24$.

Table 3
Results scheduling for MINLP.

Period (T)	Load			Generators			Energy supply		Total power loss (kW)	Mean voltage (p.u.)	Execution time MINLP (s)	Total cost (m.u.)
	Forecast (kW)	Schedule by MINLP (kW)	Cost (m.u.)	Forecast (kW)	Schedule by MINLP (kW)	Cost (m.u.)	Schedule by MINLP (kW)	Cost (m.u.)				
1	1619	1619	0	2174	1630	976	0	0	11.31	1.03	21.39	976
2	1366	1366	0	2174	1374	668	0	0	7.97	1.03	20.87	668
3	1416	1416	0	2174	1425	782	0	0	8.63	1.03	22.32	782
4	1315	1315	0	2174	1324	685	0	0	9.26	1.03	19.3	685
5	1341	1341	0	2174	1348	722	0	0	7.23	1.02	20.11	722
6	1341	1341	0	2248	1351	699	0	0	9.89	1.03	19.16	699
7	1467	1467	0	2245	1477	808	0	0	10.08	1.03	22.31	808
8	1771	1771	0	2415	1786	1000	0	0	15.02	1.03	19.12	1000
9	2504	2414	175	2423	2423	1454	0	0	9.10	1.03	19.44	1629
10	2276	2255	62	2367	2265	1342	0	0	9.65	1.03	23.11	1404
11	2378	2305	353	2444	2329	1347	0	0	23.53	1.03	23.06	1700
12	2403	2403	0	2502	2421	1409	0	0	17.84	1.03	21.55	1409
13	2352	2352	0	2505	2377	1470	0	0	24.65	1.03	22.69	1470
14	2529	2473	283	2485	2485	1452	0	0	12.15	1.03	19.56	1735
15	2605	2221	640	2247	2247	1190	0	0	25.45	1.03	22.91	1830
16	2681	2266	722	2291	2291	1328	0	0	24.75	1.03	22.42	2050
17	2529	2217	675	2242	2242	1489	0	0	24.78	1.03	18.63	2164
18	3035	2230	1791	2243	2243	1169	0	0	13.03	1.03	21.83	2960
19	3035	2163	1679	2176	2176	1388	0	0	12.68	1.02	21.42	3067
20	2985	2157	1578	2170	2170	1164	0	0	12.73	1.03	18.96	2742
21	2883	2145	1399	2170	2170	1289	0	0	24.61	1.03	21.36	2688
22	2782	2160	1242	2170	2170	1189	0	0	10.00	1.03	19.65	2431
23	2327	2327	0	2170	2170	1307	181	150	23.69	1.03	21.81	1457
24	2226	2226	0	2170	2170	1166	78	81	21.74	1.03	20.74	1247
Total									369.76	–	503.72	38,323

Table 4
Results scheduling for GA and PSCAD®.

