Optimal Design of Photovoltaic Systems Using High Time-Resolution Meteorological Data

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***Abstract*—The installation of photovoltaic (PV) plants has been expanding rapidly across the world during the last years. In this paper, a methodology for the design optimization of PV plants is presented, which, in contrast to the conventional PV plant design approaches, is suitable to be executed using high time-resolution (i.e., 1-min-average) values of the meteorological input data. Due to the nonlinear operation of the devices comprising a PV plant, this allows for the accurate estimation of the PV plant performance during its operational lifetime period. A parallel processing-based implementation of genetic algorithms has been employed, which, compared to the serial execution, provides the ability to accomplish the proposed optimal design procedure in a considerably shorter time interval. The design optimization results confirm that the proposed method successfully accounts for both the meteorological conditions and the operational characteristics of the PV plant components and incorporates their impact on the PV plant energy production and cost in the design process. Thus, the proposed optimization method allows for optimum design of PV systems, which will provide maximum economic profit during their lifetime period.**

***Index Terms*—Design, genetic algorithms (GAs), grid-connected, optimization, photovoltaic (PV) system.**

I. Introduction

THE TOTAL-INSTALLED photovoltaic (PV) capacity in the world has increased during the last 10 years by a factor of 36 [1], thus aiming to address the environmental impact of conventional electric energy production units and achieve savings in terms of CO_2 emissions. Approximately 55% of the global new PV capacity was installed in Europe during 2012, but the PV market is also expanding quickly outside Europe (e.g., in USA, Canada, China, Japan, etc.) [2]–[4].

Both the energy production of PV systems and the economic benefit achieved by the PV installations depend on the continuously varying weather conditions of the installation site. Thus, the methodologies applied to design PV systems incorporate the use of meteorological data of the installation site. An algorithm employing weather classification and support vector machines for forecasting the output power of PV systems with a 15-min time interval is proposed in [5]. The financial analysis as well as the voltage variation and power loss of the distribution feeder, in case of a 1-MW_p large-scale PV system, are presented in [6]. The PV power generation is calculated using hourly values of solar irradiation and temperature.

A method for calculating the PV array size and battery capacity, such that the reliability and cost of a standalone PV system are optimized, is proposed in [7]. During the optimization process, the performance of the PV system is simulated for a time period equal to the battery lifetime with a time step of 1 h. The optimal power capacities of PV and wind turbines in a hybrid grid-connected system are calculated in [8] by employing multicriteria decision analysis, in combination with an estimation of the hybrid system performance, based on hourly values of the meteorological conditions and load demand during a year. In [9], a methodology is proposed for determining the optimal types of PV modules and dc/ac inverters in grid-connected PV systems, which employs an optimization process based on evolutionary programming, such that PV system performance is optimized in terms of technical and economical metrics. The expected annual energy output of the PV system is estimated using the expected annual peak sun-hours for the specific tilt and orientation that the target PV array will be installed. In [10], the performance of various models for the prediction of the energy production of grid-connected PV systems is evaluated using 15-min-average values of meteorological and electrical parameters measurements.

At each time instant, the operating temperature of the PV modules as well as the corresponding power generated are determined by the ambient temperature and incident solar irradiation conditions [11]. The output power variability of large-scale solar plants is investigated in [12] using 1-min-average data. The optimum power rating of a PV inverter with respect to the PV array power under Standard Test Conditions (STC) is calculated in [13], such that the yearly averaged dc/ac energy conversion efficiency is maximized. It is also demonstrated that due to the nonlinear operation of the PV system, solar irradiation and ambient temperature data with a time resolution higher than 10 min should be used in order to derive accurate sizing results. Additionally, as analyzed in [14], the commonly used 1-h-average solar irradiation values smooth irradiation peaks, which significantly affect the energy production of the PV inverter (e.g., due to control for overloading protection, variability of efficiency with operating power level, etc.), thus necessitating the use of high time-resolution meteorological data comprised of 1-min-average values, in order to size the dc/ac inverters employed in grid-connected PV systems.

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A methodology for calculating the optimal configuration of large-scale PV plants has been presented in [15], such that the levelized cost of electricity generated by the PV system is minimized. Compared to the conventional techniques employed to design PV systems, the method in [15] has the advantage that it simultaneously takes into account during the PV system design flow all design parameters of large PV plants, which highly affect both the resulting energy production as well as the capital and lifetime maintenance costs. Such design parameters are the meteorological conditions at the installation site, the PV system components number, type, and operating specifications (e.g., power rating, operating voltage range, power processing efficiency, etc.), the arrangement of the PV arrays within the installation field, and the reduction in the power produced by the PV plant due to mutual shading between adjacent rows of PV modules. In that method, the PV plant design process is also performed using hourly average values of the solar irradiance and ambient temperature conditions, which prevail at the installation site during the entire year.

During the execution of a PV plant optimization procedure, the performance of the PV system under design is evaluated for multiple times, using an appropriate computing model of the PV plant, until the overall optimum configuration has been derived. In such a case, increasing the time resolution of the yearly meteorological data employed during the PV plant performance-evaluation process from 1 h to 1 min, in order to comply with [14], also increases the computation time required by typical desktop computers to accomplish the optimization process to a time interval of the order of many days. However, this is not practical, especially in the case that it is desirable by the designer to execute the optimization process for multiple alternative types of PV plant components (e.g., PV modules, dc/ac inverters etc.) in order to derive the most efficient structure of the PV plant under design.

