ENERGICA

ENERGY ACCESS AND GREEN TRANSITION COLLABORATIVELY DEMONSTRATED IN URBAN AND RURAL AREAS IN AFRICA

D7.1 Costs and benefits of the energy transition for the different local actors

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DEM	Demonstrator, pilot, prototype, plan designs	
DEC	Websites, patents filing, press & media actions, videos, etc.	
OTHER	Software, technical diagram, etc.	

Dissemination Level		
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CO	Confidential, restricted under conditions set out in Model Grant Agreement	
CI	Classified, information as referred to in Commission Decision 2001/844/EC	

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Project summary

The ENERGICA project has grouped 11 African-based partners and 17 European entities with offices or subsidiaries in Africa to enhance collaboration on energy access and sustainable energy development. The project's primary goal is to showcase the effective implementation of renewable energy technologies tailored to local needs.

Three demonstration sites have been established, each managed by local Energy Transition Boards overseeing community-scale Integrated Community Energy Systems (ICESs). Through these methodologies and innovative technologies, ENERGICA aims to demonstrate the positive social, environmental, technical, and economic impacts of high energy-efficiency and low carbon emission renewable energy technologies (RETs).

Specifically, the project will focus on:

- Developing innovative nano grids in rural Madagascar;
- Implementing low-tech efficient biogas systems in peri-urban Sierra Leone;
- Introducing solar-powered e-mobility solutions in urban Kenya.

By doing so, ENERGICA will highlight the benefits of renewable energy in diverse contexts across Africa.

More information on the project can be found at https://cordis.europa.eu/project/id/101037428

Executive summary

This deliverable assesses the feasibility, sustainability, and investment risks of three renewable energy demonstration projects developed within the ENERGICA framework: solar nanogrids in rural Madagascar, low-tech biogas systems in peri-urban Sierra Leone, and solar-powered e-mobility solutions in urban Kenya. The analysis combines a System Dynamics approach with a structured, semi-quantitative risk assessment to capture both long-term system behavior and short- to medium-term risks affecting implementation and investment decisions.

The System Dynamics analysis shows that adoption and scaling of renewable energy solutions are driven less by technical performance alone than by reinforcing feedbacks between affordability, user experience, infrastructure readiness, and access to finance. Across all demonstrators, early-stage conditions and the timing of inflection points are critical: targeted interventions that reduce upfront barriers and uncertainty can significantly accelerate diffusion and unlock long-term socio-economic and environmental benefits.

The complementary risk assessment identifies financial and operational risks as the dominant drivers of overall project risk across all sites. In particular, operational cost uncertainties, increasing capital costs, financing structure constraints, and off-taker risks consistently emerge as the highest-priority concerns. By contrast, social and political risks are assessed as comparatively low, reflecting generally favorable community acceptance and stable local operating conditions. Risk profiles nevertheless remain strongly context-specific, shaped by infrastructure constraints, market maturity, and institutional capacity in each country.

Overall, the results demonstrate that successful deployment of renewable energy solutions in Africa requires an integrated approach that aligns system design, financing mechanisms, and risk mitigation strategies. By linking dynamic system behavior with structured risk prioritization, this deliverable provides actionable insights to support evidence-based decision-making, investment de-risking, and policy design for scalable, sustainable energy transitions under European-supported initiatives.

ENERGICA

1. INTRODUCTION

Achieving universal access to affordable, reliable, and sustainable energy remains a central challenge for sustainable development, particularly in Sub-Saharan Africa. Despite growing deployment of renewable energy technologies, implementation at scale is often constrained by complex interactions between technical performance, financial viability, institutional capacity, market conditions, and social acceptance. These challenges are especially pronounced in decentralized and innovative energy systems, where uncertainty, path dependency, and local context strongly shape outcomes over time.

Within this context, the ENERGICA project demonstrates and assesses integrated, community-scale renewable energy solutions tailored to diverse local needs. The project focuses on three demonstration sites: solar nanogrids for rural electrification in Madagascar, low-tech biogas systems in peri-urban Sierra Leone, and solar-powered e-mobility solutions for motorcycle taxis in urban Kenya. Each demonstrator represents a distinct socio-technical configuration, embedded in different institutional, economic, and infrastructural environments.

This deliverable adopts a systems-oriented perspective to analyze both the dynamic behavior of these energy solutions and the risks affecting their deployment and investment attractiveness. Chapter 2 applies a System Dynamics approach to explore how interactions between economic, social, technical, and environmental factors shape adoption trajectories, long-term performance, and societal impacts. Chapter 3 complements this analysis by conducting a structured risk assessment, focusing on uncertainties that may threaten project implementation and financial sustainability from an investor and decision-maker perspective. Hence, this report provides a coherent analytical framework linking long-term system behavior with short- and medium-term risk considerations.

The ambition of this work is to move beyond static or purely techno-economic evaluations of renewable energy projects, by explicitly accounting for dynamic feedbacks, interdependencies, and uncertainty in complex socio-technical systems. By combining System Dynamics modelling with a semi-quantitative, multi-criteria risk assessment framework (DEMATEL–ANP), the report offers an integrated approach that captures both how energy solutions evolve over time and why certain risks become decisive for investment and implementation outcomes.

From a research perspective, the main contribution lies in demonstrating how these complementary methods can be applied jointly to real-world demonstration projects, enabling consistent comparison across heterogeneous contexts while preserving sensitivity to local conditions. The System Dynamics analysis identifies leverage points, tipping dynamics, and the role of early-stage interventions, while the risk assessment translates expert knowledge into structured priorities for risk assessment and investment decision-making. By linking system behavior, risk interdependencies, and financial considerations, the deliverable provides actionable insights for policymakers, project developers, and investors seeking to support scalable and resilient renewable energy solutions in developing contexts, in line with the objectives of European-supported energy transition initiatives. The deliverable complements the financial structures and business models developed under Deliverable D 7.3. Due to the use of sensitive data, the financial risk assessment – applying a Monte-Carlo simulation and scenario analysis to investigate the impact of financial risks on the current business models of the demonstration activities – is integrated in the confidential D7.3.

2. SYSTEM DYNAMICS MODEL

2.1 Aim and scope

Understanding the feasibility and long-term sustainability of emerging technologies requires a holistic approach that captures the complex interactions between economic, energy, social, and environmental factors. This report presents the results of a system dynamics modeling approach developed to assess the feasibility and sustainability of new technologies over time, focusing on the three use cases which are part of the ENERGICA, represented in Figure 1.

- **Solar nanogrid solution** in rural Madagascar.
  Nowadays, rural electrification in Madagascar remains a major challenge, with a low national electrification rate, around 11%. Factors such as geographical barriers, infrastructure limitations, and financial constraints have contributed to the slow pace of rural electrification: around 7% are connected to the national grid, with an average annual grid expansion rate of about 1-2%. The remaining 4% are connected to off-grid small-size grid solutions, which have emerged as a cost-effective and scalable alternative for rural communities (World Bank Open Data, 2025).

