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A NOVEL SYSTEM DYNAMICS APPROACH TO DC MICROGRID POWER FLOW ANALYSIS

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ABSTRACT

This paper employs System Dynamics (SD) to model and analyze DC power distribution systems, focusing on methodological development and using microgrids as case studies. The approach follows a bottom-up methodology, starting with the fundamentals of DC systems and building toward more complex configurations. We coin this approach "Power Dynamics," which uses stocks and flows to represent electrical components such as resistors, batteries, and power converters. SD offers a time-based, feedback-driven approach that captures component behaviors and system-wide interactions. This framework provides computational efficiency, adaptability, and visualization, enabling the integration of control logic and qualitative decision-making elements. Three case studies of microgrids powered by renewable energy demonstrate the framework's effectiveness in simulating energy distribution, load balancing, and dynamic power flow. The results highlight SD's potential as a valuable modeling tool for studying modern energy systems, supporting the design of flexible and resilient infrastructures.

1 INTRODUCTION

Global trends shift from fossil fuels toward distributed renewable energy systems due to environmental concerns and sustainable development goals. Technological advances and reduced costs have accelerated renewable adoption, driving the transition to smart microgrids. Microgrids offer local generation, intelligent load management, enhanced resilience, and flexible grid interactions, mitigating issues like severe weather impacts, aging infrastructure, cybersecurity risks, and economic inefficiencies (Hu et al. 2024). They effectively manage intermittent renewable sources, boosting energy efficiency, reliability, and sustainability, and are pivotal for future smart cities (Sodiq et al. 2019). Microgrids are complex systems integrating solar, wind, and energy storage technologies, requiring dynamic load management and system interaction modeling (Sandelic et al. 2022). DC microgrids offer advantages such as efficient renewable energy integration, reduced conversion losses, lower infrastructure costs, and compact size (Planas et al. 2015). Hybrid DC systems pairing renewable energy with storage optimize efficiency by balancing supply and demand (Gonzalez de Durana and Barambones 2018). Growing adoption in smart buildings, data centers, electric vehicles, and aircraft systems underscores the need for effective DC microgrid modeling and simulation tools.

Many papers investigate DC power flow modeling using traditional techniques and simulation approaches. Solving power flow equations, essential for determining steady-state network conditions like voltages and system losses, relies on computational methods such as Gauss-Seidel and Newton-Raphson (Montoya et al. 2018). Other applied methods include Taylor-based (Montoya et al. 2019), graph-based (Feng et al. 2018), and convex approaches (Li et al. 2018). Control systems typically treat power demand as input and generation as output, necessitating dynamic adjustments for stability (Faraji et al. 2022). Conventional grids use a slack bus, while microgrids balance power at the common coupling point (CCP) (Lone and Gupta 2023). These methods excel at steady-state analysis but have limited capability for modeling dynamics or variable generation scenarios.

Simulation techniques for microgrid modeling include agent-based simulation (ABM) (Gonzalez de Durana et al. 2014), discrete-event simulation (DES) (Fellah et al. 2021), and system dynamics (Gonzalez de Durana and Barambones 2018). ABM effectively represents generalized energy networks and investigates behavioral factors influencing microgrid decisions (Egbue and Uko 2020). DES is useful for event-driven operational management but fails to capture long-term feedback and emergent behaviors.

SD effectively captures feedback and long-term dynamics in power systems, requiring complexity enhancements for broader applicability. Hybrid approaches combining SD and ABM model multi-carrier energy networks and multi-power flows (Gonzalez de Durana and Barambones 2018). SD has also supported policy analysis and demand-side management (DSM), demonstrating utility in dynamic energy modeling (Ahmad et al. 2016). Platforms like AnyLogic facilitate flexible SD modeling and hybrid integrations, making them suitable for complex microgrid analysis (Kondoro et al. 2017; Gonzalez de Durana and Barambones 2018).

This paper introduces a novel methodological framework that applies SD to analyze power flow in DC power distribution systems. In this approach, electrical network components, nodes, lines, and loads are represented using stock-and-flow structures, enabling time-based analysis of power flow and system behavior. The methodology targets distribution networks commonly found in renewable energy microgrids. A bottom-up modeling strategy is employed: beginning with simple circuit elements (e.g., voltage dividers) and progressively integrating more complex system components, including storage devices, converters, and interconnected loads. The SD approach provides conceptual clarity, supports dynamic system visualization, and captures feedback effects and nonlinear behavior often overlooked in traditional static power flow analysis methods. The conventional methods typically rely on static, numerical analyses and neglect temporal dynamics and complex system interactions. The framework is implemented using the AnyLogic simulation platform and validated using two microgrid case studies incorporating renewable energy systems.

The remainder of this paper is organized as follows. Section 2 discusses the methodology employed in this paper, beginning with the fundamentals of power systems analysis and discussing the System Dynamics Approach. Section 3 presents modeling of power dynamics, following our bottom-up approach. Section 4 discusses the microgrid case studies that we employ to test our methodology. Section 5 concludes with our contributions and discusses potential future work.