Period (T)	Load				Generators				Energy supply			Total power loss (kW)	Mean voltage (p.u.)	Execution time GA (s)	Total cost (m.u.)
	Forecast (kW)	Schedule by GA (kW)	Simulated by PSCAD (kW)	Cost (m.u.)	Forecast (kW)	Schedule by GA (kW)	Simulated by PSCAD (kW)	Cost (m.u.)	Schedule by GA (kW)	Simulated by PSCAD (kW)	Cost (m.u.)				
1	1619	1619	1636	0	2174	1645	1668	883	0	-13	20	19.0	1.01	1.77	903
2	1366	1366	1392	0	2174	1391	1365	535	0	52	83	24.6	1.00	1.77	618
3	1416	1239	1263	53	2174	1264	1207	566	0	83	126	26.9	1.01	1.78	745
4	1315	1315	1339	0	2174	1346	1464	586	0	-95	133	30.2	1.01	1.86	719
5	1341	1341	1361	0	2174	1373	1471	636	0	-82	148	28.0	1.01	1.87	784
6	1341	1341	1367	0	2248	1371	1501	609	0	-104	198	29.6	1.01	1.88	807
7	1467	1467	1491	0	2245	1500	1605	692	0	-88	167	25.9	1.01	1.89	859
8	1771	1771	1788	0	2415	1799	1860	879	0	-52	101	19.8	1.01	1.87	980
9	2504	2403	2399	196	2423	2423	2382	1481	0	38	76	21.1	1.00	1.89	1753
10	2276	2176	2167	74	2367	2303	2153	1274	0	27	57	13.2	1.00	1.91	1405
11	2378	2378	2384	0	2444	2393	2450	1612	0	-52	117	14.5	1.00	1.89	1729
12	2403	2398	2401	55	2502	2417	2525	1447	0	-110	264	14.2	1.00	2.69	1766
13	2352	2352	2358	0	2505	2366	2345	1465	0	26	78	13.4	1.00	1.89	1543
14	2529	2472	2364	322	2485	2485	2425	1371	0	-31	87	30.4	0.97	1.90	1780
15	2605	2209	2216	648	2247	2247	2125	1327	0	100	260	9.0	1.00	2.30	2235
16	2681	2277	2283	677	2291	2291	2213	1494	0	86	198	15.5	1.01	3.70	2369
17	2529	2226	2239	555	2242	2242	2268	1576	0	-12	26	16.7	1.01	1.90	2157
18	3035	2226	2133	1757	2243	2243	2214	1502	0	-62	174	19.1	0.98	1.90	3433
19	3035	2156	2202	1522	2176	2176	2223	1556	0	24	72	44.7	1.02	1.93	3150
20	2985	2125	2174	1499	2170	2170	2122	1355	0	91	282	38.8	1.02	3.51	3136
21	2883	2131	2144	1431	2170	2170	2205	1471	0	-38	99	22.6	1.01	1.92	3001
22	2782	2147	2202	1092	2170	2170	2305	1409	0	-65	143	38.4	1.02	1.81	2644
23	2327	2139	2159	327	2170	2170	2150	1517	0	29	46	20.1	1.01	1.83	1890
24	2226	2226	2238	0	2170	2170	2182	1365	76	73	110	16.6	1.01	1.81	1475
Total												552.3	–	49.47	41,881

Table 5
Results scheduling DERs in periods 2 and 3 – PSCAD®.

Bus no.	DERs	Simulated by PSCAD (kW)		Bus no.	DERs	Simulated by PSCAD (kW)	
		Period 2	Period 3			Period 2	Period 3
1	Photovoltaic	0	0	17	Photovoltaic	0	0
	Cogeneration	0	0		Cogeneration	0	0
	Load 1	43	37		Load 17	33	34
2	Fuel cell + photovoltaic	20	20	18	Hydro small	40	40
	Hydro small	30	30		Photovoltaic	0	0
	Load 2	33	34		Load 18	33	34
3	Cogeneration	0	10	19	Cogeneration	50	50
	Photovoltaic	0	0		Photovoltaic	0	0
	Load 3	45	45		Load 19	33	34
4	Fuel cell + photovoltaic	0	0	20	Photovoltaic	0	0
	Load 4	23	22		Wind	0	0
5	Fuel cell + Photovoltaic	20	0		Load 20	33	34
	Load 5	23	22	21	Cogeneration	50	50
6	Photovoltaic	0	0		Photovoltaic	0	0
	Cogeneration	10	0		Load 21	34	34
	Load 6	74	76	22	Photovoltaic	0	0
7	Cogeneration	10	10		Load 22	35	34
	Fuel cell + photovoltaic	40	0	23	Photovoltaic	0	0
	Wind	0	200		Cogeneration	100	0
	Load 7	75	76		Load 23	154	160
8	Photovoltaic	0	0	24	Photovoltaic	0	0
	Biomass	150	150		Cogeneration	100	0
	Load 8	23	22		Wind	0	86
9	Photovoltaic	0	0		Load 24	155	160
	Load 9	23	22	25	Photovoltaic	0	0
10	Photovoltaic	0	0		Load 25	22	23
	Biomass	100	100	26	Photovoltaic	0	0
	Load 10	17	17		Cogeneration	100	100
11	Waste to energy	10	10		Load 26	24	23
	Photovoltaic	0	0	27	Fuel cell + photovoltaic	20	20
	Load 11	23	23		Load 27	22	23
12	Cogeneration	50	0	28	Photovoltaic	0	0
	Photovoltaic	0	0		Cogeneration	50	0
	Load 12	22	23		Load 28	45	45
13	Cogeneration	10	0	29	Photovoltaic	0	0
	Photovoltaic	0	0		Cogeneration	50	50
	Load 13	44	16		Load 29	74	76
14	Wind A	0	0	30	Fuel cell + photovoltaic	20	20
	Wind B	25	100		Wind	96	0
	Photovoltaic	0	0		Load 30	57	22
	Load 14	23	23	31	Photovoltaic	0	0
15	Fuel cell + photovoltaic	24	24		Cogeneration	50	50
	Load 15	22	23		Load 31	77	0
16	Biomass	100	47	32	Fuel cell + photovoltaic	40	40
	Photovoltaic	0	0		Load 32	27	23
	Load 16	23	23				
				Total	Generators (kW)	1365	1207
					Load (kW)	1392	1263