- **Low-tech efficient biogas system** in Sierra Leone.
  The Biogas Digester Project in Sierra Leone explores the potential of using food waste to generate sustainable energy while addressing waste management challenges. A low-tech, efficient biogas system presents a sustainable solution by converting food waste into a valuable energy source. This system not only generates biogas for electricity production, heating, and water purification but also reduces waste accumulation and produces organic fertilizers that enhance local agricultural productivity.

- **Solar powered e-mobility solution for motorcycle** taxis in urban areas in Kenya.
  This use case aims at transforming urban transportation in Kenya through the adoption of solar-powered e-mobility solutions for boda-bodas, the local motorcycle taxis. The project integrates electric motorcycles, battery swap stations, IoT sensors, smart meters, and solar energy to create an ecosystem that supports the transition from fuel-powered to electric mobility.

Figure 1 ENERGICA demonstration sites

A **System Dynamics model** is developed for each use case with the objective of representing and simulating the interactions among key actors and parameters within a complex socio-technical

system. The models integrate interdependencies across energy, economic, socio-cultural, and environmental domains, and are parameterized using real-world data from the demonstrators, including alternative capacity investment scenarios.
The primary objective of this modelling exercise is to assess the long-term performance, economic sustainability, and societal impacts of the three use cases. The resulting insights support evidence-based decision-making and policy development for rural electrification strategies.

2.2 Materials and methods

System Dynamics provides a powerful framework for modeling interdependent domains, allowing for a deeper analysis of how various actors behave within a multi-dimensional system over time. It is widely used in sectors like energy, public health, and environmental management to help predicting outcomes, design policies, and guide decision-making.
Through integrating real-world data from demonstrators, the models reflect realistic economic structures, accounting for market dynamics. Beyond technical and economic factors, social and cultural behavior also plays a crucial role in technology adoption and diffusion. Therefore, the models capture socio-political dynamics, community acceptance, and behavioral trends influencing the energy transition.
By simulating the interconnected elements, the system dynamics approach provides insights into the long-term viability of the technologies, supporting informed decision-making and policy development. The results contribute to a holistic understanding of the challenges and opportunities inherent in complex socio-technical systems.

In System Dynamics, **stocks and flows** are the core building blocks used to represent and analyze dynamic systems.

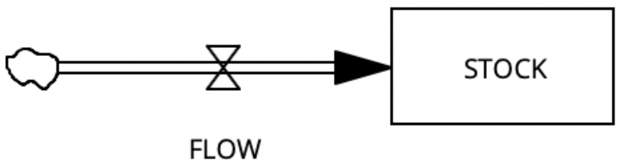

Figure 2 System Dynamics: Stocks and Flows

As shown in Figure 2, stocks are the quantities or accumulations in the system that change over time. They represent entities that accumulate or deplete, like water in a reservoir, population size, or capital in a business. Stocks only change when there is a flow, which is the rate of change that affects how stocks increase or decrease over time. Flows are typically governed by rules or conditions that describe how fast the stock is changing, like growth rates. A stock represents the current state, while the flow defines how the stock evolves. Together, stocks and flows describe how systems develop, providing insight into how entities grow, decline, or stabilize over time.
In System Dynamics, feedback loops are fundamental in shaping system behaviour over time, influencing whether a system reinforces growth or stabilizes itself.
Reinforcing loops amplify changes, driving exponential trends where an increase in one factor leads to further increases in the same direction, accelerating system evolution. The orange loop on the right-hand side of Figure 3 below illustrates this dynamic.

Conversely, **balancing loops** regulate and stabilize systems by counteracting deviations, maintaining equilibrium, and preventing excessive fluctuations. The purple loop on the left-hand side of Figure 3 represents this regulatory effect.
The interaction of feedback loops in the model generates complex, non-linear dynamics in which delayed responses can lead to unintended effects such as oscillations, inertia, overshooting, or underperformance. These delays arise when the impact of an action is not immediately observable, creating a temporal mismatch between cause and effect that influences decision-making.
In the model, **delays** are explicitly represented by double lines on causal arrows to indicate situations where relationships between variables are not instantaneous (an example is provided in Figure 3 in the left loop). Delays capture the time lag between a change in one variable and its observable effect on another, reflecting structural, behavioural, or logistical constraints inherent in complex systems. The quantitative effects of these delays are embedded in the model's assumptions, which have been calibrated using historical evidence and established findings from literature.

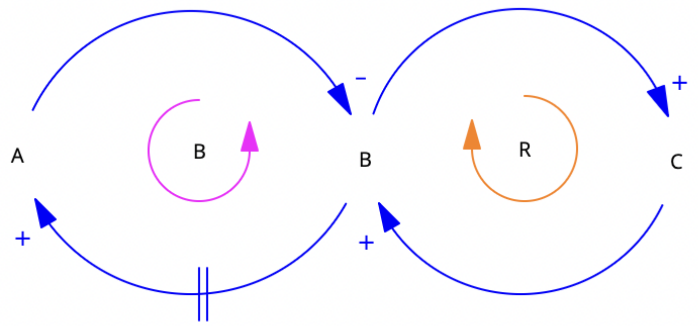

Figure 3 System Dynamics: reinforcing and balancing loops, delays

Additionally, the model adopts red arrows to represent **accessory variables** that modify or adjust scenario conditions, introducing flexibility to explore alternative futures under different assumptions. The colour red is also used to denote external qualitative actions, capturing influences that originate outside the system boundary, such as policy interventions, educational initiatives, and financial mechanisms, which play a significant role in shaping rural electrification pathways.
Qualitative variables are included where reliable quantitative data are unavailable or unsuitable for numerical modelling. These variables, highlighted in red, represent regulatory, policy, or socio-economic factors that influence scenario configurations. Their inclusion enhances the completeness of the model by ensuring that key external and non-quantifiable drivers of system behaviour are explicitly represented.

An extensive **literature review** has been conducted alongside the integration of data from the demonstrators and the outputs of other project work packages. This approach ensures a comprehensive understanding of the system by combining theoretical insights, empirical data, and real-world observations. The inclusion of outputs from other work packages ensures that the model reflects interdisciplinary perspectives, capturing the economic, energy, environmental, and socio-cultural dimensions necessary for a holistic system dynamics analysis. References to external sources from the literature review are included in the deliverable, ensuring that input data and findings are contextualized within existing research and validated against previous studies.

2.3 Vensim tool

For the System Dynamics study, the **Vensim tool** is used. Developed by Ventana Systems, Vensim is a powerful software for analysing and simulating complex systems over time.

Figure 4 shows the main user interface. It enables users to create visual models that illustrate how different factors interact through feedback loops, delays, and cause-effect relationships. Using Vensim, both causal loop diagrams and stock-and-flow models can be constructed to understand system behaviour and its evolution over time.