2 METHODOLOGY

2.1 Power Systems Analysis Fundamentals

An electric power system is a network comprising electric circuits and interconnected elements (generators, transmission lines, substations, storage devices, and loads) designed to supply, transfer, convert, store, and use electrical energy. These systems can be represented using circuit diagrams and one-line diagrams. Circuit diagrams are used to model physical components (e.g., resistors, capacitors, and voltage sources) using equivalent electrical elements, allowing for an analysis of power flow. One-line diagrams offer a graphical representation of the electric power system, simplifying multi-phase systems into simple representations that highlight connections between major components (e.g., generators, transformers, loads), to identify key nodes, buses, and connections within the system. One-line diagrams are useful for system planning, operation, and analysis.

Power distribution systems are governed by Kirchhoff's Laws, which are essential to all electrical analysis techniques. Kirchhoff's Current Law (KCL) states that the sum of currents entering a node must equal the sum leaving it, ensuring charge conservation, as shown in Equation 1. Kirchhoff's Voltage Law (KVL) states that the algebraic sum of voltages around any closed loop is zero, reflecting energy conservation, as shown in Equation 2. These laws support analytical techniques such as node and mesh analysis, Newton-Raphson, and are essential for understanding circuit behavior in simple and complex networks.

KCL ensures that charge conservation is at a node; however, it does not imply that energy conservation occurs at the same node, as this depends on the current entering and exiting the node and the voltage difference between nodes. Power requires current and voltage, and is analyzed across circuit elements, not at the nodes. This distinction is important when representing energy movement through a network. Power flow analysis applies to the Kirchhoff laws to determine voltages, currents, and power distributions under steady-state conditions. Standard numerical methods are used to solve these nonlinear equations; however, these techniques are limited in capturing time-dependent behavior in systems that contain dynamic loads, energy storage, and distributed generation.

$$\sum I_{in} = \sum I_{out} \tag{1}$$

$$\sum V_{sources} = \sum V_{drops} \tag{2}$$

2.2 System Dynamics Approach

System Dynamics (SD) is a modeling approach used for simulating the behavior of complex systems over time using stocks, flows, and feedback loops. It was originally developed to understand different processes better and is useful for investigating the effects of different policies. When applied to electrical systems, SD enables the simulation and visualization of power flows, energy transfer, and feedback effects, capturing time-dependent dynamics rather than relying on static operating points. The modeling framework in this paper is formalized through SDPgraphs, which are system dynamics-based power system graphs.

The flow element in the SDP graph represents power $p(t)$ flowing through the network edges and stock elements represent electrical nodes where power flow is accumulated as electrical energy, allowing us to model normal nodes (where accumulated energy must equal zero). This conceptual framework allows the structure of an electrical network to be represented in a form consistent with SD principles, where interdependent causal loops drive system behavior. The dynamic behavior of SD is based on finite difference equations that are described in (Forrester 1961), where SD has specific elements representing variable-type rates (named Flows) and inventory ones (named Stocks). Equation 3 is used to relate a stock s to its net input flow f, where , $s(t)$ and $f(t)$, represent the value of the stock and flow at time t, Δt is the time increment, and where $j < k$ are time instants. The net input flow measures the amount of all input flows minus all output flows. The stocks represent physical accumulation points, i.e., energy stored, or the nominal voltage on a bus. Another case can arise in which the net input flow is equal at times j and k, that is $f(k) = f(j)$. Using Equation 3, we have: $f(k) - f(j) = 0$, and $s(k) = s(j)$, and that indicates that the stock value remains constant. When electrical nodes that don't accumulate energy are modeled ($s(j) = 0$) (e.g., voltage buses), the stock is held constant (Equation 4). This ensures that flow continuity is preserved and reflects the physical behavior of electrical networks, where charge does not build up at nodes. This indicates that the stock value remains equal to zero, and this can be related to the flow continuity equation (Euler 1757), thus relating to an SD stock with an electric node. Flows represent power transfer between the system elements, which can be represented through a voltage divider.

Compared to conventional circuit solvers and numerical power flow methods, SD enables modeling continuous dynamics, discrete events, and feedback effects in systems with distributed generation, control strategies, and variable loads. While traditional methods focus on solving equilibrium states, SD supports the analysis of transient responses, energy balancing, and nonlinear interactions, thus making it useful for modern systems such as microgrids.

$$f(k) = f(j) + \Delta t\big(s(k) - s(j)\big) \tag{3}$$

$$s(k) = s(j) = 0 \tag{4}$$

3 POWER DYNAMICS MODELING

This section presents the SD modeling framework, which simulates energy flow and feedback in DC power systems. The modeling follows a bottom-up strategy, beginning with simple electrical circuits and progressively incorporating additional elements such as storage, converters, and loads. Each configuration is constructed as an SDPgraph, where system components are modeled using stocks, flows, and feedback loops to reflect their structure and dynamic behavior.

