Comparative Analysis of Hybrid Renewable Energy Systems Simulation Tools

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Abstract

The forthcoming depletion of fossil fuel reserves, currently dominating the global energy fuel mix, along with the continuous growth of electrical demand, have urged the "quest" for alternative energy resources, such as solar and wind energy, to satisfy the current electricity needs, in both urban and remote areas. The aforementioned technologies are considered capital intensive, underpinning the necessity for extensive research on that field in order to reduce costs. On the other hand, Hybrid Renewable Energy Systems (HRES), if properly sized, are considered a proven solution for achieving high economic efficiency, especially for stand-alone applications. Currently, many simulators have been developed aiming to facilitate the HRES stakeholders on planning and on designing better investments, as well as on research activities. Their thorough analysis, although complex, is strongly related to the efficient utilization of renewable energy potential and the careful design of relevant projects. This work assesses the sensitivity of two (2) commercial software packages by examining nine (9) scenarios, based on different combinations of solar and wind energy potential. The results are compared with the ESA (Energy Systems Analysis) Microgrid Simulator, developed by the Soft Energy Applications and Environmental Protection Laboratory (SEALAB) of the University of West Attica. The appraisal of the results provided a detailed assessment of the discrepancies between the selected software.

Keywords: HRES, Hybrid System, Stand-alone, Simulation, RES.

1. Introduction

The forthcoming depletion of fossil fuel reserves, currently dominating the global energy fuel mix, along with the continuous growth of electrical demand – correlated with the global population rise – have urged the "quest" for alternative energy resources, such as solar and wind energy, to satisfy the current electricity needs, in both urban and remote areas (Erdinc and Uzunoglu, 2012). However, the intermittent/stochastic nature of these resources challenges their omnipresent, environmentally-friendly and inexhaustible features, since it introduces difficulties in matching the power generation with the load demand. A common way of dealing with this generation and demand mismatch is the integration of energy storage technologies into the energy systems configurations. Integrating energy storage technologies may -under circumstances- enable maximum exploitation of renewable energy potential prevailing in a specific region (Kavadias, 2016, Kocher-Oberlehner and Peacock, 2014). Nevertheless, the aforementioned technologies are still considered capital intensive, underpinning the necessity for extensive research on that field to achieve further market maturity (Sinha and Chandel, 2014).

Hybrid Renewable Energy Systems (HRES) implemented in this context are considered as one of the most promising and reliable alternatives for the electrification of remote consumers, contributing simultaneously to the mitigation of climate change and minimization of fossil fuels usage (Kavadias, 2012). Various simulation software has been developed under the prism of serving HRES stakeholders' planning, research and development needs (Turcotte et al., 2001). Most of the software packages generate as outcome different combinations of renewable energy systems (RES) depending on the input parameters selected by the user (mainly meteorological and economic data as well as sizing constraints) (Al-Falahi et al., 2012). The different combinations proposed by the various software packages are attributed basically to the diversified control and economic strategies applied (Saiprasad et al., 2018). Their thorough analysis, albeit complex, is strongly related to the efficient utilization of the given renewable energy potential and the careful design of related projects (Kumar, 2016).

The vast majority of scientific papers in this direction analyze two (2) commercial software to conduct the pertinent simulations, namely Hybrid Optimization of Multiple Electric Renewables (HOMER) (various versions) and improved Hybrid Optimization by Genetic Algorithms (iHOGA), developed by the National Renewable Energy

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Laboratory (NREL) (HOMER Energy LLC, 2020) and the University of Zaragoza (2020) respectively. The present work assesses the sensitivity of the HOMER and iHOGA commercial software on RES potential by examining nine (9) scenarios, based on different combinations of solar and wind energy potential, aiming to cover the electricity needs of a remote domestic consumer. The results are compared with the ESA (Energy Systems Analysis) Microgrid Simulator, developed by the Soft Energy Applications and Environmental Protection Laboratory (SEALAB) of the University of West Attica (PUAS, 2017). ESA examines different hybrid energy system configurations through extensive energy analysis and produces optimized sizing results through the consideration of multiple objectives and criteria. Additionally, and besides the standard sizing algorithms, ESA supports the application of Demand Side Management (DSM) techniques through the configuration of relevant pools of flexible loads such as with the integration of electro-mobility aspects. To that end, the appraisal of the results provided a detailed assessment of the discrepancies between the selected software.

2. Methodology

A HRES comprised of photovoltaic (PV) modules, wind turbine (WT) generators, lead-acid battery banks and a converter/inverter is examined. Three (3) sites representing areas with different renewable energy (both solar and wind) potential are examined. More precisely, these areas were selected to represent low, medium and high renewable energy potential regions of the Greek territory.

The HRES architecture consists of PV modules, WT generators and lead-acid battery banks connected to a common DC busbar. The AC load (connected to the AC busbar) is electrified via an inverter, which also serves as a charge controller. Fig. 1 depicts a schematic overview of the electric circuit used for the simulations.

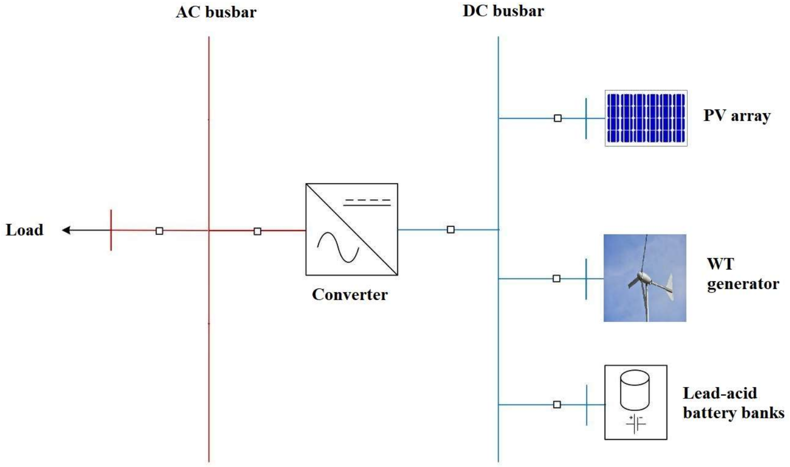


Fig. 1. Schematic overview of the electric circuit used for the simulations.