Table 6
Results voltage in periods 2 and 3 – PSCAD®.

Bus no.	Voltage (p.u.)		Bus no.	Voltage (p.u.)	
	Period 2	Period 3		Period 2	Period 3
1	0.9985	1.0016	18	0.9938	0.9989
2	0.9945	0.9994	19	0.9943	0.9997
3	0.9960	1.0007	20	0.9944	0.9999
4	0.9976	1.0022	21	0.9944	0.9999
5	1.0021	1.0067	22	0.9934	0.9983
6	1.0026	1.0072	23	0.9915	0.9966
7	1.0047	1.0081	24	0.9909	0.9957
8	1.0071	1.0104	25	1.0026	1.0073
9	1.0087	1.0120	26	1.0033	1.0083
10	1.0092	1.0124	27	1.0069	1.0130
11	1.0096	1.0127	28	1.0098	1.0165
12	1.0116	1.0144	29	1.0110	1.0180
13	1.0124	1.0150	30	1.0110	1.0184
14	1.0131	1.0156	31	1.0108	1.0183
15	1.0133	1.0158	32	1.0109	1.0184
16	1.0137	1.0164			
17	1.0137	1.0165	Mean (p.u.)	1.0038	1.0085

Some of results obtained in PSCAD® from which it was possible to analyze the transient effects and the system balance after the optimization process are shown in Figs. 11–15.

- Bus 1 – load went from 43 kW in period 2 – 37 kW in period 3:

In Fig. 11 it is possible to see a low decrease of active (pl1) and reactive (ql1) load consumption. The transient effects are irrelevant for the system.

- Bus 1 – voltage magnitude:

The impact of the total load demand decrease in the distribution network causes a voltage increase in bus 1. The voltage magnitude in bus 1 is higher than 1 p.u. at the end of period 3. The minimum voltage occurs in bus 24 with 0.9957 p.u.

- Line 0–1 – power flow and losses:

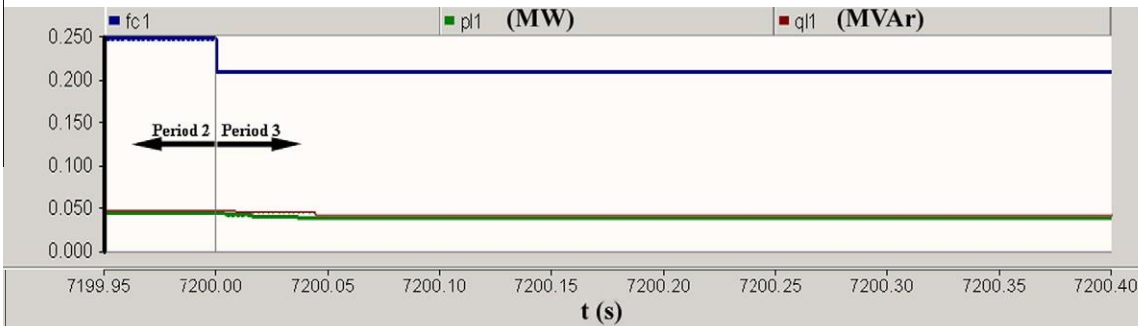

Fig. 11. Active and reactive power consumption in bus 1.

