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Tools for Analysis and Optimization of Standalone Green Microgrids

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***Abstract*—**Microgrids (small-scale power systems optimizing variable generation and loads) that use renewable energy (RE) for generation, are complex systems featuring nonlinear dynamics. Among a variety of different optimization tools, there are only a few ones that adequately consider the entire complex system. This paper evaluates applicability of two somewhat similar optimization tools tailored for standalone RE microgrids and also assesses a machine learning tool for performance prediction that can enhance the reliability of the two chosen optimization tools. It shows that one of these microgrid optimization tools has certain advantages over another and presents a detailed routine of preparing input data to simulate RE microgrid behavior. The paper also shows how neural-network-based predictive modeling tools can be used to forecast power generation time series data based on whether time series data, and therefore to enhance the effectiveness of using optimization tools.

***Keywords*—**Microgrid, renewable energy, complex systems, optimization, predictive modeling, neural networks.

I. INTRODUCTION

ENERGY independence and reliability for remote islands are compelling requirements for microgrids as seen for both the U.S. Navy and civilian communities residing on these islands. Without the capability to provide power in a sustainable and affordable manner, the ability to support either the military operations or communities found on these remote islands is significantly decreased. For these reasons, it is worthwhile to better understand the system behavior of these power systems that are typically modelled as microgrids.

Maximum sustainability for an island microgrid would be to generate all the green power on-island using on-island resources independent of any off-island resources. Many islands in recent years have worked towards attaining 100% renewable or green energy generation on-island. Introducing RE necessitates the application of powerful tools that consider the complexity of the system to thereby create the opportunity to optimize towards 100% RE.

Given the variability of RE generation serving small and disparate loads coupled with the system operation of a microgrid, these microgrids can conceivably be considered a complex system by virtue of their "interrelated, heterogeneous elements (agents and objects)" [1]. By understanding the complex system characteristics of a microgrid to potentially include emergent behavior, resilient networks [2], and synchronous states, there may be an opportunity to improve the overall efficiency of the microgrid as well as to enhance overall system reliability of the island's electrical grid through optimization of the microgrid architecture design.

This paper evaluates three tools that can be used to better design green microgrid solutions, and is organized as follows. Section II presents a short overview of the essence of microgrid systems, followed by section III that presents an overview of two software packages, EnergyPLAN and the Hybrid Optimization Model for Multiple Energy Resources (HOMER), that can be used for microgrid system analysis and optimization. Section IV proceeds with an illustration on what input data are required for microgrid system modeling, followed by section V describing the initial efforts on predictive modeling of microgrid performance using MATLAB's neural network (NN) tools. The paper ends with conclusions.

II. MICROGRID COMPONENTS

Microgrids are small scaled power systems located closer to the load than typically found in conventional power plants. A microgrid normally includes three core components: hybrid energy generation, energy storage (battery) and controls [3]. All of these components work together as a system solution to serve a nearby load.

Green microgrids leverage an alternative energy source in the power generation. Typically, but not always, this alternative energy is a RE source and is paired with traditional generation such as a diesel genset. The RE often come from solar photovoltaic (PV) or wind turbines. Besides RE, there are alternative energy sources that can still be considered green when connected to a renewable generation source, e.g. a reversible solid oxide fuel cell system.

Most microgrids are designed and installed to meet a specialized need not ideally served by the utility company. Often this need is dictated by the remoteness and dislocation of the load from a utility company such as a remote island or by loads that are deemed critical infrastructure (for example, at the U.S. Navy installations on San Nicholas Island of California, Kauai, Hawaii, and Diego Garcia of British Indian Ocean Territory).

For remote island communities, the microgrids have been used to provide greater independence, reliability and sustainability from off-island power services. As a result, these green microgrids have rather creative and complex designs.

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III. Energy System Analysis Tools

The National Renewable Energy Laboratory's (NREL) HOMER tool has been the gold standard for energy grid analysis and optimizations [4]. HOMER, the micro-power optimization tool allows designing both off-grid and grid-connected systems. HOMER can be used to perform analyses to explore a wide range of design questions, such as cost-effectiveness of different technologies as well as overall architecture and component size including RE components. It also conducts a sensitivity analysis identifying energy grid economics if component costs or loads change [4]. HOMER uses a system of graphical user interfaces (GUIs) to define the energy system (Fig. 1 shows an example of such a window defining the parameters of a wind turbine) and then allows performing optimization and sensitivity analysis addressing the aforementioned questions (Fig. 2 illustrates HOMER's graphical capabilities). HOMER is used worldwide and had been very successful.

Another tool, the EnergyPLAN, was designed by the Sustainable Energy Planning Research Group at Aalborg University in Denmark. It is intended to simulate (and optimize) energy systems, specifically green microgrids. Using a systems engineering approach, EnergyPLAN assists in the design of national energy planning strategies on the basis of technical and economic analyses of the consequences of different national energy systems and investments. It is a deterministic, hour-simulation model, aggregated in a systems description through optimizing operations and using analytical programming. The simulations include a technical simulation and a market-economic simulation.