2.1. Input Data

Three (3) sets of solar irradiation data characterized by different level of potential quality (low, medium and high) were used. The datasets include hourly values of global and diffuse solar irradiation of Typical Meteorological Years (TMY), which were selected by a relevant scientific database developed for the Greek region (Kavadias, 2016). Fig. 2 presents the monthly values of solar energy for the different profiles with annual solar energy values of 1489 kWh/m^2 for the low solar irradiation area, 1686 kWh/m^2 for the medium solar irradiation area and 1732 kWh/m^2 for the high solar irradiation area, correspondingly.

Three (3) sets of wind speed data characterized by different level of potential quality (low, medium and high) were also used (Kavadias, 2016). Fig. 3 presents the wind speed distribution of the selected profiles of annual average values of 5.48 m/s for the low wind speed profile, 6.85 m/s for the medium wind speed profile and 9.16 m/s for the high wind speed profile, respectively.

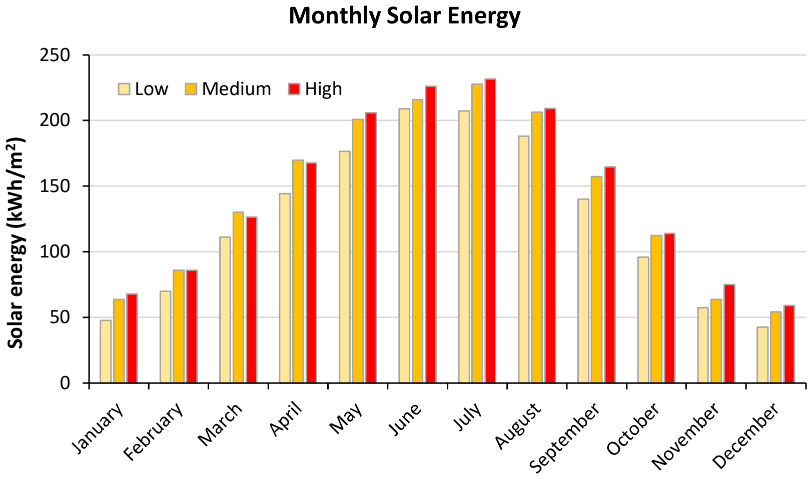


Fig. 2. Monthly solar energy variation for the three (3) selected solar irradiation profiles.

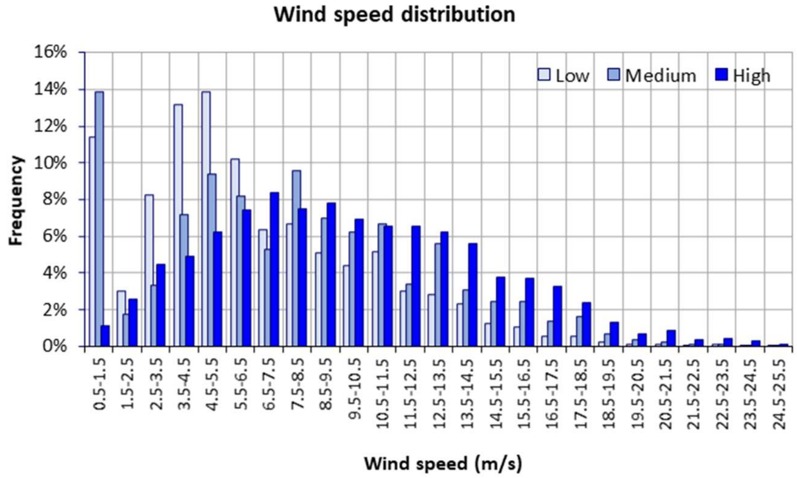


Fig. 3. Wind speed distribution for the three (3) selected wind speed profiles.

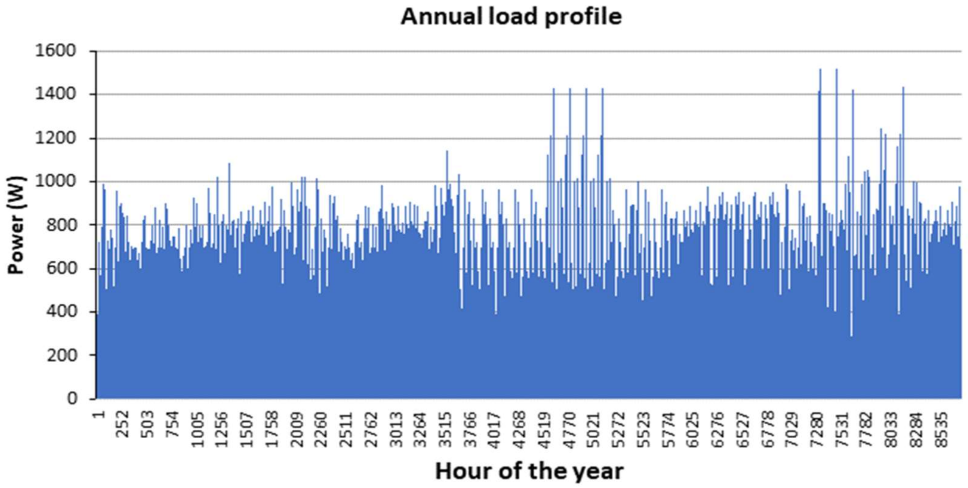


Fig. 4. Annual load profile.

