Employing Systems Engineering Tools to Analyze Green Microgrids for Remote Islands

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***Abstract*—Microgrids (small scale power systems optimizing variable generation and loads) that serve a remote island's load requirements demonstrate both the extreme challenges and opportunities in providing reliable power in remote locations. Microgrids, which provide the entire power requirements with on-island resources, can be considered complex systems. These complex systems can be modeled using a variety of tools. This paper provides an overview of different tools used to characterize different aspects of microgrids' behavior in order to improve their overall efficiency. These tools include agent-based modeling as one of a class of computational models commonly used in Systems Engineering, as well as specialized software packages specifically developed to address energy performance modeling, like EnergyPlan. A broad overview of the used methods is followed by illustration of how these tools could be applied to the analysis of a green microgrid of a remote island. The paper ends with conclusions on advantages and disadvantages of employing different tools to investigate the dynamics of remote island microgrids.**

Keywords—microgrid; complex systems; agent-based modeling, nonlinear dynamics

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 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.

Given the variability of renewable energy 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 provides an initial construct for researching the behavior of green microgrids. It reviews several approaches to conduct such a research and illustrates advantages and disadvantages of applying these methods based on a a set of data available for one of the remote islands. Specifically, Section II provides a literature review of research conducted that directly relates to this effort. Section III describes the construct and resulting architecture for microgrids. Section IV outlines existing tools that can be be used to study and optimize a green microgrid for remote islands. Section V provides illustrative examples of modeling the the very same system using different tools. The paper ends with conclusions.

II. Background

Microgrids (Fig.1) 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 generation, energy storage and controls. All of these components work together as a system solution to serve a nearby load.

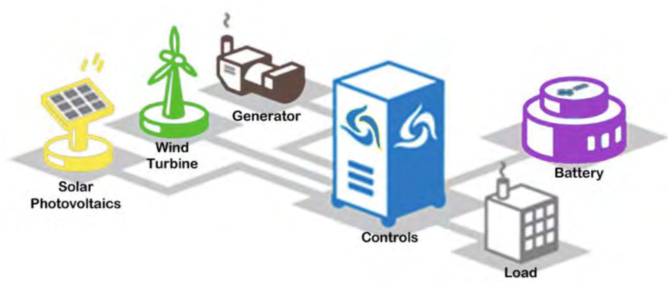

Figure 1. Microgrid components [3].

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

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

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the load from a utility company such as a remote island or by loads that are deemed critical infrastructure.

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 [4].

For U.S. Naval installations, microgrids have been used and considered primarily to serve critical infrastructure typically employed in remote locations to include San Nicholas Island of California (SNI), Hawaii, and Diego Garcia of the British Indian Ocean Territory at least.

The most recent and robust example of a military microgrid on a remote installation is the smart cybersecure microgrid installed at Camp Smith on Oahu, Hawaii. This microgrid was designed and installed to provide emergency backup power for critical infrastructure as the culmination and third and final phase of the SPIDERS (Smart Power Infrastructure Demonstration for Energy Reliability and Security) JCTD (Joint Capability Technology Demonstration). The microgrid employed hybrid power generation (diesel gensets and solar PV), power storage (lithium ion batteries), a networked control system and the first ever grid interconnect to the local utility, Hawaiian Electric Company (HECO). The interconnect created the opportunity for power factor correction, peak demand management and load shedding. SNI also represents a significant effort to provide power to a remote island infrastructure. The microgrid on SNI also uses hybrid generation (diesel gensets and wind turbines), and a simple control system.

III. Microgrids Architecting

The U.S. Department of Energy classifies a microgrid as a complex system not so much for its characteristics of emergent behavior or nonlinear dynamics, rather simply because of their use of advanced distributed energy resources (DER) components. Specifically, microgrids can include [5]

- Small, local and stand-alone power systems integrated with a larger distribution feeder
- Both energy storage and distributed generation (DG) within a small "control area"
- Variety of DG
- Plug-and-play functionality not dependent upon communications
- Single interface to power system to have seamless power transition between parallel to grid and islanded

Although there has been a steady push into architecting "smart microgrids" by optimizing the entire system, this approach has not effectively leveraged Complex Systems tools. Some consider the primary value of microgrids to have "an economic character, and to a lesser extent increased reliability and renewable energy [6]." However, for remote islands and U.S. Navy installations the primary benefit is energy security and mission assurance, not economic [6].