Major components of the EnergyPLAN user inputs include supply data, demand data, RE sources, energy plant capacities, and costs (Fig. 3 shows an example of EnergyPLAN GUI defining the wind turbine performance). Having these inputs defined, simulation produces energy balances, annual productions, fuel consumption, and total costs. Thus far EnergyPLAN has been most directly applicable to European nations, but the authors are now trying to access it for the use at U.S. Navy installations and specifically, energy usage at disparate and remote U.S. Navy facilities. A sample EnergyPLAN's output is illustrated in Fig. 3.

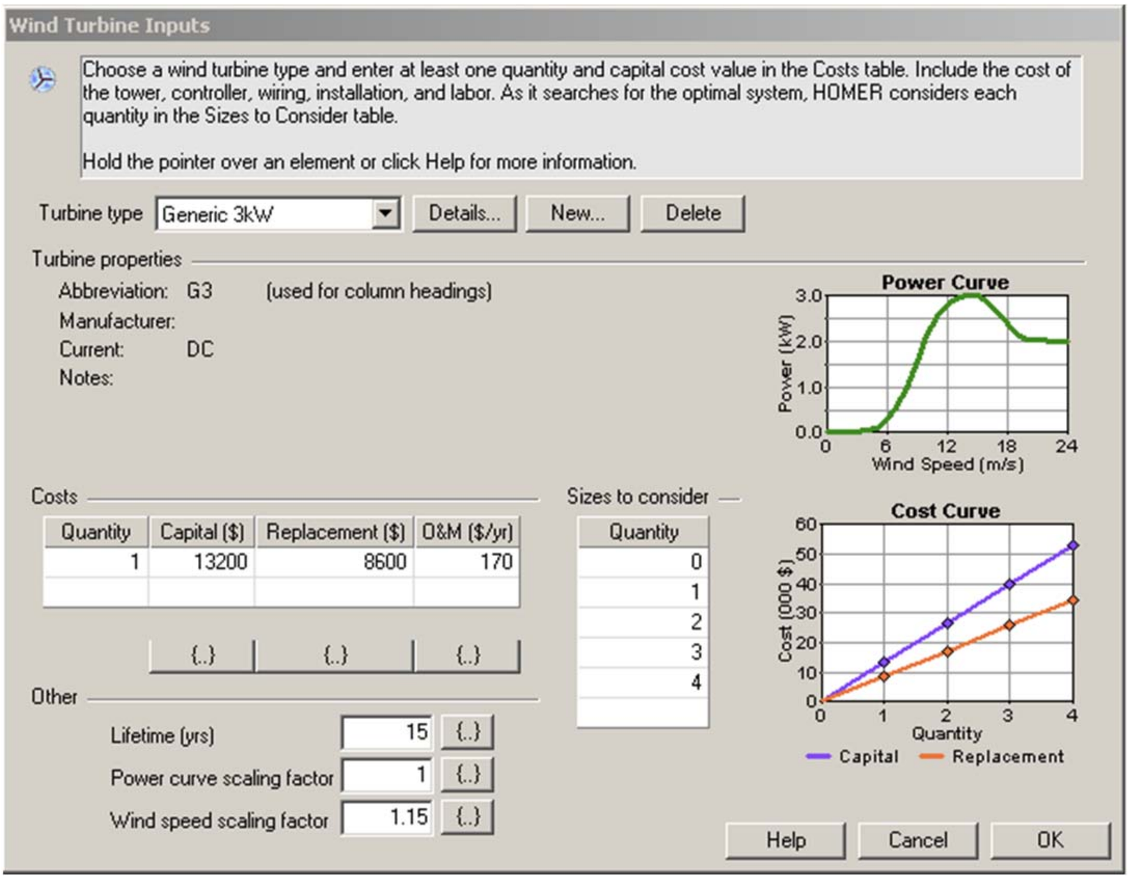


Fig. 1 HOMER's wind turbine inputs window [11]