The load profile of a HRES is of paramount importance for its sizing procedure. A 4-member dwelling was examined as a case study, representing a remote off-grid consumer with average energy requirements equal to 9.45 kWh/day. The load dataset includes hourly values of load demand measured at a 4-member dwelling of standard energy consumption and common household appliances. The final time-series were attained by merging typical weekly hourly load profiles for each month of the year (Fig. 4).

Nine (9) different scenarios (Tab. 1) of the aforementioned meteorological data were used as input parameters into the three (3) software and simulated as case studies with an hourly time-step.

Tab. 1 – Renewable energy potential combinations

Scenario	Renewable energy potential data
1	I_T = 1,489 kWh/m^2/year - $\bar{v}$ = 5.48 m/s
2	I_T = 1,489 kWh/m^2/year - $\bar{v}$ = 6.85 m/s
3	I_T = 1,489 kWh/m^2/year - $\bar{v}$ = 9.16 m/s
4	I_T = 1,686 kWh/m^2/year - $\bar{v}$ = 5.48 m/s
5	I_T = 1,686 kWh/m^2/year - $\bar{v}$ = 6.85 m/s
6	I_T = 1,686 kWh/m^2/year - $\bar{v}$ = 9.16 m/s
7	I_T = 1,732 kWh/m^2/year - $\bar{v}$ = 5.48 m/s
8	I_T = 1,732 kWh/m^2/year - $\bar{v}$ = 6.85 m/s
9	I_T = 1,732 kWh/m^2/year - $\bar{v}$ = 9.16 m/s

The system's economic parameters imported into each simulation software for conducting the pertinent analysis are presented in Tab. 2.

Tab. 2 – Data considered for economic analysis

Economic Parameter	Value
Nominal discount rate	7 %
Expected inflation rate	2 %
Project lifetime	25 years

Tab. 3 presents the economic parameters of the components selected for the relevant simulations.

Tab. 3 – HRES components' economic parameters

Component	Economic Parameter	Value
PV modules	Capital cost (€/W)	0.62
	O & M[1] cost (€/W/year)	0.01
	Lifetime (years)	25
WTs	Capital cost (€/W)	4.66
	Replacement cost (€/W)	3.34
	O & M cost (€/W/year)	0.09
	Lifetime (years)	15
Batteries	Capital cost (€/Ah)	0.68
	Replacement cost (€/Ah)	0.64
	O & M cost (€/Ah/year)	0.01
Inverter/Charge controller	Capital cost (€/VA)	0.58
	Replacement cost (€/VA)	0.52
	O & M cost (€/VA/year)	0.06
	Lifetime (years)	10

[1] O & M: Operation & Maintenance

2.2 Simulation Tools

HOMER Pro (Fig. 5) was selected as being a HRES optimization tool used by over 93,000 people worldwide (HOMER Microgrid News, 2020). The users range from energy systems integrators and utilities to military stakeholders and non-profit organizations. The software can perform detailed time-series simulations on different time-scales. The realistic modeling of renewable energy resources with a stochastic/intermittent character, such as wind and solar energy, can be attributed to software's capability for sensitivity analysis, which eliminates the uncertainty associated with input parameters, also increasing the quality of decision-making.

Name: Electric Load #1

January Profile

Hour	Load (kW)
0	207.67
1	173.32
2	298.58
3	308.4
4	341.04
5	319.99
6	251.97
7	418.05
8	748.79
9	1,529.09
10	1,658.78
11	1,426.42
12	867.14
13	512.22

Time Step Size: **60** minutes

Random Variability
Day-to-day (%): **14.157**
Timestep (%): **35.396**

Peak Month: **January**

Metric	Baseline	Scaled
Average (kWh/day)	11,860.	395.33
Average(kW)	494.17	16.47
Peak (kW)	2,770.6	92.35
Load factor	.18	.18

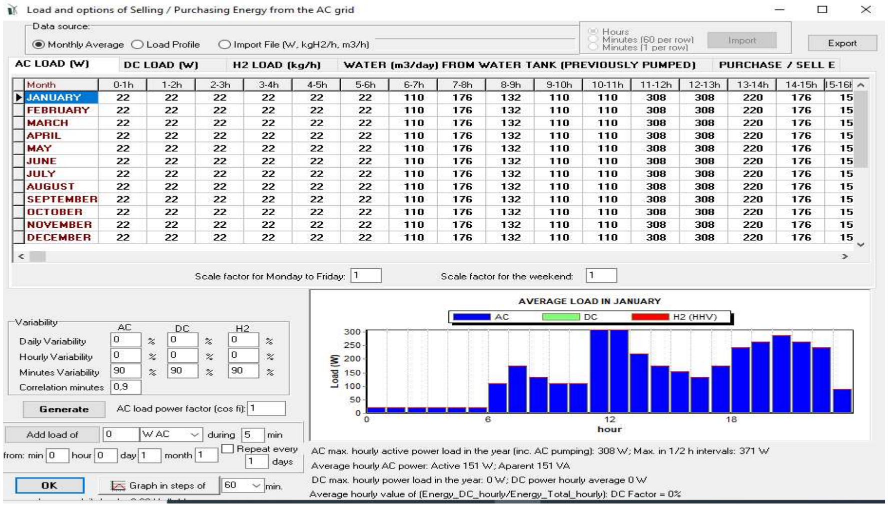
Load Type: ● AC ○ DC

Scaled Annual Average (kWh/day): 395.33

☐ Efficiency (Advanced)
Efficiency multiplier: 1
Capital cost (€): 0
Lifetime (yr): 10

Fig. 5. HOMER Pro graphics user interface.

iHOGA (Fig. 6) is a multi-objective optimization tool, which utilizes comprehensive models of the considered components (University of Zaragoza, 2020, Ganguly et al., 2017). The utilization of cutting-edge genetic algorithms renders the software capable of attaining the optimum system layout with a relatively low computational burden, considering the contradictory optimization constraints of unmet load, costs and emissions. In this context, the quality of decision-making is also enhanced.



