Resilient Network Dynamics for Food, Energy, and Water Systems

Alex Modarresi
Department of Computer Science
California State University, Northridge
Northridge CA, USA
alex.modarresi@csun.edu

John Symons
Department of Philosophy
Center for Cyber-Social Dynamics
The University of Kansas
Lawrence KS, USA
johnsymons@ku.edu

13th International Workshop on Resilient Networks Design and Modeling (RNDM)

September 20-22, 2023
Hamburg, Germany

Resilient Network Dynamics for Food, Energy, and Water Systems

Alex Modarresi
Department of Computer Science
California State University, Northridge
Northridge CA, USA
alex.modarresi@csun.edu

John Symons
Department of Philosophy
Center for Cyber-Social Dynamics
The University of Kansas
Lawrence KS, USA
johnsymons@ku.edu

***Abstract*—Developing resilience in food, energy, and water (FEW) systems is a critical priority. The structural topology of the components of complex agricultural systems interact in ways that can only be grasped via models and simulations. We extend previous work on graph models that represent complex inter-level topology. We show some results of simulating system dynamic model as a formally tractable way of understanding resilience in these systems.**

***Index Terms*—Fault taxonomy; smart agriculture, Internet of Things (IoT), resilience, technology interdependence graph**

I. Introduction

Contemporary agriculture faces a range of novel challenges. These include potential cyber-physical threats, the repercussions of climate change, complex regulatory environments, and shifting global financial conditions. The food-energy-water (FEW) nexus, owing to its highly integrated and multi-tiered nature, exhibits a heightened susceptibility to cascading failures. In previous work [1] [2] [3], we have described our approach to modeling the complex set of interacting natural and engineered FEW systems in order to understand potential vulnerabilities and increase overall resilience. That work involved beginning with abstract graph theoretic models of interacting components of the FEW system. Those models, in turn, served as the basis for simulations. In those simulations, we studied the effects of perturbations on the overall resilience of the FEW system. The present paper extends that work, offering new results that highlight the role of network architectures in interacting multi-level systems for resilient systems design.

II. Background and Concepts

To design resilient FEW systems, it is crucial that we understand the interdependency among water management practices, water purification processes, energy sources, fertilizers, and cyber infrastructures. Every one of these subsystems possesses unique configurations, characteristics, and vulnerabilities. Disturbances to any one subsystem may possibly influence other components of the FEW system.

This work was supported in part by the National Science Foundation [grant number 1856084] FEWtures project. Symons' work is also supported by US Department of Defense Contract H98230-23-C-0277 MPO

In our analysis, resilience is treated in terms of perturbations and the dynamics of the system [4]. In previous work, we described the most important faults and perturbations that contributed to failures of resilience in FEW systems and we showed how preventing, masking, or avoiding them is the first step to improving system resilience [1] [2] [3]. Our study of FEW systems draws heavily on the comprehensive literature regarding the taxonomy of faults, perturbations, reliability, availability, and dependability in engineered systems [5] [6] [7] [8] [9] [10] [11] [12].

As we discussed in [3], *system* is defined as an entity that maintains its individuality as it interacts with other entities [13]. In the case of FEW component systems, our approach regards interactions as occuring at system boundaries where services or transactions occur or are offered. System *services* are the results of integration and working several components inside the system at a specific state. A service is part of the system functionality defined in the system specification. Relations among components define the structure of the system. The interaction of systems is complicated by the important role played by economic and social factors in FEW systems [14].

In this paper, we follow the definitions provided in [3], where we defined what it means to offer a service at the system boundary. For the purpose of simplifying the simulation, each of the system components is treated as having a specific state. The overall states of these components determine the state of the system. When these components deviate from their defined states, an anomaly in the service is observed at the boundary of the system. A *service failure* takes place when the service provided deviates from the correct service. Deviations from correct services can result from *errors*. The cause of an error is called a *fault* [5]. A sudden and discontinuous state change is called *disruption* while a *disturbance* is a continuous state change for a limited time that leads to service failure. The manifested result of disruption at the system boundary is a service outage, while the result of disturbance is a service deviation that may lead to a service outage. A *perturbation* is any unintended changes in the service level resulting in disturbance and disruption caused by internal or external faults [15] [16], which is an equivalent term for service failure.