There has been some progress made by researchers from the Technical University of Denmark in developing a "Robust Optimization" approach for a microgrid's overall energy management. In this research a microgrid was modelled using agent-based modelling (ABM) by considering the following agents: a mid-size train station with an integrated solar PV, a small wind turbine power plant, and surrounding residential and small business loads.

"The system is decribed by Agent-Based Modelling (ABM), in which each player is modelled as an individual agent aiming at a particular goal, (i) decreasing its expenses for power purchase or (ii) increasing its revenues from power selling. The context in which the agents operate is uncertain due to the stochasticity of operational and environmental parameters, and the technical failures of the renewable power generators. The uncertain operational and environmental parameters of the microgrid are quantified in terms of Prediction Intervals (PIs) by a Nondominated Sorting Genetic Algorithm (NSGA-II) - trained Neural Network (NN). Under these uncertainties, each agent is seeking for optimal goal-directed actions planning by Robust Optimization (RO) [7]."

The researchers ultimately concluded that the microgrid using RO resulted in increased performance. The metrics used to evaluate performance included Loss of Load Expectation and Loss of Expected Energy. These metrics were implemented for optimization instead of designated expected values for the uncertain parameters [7].

A further progression in ABM has been made by using a hierarchical control model for microgrids through the lens of a self-organizing multi-agent system. This hierarchical control model is developed as a third generation of control theory that includes large-scale system theory and intelligent control theory. Large scale system theory combines modern control theory, the second generation employing state equation models and time domain analysis, as well as operational research using state and algebraic equation models to optimize, stabilize, and simplify large-scale models. Intelligent control theory combines control theory and artificial intelligence using a general model employing both knowledge and mathematics to design an intelligent system and its corresponding automation.

The first generation of control theory is otherwise the classical control theory. Classical control theory uses transfer functions and frequency domain analysis for single variable design of single-machine automation. This is in comparison to the advanced applications of the second generation to multi-variable system design and integrated automation.

It is this controlled object of the intelligent system that will also to green microgrids' control systems. The renewable energy generation has the same characteristics of an intelligent system that include nonlinear, time-varying, uncertainty of the controlled object and its environment. As such, self-organizing control theory can be used in this research to develop an optimized mechanism for complex self-organizing systems like green microgrids. Researchers at the China Electric Power Research Institute have proposed an intelligent control architecture based upon multi-agent and self-organizing control theory. In so doing they hope to provide a practical system solution for self-organizing control of smart distribution networks such as microgrids.

A hierarchical control structure is used combining the control structure of a large-scale system and hierarchical control structure of intelligent control system. This is then tested and verified on a distribution network with three substations and five feeders. The results suggest that the hierarchical control takes advantage of both local and global control to deliver good performance in response to changes of operation state and global coordination [8].

Practical applications of modelling microgrid controls through multi-agent systems have been applied to excess wind generation capacity. One such simulation studied integrates both real and simulated loads. In this simulation, a unique demand response program is used to have consumers increase consumption when power is cheap. This situation occurs when there is excess wind generation.

The results of this simulation are promising. The responses of both real and simulated agents proved adequate to respond to requests and events by operator agents [9].

Another promising approach to optimizing wind generation into microgrid systems was conducted based upon wind power prediction using a neural network trained by hybrid particle swarm optimization and back-propagation algorithms. The objective of this research was to determine the optimal policy to maximize benefit and minimize cost. This approach considered microgrids with different generation sources such as wind turbines and fuel generators.

Observations of wind speed over three months were used from different seasons. A hybrid optimization algorithm demonstrated a correct dynamic performance. Wind speed was predicted with good accuracy. As a result, the multi-agent architecture could be applied to realize the goal of maximizing benefits and minimizing costs [10].

Cyclostationary processes naturally arise from periodic phenomena. This can be seen in microgrids in the rotational motion of turbines and generators through their periodic AC signals. These periodic AC signals can also be created from pulse width modulation switching of inverters.

Cyclostationary data has been useful in understanding which parts of a microgrid are isolated from each other. Specifically, Wiener Orthogonality can be applied to microgrids by representing voltage time series from DC power sources. This can then help make decisions about which subsystems should be islanded [11].

The most relevant and promising research conducted to date has been to consider microgrids as a system of systems using ABM with system dynamics modelling. This has produced both emergent effects on the interconnected system that were analyzed through simulation.