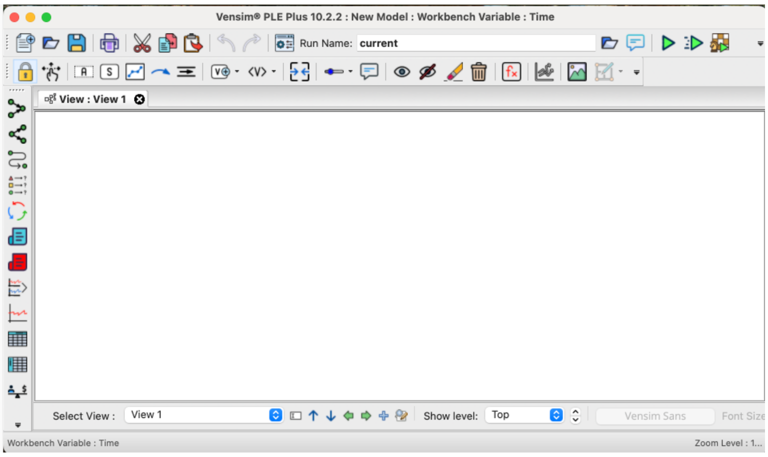

Figure 4 Vensim PLE Plus 10.2.2 user interface

The simulations in this report cover a **10-year time span** and the time step is set to one year (as shown in Figure 5), aligning with the fact that most model variables are expressed on an annual basis, ensuring consistency in calculations and analysis.

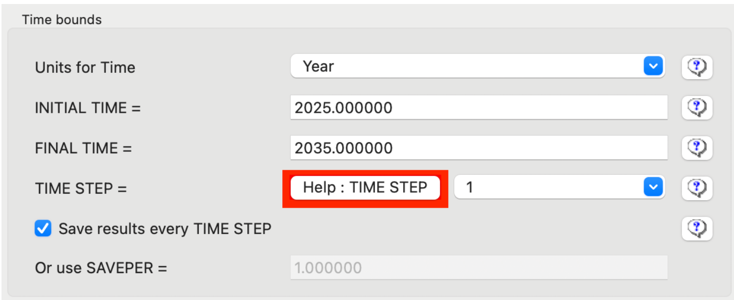

Figure 5 Vensim PLE Plus: time bounds settings

2.4 System setup in demo sites

This chapter explains how System Dynamics models are built using both qualitative and quantitative approaches. It first introduces the key ideas behind these models, including how different elements of a system are connected and influence each other. Then, it describes how the models are developed using mathematical formulas to show how different variables change over time. The chapter also presents the results of simulations run under different conditions, demonstrating how the model behaves in various scenarios.

2.4.1 Nanogrid development in Madagascar

The System Dynamics model is designed to analyse and simulate the expansion of nanogrids in rural Madagascar, helping the understanding of how nanogrid installations can evolve over time and how different factors influence their adoption.
As shown in Figure 6, the model primarily exhibits positive flows, meaning that most relationships between variables contribute to growth or reinforcement within the system.
However, there is one key exception: the relationship between rural electrification through grid expansion and rural electrification through nanogrid installations. As grid expansion progresses, it reduces the potential for nanogrids development, creating a limiting effect on the latter. This inverse relationship highlights a competitive dynamic between the two electrification approaches, where the growth of one restricts the feasibility and necessity of the other.

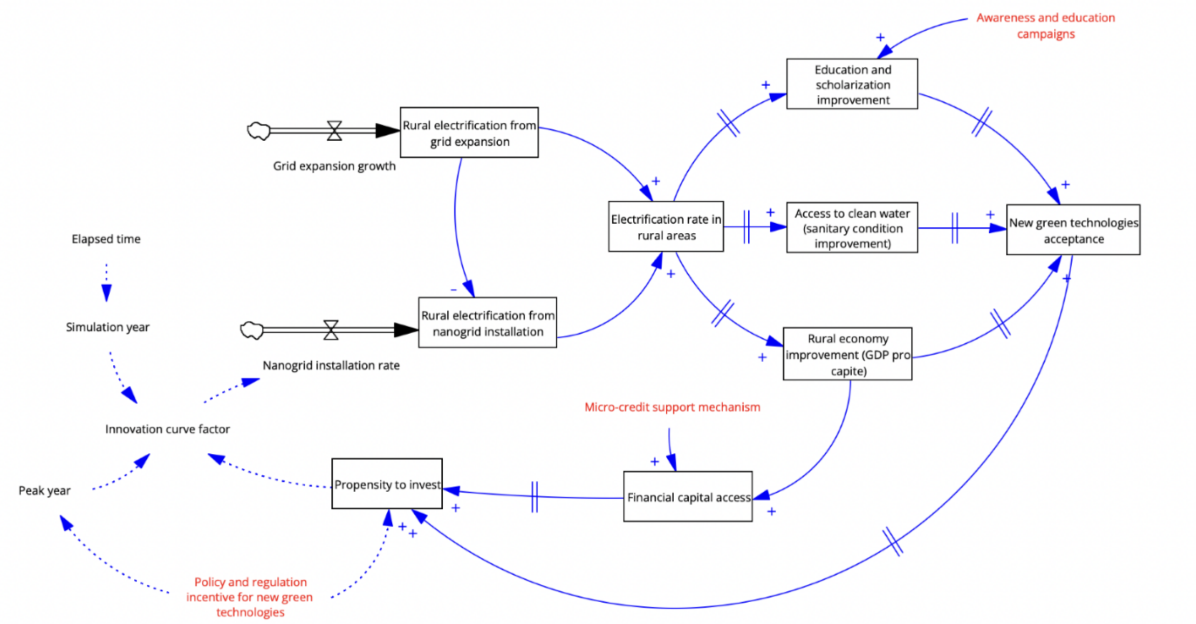

Figure 6 System Dynamics Nanogrid model

The following paragraphs provide a more detailed explanation of how the individual variables in the model are correlated.
In the System Dynamics model, *Rural electrification from grid expansion* and *Rural electrification from nanogrids* are the first two modelled stocks.
Considering the historical data available, a constant flow is modelled for *Rural electrification from grid expansion (R_G)*. The growth rate is derived from literature. (African Development Bank, 2025)

$$R_G(t) = R_G(0) + \int_{t_0}^{t} Gr_G \, dt$$

$$Gr_G = constant = 2\%$$

On the other hand, a more complex innovation S-curve (logistic growth model) is introduced for the *Rural electrification from nanogrid (R_N)*, representing a more realistic diffusion model of innovative technologies (Fitsum Getachew Bayu, 2022).
The S-Innovation Curve, presented in Figure 7, is a model used to describe the adoption of new technologies or innovations over time. It represents the diffusion of innovations in a population or market, where adoption starts slow, increases rapidly at the inflection point, and then slows down as the market reaches saturation.