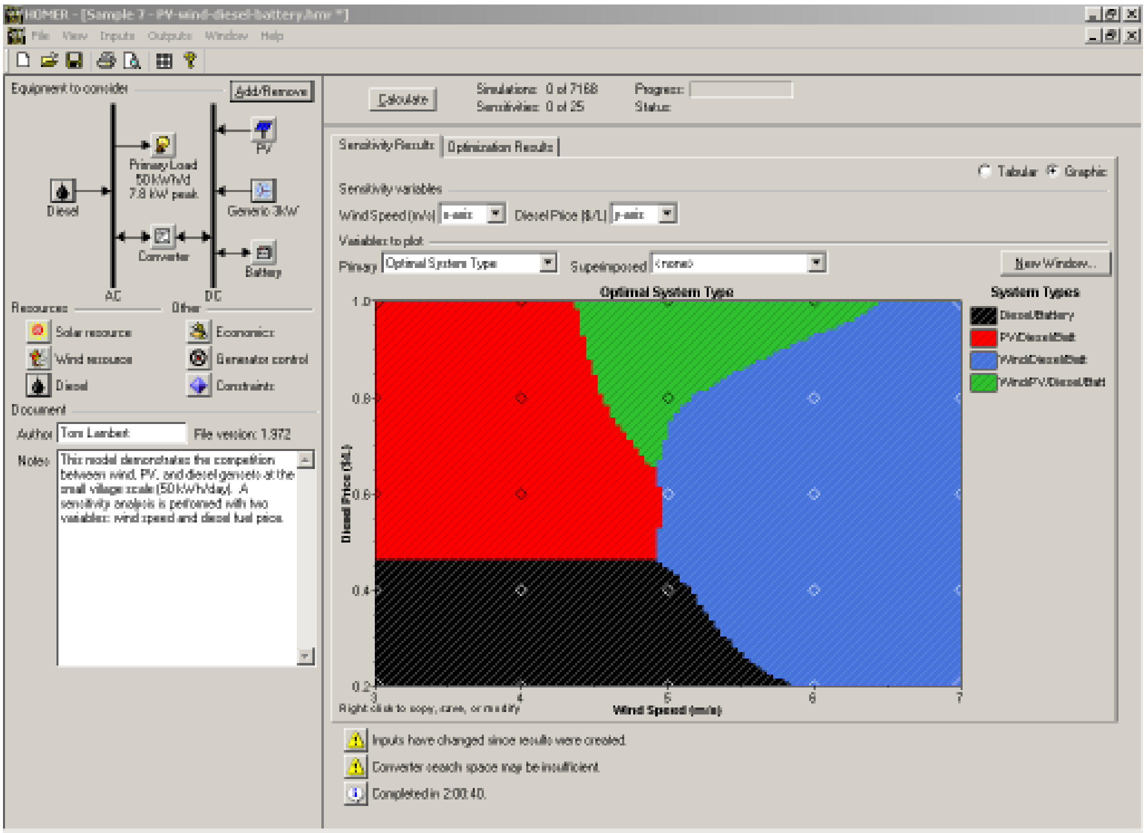


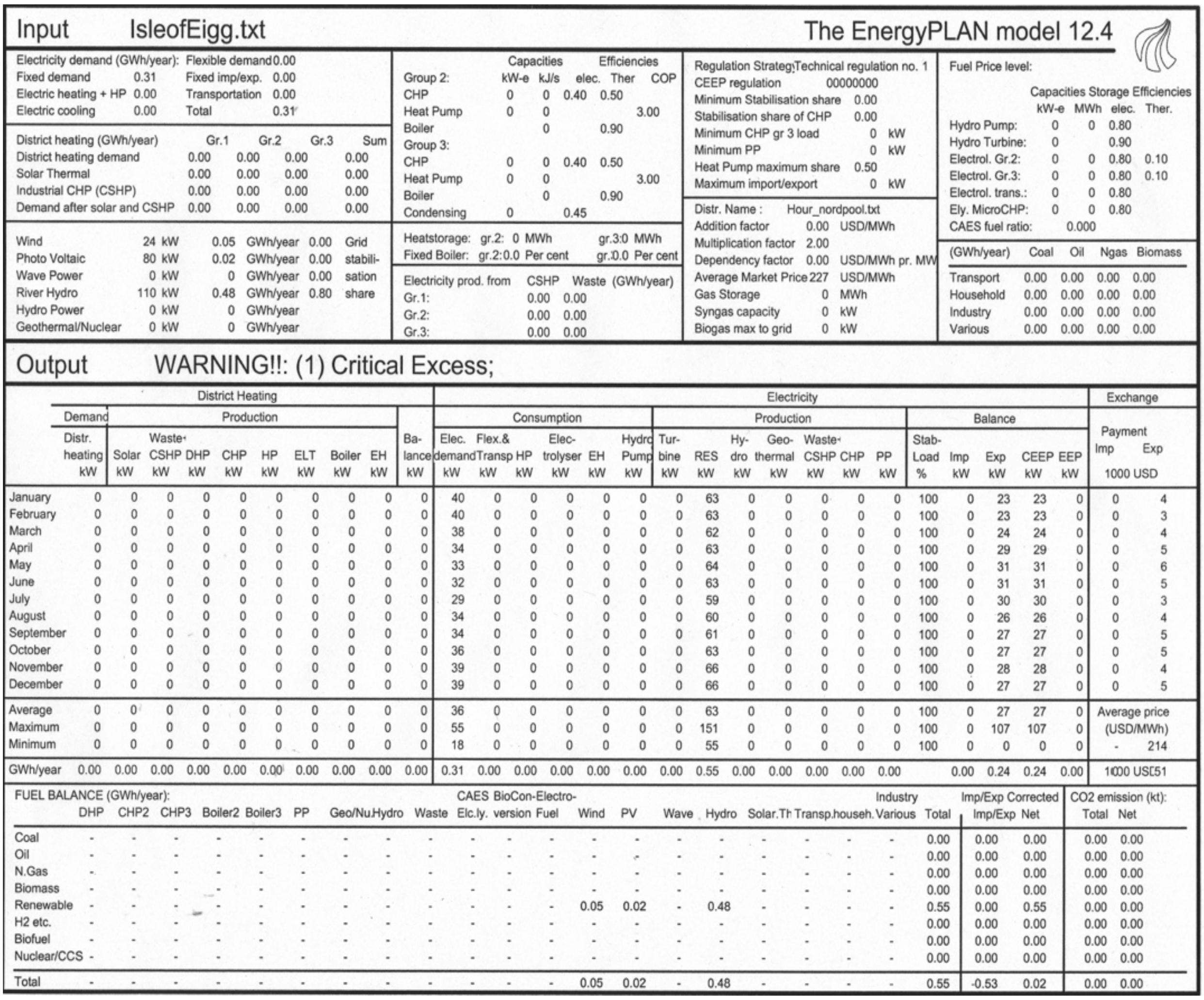
Fig. 2 HOMER's sensitivity analysis GUI [11]