3.1 Demand-Generation-Delivery Sequence and Basic Circuits

3.1.1 Demand-Generation-Delivery (DGD) Sequence

The DGD sequence represents the foundational structure of power behavior in the SD framework. When a load is activated, it creates a demand that propagates through the system and triggers a generation response. Power is then delivered through the transmission infrastructure to satisfy the load. This sequence captures the physical power flow and the causal relationships defining system behavior. In the SD model, this logic is used to structure power system components: demand originates at the load, propagates upstream, and results in energy injection at the generation source. The generator responds dynamically to voltage changes, forming a feedback loop that aligns with real-world electrical system behavior. This interaction is illustrated in Figure 1, which depicts the DGD sequence, where a user can turn on/off. sw, to connect or disconnect a load, r_o. The figure also depicts the corresponding SD model on the right.

3.1.2 Voltage Divider

A voltage divider is a linear circuit that reduces voltage through a pair of resistors connected in series. The output voltage (v_o) is a fraction of q of the input voltage v_i (Equation 5). In SD modeling, this circuit illustrates how feedback is embedded in electrical systems, where the output voltage (v_o) affects the current, i, which in turn influences, v_o, through resistive elements and forms a causal loop. The auxiliary variable v_1, is defined as $v_1 = v_i - v_o$. The SD representation of the voltage driver includes three nodes: d (demand node), o (output node), and r (reference node), a voltage generator, and two resistances. This modeling structure aligns with the SD framework by treating voltage as a stock (at a node) and current or power transfer as a flow between nodes.

In the voltage divider circuit, the generator injects power into the system. This power is distributed across the resistors in the form of voltage drops. According to KVL, the total sum of these voltage drops across the resistive elements must equal the generator's voltage. In other words, the two resistors entirely consume the total voltage supplied by the generator. To determine the efficiency of this system, we calculate the ratio of the power delivered to the load to the total power supplied by the generator. This efficiency depends on the values of the resistances in the circuit and is an important factor in understanding power distribution in more complex models.

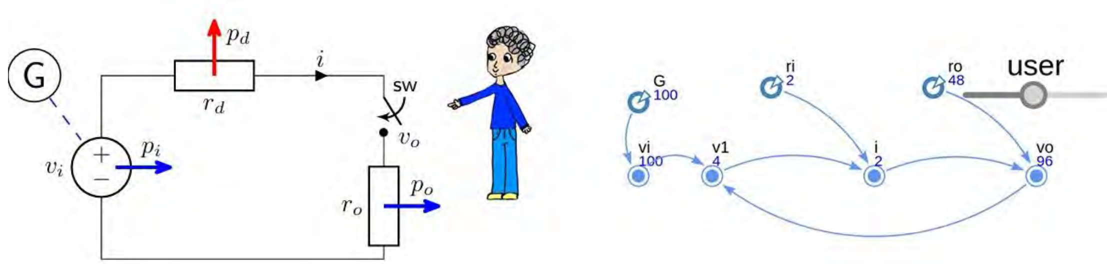

Figure 1: DGD sequence and corresponding SD model in AnyLogic.

$$v_o = q\, v_i, \text{ where } q = \frac{r_o}{r_i + r_o} \tag{5}$$

$$p_i = \frac{1}{\eta}\, p_o \tag{6}$$

$$p_o = p_i - p_d \tag{7}$$

3.2 Modeling Core Electrical Behaviors in SD

3.2.1 Power, Single-Line Diagrams (SLDs), and Hybrid Buses

In this section, we build upon the voltage divider structure introduced in Section 3.1.2 and extend the SD framework to more abstract representations of power flow using single-line diagrams and hybrid buses. In traditional power systems analysis, the power flow problem involves determining voltage magnitudes and phase angles at network buses, given that voltage and power levels at another set of buses is known. In DC systems, this problem is simplified to finding the input power p_i, given output power p_o, often under user-controlled loads, thus when efficiency, η (which is based on the equation $p_o = \eta p_i$), is known, the relationship is stated in Equation 6. Efficiency is an essential part of the proposed approach. In the SD framework, a closed voltage divider circuit implies constant stored energy, which can be zero or greater. The SD stock element represents specialized busbars for battery charging and energy storage.

SLDs offer a simplified view of bus power transfer, illustrating current conservation at nodes (Kirchoff's first law) and energy conservation across circuits (Kirchoff's second law). The output power at individual nodes is less than the input power due to losses ($p_d < p_i$, $p_o < p_i$), and total power is conserved $p_d + p_o = p_i$. To illustrate this in the SD framework, we introduce the hybrid bus, which is a component that represents the entire voltage divider and facilitates the modeling of energy dissipation. Given efficiency η, input power is calculated (Equation 6), and dissipated power (Equation 7), reflecting energy loss due to inefficiency.