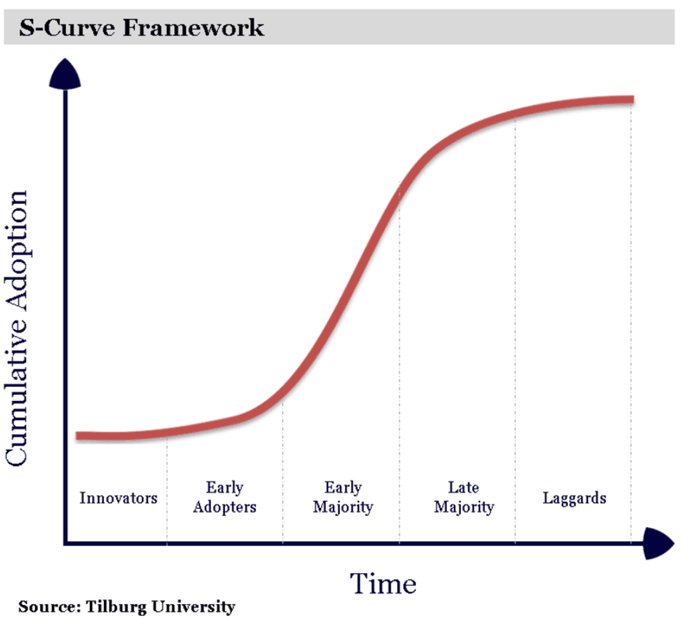

Figure 7 S-Innovation Curve framework

The S-curve represents the adoption of new technologies or innovations over time, progressing through five distinct groups:

- It begins with **innovators**, a small, risk-taking group that embraces new ideas before they are widely known or tested;
- Following them are the **early adopters**, influential individuals who recognize potential and help drive broader acceptance;
- As awareness and trust grow, the **early majority** adopts the innovation, marking the phase of rapid expansion;
- This momentum continues as the **late majority**, typically more sceptical and cautious, adopts the technology only when it becomes widely accepted and proven;
- Finally, the **laggards**, the most resistant to change, adopt only when there are no other viable options or when the innovation has become the standard. The S-curve shape reflects this gradual start, a period of rapid growth, and a final plateau as adoption reaches its maximum potential.

The **S-curve** can be modelled using the **logistic function** (I), a sigmoid curve that captures the rate of change in adoption over time. This dimensionless function describes how adoption progresses from an initial phase of slow uptake, followed by rapid growth, before eventually stabilizing as saturation is reached.

The logistic function represents the adoption level at time t, ranging from 0% to 100%, illustrating how technology spreads within a population.

$$I(t) = \frac{1}{1 + e^{-k\,(t - t_{inflection})}}$$

Where:

- k is the growth coefficient, which controls the steepness of the curve. In the SD nanogrid model this is defined by the propensity to invest. As we will see later in the model, the propensity to invest is not a fixed value, but it changes dynamically according to the scenario;
- $t\_inflection$ is the year when adoption accelerates the most.

The steepness of the S-curve (Figure 8) for nanogrid adoption is influenced by policy frameworks, regulatory measures, financial incentives, and micro-financing schemes, which can either accelerate or slow down the adoption process.
To assess different adoption trajectories, the System Dynamics model is developed for three distinct scenarios, described in Table 1 Nanogrid adoption scenarios.

Scenario	**Inflection point**	**Key factors influencing adoption**	**Growth rate**
Early adoption	2028	Strong policy support, aggressive incentives, widespread micro-financing, early adopter engagement	Rapid growth
Balanced adoption	2030	Moderate policy implementation, gradual subsidies, access to financing, public-private partnerships	Steady growth
Delayed adoption	2032	Slow policy development, limited investment, financial barriers, minimal incentives	Slow growth

Table 1 Nanogrid adoption scenarios

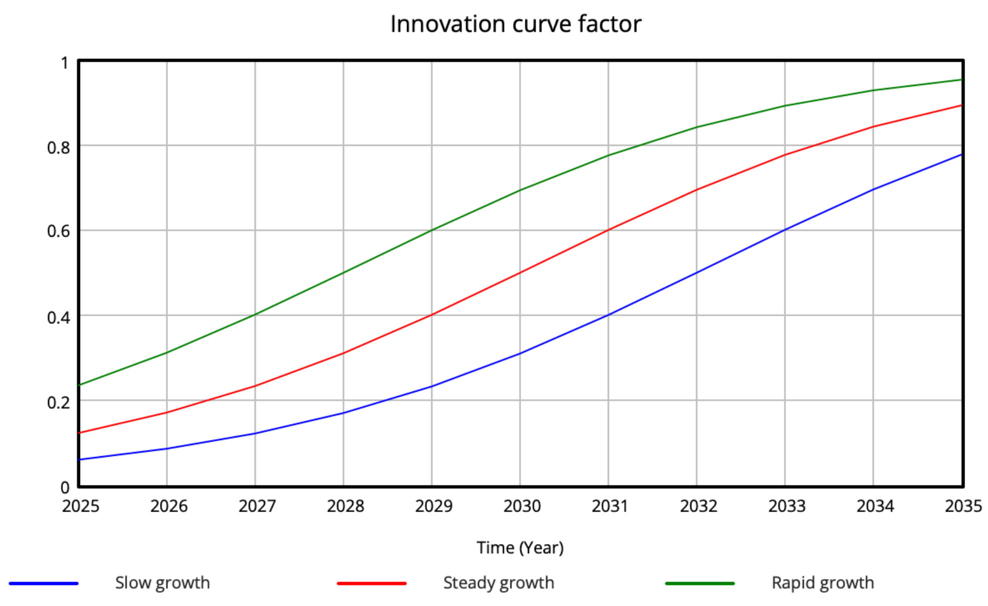

Figure 8 Nanogrid innovation curve in the different scenarios

In this context, the innovation curve factor should be interpreted as a **relative position along the S-curve**, indicating how far the system has progressed through the adoption lifecycle already described. Rather than redefining the adopter categories, the factor captures the *intensity and speed* at which the transition from early stages to mass adoption occurs under different conditions. Lower values of the innovation curve factor correspond to the initial phases of diffusion, where uptake is limited and growth is incremental, while higher values indicate that the system is approaching widespread acceptance and saturation.

An earlier inflection point, for example around 2028, implies a faster shift along the S-curve, where supportive policies, strong incentives, and accessible financing compress the time needed to move from early adopters to the early majority, resulting in rapid growth. A mid-range inflection point around 2030 reflects a more balanced progression, where adoption advances steadily as market confidence and institutional support mature gradually. Conversely, a later inflection point around 2032 signals a slower movement along the S-curve, where regulatory delays, limited incentives, and financial barriers extend the duration of early adoption phases and postpone large-scale diffusion. In this way, the innovation curve factor provides a comparative lens to assess how different policy and market environments influence the pace at which nanogrids advance through the established adoption stages toward full market penetration.