The system definition given here is recursive and can be extended to the system's components unless the components are atomic. In previous work, we explained the interaction between failures at different levels and how they can influence other systems [3]. So, for example, if failures happen at the component level and do not disrupt the whole service, then the system may offer its services in a degraded mode. The system specification identifies whether the system is in a degraded mode or failure mode. The difference between these two states identifies system resilience. If a system can return from degraded mode within an appropriate time-frame while offering basic services to its correct service mode, it is called resilient, while a failed system does not return to performing its service. Resilience is a concept that, while not always defined with pinpoint accuracy, can still be grasped through a set of general characteristics. These characteristics give us a good understanding of the essence of resilience, even if they don't meet the strict standards of a philosophical definition rooted in absolute or exclusive terms. In their work, Pipa and Symons [4] distinguished two qualities often confused with each other: robustness and resilience. Their analysis leads to the conclusion that a system can be deemed resilient based on specific criteria, even if those criteria might not capture the entire complexity of the concept. On their definition, a system can be said to be resilient if: (a) It is prepared for intervention or perturbation, (b) it maintains its identity and bounces back after perturbation, (c) it adapts in ways that are guided by its identity in a time-frame that is appropriate to its identity, (d) it learns from past perturbations or intervention. In this paper, we take this general approach to resilience as the basis for our simulation.

III. Modeling Perturbations to FEW Systems

We use the abstract smart agriculture system presented in graph theoretical terms in [3] as the base structure of the simulation. The graph is $G(V, E)$ such that V is a set of nodes or vertices representing the system entities or components, and E is a set of links or edges representing the connections between nodes. Nodes represent component systems and links show their connectivity. To distinguish kinds of links we use an edge-colored graph $\mathbb{G}_{\text{conn}} = (V_c, E_c, C, \chi)$, such that $v_i \in V_c$ is a system and $e_n \in E_c$ is a link between two adjacent systems v_i and v_j. Furthermore, C is a set of colors equivalent to the different types of flows in the graph and $\chi : E_c \rightarrow C$ is a function to assign a color to each edge. We can characterize three networks containing four nodes, including *Microgrid*, *Ammonia*, *Farm*, and *Water* [3].

We employ a directed graph to depict interdependencies among systems, as not all systems reciprocally rely on each other. These link directions illustrate the flow of items, objects, or energy. To showcase partial dependencies, we use a weighted graph where each weight indicates the degree of dependency and can correspond to the flow magnitude on the link. The weights differ based on system specifications. Figure 1 shows the graph model representing a FEW essential systems and their dependencies [3].

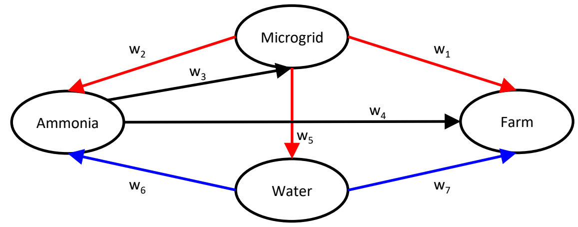

Fig. 1: A FEW abstract model

IoT enables individual system control and monitoring, thus making agriculture a cyber-physical system. The cyber layer overlays the physical system as illustrated in Figure 2. All systems link to the Internet and are accessible through cloud services. Communication links are bidirectional, symbolized by double-headed arrows in the figure.