3.2.2 Long Voltage Divider (LVD)

The LVD extends the basic voltage divider by introducing an additional resistor r_g, between the generator voltage v_g and the main divider resistance r_d, modeling power along transmission lines between the generator and the load. In this configuration, the generator supplies power p_g, a portion of which (p_{gd}) is dissipated at the resistor r_g, while the remainder, p_l, reaches the load segment. Further losses occur across the main divider resistance r_d, resulting in the final output power, p_o. This setup allows each segment's energy balance to be expressed via conservation. This structure supports the SD modeling of distributed losses and reinforces energy conservation at each hybrid bus.

3.2.3 Multiple Voltage Divider

The simple and long voltage dividers can be extended into a multiple-voltage divider with *n* stages. Each stage consists of a resistor and load, enabling a representation of distributed electrical systems, and builds on the previous examples. Each segment is treated as a localized power flow unit with input power p_{ik}, output power p_{ok}, and dissipated losses p_{dk}, governed by efficiency or resistance. Variable naming is adapted accordingly, with stage-wise voltages and resistances. This structure supports scalable SD models that preserve energy conservation at each stage.

3.3 System Dynamics Modeling of Power Systems and Elements

When creating the SD model of the Voltage Divider, stocks can have zero energy storage, as this is achievable through using a modified hybrid busbar and including it in the SD framework. We include power input, output, and dissipation, modeled in stock-and-flow structures within the SD model, with associated efficiency parameters.

3.3.1 Transmission Lines

Transmission lines transfer electrical power from generators to loads, with long-distance lines typically using high-voltage AC to minimize losses, and short-range distribution may use low-voltage AC or DC. In the SD framework, a transmission line is modeled like a voltage divider, due to its behavior, which is like a resistive element in terms of active power flow (Figure 2).

3.3.2 Transformer

An AC transformer is a device that transfers power between two circuits through electromagnetic induction, which operates at the same frequency and adjusts voltage and current levels while preserving power. The model is based on Faraday's law, which states that the rate between the input and the output voltages is equal to n, the ratio between the number of turns in their respective windings, i.e., $V_{out} = n\ V_{in}$. Efficiency is defined as the ratio between output and input powers, i.e., $\eta = P_{out}/P_{in}$. In the SD model (Figure 2), the transformer SDPGraph is represented using the same structure as the previous element, with power balance defined by efficiency. The value for efficiency is 0.99 for the transformer, compared to 0.9 for the voltage divider and line previously. Although this paper refers to DC networks, the transformer model has been included because it can be considered a direct precedent of DC-DC converters, which perform a similar function in DC networks with better efficiency.

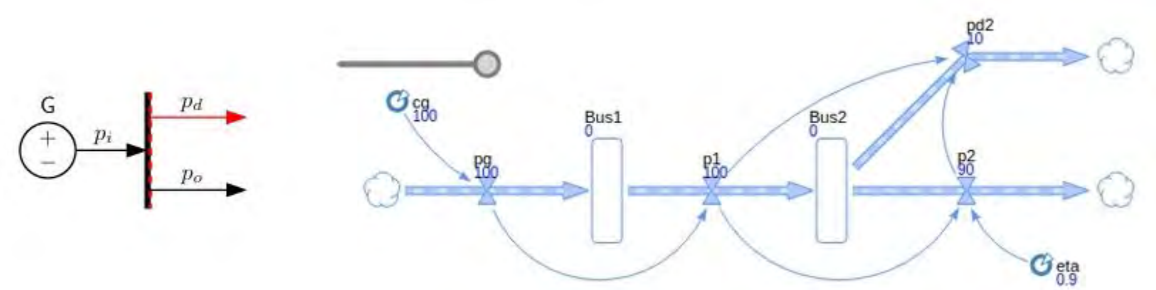

Figure 2: Transmission Line and corresponding SD.

3.3.3 Power Converters

Power converters are essential in modern energy systems, enabling voltage adaptation and current type transformation. There are two types, AC/DC and DC/DC converters. AC/DC converters transform AC into DC at a defined voltage level, commonly used in power supplies and renewable energy systems. Their efficiency ranges from 80-90%, with high-performance units reaching 95%. DC/DC converters shift DC voltage levels, which are often used in battery storage systems or DC microgrids. The DC/DC converters are highly efficient, with efficiency levels between 87% and 92%, and some reaching over 99%. In the SD model, both types share a similar structure to transformers, with an efficiency parameter of $\eta = \frac{p_o}{p_i}$The main distinction lies in the input and output currents. For illustrative purposes, Figure 3 shows the DC/DC converter SLD and its associated SD model. The AC/DC converter shares the same architecture, incorporating an AC generator as the input and connecting to a/DC load.