In this paper, the design method for the design optimization of PV plants, which has been presented in [15], is extended such that it is executed using 1-min-average values of the meteorological input data during the year. Thus, as the time-step resolution and volume of the input data processed during each step of the optimization process are increased by a factor of 60, massively parallel processing is employed to reduce computational time. Although simulation tools for PV systems exist, operating using such a low time step, it is the first time in the existing research literature that an optimization process is developed for PV systems, which is performed by employing high time-resolution solar irradiation and ambient temperature time series. In contrast to the conventional design approaches, the proposed optimization process comprises a design tool with the following advantages: 1) conforms to the time resolution requirements for designing PV systems accurately, which have been set in [13], [14] as described above and 2) it takes into account the impact of the meteorological conditions as well as the PV system components number, type, and arrangement within the installation field, on the tradeoff between the lifetime cost and the corresponding energy production of the PV plant. Thus, the proposed methodology enables to maximize the economic profit provided by the optimally designed PV system during its lifetime period and reduce the associated financial risk.

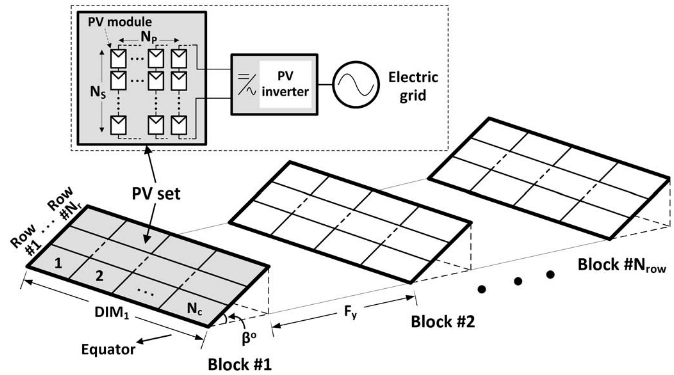


Fig. 1. Structure of the PV plant considered in the proposed optimization process.

This paper is organized as follows: the modeling of grid-connected PV systems, which is employed in the proposed design technique, is described in Section II; the optimization process using high time-resolution data is analyzed in Section III, and the PV system design optimization results are discussed in Section IV.

II. Modeling of Grid-Connected PV Systems

The PV plant structure considered in the proposed optimization process is illustrated in Fig. 1. The PV plant comprises $N_{I,o}$ PV modules, which are calculated as follows:

$$N_{I,o} = \frac{P_{\text{plant,nom}} \cdot 10^6}{P_{\text{M,STC}}} \tag{1}$$

where $P_{\text{plant,nom}}$ (MW_p) is the PV plant power rating and $P_{\text{M,STC}}$ (W) is the power rating of each PV module, both specified by the PV plant designer.

The PV modules are configured in PV sets consisting of strings with N_s series-connected PV modules ($N_s \geq 1$), while N_p identical PV strings ($N_p \geq 1$) are connected in parallel. A PV set is connected to each PV inverter in order to interface the PV generated power to the electric grid. Multiple PV sets are arranged in the installation field, in multiple blocks of length DIM_1 (m). Each block contains PV sets, which are installed in N_r nonbreaking rows along the equator-facing side of the PV plant, in order to fully exploit the available installation area. The distance between adjacent PV blocks F_y (in m, $F_y \geq 0$) is calculated also considering mutual shading among adjacent blocks, as analyzed in [15]. The tilt angle of the PV modules $\beta(^\circ)$ is constant during the operational lifetime period of the PV plant.

The target of the proposed design optimization process is to derive the optimal configuration of the PV plant, which results in the minimization of the PV plant levelized cost of generated electricity (LCOE) [16], [17]

$$\underset{\boldsymbol{X}}{\text{minimize}}\{\text{LCOE}(\boldsymbol{X})\} = \underset{\boldsymbol{X}}{\text{minimize}}\left\{\frac{C_c(\boldsymbol{X}) + C_m(\boldsymbol{X})}{E_{\text{tot}}(\boldsymbol{X})}\right\} \tag{2}$$

where

$$E_{\text{tot}}(\boldsymbol{X}) = \sum_{i=1}^{n \cdot t_{\max}} P_i(\boldsymbol{X}) \cdot \Delta t \tag{3}$$

and $C_c(\boldsymbol{X})$ (€) and $C_m(\boldsymbol{X})$ (€) are the PV plant total capital and maintenance costs, respectively, during the PV plant lifetime period; $E_{\text{tot}}(\boldsymbol{X})$ (MWh) is the PV plant total energy production during its operational lifetime; $\boldsymbol{X} = [N_s, N_p, N_r, F_y, \beta, \text{DIM}_1]$ is the vector of the design variables; $P_i(\boldsymbol{X})$ (W) is the power produced by the PV plant at the ith time step; n is the PV plant lifetime period (e.g., 20–25 years); Δt is the simulation time step, which is set equal to either 1 h or $1\ \text{min} = 1/60\ \text{h}$, as defined by the PV plant designer and $t_{\max} = 8760$ or $t_{\max} = 525\,600$ for 1-h and 1-min time steps (i.e., Δt), respectively, of the meteorological input data.

The maximum permissible value of series-connected PV modules $N_{s,\max}$ is calculated considering the technical characteristics of the PV modules comprising the PV plant, such that the maximum possible voltage developed across the PV inverter input terminals during the year is within the maximum limit specified by its manufacturer. Also, the maximum permissible number of parallel-connected strings within each PV set, $N_{p,\max}$, is calculated such that the dc/ac inverter dc input power is also within its specifications. Thus, the optimal value of LCOE in (2) is calculated by the proposed optimization process, subject to the following constraints:

$$\text{DIM}_1 \leq \text{DIM}_{1,\max} \tag{4}$$

$$F_y \geq 0 \tag{5}$$

$$0^\circ \leq \beta \leq 90^\circ \tag{6}$$

$$1 \leq N_s \leq N_{s,\max} \tag{7}$$

$$1 \leq N_p \leq N_{p,\max} \tag{8}$$

where $\text{DIM}_{1,\max}$ (m) is the maximum permissible length of the PV blocks comprising the PV plant, and its value is specified by the PV plant designer according to the length of the equator-facing side of the PV plant installation field.