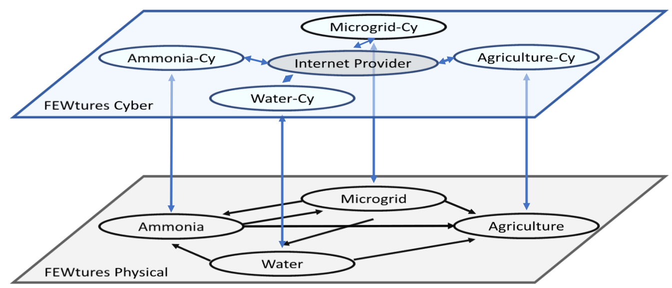

Fig. 2: A FEW cyber-physical abstract model

It is important to recognize that because the FEW system, which combines both engineered and biological systems, that any model must tackle systems with radically differing degrees of resilience operating on different time-frames. For example, a farm's biological systems are typically capable of withstanding a range of short-term faults and perturbations. However, the recovery time of many natural systems may be slower after very significant perturbations. As we discussed in [3] in engineered systems, especially those without fault tolerance mechanisms, the system state changes quickly when the fault presents itself and the system may lose its normal functionality suddenly. If the fault is persistent with a severe effect in engineered systems, the system cannot offer any services, while in biological systems, because of adaptation there, a new service can appear after the cessation of the fault. This type of change is common in social and ecological systems and contrasts sharply with the nature of failure in typical engineered systems.

It is important to recognize that faults and perturbations are inevitable [17]. When systems are more interconnected, their structural topology and interdependency usually become more complex. This complexity can affect the system's overall function. For instance, the topology of a power grid can impact the stability of power transmission, which can affect water treatment systems' operation and the production of ammonia fertilizer for agriculture. These, in turn, can impact crop yields and profitability.

A. Simulation Model and Analysis

Stella [18] is a system dynamic simulation environment supporting discrete event and agent-based simulation techniques. We use this environment to model the components and relationships of a FEW system. We use the combination of system dynamic and discrete event techniques to study the effect of external and internal faults on the overall performance of the system. We design the model to represent the same structure illustrated in Figure 1. The high-level model of the system is shown in Figure 3, which is an extended version of our previous study [3] with more capability to simulate faults. Each node in Figure 1 has been implemented as a module with their details in Stella. The connections in Figure 3 are flows between modules equivalent to edges in the graph model and feedback loops to exchange control information. In the real world, the feedback loops construct the cyber-physical system. The color-coded links represent a different type of flow in the system, though the colors do not have any meaning to Stella. Circles provide input values to the model or store results. Input values can be constants or mathematical functions changing during the simulation. Each input is evaluated in each simulation step and is fed to the model. We explain each component of the model in the following.

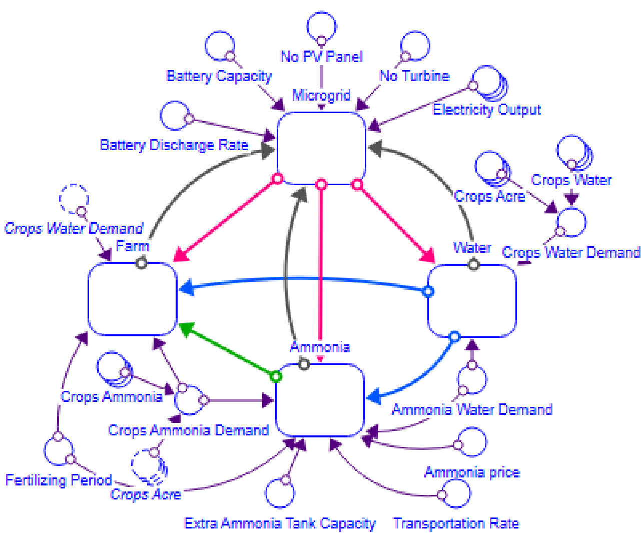

Fig. 3: Simulation model

We consider an isolated microgrid in this model designed only for FEW operations. This assumption helps to study the system's sustainability more effectively compared to the connected microgrid. In a connected microgrid, any challenges to the electrical grid may propagate to the microgrid. Our future plan is to study the resilience of this option on a FEW system.