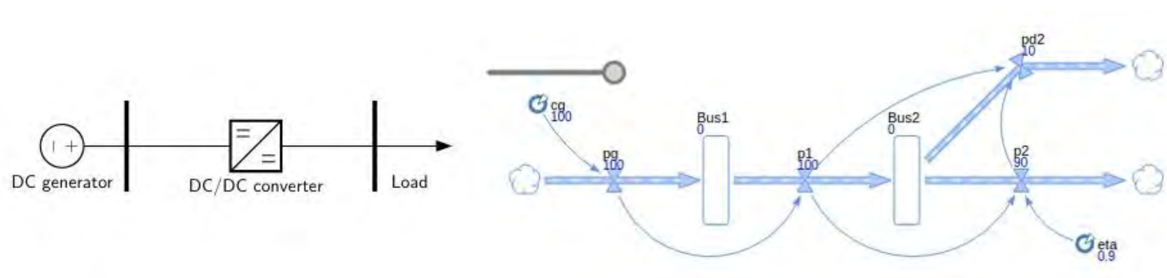

Figure 3: DC/DC converter SLD and corresponding SD model.

3.3.4 Energy Storage Elements

In SD modeling, energy storage is represented as a stock, with stored energy, e, governed by a differential equation (Equation 8), where p_i is input(charging) power and p_b is output (discharging power). This supports flexibility of varying battery behaviors, including simultaneous or independent charge/discharge flows, depending on system design. Charger and battery storage characteristics define the flow limits and efficiencies modeled within the SD model.

$$\frac{de}{dt} = p_i - p_b \tag{8}$$

3.3.5 Interrupters

Circuit breakers and interrupters disconnect power flow in a line; however, SD does not support direct line cuts. To replicate this behavior, we model the effect indirectly using power loss. When the breaker is closed, lost power is $p_l \approx 0$, and the output power is $p_2 = p_1$, and efficiency is $\eta = 1$, due to efficiency being modeled as p_2 divided by p_1. When open, $p_2 = 0$, and $p_l = p_1$, giving $\eta = 0$. Thus, efficiency dynamically reflects the breaker state, and in the simulation, this is modeled using the variable pd, which is left undefined at start time and can be set by the user at runtime to emulate manual switching behavior.

3.3.6 Exogenous Actions and Smart Meter Integration

The previous subsections focused on internal power system components, however, external variables, such as user inputs and sensor feedback, can also influence real-world systems. In SD models, exogenous variables (e.g., user inputs, real-time sensor data) can drive dynamic behaviors and are essential in simulating modern grid operations and resilience strategies. Example applications of power systems are smart meters, which provide real-time measurements (e.g., power values) to monitor line flows and detect disruptions. They can enable grid optimization and enhance cybersecurity, especially when using SD to simulate grid vulnerabilities and system responses. Smart meters contribute to cybersecurity and grid resilience in modern systems through: (1) Proactive Vulnerability Assessment, (2) Anomaly detection, (3) Secure communication protocols, (4) Segmentation, (5) Intrusion Detection Systems (IDS) for early threat detection, (6) Proactive monitoring and threat mitigation. SD can enable the simulation of these different interactions by capturing the behavior of how smart meter data, communication layers, and operator responses affect grid stability over time. This can extend the presented modeling approach beyond simulating power flow, support cyber-physical resilience analysis, and provide informed operation decision-making in modern energy systems.

4 MICROGRID CASE STUDIES

This section presents case studies that demonstrate the application of the proposed SD methodology in modeling electrical power systems. The first case study models CubeSat's electronic power system (EPS) using SD to simulate energy generation, storage, and consumption dynamics in orbit. The other examples focus on residential energy systems powered by renewable sources and explore dynamic power management, load balancing, and system resilience. The first microgrid case study incorporates solar and wind energy to supply four residential units, highlighting generation variability and demand-side dynamics. The second extends this to six units, incorporating a hybrid SD-ABM approach to simulate household behaviors and cyber threats, offering insights into grid adaptability and cybersecurity resilience. Together, these cases illustrate the flexibility and scalability of the SD framework in analyzing modern, distributed energy systems. The DC/DC and AC/DC converters used in the microgrid, and CubeSat examples are modeled using the same structural representation as transformers, described in Section 3.3.2, highlighting the role of transformer dynamics in enabling high-efficiency energy conversion.

4.1 Basic Microgrid Structure and SD Model

The case studies in this paper will share a common microgrid circuit, and the basic circuit is displayed in Figure 4 on the right. The circuit consists of three voltage sources v_1, v_2, v_3, with internal resistances r_1, r_2, r_3, connected in parallel to a bus (node d). There are four loads R_1, R_2, R_3, R_4, which are also connected in parallel to another bus (node o), with a transmission line of resistance r_d, linking both banks. This structure follows the LVD model and replaces the voltage generator with three separate ones and the load resistor with four separate ones.

Figure 4 illustrates the corresponding SLD of the basic circuit of a microgrid on the left, with three generators in parallel G_1, G_2, G_3, and these inject power flows p_{g1}, p_{g2}, p_{g3}. There are four load resistors in parallel, R_1, R_2, R_3, R_4, and the consumption at each of these loads is $p_{l1}, p_{l2}, p_{l3}, p_{l4}$. Power losses on both the generator and load sides are captured as $\sum p_{gd}$ and $\sum p_{go}$, with the total power transferred across the line represented by p_1(Figure 4). This resultant SLD forms the basis for the SD implementation of the case studies presented in this paper.