Data source: ● Monthly Average ○ Load Profile ○ Import File (W, kgH2/h, m3/h)
○ Hours
○ Minutes (60 per row)
○ Minutes (1 per row)

Month	0-1h	1-2h	2-3h	3-4h	4-5h	5-6h	6-7h	7-8h	8-9h	9-10h	10-11h	11-12h	12-13h	13-14h	14-15h	15-16
JANUARY	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
FEBRUARY	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
MARCH	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
APRIL	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
MAY	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
JUNE	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
JULY	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
AUGUST	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
SEPTEMBER	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
OCTOBER	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
NOVEMBER	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15
DECEMBER	22	22	22	22	22	22	110	176	132	110	110	308	308	220	176	15

Scale factor for Monday to Friday: 1
Scale factor for the weekend: 1

Variability

	AC		DC		H2	
Daily Variability	0	%	0	%	0	%
Hourly Variability	0	%	0	%	0	%
Minutes Variability	90	%	90	%	90	%
Correlation minutes	0,9					

AC load power factor (cos fi): 1

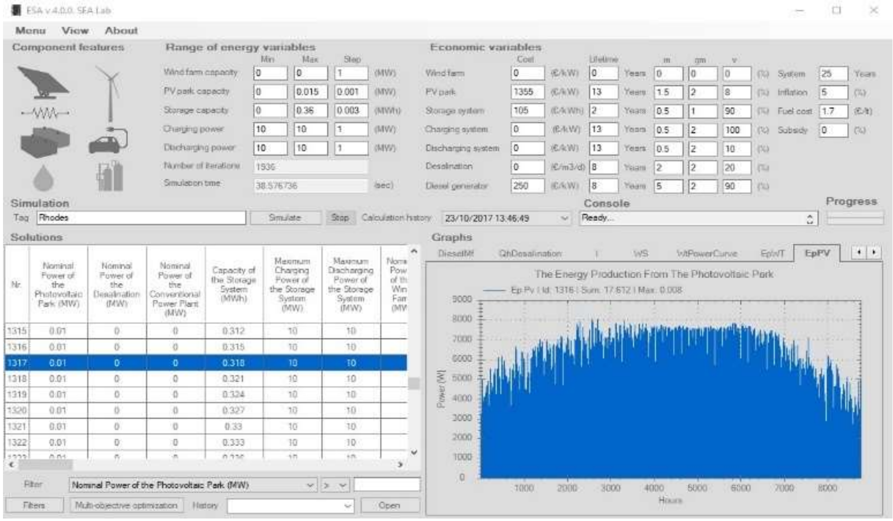
Add load of 0 W AC during 5 min
from: min 0 hour 0 day 1 month 1 ☐ Repeat every 1 days

Graph in steps of 60 min.

AC max. hourly active power load in the year (inc. AC pumping): 308 W; Max. in 1/2 h intervals: 371 W
Average hourly AC power: Active 151 W; Aparent 151 VA
DC max. hourly power load in the year: 0 W; DC power hourly average 0 W
Average hourly value of (Energy_DC_hourly/Energy_Total_hourly): DC Factor = 0%

Fig. 6. iHOGA graphics user interface.

ESA Microgrid Simulator (Fig. 7) can examine various hybrid energy system configurations, aiming at their optimization via the application of multiple objectives (PUAS, 2017). Except for HRES sizing, the specific software is able to implement advanced energy management strategies, such as with DSM techniques and relevant embedded elements, e.g. electric vehicles, desalination units, etc. The software was developed in the programming language C# by SEALAB.



	Min	Max	Step	
Wind farm capacity	0	0	1	(MW)
PV park capacity	0	0.015	0.001	(MW)
Storage capacity	0	0.36	0.003	(MWh)
Charging power	10	10	1	(MW)
Discharging power	10	10	1	(MW)

Number of iterations 1536
Simulation time 38.576736 (sec)

	Cost		Lifetime		m	gm	v	
Wind farm	0	(€/kW)	0	Years	0	0	0	(%)
PV park	1355	(€/kW)	13	Years	1.5	2	8	(%)
Storage system	105	(€/kWh)	2	Years	0.5	1	90	(%)
Charging system	0	(€/kW)	13	Years	0.5	2	100	(%)
Discharging system	0	(€/kW)	13	Years	0.5	2	10	(%)
Desalination	0	(€/m3/d)	8	Years	2	2	20	(%)
Diesel generator	250	(€/kW)	8	Years	5	2	90	(%)

System 25 Years
Inflation 5 (%)
Fuel cost 1.7 (€/lt)
Subsidy 0 (%)

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Nr.	Nominal Power of the Photovoltaic Park (MW)	Nominal Power of the Desalination (MW)	Nominal Power of the Conventional Power Plant (MW)	Capacity of the Storage System (MWh)	Maximum Charging Power of the Storage System (MW)	Maximum Discharging Power of the Storage System (MW)
1315	0.01	0	0	0.312	10	10
1316	0.01	0	0	0.315	10	10
1317	0.01	0	0	0.318	10	10
1318	0.01	0	0	0.321	10	10
1319	0.01	0	0	0.324	10	10
1320	0.01	0	0	0.327	10	10
1321	0.01	0	0	0.33	10	10
1322	0.01	0	0	0.333	10	10

Filter Nominal Power of the Photovoltaic Park (MW) >

Fig. 7. ESA graphics user interface.