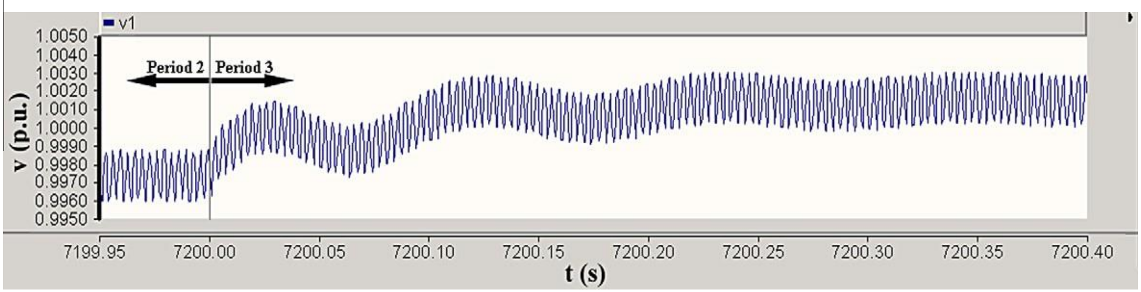

Fig. 12. Bus 1 voltage magnitude.

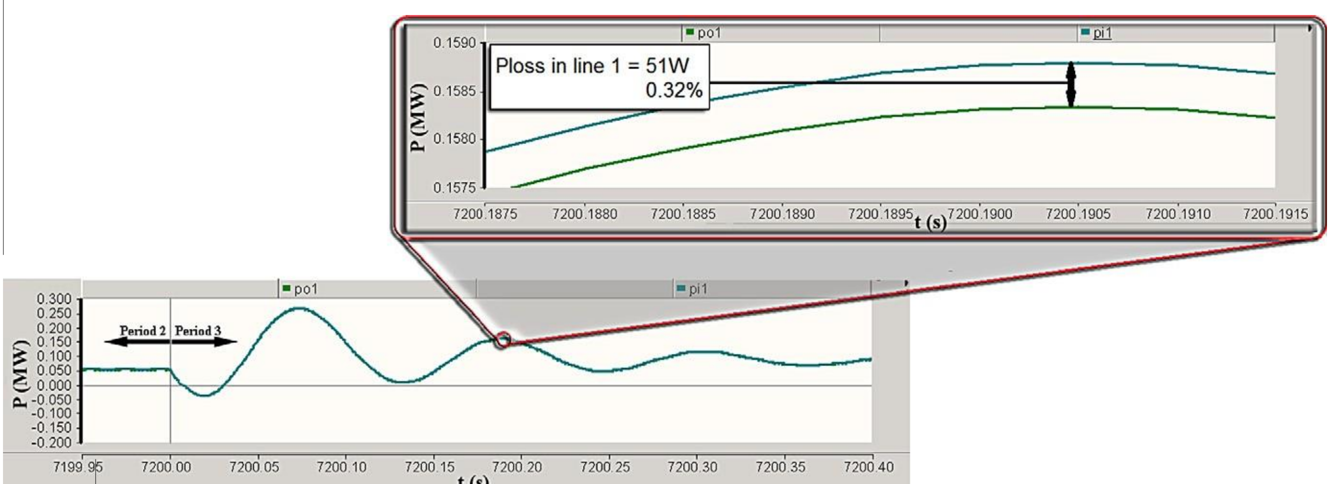

Fig. 13. Power flow and losses in line 0–1.

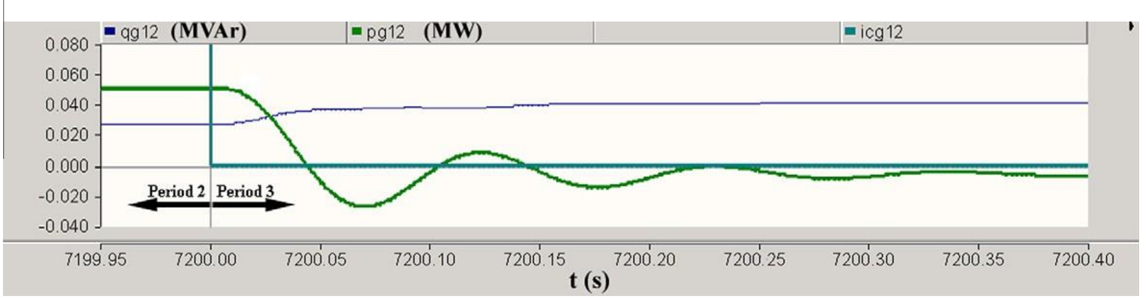

Fig. 14. Active and reactive power generation in CHP, installed in bus 12.