Microgrids have been viewed as Complex Computer Systems. A microgrid model using this approach was simulated to include the following elements:

- Diesel generator
- Wind power generator
- PV
- Battery storage
- Two loads
- Substation

An ABM to simulate the microgrids was built using AnyLogic and a two-layer structure. The logical layer was used for real time agent communication. The physical layer integrated technical power flow calculation results. The two together delivered real-time simulations of the microgrid.

This model offers one framework for implementing microgrids using a complex systems approach. Although this model does create many options, it still needs expanded. Expansion for instance could ensure intelligent control of energy storage devices. Modularization of the microgrid model is an important factor in microgrid design [12].

IV. Tools for Microgrid Optimization

There are several tools available to both evaluate and potentially improve efficiencies of green microgrids. Some of these tools are as follows.

A. Agent-Based Modeling

Agent-based modeling is one tool used in evaluating complex systems by classifying the respective and dynamic components of the system as agents. Each agent's behavior can be modeled over time using simulation tools such as open source software like NetLogo.

ABM can be used to model the microgrid and simulate its behavior over time (Fig. 2). Overall performance of the microgrid in different models can be evaluated to understand how complex systems theory can be applied to improving the microgrid's performance.

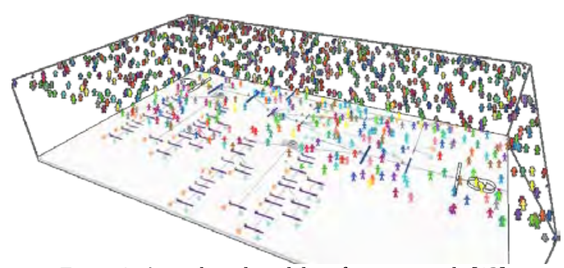

Figure 2. Agent based modeling for smart grids [13].

ABM has been used for wind turbines using a mathematical model for wind energy generated as a factor of the wind speed and a state chart describing behavior and states of wind turbines as depicted in Fig. 3.

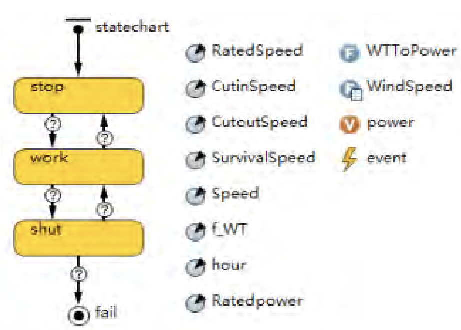

Figure 3. State chart of wind turbine agent [14].

PV systems use a mathematical model for energy generated as a function of PV surface temperature, irradiance and rated power output. The state chart for PV can be seen in Fig. 4.

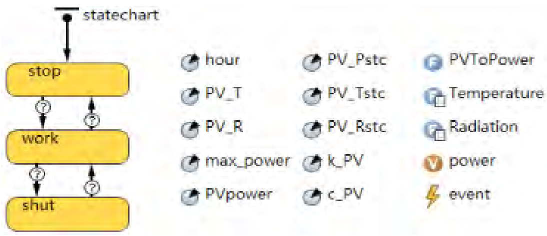

Figure 4. State chart of PV agent [14].

B. Modeling in MATLAB/SIMULINK Development Environment

All networked microgrids employ a control system. The characteristics and design of the control system chosen can be evaluated using MATLAB's Controls Systems toolbox. It is expected that the superior behavioral characteristics of the more capable microgrids is directly related to the choice and logic of the control system.

For example, MATLAB/SIMULINK development environment has been used in a loop microgrid system composed of loads, Superconducting Magnetic Energy Storage (SMES), and renewable energies such as solar and wind generators [15]. The system was simulated using MATLAB to prove that power flow can be controlled. This was modelled using control blocks in MATLAB and applied to the microgrid system (PSIM) as depicted in Fig. 5.

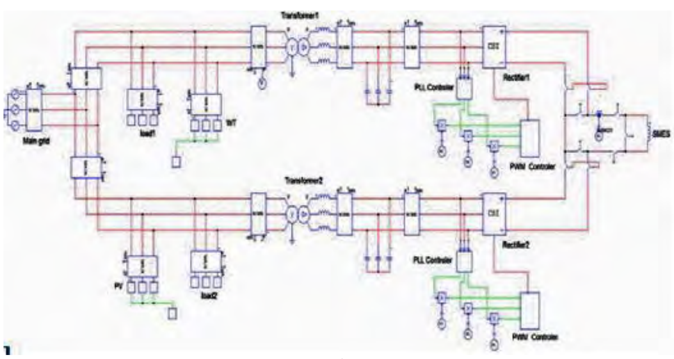

Figure 5. Simulation model of PSIM using MATLAB [15].