3. Results

3.1 System Sizing for Optimum Economic Results

According to the results obtained, iHOGA maintains both the battery bank capacity and the total nominal wind power constant (except for scenario 9) and therefore their relevant contribution to load requirements (Tab. 4). The software opts for diversifying solar power accordingly to respond to load demand. On the other hand, HOMER Pro adopts a different dispatch strategy. The software retains constant the nominal wind power and opts for diversifying both the solar power and the storage capacity. It is also noticeable that for scenarios 1 and 4 (where low wind potential is present) HOMER Pro has selected only PV panels and battery banks to cover the load demand.

Tab. 4 – Overview of the sizing parameters generated by HOMER Pro and iHOGA for optimum economic results

Scenario	PV power (kW$_p$)		Wind power (kW)		Storage capacity (kWh)	
	HOMER	iHOGA	HOMER	iHOGA	HOMER Pro	iHOGA
1	10.30	4.26	0	0.66	22.85	31.1
2	5.47	4.26	0.91	0.66	10.55	31.1
3	3.07	1.30	0.91	0.66	10.55	31.1
4	7.47	4.26	0	0.66	15.82	31.1
5	5.09	4.26	0.91	0.66	10.55	31.1
6	2.90	1.30	0.91	0.66	10.55	31.1
7	3.87	4.26	0.91	0.66	15.82	31.1
8	4.07	4.26	0.91	0.66	10.55	31.1
9	2.27	1.30	0.91	1.32	10.55	31.1

For all the scenarios examined, the PV contribution generated by HOMER Pro is higher than the relevant one generated by iHOGA (Tabs. 4 and 5). On the other hand, HOMER Pro has selected a lower storage capacity to respond to load requirements in comparison to iHOGA. Tab. 5 presents the simulation results from both HOMER Pro and iHOGA for the energy distribution of the examined HRES for optimum economic results.

Tab. 5 – Overview of the energy results generated by HOMER Pro and iHOGA for optimum economic results

Scenario	Excess energy (kWh/year)		Energy delivered by PV (kWh/year)		Energy delivered by WT (kWh/year)	
	HOMER	iHOGA	HOMER	iHOGA	HOMER	iHOGA
1	8,908	1,446	12,797	3,917	0	1,775
2	6,163	2,137	6,811	3,917	3,079	2,439
3	4,269	324	3,820	1,205	4,154	3,198
4	6,460	1,844	10,331	4,404	0	1,747

5	6,389	2,570	7,034	4,404	3,079	2,411
6	4,448	563	4,015	1,355	4,154	3,156
7	3,716	1,800	5,373	4,403	2,145	1,747
8	4,997	2,539	5,653	4,402	3,079	2,410
9	3,589	367	3,156	1,354	4,154	3,155

The smaller size of battery banks results in lower values of autonomy as achieved with HOMER Pro compared to iHOGA (Tab. 6), considering two (2) days of autonomy as the calculation base, which are considered as a common engineering practice in such projects. HOMER Pro generates in all cases higher amounts of excess energy (ranging from 2 to over 13 times) in comparison with iHOGA (Tab. 5), which is mainly attributed to the straightforward control strategy adopted by iHOGA (Saiprasad et al., 2018). Tab. 6 depicts the simulation results from both HOMER Pro and iHOGA for the unmet load and the battery bank's autonomy of the examined HRES for optimum economic results.

Tab. 6 – Unmet load and battery banks' autonomy generated by HOMER Pro and iHOGA for optimum economic results

Scenario	**Unmet load (kWh/year)**		**Days of autonomy**	
	HOMER Pro	**iHOGA**	**HOMER Pro**	**iHOGA**
1	26.27	96.45	1.93	2.17
2	37.85	73.50	0.89	2.17
3	17.54	150.22	0.89	2.17
4	38.75	44.82	1.34	2.17
5	40.55	46.94	0.89	2.17
6	3.35	24.66	0.89	2.25
7	5.46	21.37	1.34	2.17
8	32.47	34.31	0.89	2.17
9	5.85	99.42	0.89	2.17

The HRES profitability is determined by NPC and LCOE. Tab. 7 accumulates the simulation results from both HOMER Pro and iHOGA for the economic parameters of the examined HRES. These results refer to optimum values produced for the Net Present Cost (NPC) and the Levelized Cost of Electricity (LCOE), respectively. According to Tab. 7, a significant difference is noted between the iHOGA and HOMER Pro in terms of LCOE results. On the other hand, smaller discrepancies are noted in terms of NPC, which however diminish with the improvement of the solar and wind energy potential quality. These discrepancies can be attributed to different control strategies and economic models adopted by each software. More precisely, HOMER Pro uses the real discount rate to account for the time value of money (HOMER Energy LLC, 2020). In contrast, iHOGA considers both the inflation and interest rates for economic calculations. Moreover, iHOGA utilizes advanced models for the battery banks' lifetime calculation, rendering the respective economic results more realistic (University of Zaragoza, 2020).