The power flow in the line between bus 0 and bus 1 increases after the optimization for period 3. Before the optimization process, the power flow is 52 kW from bus 1 to bus 0 and, after the optimization process, the load flow is 83 kW in the same

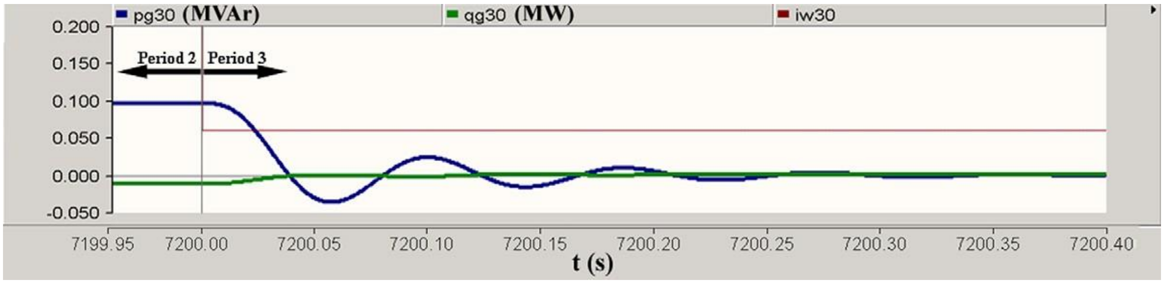

Fig. 15. Active and reactive power generation in Wind, installed in bus 30.

direction. This increase results from the lower energy price of the external supplier. The power losses in line 0–1 are equal to 51 W (0.32%).

- Bus 12 – the cogeneration unit has been taken out of service:

The active power decrease to zero leads to an oscillation during 1s. With the CHP generator out of service, there is a decrease in the reactive power consumption in bus 12. As the capacitor bank is kept in service, the corresponding reactive power is injected in the distribution network.

- Bus 30 – wind generator has been taken out of service:

The active power decrease to zero leads to an oscillation during 1.5 s. The reactive power is zero because there are not capacitor banks connected to bus 30.

- Bus 30 – load went from 57 kW in period 2 – 22 kW in period 3 (Fig. 16):

In order to show the advantages of the proposed methodology with an optimization process, the same process without optimization, that is with all the available DER connected, has been simulated. Table 7 shows the results of the process without optimization.

Analyzing the results presented in Table 4 and in Table 7, it is possible to conclude that the process without optimization results in higher operation costs, with a difference of 9814 m.u. at the end of the 24 periods. Regarding the Total Power Losses there is an increase of 3112 kW in relation to the optimized process. The power losses values show that implement methodology makes the system operation efficient. At the same time, the obtained lower power flows increase the system reliability and make the eventually required configurations, after incident situations, more efficient than the non optimal ones. Comparing the mean voltages on the buses, the optimization process presents the best results with voltage levels near to 1 p.u.

The proposed method allows to adjust and control remotely the DER in response to the load forecasting, the available generation and the variation in the DER costs and suppliers' price. Its use allows increasing the system efficiency and stability, relieving the operator of the repetitive tasks.

5. Conclusions

The present paper proposed a short-term energy resource management methodology for smart grids. This methodology involves day ahead, hour ahead and five minutes ahead scheduling. Short-term scheduling is used to reschedule the previously obtained schedule taking advantage of the better accuracy of short-term wind forecasting in order to obtain more efficient resource scheduling solutions.

The used optimization is based on a Genetic Algorithm (GA) approach that has proved to achieve a satisfactory cost operating point in a competitive time. The obtained solution feasibility is technically validated using realistic power system simulation. The use of adequate models of the considered generation technologies allows to analyze transient behavior and to adopt adequate implementation plans for the optimal solutions. The proposed method has been implemented using MATLAB® as the programming environment. MATLAB® is connected to PSCAD®, allowing improving the potential of both applications and automating the obtained solution analysis.