The values of $C_c(\boldsymbol{X})$, $C_m(\boldsymbol{X})$, and $E_{\text{tot}}(\boldsymbol{X})$ in (2) are calculated for each set of the decision variables values $\boldsymbol{X}$, which are produced during the optimization process, using the mathematical models of the PV plant devices and components described in [15]. The PV modules degradation rate during the PV plant lifetime period as well as the mean time between failures (MTBF) of the dc/ac inverters, which are provided by their manufacturers and affect the values of $E_{\text{tot}}(\boldsymbol{X})$ and $C_m(\boldsymbol{X})$, respectively, are also considered during this process, as analyzed in [15]. The calculation of the optimal values of the PV plant design variables $\boldsymbol{X}$ and LCOE is performed using (2), as analyzed in the following section.

III. Optimization Process Using High Time-Resolution Meteorological Data

A flowchart of the proposed design optimization process is presented in Fig. 2. The PV plant designer inputs the cost and operating specifications of the PV modules (e.g., open-circuit voltage at STC, power rating, etc.) and dc/ac inverters (e.g., dc input voltage range, power conversion efficiency curve, etc.), which are employed in order to build the PV plant as well as the time-series of 1-min-average (or 1-h-average, depending on the desired time-step value) solar irradiance on horizontal plane and

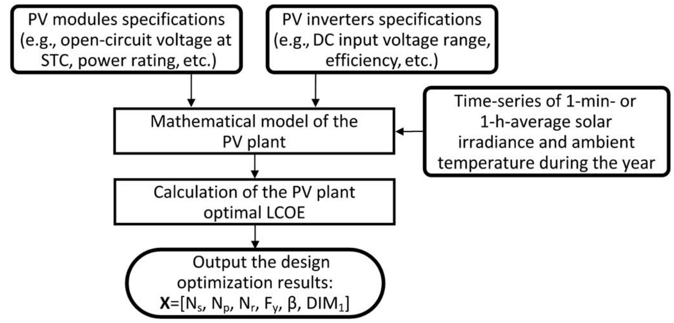


Fig. 2. Flowchart of the proposed optimal design process.

ambient temperature conditions during the year at the installation site. The power generated by the PV modules and dc/ac inverters, respectively, is calculated for each time instant considering both their operating specifications, which have been input by the PV inverter designer and the ambient temperature and incident solar irradiation meteorological conditions. The magnitude of the voltage applied at the dc/ac inverter input terminals depends on: 1) the MPP voltage of each PV module, which is calculated at each time step using the corresponding values of incident solar irradiation and ambient temperature, as well as the operating specifications of the PV module under STC, as analyzed in [15] and 2) the number of series-connected PV modules in each PV set N_s, which is a design variable, and its optimal value is derived during the evolution of the proposed optimization process. If at any time step, the voltage generated by the PV set is calculated to be less than the minimum operating dc input voltage of the dc/ac inverter, then the power generated by the dc/ac inverter is set equal to zero. The same pattern of yearly meteorological conditions is repeated for each year of the PV plant lifetime period, but the PV modules performance is progressively degraded during that time interval, thus affecting the resulting values of $P_i(\boldsymbol{X})$ in (3) according to [15]. The solar irradiation incident on a PV module with tilt angle $\beta(^\circ)$ is calculated from the corresponding input data on horizontal plane, using the Hay-Davies-Klucher-Reindl (HDKR) model [18], [19], which is suitable for application in solar irradiation data with an 1-min time resolution. The optimal values of LCOE and the corresponding design variables [i.e., vector $\boldsymbol{X}$ in (2)] are derived using genetic algorithms (GAs), due to their computational efficiency when applied to solve complex optimization problems. A population of chromosomes of the GA-based optimization process is composed of multiple alternative values of the decision variables vector $\boldsymbol{X}$. During the evolution of the optimization process, subsequent generations of the GA population are produced using the Selection, Crossover, Elitism, and Mutation operations [20]. For each chromosome $\boldsymbol{X}$, in all GA generations, the LCOE objective function is calculated using (2). This process is executed iteratively until a termination criterion is satisfied.

Targeting to speedup the execution of the optimization process, a parallel-processing-based architecture of GAs has been employed in the proposed methodology. Thus, two alternative types of parallel GAs were implemented in order to investigate their performance when executing the proposed PV plant optimal-design process. The first algorithm follows the classical Master–Slave model, while the second algorithm uses dynamic

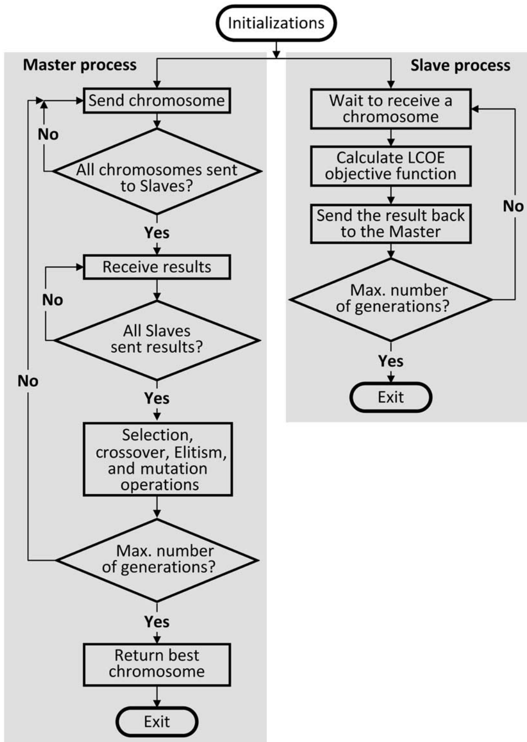


Fig. 3. Flowchart of the Master–Slave algorithm.

subpopulations (demes) of chromosomes, which change during the execution of the optimization process.