Building on this interpretation, the innovation curve factor is used as a dynamic modifier of the projected installation growth, translating different adoption speeds and inflection timings into quantitative effects on deployment trajectories.

The rural electrification rate through nanogrids is modelled as the time integral of the nanogrid installation growth rate, calculated as the projected average increase in nanogrid deployments multiplied by the innovation factor.

$$R_N(t) = R_N(0) + \int_{t_0}^{t} Gr_N \, dt$$

$$Gr_N = Gr_{avg} * I(t)$$

Where:

- $R_N(t)$ is the electrification rate in rural areas, dimensionless variable;
- $R_N(0)$ is the initial electrification rate derived from literature;
- Gr_N Is the electrification rate from nanogrid installation;
- $Gr_{avg} = 0.36$ is the average growth rate derived from literature (World Bank Open Data, 2025).

Figure 7 illustrates how the same average growth rate can lead to markedly different electrification trajectories once it is modulated by the innovation factor. For example, under the rapid growth scenario, the higher innovation factor after the early inflection point accelerates the effective installation rate, resulting in a steeper curve and a faster accumulation of nanogrid installations over time. In contrast, the slow growth scenario shows how a lower innovation factor dampens the installation rate in the early years, delaying scaling despite the presence of underlying growth potential. The figure can therefore be used to compare scenarios and assess how policy, financing, and market readiness translate into different installation rates over time, ultimately influencing how quickly rural electrification targets can be achieved.

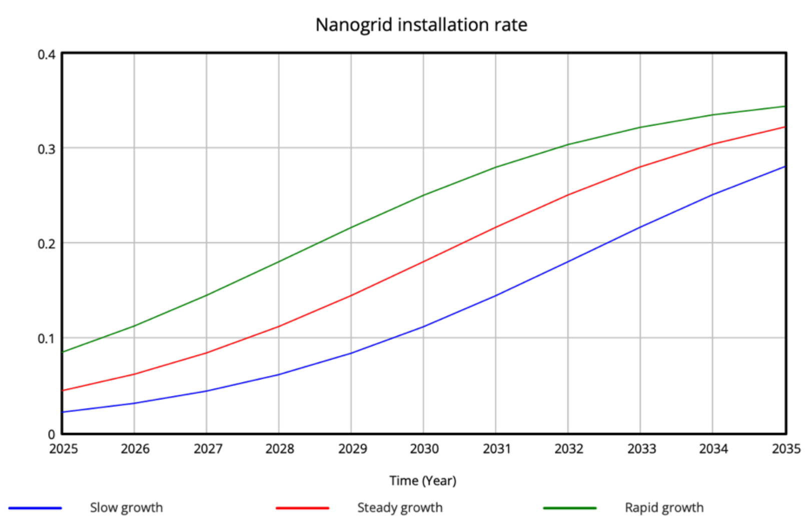

Figure 9 Nanogrid installation rate in the different scenarios

The total rural electrification rate in Madagascar is determined by the combined contribution of grid expansion efforts and the adoption of solar-powered nanogrids.

$$R_R(t) = R_G(t) + R_N(t)$$

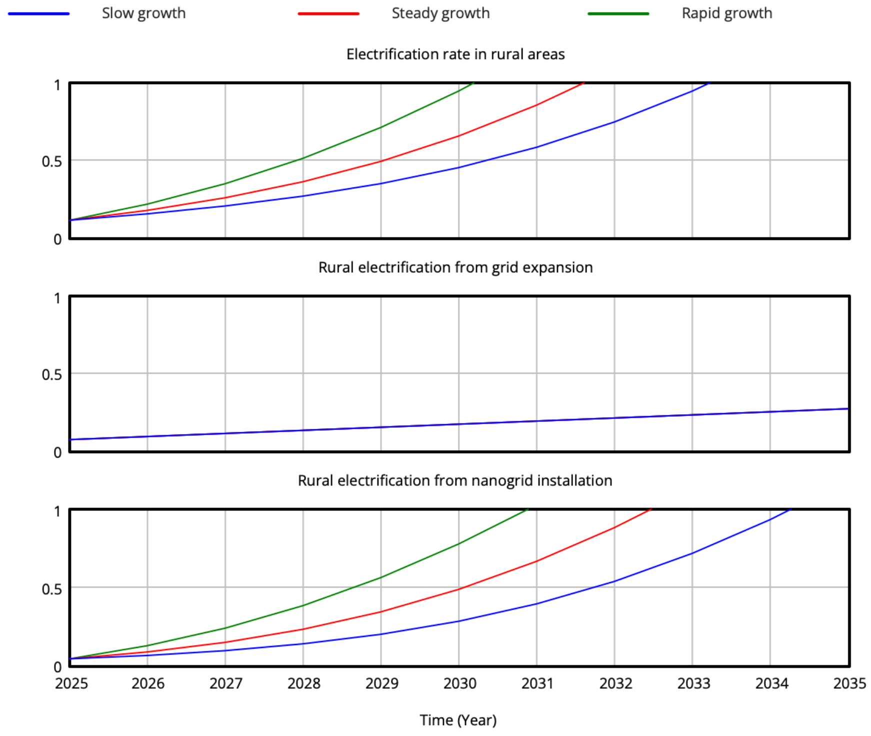

Figure 10 Rural electrification rate progress as combined effect of national grid expansion and nanogrid growth

Figure 10 shows that as the national grid expands at a slow but steady pace, the long-term role of nanogrids in rural electrification is expected to gradually decline. However, in the short term, nanogrids development remains essential for accelerating electrification and achieving mid-term Sustainable Development Goal (SDG) targets, particularly the 70% electrification goal by 2030. (A New Electrification Model to End Energy Poverty, 2025). This target, while ambitious, is only attainable under a rapid growth scenario, requiring strong policy support, aggressive incentives, widespread micro-financing, and active early adopter engagement to drive large-scale adoption and sustainable implementation.

Studies have demonstrated that rural electrification rates play a crucial role in shaping local **economic development**, **educational opportunities**, and **access to clean water**, driving significant improvements across these sectors.

Economic growth can be directly impacted by electrification, as access to reliable electricity supports small businesses, agriculture, and industrial development. For instance, electrification enables the use of modern technologies such as irrigation systems, food processing, and machinery, boosting productivity and income. Additionally, nanogrid installations require local entrepreneurs to embrace the challenge of integrating new technologies into their businesses, offering them opportunities to innovate and grow. By participating in the expansion of nanogrids, entrepreneurs not only contribute to local development but also position themselves as key players in the renewable energy sector, further boosting economic activity in rural communities.