The case study included in the paper illustrates a 33 bus distribution network with high penetration of renewable generation and consumers with demand response contracts.

The proposed methodology demonstrated to be able to provide users with significant cost reductions, lowering the power losses and resource use costs. Moreover, it includes an automatic analysis of the power system simulation, which is based on the use of PSCAD®.

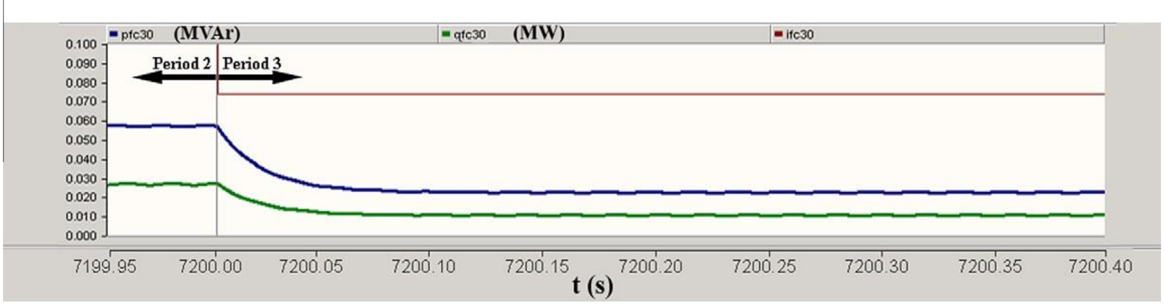

Fig. 16. Active and reactive power consumption in bus 30.

Table 7
Results PSCAD® without optimization.

Period (T)	Load			Generators			Energy supply			Total power loss (kW)	Mean voltage (p.u.)	Total cost (m.u.)
	Forecast (kW)	Simulated by PSCAD (kW)	Cost (m.u.)	Forecast (kW)	Simulated by PSCAD (kW)	Cost (m.u.)	Forecast (kW)	Simulated by PSCAD (kW)	Cost (m.u.)			
1	1619	1489	0	2174	2151	974	0	−518	778	143.6	0.92	1752
2	1366	1257	0	2174	2221	1037	0	−820	1313	143.6	0.92	2350
3	1416	1303	0	2174	2196	1101	0	−749	1124	143.6	0.92	2225
4	1315	1210	0	2174	2043	1065	0	−689	965	143.6	0.92	2030
5	1341	1234	0	2174	2153	1079	0	−775	1396	143.6	0.92	2475
6	1341	1234	0	2248	2302	1278	0	−925	1758	143.0	0.92	3036
7	1467	1364	0	2245	2296	1245	0	−790	1501	141.9	0.93	2746
8	1771	1647	0	2415	2387	1363	0	−582	1135	158.0	0.93	2498
9	2504	2329	0	2423	2450	1633	0	50	100	170.9	0.93	1733
10	2276	2117	0	2367	2322	1646	0	−32	66	173.5	0.93	1712
11	2378	2212	0	2444	2504	1344	0	−131	301	161.1	0.93	1645
12	2403	2235	0	2502	2523	1483	0	−121	289	167.4	0.93	1772
13	2352	2187	0	2505	2520	1405	0	−165	496	167.7	0.93	1901
14	2529	2352	0	2485	2498	1209	0	27	76	173.2	0.93	1285
15	2605	2423	0	2247	2220	1225	0	375	974	171.6	0.93	2199
16	2681	2493	0	2291	2315	1267	0	337	774	158.6	0.93	2041
17	2529	2352	0	2242	2224	1011	0	271	595	142.5	0.93	1606
18	3035	2823	0	2243	2235	1136	0	731	2047	143.2	0.93	3183
19	3035	2792	0	2176	2101	964	0	835	2505	144.0	0.92	3469
20	2985	2746	0	2170	2151	1072	0	741	2296	145.8	0.92	3368
21	2883	2652	0	2170	2137	893	0	661	1718	145.8	0.92	2611
22	2782	2559	0	2170	2100	1065	0	605	1572	145.8	0.92	2637
23	2327	2141	0	2170	2195	928	0	92	147	145.8	0.92	1075
24	2226	2048	0	2170	2201	334	0	−7	11	145.8	0.92	345
Total										3664	–	51,695

Acknowledgements

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