A. Master–Slave Algorithm

The Master–Slave algorithm comprises one of the most widely applied techniques in parallel-processing-based implementations of GAs [21]. A flowchart of the Master–Slave GA parallel process is illustrated in Fig. 3. The PV plant optimization procedure is performed using a Master and several Slave processes, which are executed concurrently in different computer processors. A constant number of chromosomes (population) are initially created randomly by the Master process and then they are sent for evaluation to the Slave processes (one chromosome per Slave process). The Slaves wait until a new chromosome is received for evaluation. Once a new chromosome is received, the Slave processes evaluate the PV plant LCOE objective function given by (2), using the values of the design variables contained in their chromosome, which comprise vector $\boldsymbol{X}$ in (2) and send the corresponding results back to the Master process. When all Slave processes accomplish this task, the Master performs the GA operations (i.e., Selection, Crossover, Elitism, and Mutation) for the entire population and creates the new population of the next generation. The procedure described above is repeated until a predefined, maximum number of population generations have evolved, which is selected such that the optimum set of the PV plant design variables $\boldsymbol{X}$, providing the minimum value of LCOE, has been derived at the end of the optimization process.

Using the Master–Slave algorithm, significant acceleration in the execution time of the optimization process is achieved, since the evaluation of the LCOE objective function is performed concurrently for all chromosomes of the population. However, the Master process has to wait until the last Slave finishes its evaluation, in order to proceed to the application of the GA operations for the creation of the new population. This introduces a significant delay, since all Slaves that have completed the LCOE objective-function evaluation remain idle until the last Slave finishes its evaluation too and send the result back to the Master. In such a case, the utilization efficiency of the computer processors, which has been devoted to execute the optimization task, is reduced.

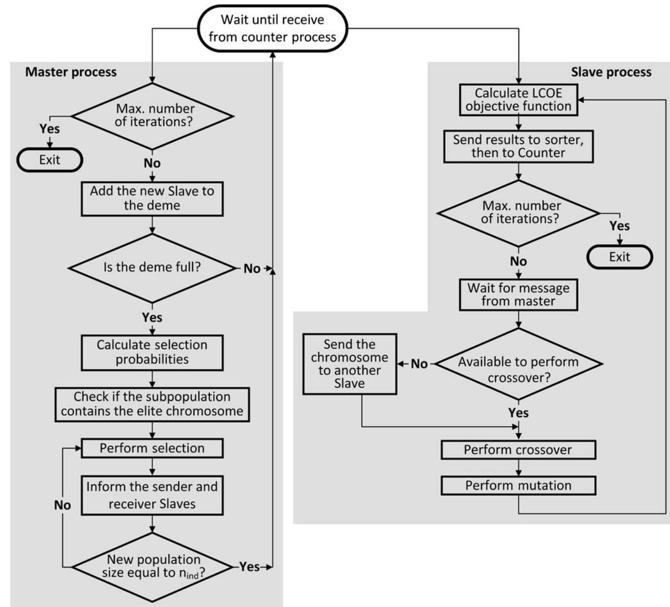


Fig. 4. Flowchart of the Dynamic Demes algorithm.

B. Dynamic Demes Algorithm

The Dynamic Demes algorithm improves computer processor utilization compared to the Master–Slave algorithm described above [22]. In this method, the GA chromosomes are organized in subpopulations (demes), which change dynamically during the evolution of the PV plant design optimization process. When a predefined number of chromosomes finish the evaluation of the PV plant LCOE objective function given by (2), then these chromosomes are grouped into a deme in which the Selection, Crossover, and Elitism operations are applied. Then, each chromosome performs the Mutation operation on itself. The Dynamic Demes algorithm continuously creates demes of chromosomes that have finished their evaluation of the LCOE objective function during the PV plant optimization process and then creates new chromosomes from each deme.

A flowchart of the Dynamic Demes algorithm is depicted in Fig. 4. The randomly initiated chromosomes are distributed by a Counter process to the Slave processes for the calculation of the corresponding LCOE objective-function values. Multiple Master processes may exist and each one of them controls a subpopulation of chromosomes. The total number of Masters employed is selected such that the time spent by the Slaves while waiting until assigned to a subpopulation is minimized [22]. The Masters are notified by the Counter process to collect chromosomes that have finished the evaluation of the PV plant LCOE objective function. This is performed through an appropriate message containing an identifier and the corresponding LCOE objective-function value for each Slave which has finished the evaluation of the objective function corresponding to a chromosome. Also, the Counter process checks whether the maximum number of evaluated chromosomes, which is defined at the beginning of the optimization process, has been reached. In this case, the Counter process sends a message to the Master and Slaves to terminate their execution. Else, the Counter assigns the Slave that has just finished the evaluation of the LCOE objective function to the subpopulation (deme) of a Master and informs that Slave to wait until notified by the Master to perform the GA operations, as analyzed next.