The SD model implementation applies to a standard hybrid bus configuration and ensures that each bus satisfies the condition: $\Sigma_p = 0$ (Figure 5). Generator-side losses, transmission losses, and load-side distribution are modeled using efficiency parameters, and input/output flows are managed with interactive sliders. In the SD model, one generator operates as a slack generator, automatically adjusting its output to maintain power balance and satisfy $\Sigma_p = 0$.

4.2 CubeSat Electrical Power System Modeling

This case study applies the SD framework to model the EPS of a CubeSat. The CubeSat is a mini satellite used for space research and deployed in low Earth orbit for Earth observation, technology demonstration, or experiments or projects. The EPS is responsible for the generation, storage, distribution, and management of a satellite's electric power. A CubeSat consists of the following features: solar panels for energy generation, batteries for storage, and electronic subsystems for consumption. The CubeSat alternates between sunlight and eclipse periods during its operation, where the battery is charged during sunlight exposure, and power is distributed to power the CubeSat during the eclipse period, thus developing a model that can provide insights into strategies for energy availability, system reliability, and power allocation.

The SD modeling process for the EPS of a CubeSat is a six-step process. First, we define system boundaries and components, including solar generation, battery storage, and subsystem loads. Second, we represent key energy nodes as SD stocks, such as battery charge level and available solar power generated. Third, we model power flows between solar panels, battery, and loads based on orbital lighting conditions and system demand. We include control logic using SD Flows to simulate energy regulation, critical load prioritization, and safe-mode behavior during low-power events. Fifth, we run dynamic simulations (e.g., high-demand scenario, contingency operations) over multiple orbit cycles to evaluate energy efficiency, load allocation, and system behavior. The final step is refinement and optimization of the model, which involves a sensitivity analysis.

The SD model for the CubeSat EPS is shown in Figure 6, where the model captures energy generation from two solar arrays and distributes it into two subsystem loads. Battery behavior is modeled as a central stock, with inflow during sunlight and discharge during eclipse. This case study highlights the SD's strengths in modeling time-dependent, resource-constrained systems and the modular nature of this approach, which can be extended to model larger satellite networks and incorporate adaptive control strategies or integrated thermal/power co-models. There is also the capability to analyze different scenarios under variable orbital conditions, such as solar degradation or battery aging.

4.3 Renewable Microgrid for Four Residential Units

This example uses SD to model a microgrid that integrates renewable energy (solar, wind) to supply four residential units, and a large battery and a slack generator support the microgrid. The implementation is illustrated in Figure 7. This allows for an insight into energy generation, load balancing, and dynamic power distribution when considering variations in renewable energy and household demand. Solar (gsun) and wind (gwind) generation are predefined inputs, while household demand powers (p_1, p_2, p_3, p_4), given by the demands $d_{p1}, d_{p2}, d_{p3}, d_{p4}$are driven by individual load profiles (dpf1, dpf2, dpf3, dpf4). The amount of power here is absorbed from bus d, and then, through feedback, it asks for power pd.

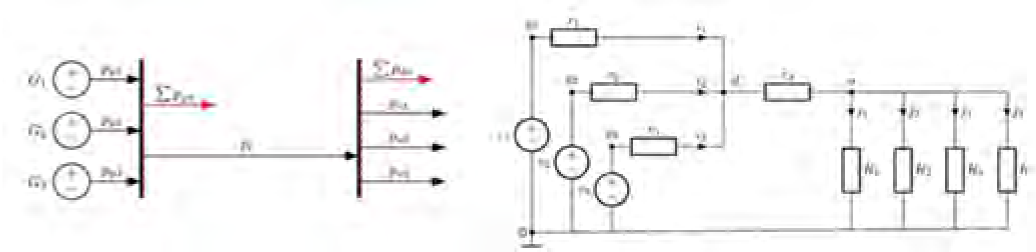

Figure 4: Basic microgrid circuit (right) and corresponding SLD (left).

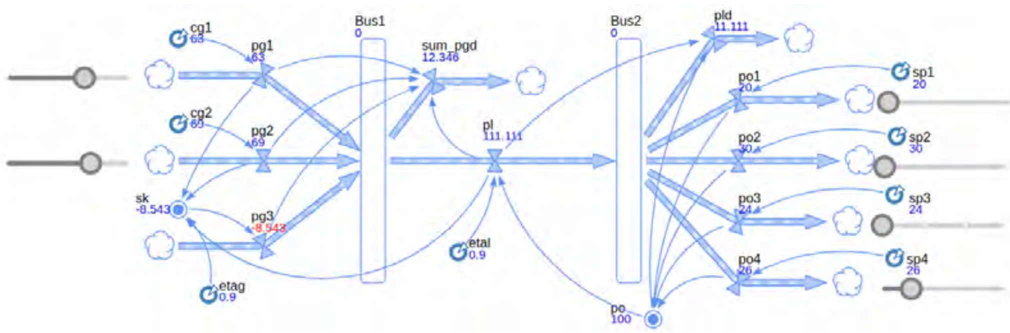

Figure 5: SD implementation of the basic microgrid model in AnyLogic.