In the System Dynamics model, Gross Domestic Product (**GDP) per capita** in rural Madagascar is used as a **proxy for economic growth**. Extensive literature indicates a strong positive correlation between electricity access and economic development, particularly in developing regions. Studies suggest that a 10% increase in electrification can lead to a 1.5–2% rise in GDP, highlighting the significant impact of improved energy access on local economies. (Kenneth Lee, 2020).

$$GDP(t) = GDP(0) * (1 + GDP_{rate} * R_R)$$

Where:

- $GDP\ (0)$ is the initial Gross Domestic Product of $460 per capita (World Bank Open Data, 2025);
- GDP_{rate} is the growth rate defined by the correlation presented in the previous paragraph;
- R_R is rural electrification, as previously defined.

As rural economies progress, **access to financial capital** naturally improves. With economic growth in rural areas, both individuals and local businesses experience increased opportunities to secure funding, whether through microfinance institutions, cooperatives, or community-based lending programs. The rise in income levels and economic stability in rural communities enables people to invest in businesses, agricultural improvements, and sustainable technologies like nanogrids. Additionally, a more robust rural economy attracts financial institutions and external investments, which provide better access to credit and financial services. This creates an environment where local entrepreneurs and farmers can take advantage of new opportunities, contributing to the overall growth and innovation within the rural economy. Thus, as rural economies advance, financial capital becomes more accessible, promoting further development and investment in sustainable solutions.
The model incorporates a logistic growth function to represent access to financial capital as a function of GDP per capita, a dimensionless variable This approach captures the nonlinear nature of financial accessibility, where initial growth is slow, accelerates with economic development, and eventually stabilizes as financial markets mature.

$$AFC(t) = AFC(0) * \frac{1}{1 + e^{-k(GDP(t) - GDP_{th})}}$$

Where:
- $AFC(0)$ is the access to financial capital rate at initial time;
- k = 0,002 is the growth rate, how fast financial capital access improves with GDP per capita. A low value ensures a realistic growth for rural areas and prevents unrealistic jumps at low GPD levels;
- GDP_{th} = 1500 $ the inflection point, when financial capital access reaches 50%. It is estimated in a conservative way to reflect the rural economy development.

The values of the growth rate *k* and the GDP threshold (GDP_{th}) were selected based on a review of the literature on financial inclusion, rural electrification, and technology adoption in low- and middle-income economies (Zaheer Abbas, 2020).
Following this model, as GDP per capita increases, financial access improves slowly at first, then accelerates until reaching a plateau with high incomes.
Figure 11 illustrates how these two variables change across the different scenarios.

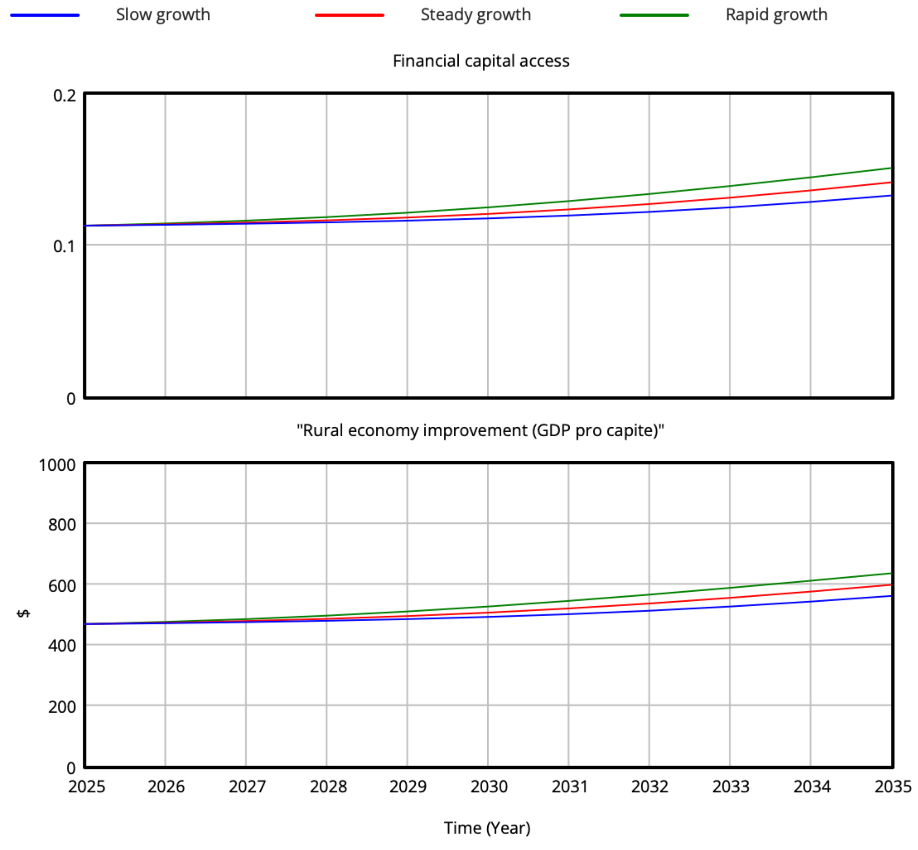

Figure 11 Rural economy improvement and financial capital access

Another relevant social effect of rural electrification is the improvement of children's **educational attainment** particularly at the secondary education level. Access to electricity reduces the time children spend on labour-intensive household activities, such as fetching water or walking long distances, allowing more time to be allocated to school-related activities. This increased availability of time, combined with improved study conditions, contributes to higher school enrolment and completion rates. Studies have quantified this relationship indicating that a 10% increase in rural electrification is associated with an average 6% increase in secondary educational attainment (Action Education, 2024).

$$E(t) = E(0) * (1 + E_{rate} * R_R)$$

The dimensionless equation parameters were defined based on values and relationships reported in the literature review:

- $E(0)$ is the initial educational attainment rate, which establishes around 35% (Action Education, 2024);
- E_{rate} reflects the impact of electrification on education in rural regions, as previously described;
- R_R Is the rural electrification rate as previously defined.

Figure 12 illustrates the evolution of this system variable across the different scenarios.

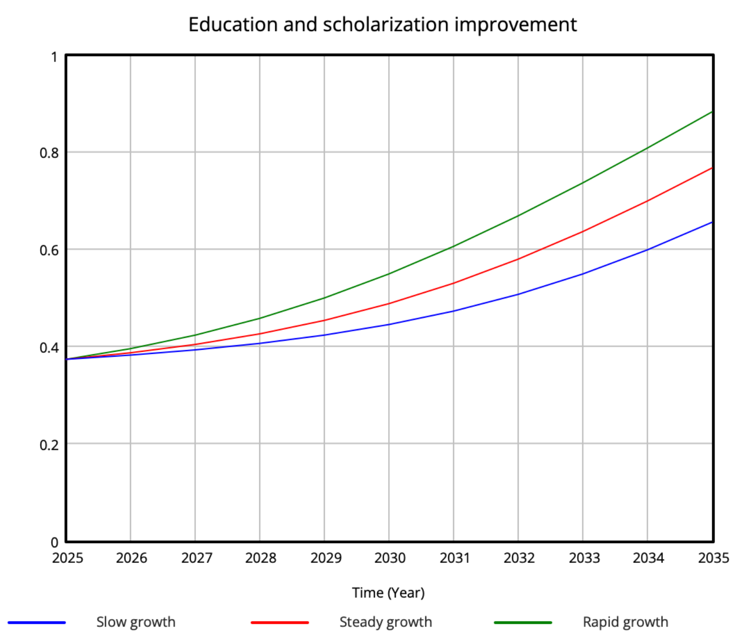

Figure 12 Increase of educational attainment with progressing electrification

Furthermore, electrification can play a vital role in improving **access to clean water**, a fundamental necessity for public health, and well-being. By powering water purification and pumping systems through nanogrids, electrification ensures a reliable supply of safe drinking water and enables other essential water-related services. Improved water access is critical in reducing waterborne diseases, directly enhancing community health outcomes.