A Sorter process is also employed, aiming to decongest the Counter process from functionalities that delay its operation, in order to achieve a more efficient utilization of the available computer processors. The Sorter process receives the identifier of each Slave, as well as the value of the evaluated LCOE objective function and the genes of the corresponding chromosome [i.e., vector $\boldsymbol{X}$ in (2)]. The Sorter compares the evaluation results received by each Slave with the best solutions of the PV plant design optimization problem, which have been derived so far, in order to detect the overall optimum structure of the PV plant. The Master, Slave, Counter, and Sorter processes are executed concurrently in different computer processors.

When the number of chromosomes collected by each Master process reaches a predefined number of chromosomes n_{ind} comprising a subpopulation, the Master calculates the probabilities for executing the Selection operation according to the roulette–wheel method and sends the appropriate messages to the corresponding Slave processes. These messages contain the identifier of the Slave that the receiver Slave must exchange genes with and a crossover mask, which is the same for both Slave processes selected, indicating the genes to be exchanged. If the same chromosome is selected for Crossover multiple times, then the corresponding Slave is directed by the Master process to send that chromosome to another Slave for the application of the Crossover operation. Also, if the best chromosome exists in its subpopulation, the Master informs the corresponding Slave process through the above messages, to perform only the Elitism operation for that chromosome (i.e., to keep that chromosome unchanged). Thus, it is ensured that the best chromosome detected (i.e., the chromosome with the optimal LCOE objective-function value) will be maintained until the end of the optimization process.

After the execution of the Crossover and Mutation functions, the operation of each Slave is reinitiated, by evaluating the objective function for the new chromosome created after the application of the GA operations. When the number of new chromosomes created by the Master process after the application of the Selection, Crossover, and Elitism operations is equal to n_{ind}, then the Master waits until new chromosomes are received again from the Counter process in order to repeat the previous steps. If a termination message is sent by the Counter to the Master process, then the Master informs all Slaves of its subpopulation at that moment to terminate their operation and finishes its execution.

The procedure described above continues until a predefined number of chromosomes of the GA population have accomplished the LCOE objective-function evaluation. This number is specified by the designer, such that it is guaranteed that convergence to local optimum points is avoided and the global optimum value of the LCOE objective function has been derived at the end of the optimization process [20].

IV. Design Optimization Results

The methodology described in Sections II and III has been applied for the design optimization of a 100-kW PV system installed in Chania, Greece (latitude: 35.53°, longitude: 24.06°) using the 1-h- and 1-min-average values, respectively, of experimental measurements of solar irradiation and ambient temperature during the year at the installation site. The optimization process has been implemented in the form of a software program developed using the C/C++ programming language. For interprocess communication during the execution of the Master–Slave and Dynamic Demes algorithms, the MPI library was used [23], [24]. The Grid Computer of the Technical University of Crete has been used for executing the parallel-processing algorithms of the proposed PV plant design optimization procedure. The Grid Computer comprises 44 Hewlett Packard Proliant BL465c server blades, each containing two dual-core 2.6 GHz AMD Opteron processors with 4 GB of memory. A subset of these server blades was used to serve as computer processors in the evaluation of the proposed design process, as analyzed next. The Master–Slave algorithm has been implemented with a population size of 26 chromosomes, which is equal to the number of Slave processes used, while an additional processing unit has been used to execute the Master process. The number of generations evolving until the GA-process termination has been set equal to 150. The Dynamic Demes algorithm has been implemented using two Master processes and the number of chromosomes in the subpopulation of each Master has been set equal to $n_{ind} = 6$. The maximum number of evaluated chromosomes has been set equal to 4500. The number of the Slave processes is 28, while, additionally, two processing units of the Grid Computer were used for executing the Counter and Sorter processes. For the GA implementation of both the Master–Slave and Dynamic Demes algorithms, the roulette-wheel method has been applied for performing the Selection operation. The probabilities of uniform Crossover and uniform Mutation operations [20] have been set at $p_{\mathrm{cross}} = 0.5$ and $p_{\mathrm{mut}} = 0.3$, respectively, while the number of elite chromosomes is equal to one. The values described above were selected after performing multiple executions of the proposed PV plant design optimization process, such that convergence to the global optimum is achieved with the minimum execution time.

The PV modules considered in the optimization process for building the PV plant under design feature an MPP voltage of $V_{\mathrm{oc,STC}} = 33.7$ V, an MPP power of $P_{m,\mathrm{STC}} = 127$ W and a short-circuit current of $I_{\mathrm{sc,STC}} = 5.26$ A under STC. Also, the PV plant design optimization was performed based on three alternative types of commercially available dc/ac inverters with different operating specifications. The operating specifications (e.g., dc input voltage range, power conversion efficiency curve, etc.) of the dc/ac inverters, provided by their manufacturers, were

TABLE I
DESIGN OPTIMIZATION RESULTS OF THE MASTER–SLAVE AND DYNAMIC DEMES ALGORITHMS FOR VARIOUS DC/AC INVERTER TYPES

DC/ac type	Parallel algorithm	Time resolution	N_s	N_p	N_r	$\beta\,(^o)$	$\mathrm{DIM}_l\,(m)$	LCOE $(€/MWh)$
Type #1	Master-Slave	1 h	14	3	2	25.4	201.4	120.55
		1 min	12	3	2	41.46	200.01	135.61
	Dynamic Demes	1 h	14	3	3	24.72	217.82	120.84
		1 min	12	3	2	41.81	214.61	135.64
Type #2	Master-Slave	1 h	23	2	3	25.66	210.34	129.33
		1 min	19	2	3	27.93	201.99	132.84
	Dynamic Demes	1 h	23	2	3	26.42	227.82	129.38
		1 min	19	2	4	25.46	234.46	133.06
Type #3	Master-Slave	1 h	14	4	2	26.14	201.17	141.60
		1 min	12	4	2	26.41	200.70	141.89
	Dynamic Demes	1 h	14	4	2	29.0	213.98	141.81
		1 min	12	4	2	29.01	209.12	142.03