We examine frequent internal and external microgrid faults. Weather conditions, like changing wind speeds or cloud coverage, are common external faults that moderately impact wind turbines and solar panels' electricity production. Though resources are available to identify the average of sunny days [19] or wind speed in a certain location [20], deviation from the average value is inevitable. Minor weather changes can disrupt ill-prepared microgrids, and global warming exacerbates these shifts. Two primary solutions to weather-related failures are adding more renewable resources and utilizing battery storage. In isolated grids, battery storage is cost-effective and logical, as surplus electricity can't be sold. Here, batteries are charged with any excess electricity.

A key external fault for the microgrid is fluctuating electricity demand in its subsystems. The ammonia system requires a consistent electricity amount, posing no significant demand threats, but it consumes most of the electricity in smaller farms. The farm's irrigation system periodically alters electricity demand, but its max consumption is predefined. Similarly, the water system has a set pumping capacity, though electricity shortages can have varying impacts during simulations.

The major internal fault of the microgrid is equipment failure. However, solar panels and wind turbines are relatively reliable. For example, photovoltaic modules have warranties of up to 20 years while their mean time between failure (MTBF) are over 100 years [21]; therefore, we ignore such faults in the simulation.

We use the information in Table I for the capital and operational costs [22] for the microgrid equipment. Electricity generation with wind turbines depends on many factors, including wind speed and the length of the turbine blades, although their production efficiency does not exceed 30% with current technology [23].

We assume that wind turbines can generate electricity 24 hours a day. However, electricity generation by solar panels depends on the weather condition and the installation site [19]. The peak sun hours vary between 2.2 to 7.4 hours around the globe. We consider 5 hours a day for this simulation. Figure 4 shows the structure of the microgrid module. In the module, generated electricity is distributed with priority. The highest priority assigns to the water module, followed by the farm and ammonia modules.

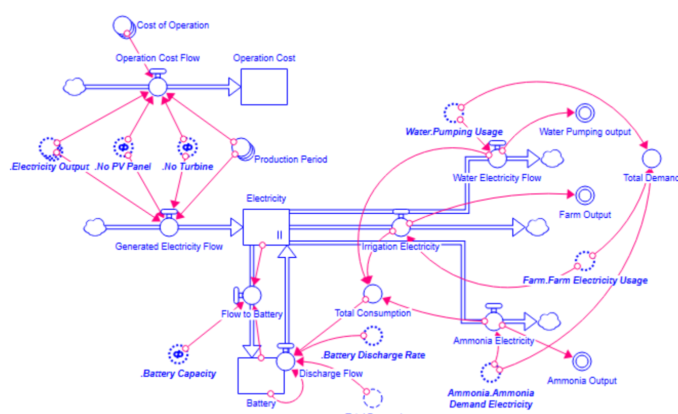

Fig. 4: The microgrid module

The farm module simulates irrigation and ammonia fertilizer usage, with needs based on crop types per acre inputted.

Technology	Capital Cost ($/W)	Operating Cost($/kWh)	Production per Unit	Production hour per Day
Wind turbine	$0.991 to $1.315	Less than 0.01	Variable	24
Photovoltaic Solar	$2.65	Less than 0.01	400 W/m^2	2.2 to 7.4
600 kW Battery Storage	$0.47	Negligible	2400	Variable

TABLE I: Energy Cost

Water and ammonia availability are dictated by their respective modules. A shortage of these resources can cause significant issues in the module. Persistent water scarcity can render farming unfeasible in an area, leading to broader socioeconomic impacts and potential cascading failures. While our hydrology team studies West Kansas water resources, this simulation only accounts for random seasonal effects.

The farm module's fertilizer needs primarily depend on electricity, with a smaller water requirement compared to irrigation. While a lack of fertilizer doesn't have devastating effects, it does decrease crop yields and profits.