Compared to HOMER, EnergyPLAN does not allow conducting optimization and sensitivity analysis by itself, however it is relatively easy to develop a wrapper and then use external optimization tools (e.g., MATLAB Optimization toolbox). Also, although EnergyPLAN does not offer a similar GUI as HOMER, it does provide standard distribution profile time series datasets for many generation and load profiles [5].

Among the two aforementioned tools, for a specific application in which the authors are interested (to model microgrids), EnergyPLAN seems to have certain advantages over HOMER. Specifically,

- EnergyPLAN has been developed and tailored to be used to simulate a 100% RE system for Denmark. As such it includes the ability to add a plethora of RE options to the traditional energy grid. The result is a fully analyzed, both technical and economic, hybrid mircogrid for decision makers to choose the best course of action;
- RE systems, like wind energy, tend to fluctuate greatly throughout any measured time period. Since EnergyPLAN considers the three primary sectors of an energy system to be electricity, heat, and transport, integration of these fluctuating sectors becomes more of an issue. This is even more pronounced when these RE sources come to achieve more penetration in the grid. To this end, EnergyPLAN enables both greater flexibility and reality by permitting the system evaluation to include combined heat and power (CHP) plants, heat pumps, electric vehicles, and hydrogen [6];
- HOMER does not account for transients of equipment and can lead to the output showing certain pieces of equipment, such as diesel genset, being switched on and off more often than may be realistic. This can lead to errors in the outputs;
- HOMER will always optimize for cost first, not the best technical solution. EnergyPLAN, however allows optimizing for both technical solution and cost. Moreover, it allows simulating the costs of an energy system in four areas [7], specifically a) fuel costs, which includes purchasing/handling/taxes in relation to each fuel, b) investment costs including required capital costs, the lifetime of each unit, and the interest rate on repayments, c) operation costs that include both variable and fixed operation and maintenance costs for each production unit, and d) any extra costs not accounted for in the program by default, for example the cost of insulating houses for increased energy efficiency, etc.;
- EnergyPLAN software is a free download;
- The user interface is designed as a series of tab sheets and stacked side columns. Therefore, jumping between sections and inputting data is very quick and easy. Also, there is online training available from the EnergyPLAN website;

The following section describes the inputs that are necessary to run the EnergyPLAN microgrid modeling.