TABLE II
EXECUTION TIMES AND SPEEDUP OF THE PROPOSED OPTIMIZATION PROCESS FOR VARIOUS POWER RATINGS OF THE PV PLANT

$P_{\text{plant,nom}}$ (MW)	Time step	T_{obj} (s)	T_{ser} (s)	T_{par} (Master–Slave, in s)	T_{par} (Dynamic-Demes, in s)	Speedup (Master–Slave)	Speedup (Dynamic-Demes)
0.1	1 h	0.992	3868	479	358	8.08	10.81
	1 min	96.43	376 081	28 558	19 196	13.2	19.6
0.5	1 h	6.656	25 959	2067	1528	12.56	16.99
	1 min	519.13	2 024 613	144 971	102 357	13.97	19.78
1	1 h	14.162	55 231	4333	3063	12.75	18.03
	1 min	1946.73	7 738 358	576 628	396 635	13.42	19.51

input in the proposed design optimization process, as described in Section III.

The design optimization results in case of the time step employed in the optimization process is 1 h and 1 min, respectively, are summarized in Table I for both the Master–Slave and Dynamic Demes algorithms. For a 100-kW power rating, all PV modules are installed within one block of PV sets (Fig. 1), thus parameter F_y has not been included in Table II. It is observed that a different optimal PV plant configuration, in terms of the optimal values of the design variables [i.e., vector $\boldsymbol{X}$ in (2)], has been derived for each dc/ac inverter type, parallel-processing algorithm, and time step considered in the optimization process. The dc/ac inverter type is a very important factor in the design of the PV system, since it affects both the energy production and the total economic cost of the PV plant. During the stochastically varying solar irradiation and ambient temperature meteorological conditions, which affect the voltage and power produced by the PV modules, the dc/ac inverters operate under continuously changing dc input voltage and power levels. Thus, due to different dc input voltage ranges and power conversion efficiency curves, which are featured by dc/ac inverter types #1–3 according to their design characteristics and operating specifications, a different set of optimal values of the design variables have been derived in each case investigated in Table I. Different optimization results are also produced in case that alternative operating specifications of the PV modules and/or time-series of the meteorological conditions are input in the proposed optimization process by the PV plant designer. Applying 1-hour-average values of the meteorological input data, results in smoothing of the solar irradiation and ambient temperature variability. Since, as demonstrated in [15], the cost and power production models of the devices and components comprising the PV plant are nonlinear functions of the optimization problem design variables [i.e., $\boldsymbol{X}$ in (2)], different optimal configurations of the PV plant (Fig. 1) are derived for 1 h and 1-min time steps, respectively. If meteorological data with a 1-h resolution are considered in the optimization process, then the overall minimum LCOE value is provided by dc/ac inverter type #1, while dc/ac inverter type #2 is the overall optimum type for meteorological data series with an 1-min time step. Employing a 1-min time step enables to accurately estimate the energy-production performance of the PV plant and select the appropriate values of the design variables, which minimize the PV plant LCOE. However, depending on the dc/ac inverter type, the optimal values of LCOE derived using an 1-h time-resolution differ by 0.2%–12.5% from the corresponding values produced when 1-min time series are employed, thus indicating the inadequacy of 1-h resolution to accurately integrate into the design process the attributes of the factors affecting the PV plant operation. According to its operating specifications, dc/ac inverter type #3 features a wider dc input voltage range, compared to dc/ac inverter types #1 and #2. Thus, its energy production is less sensitive to the smoothing effect which is imposed when 1-h-average meteorological data are input in the proposed optimization process. This results in relatively small differences between the optimal LCOE values for 1 h and 1 min time resolutions, respectively, for this dc/ac inverter type. For all dc/ac inverter types, the Master–Slave and Dynamic Demes algorithms produced approximately equivalent solutions for both the 1-h and the 1-min time resolutions, since the corresponding optimal LCOE values differ by 0.1%–0.2%.

For sizes of the Master–Slave algorithm population and the Dynamic Demes algorithm subpopulations in the range of 14–40, if the dc/ac inverter type #1 is employed for building the PV plant, both parallel algorithms were capable to converge to the global optimum LCOE value, which has been detected using an exhaustive search process, with an accuracy of 99.8%–99.9% and 98.4%–99.8 %, respectively. While the Master–Slave algorithm converges with a small deviation from the optimal solution for any number of chromosomes in its population, the deviation of the Dynamic-Demes algorithm is affected by the number of population chromosomes. In the latter case, the deviation from the global optimum solution is minimized for a population size of 25–35 and a subpopulation size of $n_{\text{ind}} = 2 - 6$.

According to the optimization results, although a higher amount of energy is produced by a PV plant comprised of dc/ac inverters of type #3, the optimal PV plant configuration, which minimizes the PV system LCOE, for $\Delta t = 1$ h and $\Delta t = 1$ min is provided by dc/ac inverters of type #1 and #2, respectively. Depending on the dc/ac inverter type, the optimal values of E_{tot} and cost, which result for $\Delta t = 1$ h and $\Delta t = 1$ min, deviate by $-12.4\% - 2.9\%$ and $-1.5\% - 4.6\%$, respectively. Thus, due to the nonlinear operation of the devices comprising the PV plant, using input data with a 1-h time step deteriorates the accuracy of the energy production and cost calculations during the PV plant optimal design process.