C. Nonlinear Dynamics Modeling

Given that the behavior of the microgrid system is often not explained as the sum behavior of the parts, these microgrids categorically can be classified as being nonlinear dynamic systems. It is neither expected that the microgrid systems will be adaptive or chaotic, but the significance of being nonlinear dynamic in nature should be studied.

Nonlinear dynamics of each distributed generation in a microgrid have been formulated on its own *d-q* (direct-quadrature) reference frame. An adaptive feedback linearization-based tracking synchronization using the Lyapunov function technique was used to design the distributed controllers. This simulation proved that the proposed controller provided the synchronization for the output voltage of the distributed generation [16].

D. System Dynamics Modeling

Flow and storage of energy storage devices have been modeled using System Dynamics Modeling (SDM), a tool that relates stocks and flows mathematically in a temporal environment. Stock is defined storage capacity of the microgrid system. Flows describe how the stocks change over time and the dynamics of the system. This model can be represented as depicted in Fig. 6.

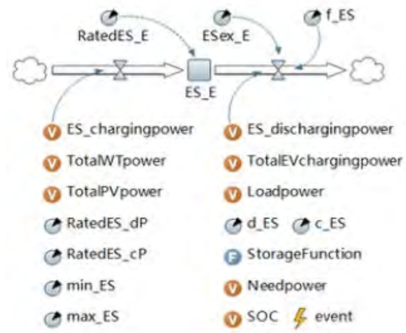

Figure 6. Flowchart of storage device [13].

The findings for a microgrid-electric vehicle system indicated that charging the electric vehicles at night result in maximum discarded energy. As a result of the ABM and SDM, a cascade charging is proposed [13].

E. Utilizing Microsoft Excel Solver

To optimize the microgrid being studied, a formulation will be built that is expected to be multi-objective, mixed-integer and nonlinear. As such, Microsoft Excel's Solver will be initially used to find an optimal solution that is of course feasible. The feasibility of the solution is established by constraints governing the requirements for the load and the capabilities of both the generation, storage and overall system.

The objective functions maximize reliability, penetration of renewables onto grid, and minimize costs. A multi-scenario, multi-objective optimization method of a grid-parallel microgrid was presented based on application scenarios classification. This method can not only access microgrid costs and benefits under different scenarios, but also evaluate the microgrid architectures from different aspects including construction and operation costs, customer outage costs and the environment. The use of battery and diesel generators in different scenarios decreases the difference between load and renewable resources output thereby increasing the penetration of renewable energy. Although the increased use of diesel generators has higher emissions, the total emission level is still much lower than that of a traditional power system. The findings suggest the optimal microgrid configuration is in fact determined by the multi-scenario, multi-objective optimization method being much better than that of a mono-scenario, mono-objective optimization method.

This problem formulation was described as optimizing a microgrid configuration under different scenario constraints to minimize lifecycle cost, energy cost, and emissions while maximizing penetration of renewable energy. Constraints included energy conservation, reliability, power output ranges, battery state of charge parameters, minimum required life of battery, maximum yearly emissions, and minimum renewable energy penetration [17].

One such recent, multi-objective optimization example was applied to islanded microgrids. The optimization minimized two objectives: fuel loss and power losses. A NSGA-II was used to solve the optimization problem. This research concluded the addition of DERs and the use of load management and a supply optimization algorithm decreased line losses and fuel costs dramatically. Of note is that the fuel price per kWh produced is reduced by an average of 33% [18].

V. Examples of Utilizing Different SE Tools

In the final manuscript this will be the key section where the aforementioned tools will be used to model microgrids of Isle of Eigg and SNI. Table 1 shows some of the data characterizing these two somewhat similar (population, remoteness) islands.

Table 1. Microgrid power system characteristics

Component	**Isle of Eigg** [19]	**SNI** [20]
Peak load (KW)	92.3	700 - 1150
Demand (MWh/year)	312.44	5644.77
Wind turbine capacity (KW)	24	700
Solar PV capacity (KW)	79.8	1
River hydro capacity (KW)	110	0
Diesel genset capacity (KW)	128	3021
Battery storage (Kwh)	720	0
Controls system	Smart inverters	4160V underground distribution system

Conclusions

A variety of the tools usually used to analyze complex systems can be utilized to optimize microgrids. The paper reviews these tools and showed examples of utilizing them to model and analyze microgrid systems on Isle of Eigg, Scotland and San Nicholas Island, California. The final version of the paper will have more specific conclusions based on the outcomes of Section V. Ideally, the modelling results will be synthesized to create useful knowledge to alter the controls systems solution for future microgrids.