	District Heating Demand Distr. heating kW	DH Production Solar kW	Waste CSHP kW	DHP kW	CHP kW	HP kW	ELT kW	Boiler kW	EH kW	Balance kW	Electricity Consumption Elec. demand kW	Flex.& Transp kW	HP kW	Elec-trolyser kW	EH kW	Hydro Pump kW	Electricity Production Tur-bine kW	RES kW	Hy-dro kW	Geo-thermal kW	Waste CSHP kW	CHP kW	PP kW	Balance Stab-Load %	Imp kW	Exp kW	CEEP kW	EEP kW	Exchange Payment Imp 1000 USD	Exp 1000 USD
January	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	63	0	0	0	0	0	100	0	23	23	0	0	4
February	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	63	0	0	0	0	0	100	0	23	23	0	0	3
March	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	62	0	0	0	0	0	100	0	24	24	0	0	4
April	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	63	0	0	0	0	0	100	0	29	29	0	0	5
May	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	64	0	0	0	0	0	100	0	31	31	0	0	6
June	0	0	0	0	0	0	0	0	0	0	32	0	0	0	0	0	0	63	0	0	0	0	0	100	0	31	31	0	0	5
July	0	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	59	0	0	0	0	0	100	0	30	30	0	0	3
August	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	60	0	0	0	0	0	100	0	26	26	0	0	4
September	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	61	0	0	0	0	0	100	0	27	27	0	0	5
October	0	0	0	0	0	0	0	0	0	0	36	0	0	0	0	0	0	63	0	0	0	0	0	100	0	27	27	0	0	5
November	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	66	0	0	0	0	0	100	0	28	28	0	0	4
December	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	66	0	0	0	0	0	100	0	27	27	0	0	5
Average	0	0	0	0	0	0	0	0	0	0	36	0	0	0	0	0	0	63	0	0	0	0	0	100	0	27	27	0	Average price	
Maximum	0	0	0	0	0	0	0	0	0	0	55	0	0	0	0	0	0	151	0	0	0	0	0	100	0	107	107	0	(USD/MWh)	
Minimum	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	55	0	0	0	0	0	100	0	0	0	0	-	214
GWh/year	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	0.00	0.00	0.00	0.00	0.00	0.00	0.55	0.00	0.00	0.00	0.00	0.00		0.00	0.24	0.24	0.00	1000 USD	51

FUEL BALANCE (GWh/year):

	DHP	CHP2	CHP3	Boiler2	Boiler3	PP	Geo/Nu.	Hydro	Waste	Elc.ly.	CAES	BioCon-version	Electro-Fuel	Wind	PV	Wave	Hydro	Solar.Th	Transp.	househ.	Industry Various	Total	Imp/Exp Corrected Imp/Exp	Net	CO2 emission (kt): Total	Net
Coal	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.00	0.00	0.00	0.00
Oil	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.00	0.00	0.00	0.00
N.Gas	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.00	0.00	0.00	0.00
Biomass	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.00	0.00	0.00	0.00
Renewable	-	-	-	-	-	-	-	-	-	-	-	-	-	0.05	0.02	-	0.48	-	-	-	-	0.55	0.00	0.55	0.00	0.00
H2 etc.	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.00	0.00	0.00	0.00
Biofuel	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.00	0.00	0.00	0.00
Nuclear/CCS	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.00	0.00	0.00	0.00
Total	-	-	-	-	-	-	-	-	-	-	-	-	-	0.05	0.02	-	0.48	-	-	-	-	0.55	-0.53	0.02	0.00	0.00

Fig. 3 Sample EnergyPLAN output

IV. ENERGYPLAN REQUIRED INPUTS

The following steps outline the base required steps to construct a reference with EnergyPLAN:

1) Diesel genset hourly data for a year (percentage of installed capacity). This may require local data collection or, if available, downloading data from a remote networked computer;
2) Wind turbine hourly data for a year (percentage of installed capacity);
3) Solar PV hourly data for a year (percentage of installed capacity);
4) The total annual production/demand (TWh/year);
5) The installed supply capacities (MW) of all supply sources at a specific site;
6) Installation costs (these costs include overall investments, fixed operations and maintenance, variable operation and maintenance, fuel, and transportation);
7) Weather data (that can be accessed from one of the weather websites that stores past data, e.g. National Weather Service Climate Services or W Weather Underground).

Fig. 4 shows a typical energy system block diagram as created in EnergyPLAN, and Figs. 5 and 6 show examples of yearly data (8760 data points). All distribution files as for EnergyPLAN are supposed to be saved in the ASCII (.txt) format. Specifically, for the annual distributions files that contain data points, the data points can be normalized upfront (to reside between 0 and 1), representing 0-100% of production or demand or saved as is (in this case EnergyPLAN will index the distribution automatically).

Once all these data, characterizing a reference model, are entered into the system, simulations can be run. Adding in proposed RE energy sources and analyzing how the model changes in terms of both technical outputs and economic outputs enables performing optimization and sensitivity analysis.

Obtaining raw data and converting it into usable data for EnergyPLAN might require a considerable amount of effort including data conditioning and synchronization, outlier removal, etc. For example, Fig. 6 (b) features a couple of obvious outliers and two missing points, and Fig. 7 provides a graphical view of analyzing some particular dataset featuring quite a few missing points that needed to be filled in somehow.

Hence, data preparation may involve data forecasting as addressed in the next section.