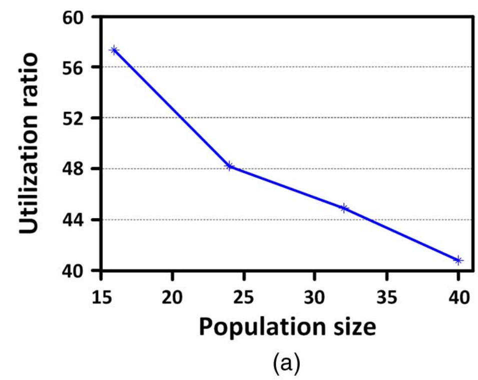
If the performance of the PV plant is estimated using meteorological input data with a 1-h time resolution, but the optimal values of N_s, N_p, N_r, F_y, β, and DIM_1, which had been derived using 1-min-resolution data are used to configure the PV plant, then depending on the dc/ac inverter type, the resulting values of $LCOE$, E_{tot}, and total cost [i.e., $C_c(\boldsymbol{X}) + C_m(\boldsymbol{X})$ in (2)] deviate from the corresponding values presented in Table I by 2.8%–12.9%, $-12.8\%–0.2\%$, and $-1.5\%–4.6\%$, respectively. Such large deviations dictate the use of time-series with a 1-min time step during the PV plant design in order to accurately estimate the PV plant performance in terms of both energy production and cost.

The utilization ratio u_r of the computer processors operating in parallel is a performance metric of parallel processes and its value is calculated using the following equation:

$$u_r = \frac{T_{\text{slaves}}}{T_{\text{tot}}} \tag{9}$$

where T_{slaves} (s) is the total time that all Slave processes are performing computations (the time spent on interprocess communication is excluded) and T_{tot} (s) is the total execution time required to accomplish the design optimization process of the PV plant.

The experimentally measured values of u_r for various values of computer processors, each devoted to a chromosome of the GA population, for the Master–Slave and Dynamic Demes algorithms, in case that a dc/ac inverter of type #1 is used and $\Delta t = 1$ min, are illustrated in Fig. 5. In case of the Dynamic Demes algorithm, the experimentally measured values of u_r corresponding to various values of n_{ind} in the subpopulation are also presented in Fig. 5. Compared to the Dynamic Demes algorithm, where at least 80% of the available processing units are used for calculations, low utilization percentages result for the Master–Slave architecture, which further decrease significantly as the number of available computer processors (i.e., total number of Slave processes) is increased.



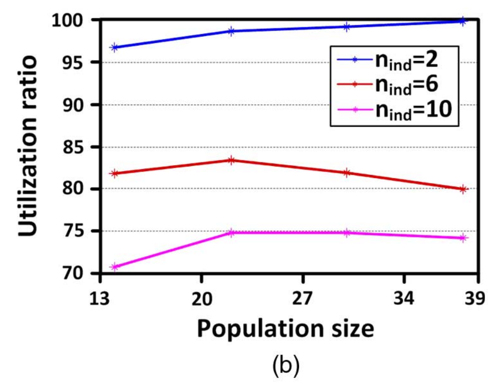


Fig. 5. Utilization ratio u_r for various values of computer processors in case that a dc/ac inverter of type #1 is used and $\Delta t = 1$ min: (a) Master–Slave algorithm; and (b) Dynamic Demes algorithm.

Due to the nonlinear nature of the PV plant design-optimization problem [15], which is investigated in this paper, the impact of time step of the meteorological input data on the design optimization results has also been explored for additional PV plant power ratings of typically installed PV systems. Thus, the proposed optimization process has also been applied for the design optimization of large-scale PV plants with $P_{\text{plant,nom}}$ values of 0.5 and 1 MW, respectively, comprising the dc/ac inverter of type #2, which provided the minimum LCOE in the 100-kW PV system with the 1-min-resolution meteorological input data. The Master–Slave algorithm has been applied in these design cases, since, according to the optimization results presented in Table I, it was capable to derive slightly better optimal solutions for both the 1-h and the 1-min time resolutions of the meteorological input data. The corresponding optimal values of $LCOE$, E_{tot}, and total cost [i.e., $C_c(\boldsymbol{X}) + C_m(\boldsymbol{X})$ in (2)], which are typically used to assess the performance of PV plants, for $\Delta t = 1$ h and $\Delta t = 1$ min, respectively, are illustrated in Fig. 6. It is observed that increasing the nominal power rating of the PV plant, the LCOE is not increased proportionally, since both the PV plant total cost and total energy production also increase at higher power ratings of the PV plant. Due to smoothing of the solar irradiation and ambient temperature variability in case that

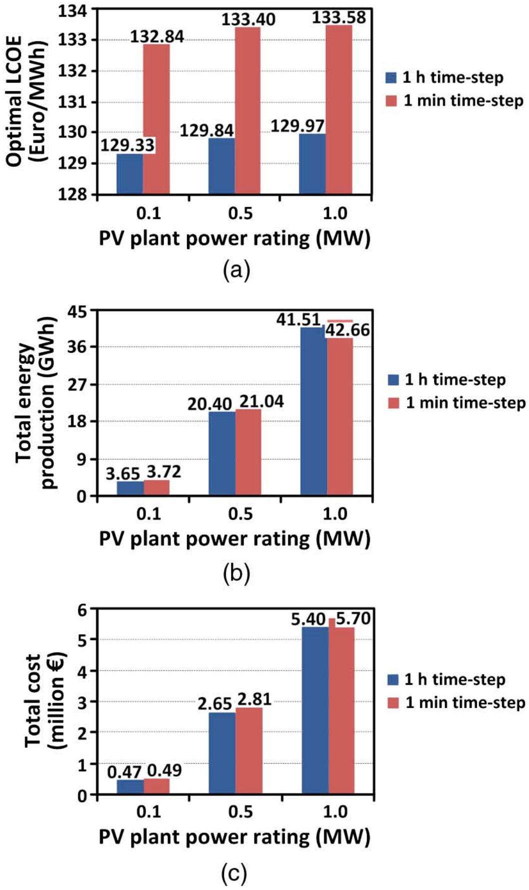


Fig. 6. Optimization results for $P_{\text{plant,nom}} = 0.1 - 1$ MW, $\Delta t = 1$ h and $\Delta t = 1$ min, in case that the Master–Slave algorithm is applied: (a) optimal LCOE; (b) total energy production; and (c) total cost.