In Madagascar, for instance, diarrheal diseases remain the second leading cause of death after malaria, affecting 51% of children under the age of five (World Bank Open Data, 2025).

Expanding electrification, therefore, not only supports economic and social development but also has a direct, life-saving impact on public health.

Despite positive improvements in the past years, inequalities persist in access for drinking water, sanitization services and hygiene. A quarter of the population in rural areas do not have access to safe and constant drinking water.

Multiple experimental studies have confirmed a strong correlation between electrification and improved access to clean water, primarily through the operation of pumping and sanitation systems. With reliable electricity, these systems function more efficiently, expanding water availability and improving quality. Based on observed trends, it is estimated that a 10% increase in electrification leads to an average 5% increase in access to clean water, highlighting the critical role of energy access in enhancing public health and sanitation infrastructure (African Development Bank, 2025).

$$W(t) = W(0) * (1 + W_{rate} * R_R)$$

The dimensionless equation parameters were defined based on values and relationships reported in the literature review:

- $W(0)$ is the initial access to clean water rate, which establishes around 75% (World Bank Open Data, 2025);
- W_{rate} reflects the impact of electrification on access to clean water in rural regions, as previously described;
- R_R Is the rural electrification rate as previously defined.

Figure 13 illustrates the evolution of this system variable across the different scenarios.

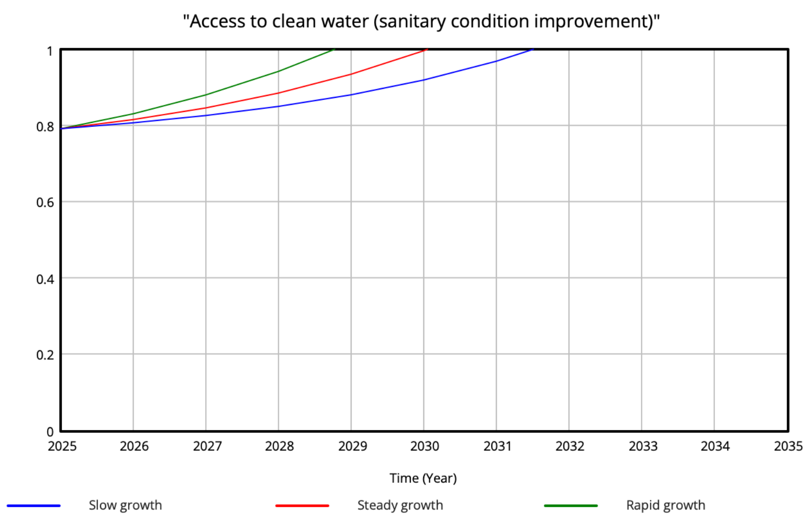

Figure 13 Access to clean water with progressing electrification

The development of rural economy, the increase in educational attainment and access to clean water can all play a crucial role in driving the acceptance of green energy technologies in the rural areas. Each of these factors, while varying in their impact, can contribute positively to the adoption process. A thriving local economy encourages investment in sustainable solutions, making nanogrids solutions more accessible and desirable. The improvement in education fosters awareness and understanding of the benefits of clean, renewable energy, while access to clean water enhances the quality of life, thus creating a conducive environment for embracing green technologies.
Despite the differing reasons behind this adoption, whether economic incentives, educational advancements, or improved living conditions, all these factors converge to create a positive feedback loop that encourages the widespread acceptance of nanogrids as an essential component of rural development and sustainability.

In the system dynamics model, **social acceptance** of new green technologies is represented through a dimensionless proxy indicator that aggregates three contributing factors with differentiated weights: 50% for GDP (GDP_w), 35% for educational attainment (E_w), and 15% for access to clean water (W_w).
Based on literature, it is assumed that the initial acceptance level is approximately 40%**,** as derived from previous studies on similar contexts. (Social Acceptance of Renewable Energy: Some Examples from Europe and Developing Africa, 2024).

$$A(t) = A(0) * (1 + \frac{GDP(t) - GDP(0)}{GDP(0)} * GDP_w + \frac{E(t) - E(0)}{E(0)} * E_w + \frac{W(t) - W(0)}{W(0)} * W_w)$$

Figure 14 illustrates the evolution of this system variable across the different scenarios.

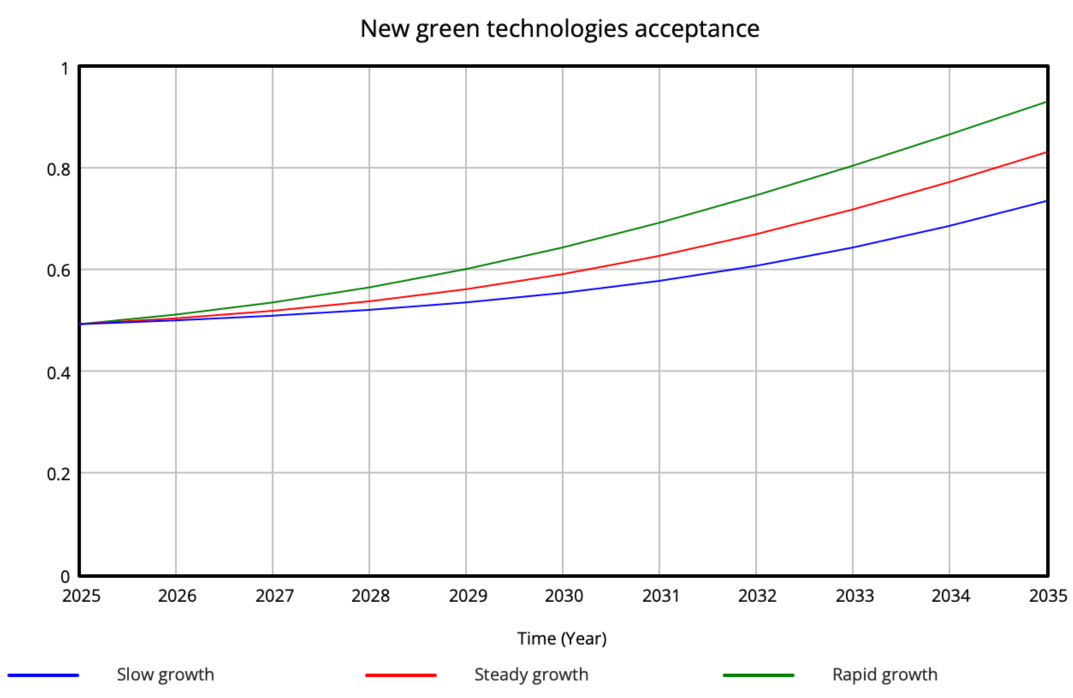

Figure 14 New green technologies social acceptance with progressing electrification