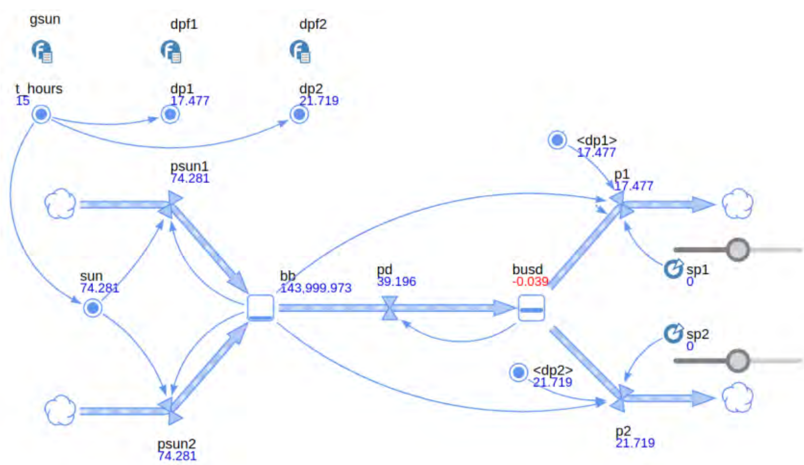

Figure 6: SD implementation of the CubeSat EPS.

The battery charges via excess solar and wind generation and discharges when household demand exceeds renewable generation. Power flows to the homes are only allowed if the battery energy exceeds a defined threshold to simulate operational thresholds. The initial battery capacity is 40 Wh, and feedback mechanisms manage charge/discharge flows in real time. Interactive slides can modify demand or supply parameters within a controlled range, supporting scenario analysis. A slack generator injects balancing power to maintain zero net energy at the generation-side bus. The SD model uses feedback to control flows, ensuring that all buses satisfy $\Sigma_p = 0$, and simulates load balancing and storage dynamics under variable renewable supply.

Compared to traditional power flow solvers, which typically evaluate steady-state behavior, the SD-based approach allows us to model how power generation, storage, and demand interact dynamically over time. This supports scenario testing with renewables and control strategies, capturing feedback-driven interactions that reveal system dynamics often missed by equilibrium-based models.

4.4 Microgrid for Six Residential Units

The final case study applies SD to model a microgrid serving six interconnected households powered by solar panels, wind turbines, and energy storage, aiming for self-sufficient and efficient energy use (Gonzalez de Durana and Barambones 2018). A Point of Common Coupling (PCC) manages energy exchange with the external grid (Figure 8). Solar and wind generation are modeled using GRETA-based profiles, while each home includes battery storage for load-based charging/discharging. A pumped water storage system linked to the wind turbine stores surplus energy via gravitational potential.

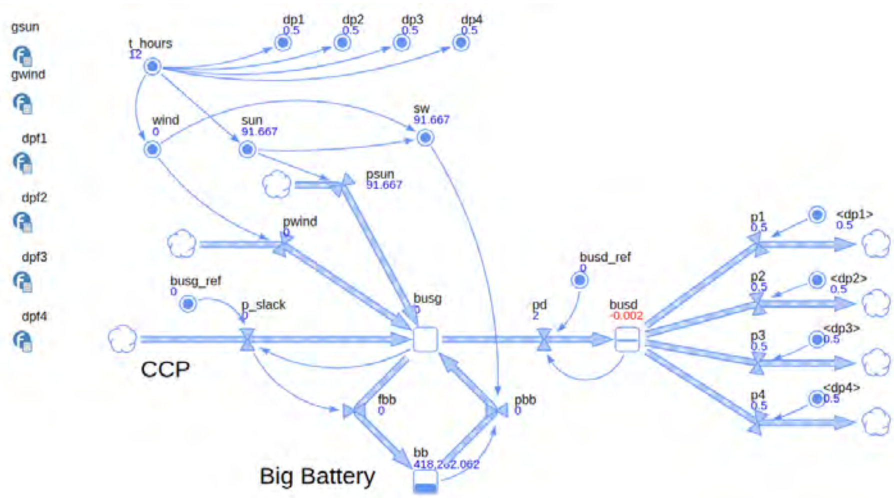

Figure 7: Microgrid model of four residential households.