The irrigation system has a preset maximum water-pumping capacity and operates seasonally. System failure, though rare, can range from severe to catastrophic, depending on its timing. A failure early in the season, during germination, is most detrimental. In reality, farmers often maintain and repair systems pre-season due to its importance to yields and profit. Our simulations don't currently factor in this fault due to insufficient data on crop yields. Fertilizer usage is similar, but its deficiency isn't as impactful as water's.

The water module in the model simulates water availability to the entire system. The pumping capacity can be initialized before the simulation. Two sources of water are simulated in the module; surface and underground water. Drawing water from both sources is subject to external policy/regulation determining how much water may be used. This external policy is treated as an external fault to the water module that subsequently affects the farm and ammonia modules through the failure to provide the necessary water. To implement this fault in the module, we consider the water level in wells. Extensive pumping decreases the water level, especially if the water drawn is more than the incoming flow to the well. If the water level goes below a predetermined value, the pumping should be stopped for some predetermined period to avoid damaging the aquifer. The incoming water flow to the well can be initialized. After passing the period, the water level is checked, and pumping starts if the water level has improved.

Another external fault of this module is the availability of electricity. Shortage of electricity disrupts pumping. As mentioned, the highest priority of electricity distribution is assigned to this module. If there is no water from the water module, irrigation and ammonia production is disrupted. However, more study is required to identify priority of modules to receive electricity. As mentioned, the ammonia system needs less water and more electricity compared to the farm. In a critical situation, when the resources are scared during a challenge, the decision should be made about which system provides more profit in a certain time.

Within the system, pump malfunction is a prominent potential internal fault, jeopardizing the operations of both the farm and ammonia systems. The repercussions on the farm system are largely time-sensitive: a mishap during the irrigation phase can have devastating consequences, whereas an off-season perturbation is usually less damaging. Conversely, any disruption to the water system halts ammonia production for its duration, leading to daily profit reduction. Diligent maintenance of the pumps can mitigate the likelihood of such disruptions.

The ammonia module simulates a solid oxide electrolysis cell (SOEC) with an exothermal Harber-Bosch Reactor to produce ammonia [24]. This technology requires 334 KW per day to produce one ton of ammonia [25]. We consider the same energy consumption pattern in this simulation.

Electricity and water provided by the microgrid and water systems are two major external sources of faults in this module. Electrical fluctuations during production can harm the system, extend production times, and diminish profits. Without additional resources, this fault could frequently occur with significant impacts. Water shortages, while more predictable and of longer duration, lead to considerable profit loss. To counter brief electrical disruptions, we've incorporated battery storage in the module. However, given the infrequency of water shortages, we've opted not to include additional water storage in the system.

For optimal profitability, ammonia production should be consistent throughout the year. While a portion of the produced ammonia is utilized in the farm module, the surplus needs storage for eventual sale. This necessitates an ammonia storage tank. However, the tank's capacity and transportation intervals introduce potential issues. If the tank reaches its capacity, production must halt. Similarly, any disruptions in transportation can lead to the tank filling up, necessitating a pause in production. Notably, the tank's size can influence the frequency of transportation.

We simulate the model with sensitivity analysis for a sample farm under normal operating conditions where resources are sufficient. During the analysis, the number of PV panels and wind turbines changes as indicated in Table II to realize the proper amount of electricity for the system and the operation cost. The analysis is performed over 10 runs. In each run, external faults are also imposed on the model that affects the amount of electricity and ammonia production and available water. All the results are shown with a 95% confidence interval. Table II shows the simulation parameters and the type of failure distribution imposed on the model. The *external* values in the table show that faults happen outside the module, but they affect the module. The *constant* shows constant values during the simulation, but they are adjustable.