Tab. 7 – LCOE and NPC values generated by HOMER Pro and iHOGA for optimum economic results

Scenario	**NPC (€)**		**LCOE (€/kWh)**	
	HOMER	**iHOGA**	**HOMER Pro**	**iHOGA**
1	40,173	33,171	0.83	0.40
2	37,753	33,171	0.78	0.39
3	33,449	33,138	0.69	0.40
4	37,539	33,171	0.77	0.39
5	37,401	33,171	0.77	0.39
6	33,328	31,808	0.68	0.37
7	37,471	33,171	0.77	0.39
8	36,649	33,171	0.76	0.39
9	33,230	33,138	0.70	0.40

3.2 Power Reliability Calculations for Optimum Economic Results

Each simulation tool has a diversified visualization of the results. Thus, in an attempt to carry out reasonable and justified comparisons, only three (3) Power Reliability Indicators were examined (Guzmán Acuña et al. 2017, Kavadias, 2012, Singh and Bagchi, 2010):

- Loss Of Power Supply Probability (LOPSP):

$$LOPSP = \frac{unmet\ load\ \left(\frac{kWh}{year}\right)}{overall\ energy\ demand\ \left(\frac{kWh}{year}\right)} \quad \text{(eq. 1)}$$

- Level of Autonomy (LA):

$$LA = 1 - LOPSP \quad \text{(eq. 2)}$$

- Expected Unserved Energy (EUE), i.e., the sum of the unmet load demand during the simulation year (in kWh/year).

The lower flexibility noted by iHOGA regarding resources allocation led to higher values of annual unmet load compared to the relevant ones generated by HOMER Pro (Tab. 6). In their turn, the higher amounts of unmet load generated by iHOGA, for all the examined scenarios, have a substantial influence on Power Reliability Indicators calculations, hence, leading to smaller levels of autonomy for the stand-alone configurations examined. More precisely, the unmet load values calculated by iHOGA are 1.15 to approximately 17 times greater than the relevant values calculated with HOMER Pro. Figs. 8 - 10 visualize the discrepancies between the values calculated for LOPSP, LA and EUE respectively, based on the simulation results of HOMER Pro and iHOGA.

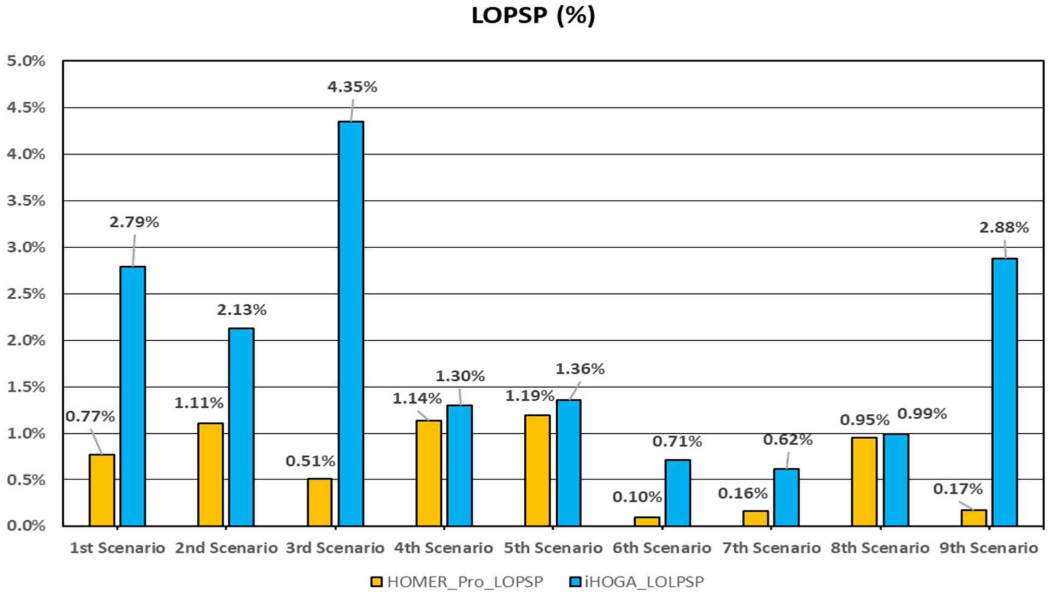

Fig. 8. LOPSP discrepancies for the nine (9) scenarios simulated with HOMER Pro and iHOGA.

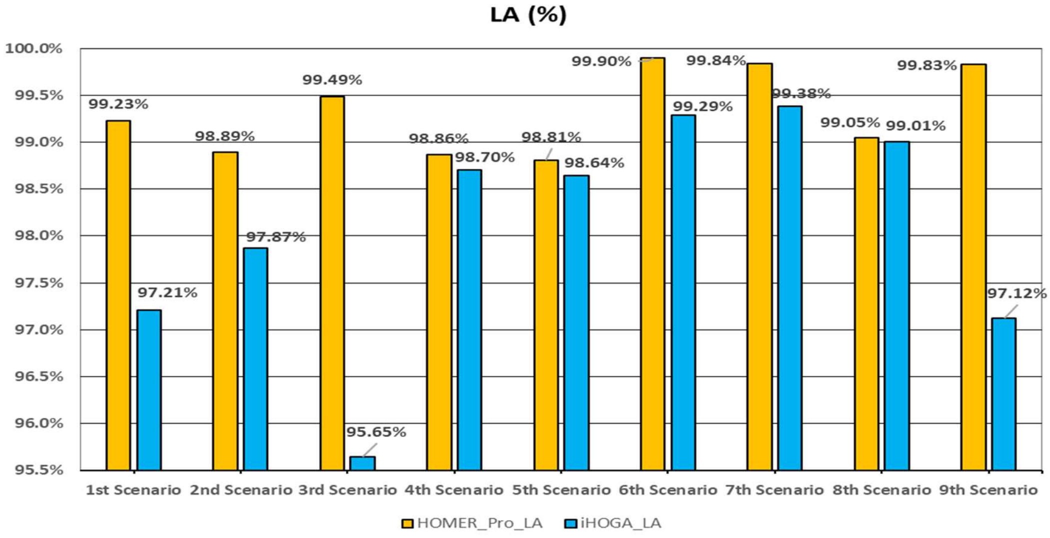

Fig. 9. LA discrepancies for the nine (9) scenarios simulated with HOMER Pro and iHOGA.