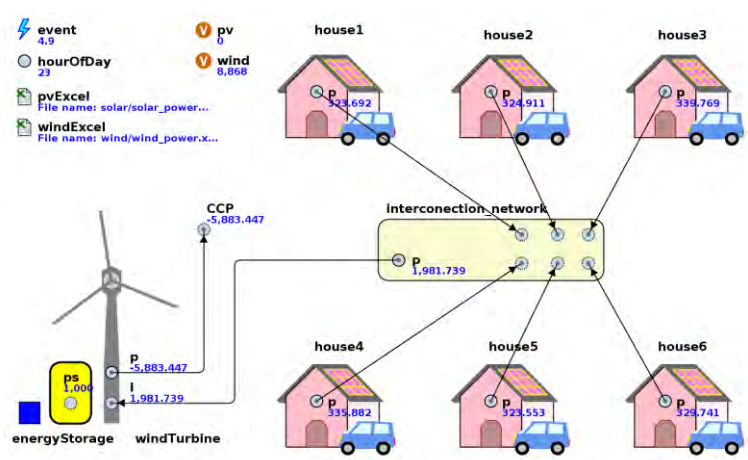

Figure 8: SD model of six households with shared wind turbine and PCC connection.

Each home is modeled as an agent with SD logic for energy generation, storage, and consumption (Figure 9). Homes include multiple appliances, can consume, store, or feed energy into the grid, and use discrete events for managing power flows. A central node (z) allocates energy, while storage (yellow "P" in Figure 9 on the left) captures surplus and discharges during deficits—dynamic demand and real-time feedback support local energy optimization. A wind generator agent similarly employs SD to model power output, storage, and load balancing (Figure 9). A central node (z) manages storage, grid, and consumption interactions. A yellow "P" variable in the wind turbine Agent on the right in Figure 9 relates to power generation capacity or wind speed influence. The model integrates SD and ABM in Anylogic, enabling dynamic interactions among households, generators, and energy storage systems. Each agent responds autonomously to generation variability, storage levels, and load demands. This hybrid approach captures decentralized control strategies and adaptive behaviors, demonstrating how SD and ABM can jointly simulate resilient, renewable-powered energy networks.

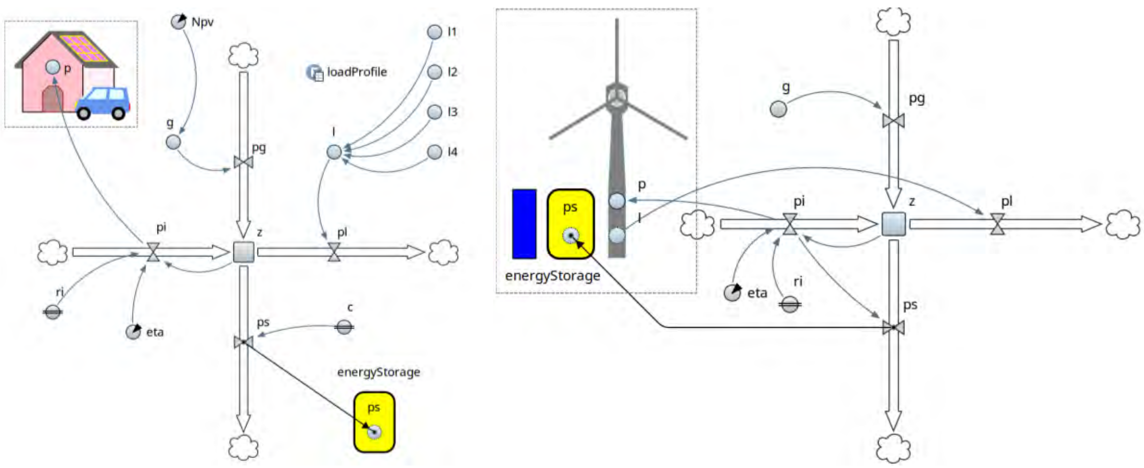

Figure 9: SD of residential household agent (left), and SD of wind turbine agent (right).

5 CONCLUSION AND FUTURE WORK

This paper has presented Power Dynamics, a methodology that applies SD to model and analyze DC distribution systems, focusing on renewable energy microgrids. In this approach, electrical network nodes are represented as Stock elements, and power transfers are modeled as flows. This enables a dynamic visualization of power evolution over time and facilitates the study of system behavior beyond traditional static equilibrium conditions. The power dynamics methodology provides computational efficiency, visualization of energy networks, and scalability. The work aims to further the understanding of the complex interdependencies that occur within energy systems through the use of SD, as this allows us to capture the dynamic feedback loops, and interactions that occur, and offers a framework for modeling DC power systems, such as renewable energy microgrids, as demonstrated in this paper.

This research emphasizes the systemic interactions of power generation and consumption within critical infrastructures. Grafius et al. (2020) highlight that infrastructure networks function as complex adaptive systems with interdependencies affecting resilience and efficiency. Energy systems are embedded in broader socio-technical and cyber-physical contexts, where dynamic feedback loops impact operational stability. The proposed SD approach captures time-dependent power flows, storage dynamics, and control actions more effectively than steady-state methods, essential for renewable microgrids and CubeSats. Future research can apply SD to analyze resilience against cybersecurity threats and explore hybrid models integrating ABM, DES, and Machine Learning techniques (Elkamel et al. 2023; Ibrahim et al. 2023). The AnyLogic platform enables flexible and scalable integration of these methodologies.

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