Figure 5 shows cost of electricity production per day during

Simulation Parameter	Value	Failure distribution
Wind turbine	25 to 35	Constant
PV panel	300 to 450	Constant
Wind energy	8 KW	Normal dist.
PV energy	400 W/m^2	Linear
Ammonia production	1 tone/day	External
Water (ammonia)	1588 liters	External
Fertilization period	180	Constant
Crops ammonia demand	Normal dist.	External
No. Crops	3 (adjustable)	Constant
Unit of planting	Acre	Constant
Irrigation	Normal dist.	External
Irrigation capacity	500 m^3/day	Linear/external
Duration	365 days	NA
No. of run	10	NA
Delta time	0.25	NA

TABLE II: Simulation Parameters

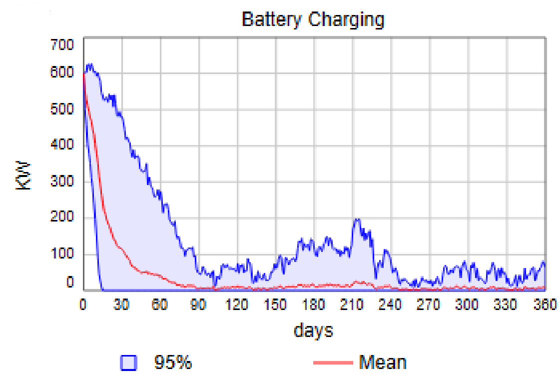

Fig. 6: Battery charging per year

a year over 10 runs. The optimum electricity production is 584 KW per day, resulting from 340 PV panels and 32 wind turbines (not shown in this Figure). Since the delta time is 0.25 in the simulation, four samples are calculated in each time unit. Moreover, The maximum operation cost is around 4 dollars per day. Fluctuations in electricity generation per day are due to the changes in wind speed and the sunlight period.

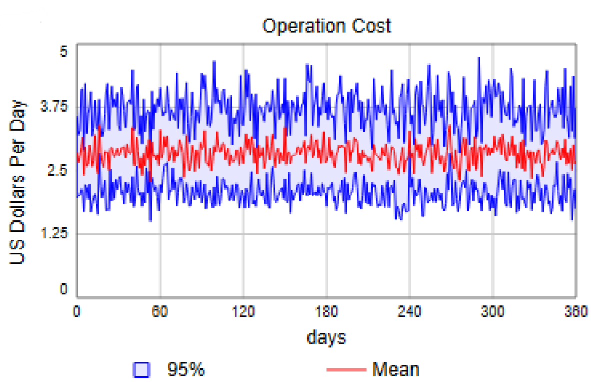

Fig. 5: Operation cost per day

Figure 6 illustrates the battery charging pattern over 10 runs with sensitivity analysis when the number of PVs and wind turbines changes. It is assumed that the battery is fully charged at the beginning of the simulation. However, the mean value shows that, in average, the battery charge is close to zero during the simulation. It implies that the system cannot even tolerate any small fluctuation in electricity production in many situations resulting in failure in other systems.

Figure 7 represents the water drainage process. The water needed for ammonia production is minimal compared to that for farm irrigation. Consequently, water usage outside of irrigation seasons is virtually nil. As seen in the figure, there are days when the system demands its maximum water capacity. On such days, the ammonia module lacks the necessary water, halting ammonia production. A consistent amount of water is essential for ammonia production, resulting in a steady line on the graph during periods when water is only used for this purpose. Readings below 1,588 liters per day suggest a fault, which could arise from pump malfunctions, electricity production issues, or fluctuating water levels. It's important to note that irrigation takes precedence over ammonia production. Thus, in situations of limited water supply for both needs, priority is given to the irrigation system. This aligns with findings from the ammonia module, which noted water shortages during the simulation.