Acknowledgment

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References

[1] C. S. E., Bale, L. Varga, and T. J. Foxon, “Energy and complexity: New ways forward,” Applied Energy, vol. 138, pp. 150-159, January 2015.

[2] E. A. Kremers, “Modelling and simulation of electrical energy systems through a complex systems approach using Agent-Based Models,” Karlsruhe: KIT Scientific Publishing, 2013.

[3] C. Walsh, “Microgrid regulatory policy in the U.S.,” CIVICSOLAR, 2014.

[4] Anderson, W.W., and Yakimenko, O.A., “Comparative Analysis of Two Microgrid Solutions for Island Green Energy Supply Sustainability,” to appear in the proceedings of the 6th International Conference on Renewable Energy Research and Applications, San Diego, CA, November 5-8, 2017.

[5] “Appendix B3: A systems view of the modern grid ADVANCED COMPONENTS,” U.S. Department of Energy. Office of Electricity Delivery and Energy Reliability, March 2007.

[6] F. D. Wattjes, and J. G. Slootweg, “Design considerations for smart microgrids,” IEEE Power Engineering Conference (UPEC), 2013.

[7] “Energy research: recent research from Technical University highlight findings in energy research (An integrated framework of agent-based modelling and robust optimization for microgrid energy management),”Energy Weekly News, Sep. 5, 2014, p.404.

[8] L. Jianfang, S. Xiaohui, and M. Xiaoli, “Hierarchical control model of smart distribution network based on self-organizing multi-agent system,” IET International conference on renewable power generation, 2015 , pp 1–6.

[9] L., Gomes, T., Pinto, P., Faria, and Z. Vale, “Distributed intelligent management of microgrids using a multi-agent simulation platform. IEEE Symposium on Intelligent Agents (IA), 2014, pp. 1–7.

[10] D. O. Elamine, E. H. Nfaoui, B. Jaouad, “Multi-agent architecture for smart micro-grid optimal control using a hybrid BP-PSO algorithm for wind power prediction.” 2nd World Conference on Complex Systems, 2014, pp. 554–560.

[11] S. Talukdar, M. Prakash, D. Materassi, and M. V. Salapaka, “Reconstruction of networks of cyclostationary processes,” 54th IEEE Conference on Decision and Control, 2015, pp. 1–6.

[12] E. Kremers, P. Viejo, O. Barambones, and J. G. Durana, “A complex systems modeling approach for decentralised simulation of electrical microgrids,” 15th Interational Conference on Engineering of Complex Computer Systems, 2015, pp. 1–10.

[13] “Agent Based Modeling for smart grids,” Joint Research Centre, European Commission, 2016. [http://ses.jrc.ec.europa.eu/agent-based-modelling-smart-grids, accessed 20 December 2016.]

[14] Y., Li, J., Wang, P. Han, and X. Song, “Modeling and optimization oriented to the micro-grid-EV joint system,” 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), 2016.

[15] Y. Kawahara, T. Masuda, M. Miyatake, and O. Sakamato, “Power compensation in the microgrid by SMES using the current source inverters,” 17th International Conference on Electrical Machines and Systems, 2014.

[16] A. Bidrim, F. Lewis, A. Davouci, and S. S. Ge, “Adaptive and distributed control of nonlinear and heterogeneous multi-agent systems,” 52nd IEEE Conference on Decision and Control, 2013.

[17] C.-S. Wang, B. Yu, J. Xiao, and L. Guo, “Multi-scenario, multi-objective optimization of grid parallel microgrid,” Electric Utility Deregulation and Restructuring and Power Techologies, 2011.

[18] H. Fathi, E. Beshr, and M. Eteiba, “Mult-objective optimization of islanded microgrids,” IEEE International Conference on Electrical, Computer and Communication Technologies, 2015.

[19] L. Breen, “Modeling, Optimisation and the Lessons Learned of a Renewable Based Electrical Network – The Isle of Eigg,” University of Strathclyde, 2015.

[20] A. Kandt, and A. Walker. “San Nicolas Island, CA Renewable Community Plan Outline, Baseline Development, and Initial Renewable Assessment,” National Renewable Energy Laboratory. September 2008.