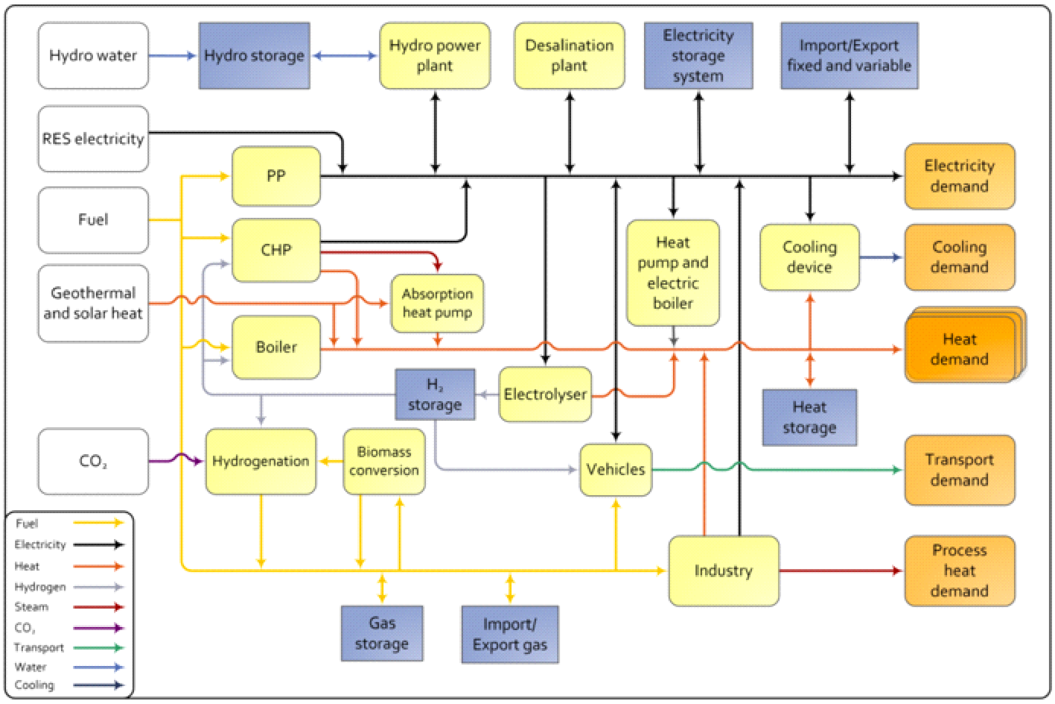


Fig. 4 Typical energy system in EnergyPLAN

V. Forecasting PV Generation

This section presents an approach that can be used to fill in missed data and forecast future energy supply. As an example, predictive modelling is used to approximate future solar PV electrical generation. Hourly weather data input into the NN application in MATLAB allows training the network to learn how to predict the target time series output. The intent of doing this is to validate if the weather data could in fact be used to predict solar generation. If the solar PV generation could be predicted with accuracy, then the microgrid's load would also be predicted with the intent of ultimately using these future values of generation and load to optimize the microgrid. An objective function to equalize the generation and load would then be used while seeking to minimize costs and maximizing efficiency. This optimal solution could be used to influence the construct (how much and which type of RE generation and storage) modeled in EnergyPLAN.

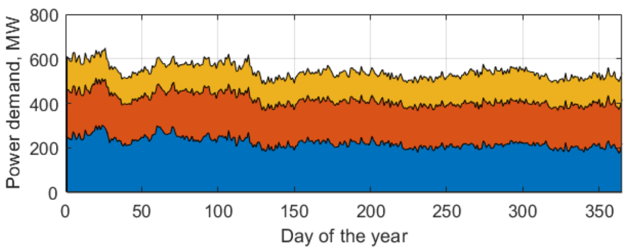
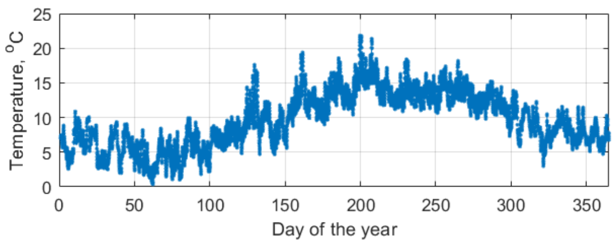
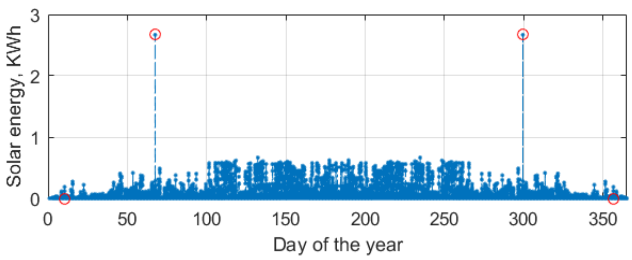


Fig. 5 Sample of yearly power demand as recorded by three gauges

In this example, the hourly data for solar PV generation was manually built by pulling generation data for the Isle of Eigg, Scotland directly from the installer's website [8], [9]. Similarly, 8,760 data points of weather data representing temperature, relative humidity, barometric pressure, wind speed and direction, rainfall, snowfall, and snow depth was downloaded from the Solar Radiation Data (SODA) website [10].