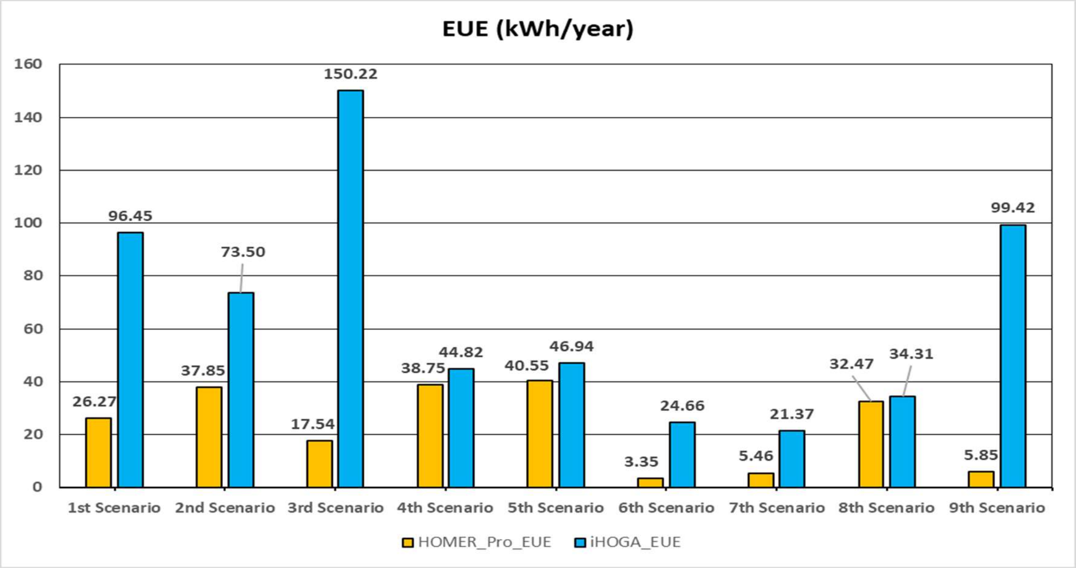

Fig. 10. EUE discrepancies for the nine (9) scenarios simulated with HOMER Pro and iHOGA.

It is noteworthy that the minimum value for LA attained with iHOGA is equal to 95.65%, while the relevant value attained with HOMER Pro is 98.81%. Thus, when power reliability optimization goals are set as a priority, HOMER Pro can be considered preferable than iHOGA, due to its dispatch strategy. The opposite is valid when economic optimization goals are set as a priority.

3.3 System Sizing for Minimum Unmet Load

As also valid for the simulations on the optimum economic results, iHOGA maintains constant both the storage capacity and the total nominal wind power (except for scenario 5) as well as their relevant contribution to load requirement (Tab. 8). The software opts for diversifying the solar power accordingly to respond to load variation. On the other hand, HOMER Pro depicts a different dispatch strategy. The software maintains constant only the nominal wind power (except for scenario 1) and opts for diversifying both the solar power and the storage capacity. Additionally, the configurations generated by both software include all energy resources, in contrast to the simulations for the optimum economic results. Tab. 8 provides an overview of the simulation results generated by both HOMER Pro and iHOGA for the sizing parameters of the examined HRES for a minimum unmet load.

Tab. 8 – Overview of the sizing parameters generated by HOMER Pro and iHOGA for minimum unmet load

Scenario	PV power (kW_p)		Wind power (kW)		Storage capacity (kWh)	
	HOMER	iHOGA	HOMER	iHOGA	HOMER	iHOGA
1	4.61	9.43	1.83	0.66	12.76	31.1
2	5.47	9.10	0.91	0.66	10.55	31.1
3	3.07	4.23	0.91	0.66	10.55	31.1
4	5.42	7.46	0.91	0.66	21.12	31.1
5	5.09	9.10	0.91	1.98	10.55	38.8
6	2.90	4.23	0.91	0.66	10.55	31.1
7	3.87	6.50	0.91	0.66	15.82	31.1
8	4.07	6.50	0.91	0.66	10.55	31.1
9	2.27	4.23	0.91	0.66	10.55	31.1

For all scenarios examined, the PV contribution generated by HOMER Pro is lower than the one generated by iHOGA, in contrast to simulations conducted for the optimum economic results (Tabs. 8 and 9). Moreover, HOMER Pro has selected lower battery banks' capacity to respond to load requirements. In 5 out of 9 scenarios (except for scenarios 1, 2, 5 and 7), HOMER Pro generated higher amounts of excess energy in comparison with iHOGA (Tab. 9). Tab. 9 presents the energy distribution generated by both HOMER Pro and iHOGA for the examined HRES for minimum unmet load.

Tab. 9 – Overview of the energy distribution generated by HOMER Pro and iHOGA for minimum unmet load

Scenario	Excess energy (kWh/year)		Energy delivered by PV array (kWh/year)		Energy delivered by WT array (kWh/year)	
	HOMER	iHOGA	HOMER	iHOGA	HOMER	iHOGA
1	5,577	6,143	5,738	8,738	3,604	1,775
2	6,163	6,575	6,811	8,437	3,079	2,439
3	4,269	2,859	3,820	3,917	4,154	3,198
4	5,832	5,182	7,490	7,792	2,145	1,747
5	6,389	12,522	7,034	9,486	3,079	7,235
6	4,448	3,602	4,015	4,404	4,154	3,156
7	3,716	4,143	5,373	6,775	2,145	1,747
8	4,997	4,873	5,653	6,773	3,079	2,410
9	3,589	3,302	3,156	4,403	4,154	3,155

The differences noted between the NPC values generated by the two (2) software (Tab. 10) follow the same tendency as the one noted during the simulations for optimum economic results. Discrepancies can be noted only for scenarios 2 and 5, under which the NPC values generated by iHOGA are higher than the ones generated by HOMER Pro. On the other hand, for all examined scenarios (except for scenario 5), the LCOE values generated by HOMER Pro are approximately 80% greater than the ones generated by iHOGA. Tab. 10 gives an overview of the simulation results generated by both HOMER Pro and iHOGA for the economic parameters of the examined HRES for minimum unmet load.