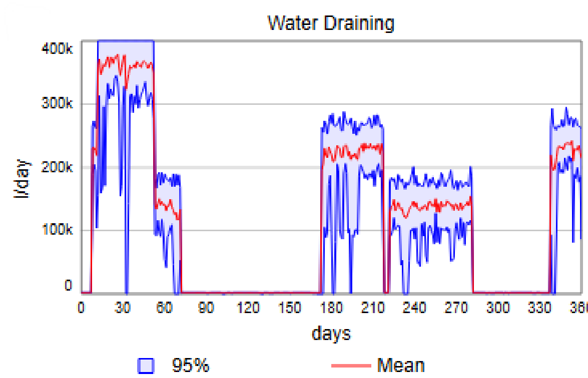

Fig. 7: Water draining from surface and ground resources

Figure 8 shows the volume of ammonia reserved for sale. We've incorporated a storage tank specifically for any surplus ammonia intended for sale. In this model, the tank's capacity is capped at 20 tons. Every 90 days, stored ammonia is shipped out for sale, utilizing a transportation vehicle with a 10-ton capacity. Notably, the first shipment occurs 30 days in, but doesn't use the vehicle's full carrying capacity. Conversely, after the second shipment, residual ammonia remains in the tank. This suggests that, in future scenarios, the tank may fill up before scheduled transportation, potentially interrupting ammonia production.

Figure 9 highlights the profits from ammonia. There's a noticeable gap between the peak and trough earnings. Given that water is generally abundant and the ammonia tank is not at capacity (Figure 8), this variance stems primarily from electricity availability. Thus, augmenting our electricity resources is likely to increase the profits from ammonia production.

The results of the simulation illustrate that how faults in

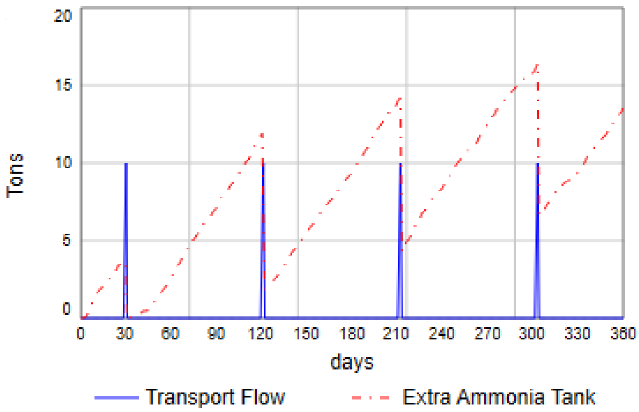

Fig. 8: Sales and transportation pattern

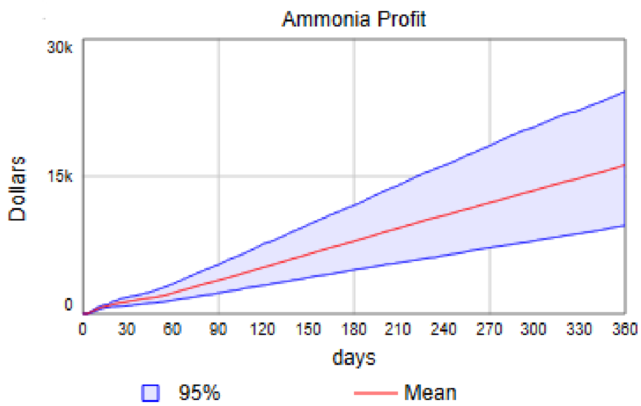

Fig. 9: Ammonia profit

a FEW system affect different components and due to the interconnections among these systems, failures happen in ways that can be shown via the simulation.

IV. Conclusion

The overarching goal of our project is to provide decision-support tools that allow communities and policymakers to design resilience into complex smart agriculture systems. In this paper, we use our abstract model to design a simulation tool for a FEW system and provide a framework to demonstrate where and how common faults in such systems should be implemented to study the resilience of the system.

References

[1] A. Modarresi and J. Symons, "Modeling resilience for sustainable food, energy, and water systems," in *AGU Fall Meeting Abstracts*, vol. 2021, pp. IN45F–0501, 2021.

[2] A. Modarresi and J. Symons, "Technological heterogeneity and path diversity in smart home resilience: A simulation approach," *Procedia Computer Science*, vol. 170, pp. 177–186, 2020.

[3] A. Modarresi and J. Symons, "Failures to food, energy, and water systems: Mapping and simulating components to improve resilience," in *SmartNets 2023 International Conference on Smart Applications Communications and Networking*, pp. 1–6, IEEE, 2023.