(a)



(b)

Fig. 6 Samples of yearly temperature data (a), and solar energy generated (b)

The first attempt to apply predictive modelling to these datasets was done using MATLAB's NN Fitting Application commonly used to solve input-output fitting problems with two-layer feed-forward NNs. The weather data were used as the numeric input that NN will map to the numeric targets of solar generation as the output. The NN was trained best using Levenberg-Marquardt backpropagation. The model is presented in Fig. 8.

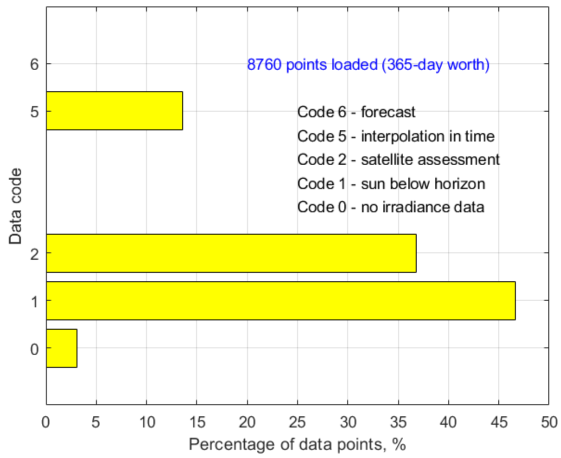


Fig. 7 Example of data point analysis

The regression *R* values, an indicator of correlation between the actual and desired outputs, did not exceed 0.913 and the aggregate (training, validation, and rest) *R* value was 0.911 as can be seen in Fig. 9. The best validation performance featured a Mean Squared Error (MSE), the average squared difference between outputs and target values, of 0.0037 at epoch 18.

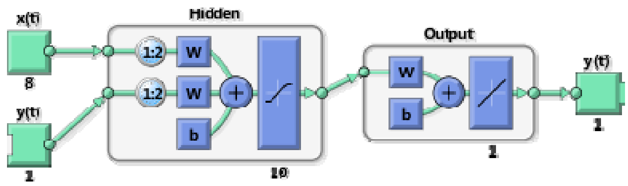


Fig. 8 Two-layer feed-forward NN training model

MATLAB's NN Time Series application was then used to predictively model the PV generation. This tool is intended to solve nonlinear time series problems with a dynamic NN. Given the inherent nonlinear nature of weather, this tool seemed very appropriate. Specifically, the nonlinear autoregressive with External (Exogenous) Input (NARX) was used to predict the PV generation time series using both past time series values of PV generation and weather. The results using Levenberg-Marquardt for training produced *R*-values that did not exceed 0.92 with an aggregate *R* of 0.91. The NARX model can be seen in Fig. 10. In this figure, *x*(*t*) is the weather time series data, *y*(*t*) is the solar PV generation time series data and there are 10 neurons.

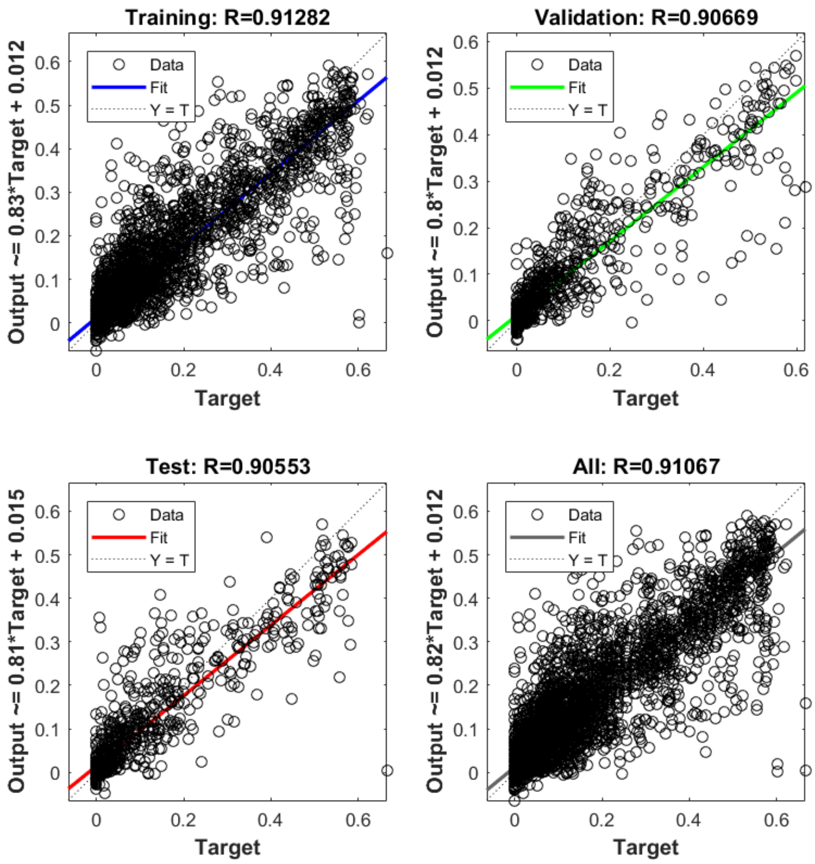
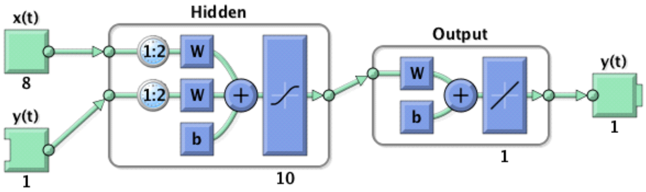