Tab. 10 – Overview of the LCOE and NPC generated by HOMER Pro and iHOGA for minimum unmet load

Scenario	NPC (€)		LCOE (€/kWh)	
	HOMER	iHOGA	HOMER	iHOGA
1	43,881	39,378	0.83	0.50
2	37,753	38,980	0.78	0.45
3	33,449	33,171	0.69	0.40
4	37,539	37,052	0.77	0.43
5	37,401	55,370	0.77	0.64
6	33,328	31,842	0.68	0.37
7	37,471	35,883	0.77	0.42
8	36,649	35,883	0.76	0.42
9	33,230	33,171	0.70	0.40

4. Comparison of simulation results with ESA software

For all scenarios examined, ESA opted to cover the load demand only with WTs (Tab. 11). The greater capacity of WTs generated by ESA increased the amount of energy delivered by WTs, compared to HOMER Pro and iHOGA. The storage capacities generated by ESA are higher than the relevant ones generated by HOMER Pro for all scenarios examined (Tab. 11). Tab. 11 presents a comparison of the simulation results for the sizing parameters generated by the three (3) simulation software for optimum economic results.

Tab. 11 – Comparison of the simulation results for the sizing parameters generated for optimum economic results

Scenario	Batteries capacity (kWh)			Energy delivered by WT array (kWh/year)		
	HOMER	iHOGA	ESA	HOMER	iHOGA	ESA
1	22.85	31.1	24	0	1,775	9,989
2	10.55	31.1	30	3,079	2,439	9,989
3	10.55	31.1	20	4,154	3,198	9,989
4	15.82	31.1	32	0	1,747	10,171
5	10.55	31.1	32	3,079	2,411	10,171
6	10.55	31.1	16	4,154	3,156	9,989
7	15.82	31.1	16	2,145	1,747	9,989
8	10.55	31.1	28	3,079	2,410	20,341
9	10.55	31.1	18	4,154	3,155	9,989

On the other hand, except for scenarios 4 and 5, iHOGA generated higher values for the storage than ESA. Except for scenario 8, the excess energy generated by ESA is lower than the one generated by HOMER Pro (Tab. 12). Finally, for all scenarios examined, iHOGA generated smaller amounts of excess energy than ESA. Tab. 12 depicts a comparison of the simulation results for the energy distribution generated by the three (3) simulation software for optimum economic results.

Tab. 12 – Comparison of the simulation results for the energy distribution generated for optimum economic results

Scenario	Unmet load (kWh/year)			Excess energy (kWh/year)		
	HOMER	iHOGA	ESA	HOMER	iHOGA	ESA
1	26.27	96.45	0	8,908	1,446	3,485
2	37.85	73.50	0	6,163	2,137	3,485
3	17.54	150.22	13.80	4,269	324	3,485
4	38.75	44.82	0	6,460	1,844	3,694
5	40.55	46.94	0	6,389	2,570	3,694
6	3.35	18.43	100.08	4,448	563	3,179
7	5.46	21.37	100.08	3,716	1,800	3,179
8	32.47	34.31	131.14	4,997	2,539	9,072
9	5.85	99.42	134.59	3,589	367	3,573

5. Conclusions

The current work provided an overview of the sensitivity and diversified dispatch strategy of two (2) commercial simulation tools by carrying out simulations with nine (9) scenarios of representative renewable energy potentials (solar and wind energy). The two (2) commercial software examined (HOMER and iHOGA) were also compared with the ESA Microgrid Simulator, developed by the SEALAB of the University of West Attica. Two (2) categories of optimization targets were selected (economic and power reliability), leading to different sets of results. The results, concerning mainly the contribution of each RES, the volume of excess energy generated and the relevant volume of unmet load were accumulated in dedicated Tables for further process and analysis. Subsequently, the results were evaluated based on the Power Reliability Indicators selected.

The results have shown discrepancies between the simulation tools, which are mainly attributed to the energy management plan applied in each one of them. Under the precondition of zero load rejection (100% autonomy), the configuration with the minimum LCOE was different between the tools, some proposing higher storage capacity or granting priority to wind power. The results were also impressive in respect of the direct contribution of solar and wind energy to the load demand and the amount of energy directed (attributed) to demand through the storage system. By comparing the proposed configurations for different renewable energy potential scenarios, their sensitivity was assessed, while producing the most cost-efficient HRES configurations on the basis of different dispatch strategies that each software package uses.

Long-term research and development efforts in the scientific field of HRES shall contribute to reduce the gap between emerging technologies and modeling capabilities, rendering possible simulations of increased accuracy. It would be vital to act in advance and incorporate DSM, load control, financial planning and forecasting techniques in the HRES operational control. The implied optimized planning could contribute to further reduction of the total system cost.

In addition, an attempt to model in depth emerging renewable energy technologies that haven't been currently explored in great detail, such as tidal, wave and hydrokinetic energy, shall be performed. Finally, an aspect of long-term work would include the extended simulation of HRES configurations integrating various forms of energy storage technologies.

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