[4] F. Pipa and J. Symons, "Towards an understanding of resilience with complex networks," in *Proceedings of the 6th annual symposium on hot topics in the science of security*, pp. 1–1, 2019.

[5] A. Avizienis, J.-C. Laprie, B. Randell, and C. Landwehr, "Basic concepts and taxonomy of dependable and secure computing," *IEEE transactions on dependable and secure computing*, vol. 1, no. 1, pp. 11–33, 2004.

[6] A. Avižienis, J.-C. Laprie, and B. Randell, "Dependability and its threats: a taxonomy," in *Building the Information Society*, pp. 91–120, Springer, 2004.

[7] A. Avizienis and J. P. Kelly, "Fault tolerance by design diversity: Concepts and experiments," *Computer*, vol. 17, no. 08, pp. 67–80, 1984.

[8] J. von Knop *et al.*, "Basic concepts and taxonomy of dependable and secure computing1," *A Process for Developing a Common Vocabulary in the Information Security Area*, vol. 23, p. 10, 2007.

[9] J. E. Hosford, "Measures of dependability," *Operations Research*, vol. 8, no. 1, pp. 53–64, 1960.

[10] J.-C. Laprie, "Dependable computing and fault-tolerance," *Digest of Papers FTCS-15*, vol. 10, no. 2, p. 124, 1985.

[11] J.-C. Laprie, "Dependability: Basic concepts and terminology," in *Dependability: Basic Concepts and Terminology*, pp. 3–245, Springer, 1992.

[12] F. Cristian, "Understanding fault-tolerant distributed systems," *Communications of the ACM*, vol. 34, no. 2, pp. 56–78, 1991.

[13] J. Symons, "The individuality of artifacts and organisms," *History and philosophy of the life sciences*, pp. 233–246, 2010.

[14] J. Symons and S. Elmer, "Resilient institutions and social norms: Some notes on ongoing theoretical and empirical research," *Merrill Series on The Research Mission of Public Universities*, 2022.

[15] B. Mekdeci, A. M. Ross, D. H. Rhodes, and D. E. Hastings, "A taxonomy of perturbations: Determining the ways that systems lose value," in *2012 IEEE International Systems Conference SysCon 2012*, pp. 1–6, IEEE, 2012.

[16] H. Wang, Y. Mitake, Y. Tsutsui, S. Alfarisi, and Y. Shimomura, "A taxonomy of product–service system perturbations through a systematic literature review," *Journal of Risk and Financial Management*, vol. 15, no. 10, p. 443, 2022.

[17] C. Perrow, *Normal accidents: Living with high risk technologies*. Princeton university press, 1999.

[18] "Isee systems website." https://www.e-education.psu.edu/eme801, 2023. Accessed on April 2023.

[19] "Solar resource maps and data." https://www.nrel.gov/gis/solar-resource-maps.html, 2023. Accessed on August 2023.

[20] "U.s. average annual wind speed at 30 meters." https://windexchange.energy.gov/maps-data/325, 2023. Accessed on August 2023.

[21] B. Jablonska, H. Kaan, M. Van Leeuwen, G. De Boer, H. H. Moor, and K.-V. D. AL, "Pv-prive project at ecn. five years of experience with small-scale ac module pv systems," 2005.

[22] P. EME 801: Energy Markets and Regulation, "Energy markets, policy, and regulation." https://www.e-education.psu.edu/eme801, 2020. Accessed on April 2023.

[23] "Wind turbine calculator." https://www.omnicalculator.com/ecology/wind-turbine, 2023. Accessed on August 2023.

[24] C. O. Ofori-Bah and V. Amanor-Boadu, "Directing the wind: Techno-economic feasibility of green ammonia for farmers and community economic viability," *Frontiers in Environmental Science*, vol. 10, p. 2530, 2023.

[25] "Nel hydrogen website." https://nelhydrogen.com/, 2023. Accessed on April 2023.