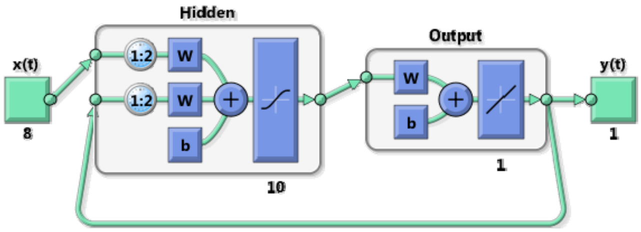
Fig. 9 NN training regression

Comparatively, the NARX predictive modelling produced similar results for regression as can be seen by the regression plot in Fig. 11. The best validation performance was a MSE of 0.0035 at epoch 24. These results were obtained in less than half of the processing time as the two-layer feed-forward NN and given their significantly similar *R*-values were deemed acceptable without any need or real benefit deemed to increase the neurons.

The NARX modelling proved that the target solar PV generation data time series could be reliably trained to the weather data time series.



(a)



(b)

Fig. 10 NARX NN open-loop (a) and close loop (b) training model

VI. Conclusions

This paper presented an overview of EnergyPLAN versus HOMER software tools that can be used to assist exploring and optimizing green microgrids on isolated locations and showed some preliminary the results of their modeling using EnergyPLAN software package. Additionally, MATLAB's predictive modeling tool was applied to an island's microgrid data to evaluate its usefulness in further enhancing these optimization tools and suggested that the PV generation time series data could be predicted using weather time series data.

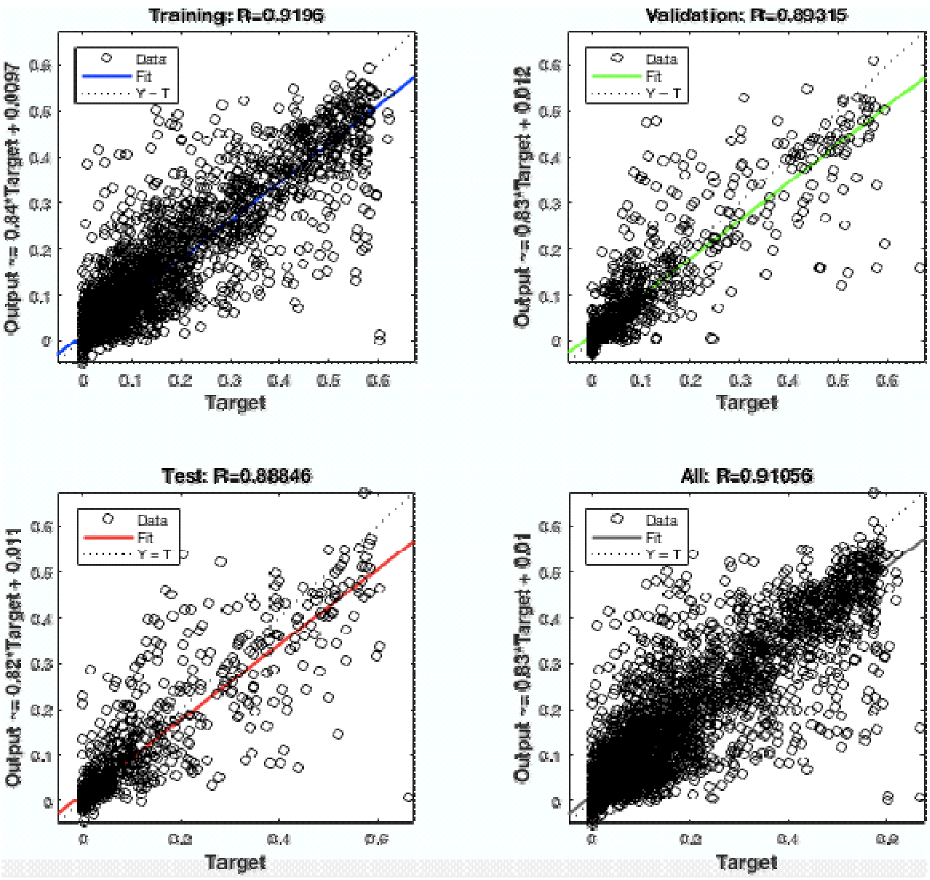


Fig. 11 NARX NN training regression

Acknowledgments

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