1-h-average meteorological data are applied, as analyze above, the optimization process converged to different optimal configurations of the PV plant in case of 1 h and 1 min time steps, respectively, for the same nominal power rating of the PV plant. Thus, depending on the PV plant power rating, the values of LCOE, E_{tot}, and total cost for the PV plants, which have been optimally designed using input data with an 1-h time step differ by the corresponding solutions obtained using meteorological values with an 1-min time resolution by 2.7%–2.8 %, 1.9%–3.1%, and 4.6%–5.9%, respectively.

The speedup gained by the parallel execution of the PV plants optimization algorithm is given by

$$\text{Speedup} = \frac{T_{\text{ser}}}{T_{\text{par}}} \tag{10}$$

where T_{ser} (s) is the execution time of the proposed PV plants optimization procedure when using a standard desktop PC, which provides a serial execution of the optimization algorithm and T_{par} (s) is the total time required for executing the proposed parallel-processing-based optimization process in the Grid Computer.

Since the execution time of the serially executed optimization process of the PV plant is very high in case that meteorological input data with an 1-min resolution are employed, such that it is not feasible to measure it in an actual implementation, the value of T_{ser} has been estimated by summing the execution times for each chromosome in each generation of the parallel Master–Slave algorithm. The resulting execution times and speedup of the proposed design optimization process for various power ratings of the PV plant are presented in Table II. It is observed that using the parallel-processing-based implementation of the proposed optimization algorithm, it is feasible to derive optimal configurations of the PV plant using high time resolution (i.e., 1 min) meteorological data in relatively short time intervals. Else, an extremely long execution time would be required or the use of low resolution time series (e.g., 1 h) would be imposed, which, as demonstrated above, deteriorates the accuracy of the optimization results. Due to the highly nonlinear nature of the PV plant design optimization problem, although the time step resolution is increased from 1 h to 1 min by a factor of 60, the time required to calculate the LCOE objective function (i.e., T_{obj} in Table II) is increased by 78–138 times. During the computation of the LCOE objective function, the interdependencies of the performances of the individual PV modules installed in the PV plant (e.g., due to mutual shading between adjacent rows of PV modules) are also taken into account. Thus, by increasing the power rating of the PV plant requires the arrangement of more PV modules in the available installation area, which increases the required execution time of the computations performed in order to calculate the value of the LCOE objective function.

For meteorological input data with a 1-min time resolution the speedup remains relatively constant, and it is higher than that resulting with an 1-h resolution by 5.4%–81.3 %, due to the different complexities of the LCOE objective function for each value of $P_{\text{plant,nom}}$ considered in Table II. If 1-h resolution input data are employed, the LCOE objective function is calculated in less time, so the waiting time at the intermediate steps of the Master–Slave and Dynamic Demes algorithms is relative short, although it increases with the value of $P_{\text{plant,nom}}$. Thus, since the execution time required by the serial execution is not highly prolonged, less speedup is gained by applying the GA parallelization. In contrast, in case that meteorological data with an 1-min time step are input in the proposed PV plant design optimization process, the calculation of the LCOE objective function is more time-consuming, such that for all values of $P_{\text{plant,nom}}$ a higher speedup is provided by the parallel-process-based GA implementation. The speedup offered by the Dynamic–Demes optimization algorithm is higher than that of the Master–Slave algorithm for all values of $P_{\text{plant,nom}}$ by 33.8%–48.5%.

The capability of the proposed GA-based optimization process to avoid convergence to local minimum points and derive the global optimum solution, has been verified by also executing an exhaustive-search algorithm for computing the LCOE objective function over a wide range of values of the design-variables vector [i.e., $\boldsymbol{X}$ in (2)].

V. Conclusion

The installation of PV plants expands rapidly across the World during the last years, thus dictating the employment of efficient PV-plant design techniques for maximizing their performance. However, due to the nonlinear operation of the devices comprising a PV plant, the use of meteorological data with a 1-h time resolution, which is typically employed by the conventional PV plant design methodologies and tools, results in a significant reduction in the accuracy of the energy production estimations performed during the design process of the PV plant.

In this paper, a methodology for the design optimization of PV plants has been presented, which is based on a parallel-processing-based implementation of GAs. In contrast to the conventional PV plant design approaches, the proposed optimization technique is capable to be executed using high time resolution (i.e., 1-min) values of the meteorological input data, thus increasing the time step resolution and volume of meteorological input data processed during each step of the optimization process by a factor of 60. This issue is addressed in this paper for the first time in the existing research literature. The design optimization results indicate that the proposed method is capable to successfully explore during the PV plant design process the impact of both the installation-site meteorological conditions and the operational characteristics of the devices comprising the PV plant, on its energy production and cost. Also, the parallel-processing-based implementation of GAs offers significant speedup compared to the serial execution, thus accomplishing the PV plant optimal-design procedure in a considerably shorter time interval. By applying the proposed method using high time-resolution meteorological input data, the energy-production performance and cost of the PV plant during the optimal design process are estimated accurately. Thus, the PV systems which have been optimally designed according to the proposed technique, provide maximum economic profit during their lifetime period and, simultaneously, lower financial risk.

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