The propensity to invest in new technologies such as nanogrids can be influenced by social acceptance of green technologies, but also financial capital access. While social acceptance shapes the willingness of communities to embrace these innovations, recognizing the value and benefits of these sustainable solutions, financial accessibility enables individuals and businesses to secure funding, which has a significant impact on the ability to invest in innovative solutions. As financial resources become more available, the capacity for investment in technologies like nanogrids increases.

In the System Dynamics model the **propensity to invest** is modelled as a combination of both factors (as shown in Figure 15), where financial capital access is given a higher 60% weight, reflecting its stronger influence on investment decisions. The remaining 40% is assigned to social acceptance, acknowledging its importance but recognizing that financial capability often acts as the primary driver for new technology adoption (Fitsum Getachew Bayu, 2022).

$$P_I(t) = \frac{(AFC(t) \cdot AFC_w + A(t) \cdot A_w)}{AFC(t) + A(t)}$$

Where:

- P_I Is the propensity to invest, dimensionless variable;
- $AFC(t)$ is the financial capital access as defined previously;
- AFC_w is the relative weight of financial capital access as derived from literature insights;
- $A(t)$ is the social acceptance as defined previously;
- A_w is the relative weight of social acceptance as derived from literature insights.

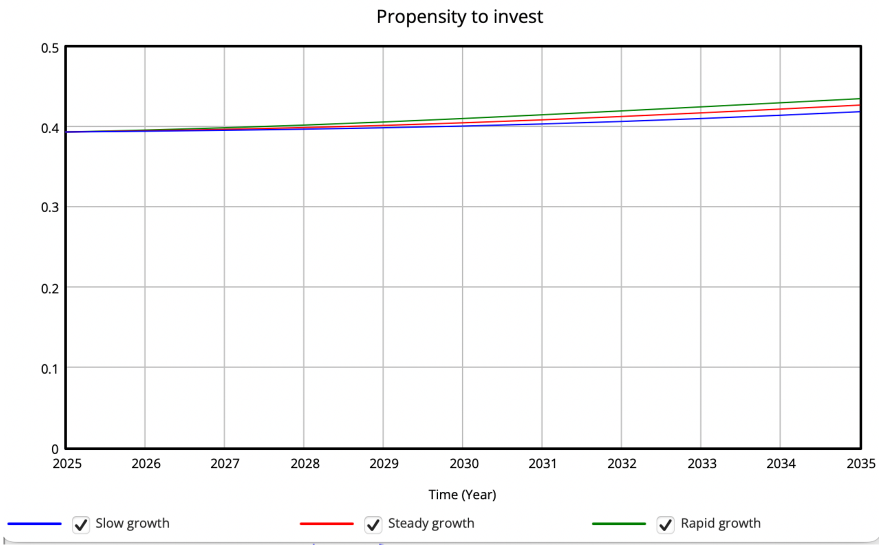

Figure 15 Propensity to invest in green technology with progressing electrification

Hence, the propensity to invest influences the adoption rate of nanogrids, thereby closing the feedback loop in the System Dynamics model.

The investment propensity directly impacts the installation rate of nanogrids, as higher investments lead to faster adoption and greater deployment of these technologies in rural areas. In turn, as the adoption rate increases, the availability of nanogrids grows, which can further improve access to financial capital and social acceptance of the technology. This creates a positive feedback loop where more investment leads to wider adoption, and wider adoption stimulates higher investment, reinforcing the cycle.
The model thus captures the dynamic interaction between these elements, ensuring that changes in financial resources and social perception can both accelerate and stabilize the growth of nanogrid technologies, ensuring a sustainable pathway to rural electrification.

2.4.2 Low-tech efficient biogas system in peri-urban Sierra Leone

Food waste management poses a significant challenge in peri-urban areas of Sierra Leone, where inadequate infrastructure and informal disposal practices exacerbate environmental degradation and public health risks.
This section examines the feasibility of implementing a **community-based biogas digester** that utilizes food waste as its primary feedstock. The study focuses on peri-urban villages, where food waste generation presents both a challenge and an opportunity for sustainable energy production.
The successful implementation of such a system depends on two key factors: the **efficiency of waste collection processes** and the **level of community participation**. Without effective waste aggregation and consistent engagement from residents, the potential for biogas production may be limited. While businesses actively pre-sort waste, household participation remains uncertain, posing challenges for consistent waste supply.

To assess the feasibility and effectiveness of this approach, the System Dynamics model analyses three distinct waste collection scenarios, for a single low-tech biogas system. This evaluation helps identifying the key factors influencing waste collection efficiency and their impact on the overall system's sustainability.

Assuming a **medium-sized village in Sierra Leone** consists of 2,000 people, existing literature estimates annual food waste generation at 154 tons/year (Solid Waste Management Study for Freetown, Sierra Leone, 2024). Of this, approximately 50% (72.5 tons/year) is suitable for use in a biogas digester (IRENA, 2016).
For reference, the ENERGICA data book of the demonstrator indicates that a single biodigester requires 220 tons of feedstock per year to operate efficiently. Given this requirement, a single village alone would fall significantly short of supplying the necessary waste, necessitating a multi-village waste collection strategy to sustain the biodigester. To bridge this gap, different waste collection efficiency scenarios are considered, as described in Table 2.

Scenario	Inflection point	Key factors influencing adoption	Growth rate
Early adoption	2028	Strong waste collection program, economic incentives for participation, community training, logistical support	Rapid growth
Balanced adoption	2030	Basic community engagement, small-scale collection system, some economic incentives	Steady growth
Delayed adoption	2032	Limited awareness, lack of infrastructure, weak incentives, no organized collection system	Slow growth

Table 2 Low-tech efficient biogas system growth scenarios

As shown by the diagram in Figure 16, the efficiency of food waste collection for biogas production in peri-urban Sierra Leone is influenced by several key factors. Awareness and community participation play a crucial role, without proper education on the benefits of waste-to-energy conversion, households may be less inclined to separate and contribute their organic waste. Infrastructure and logistics are also critical; villages with no organized collection system or proper transport mechanisms will struggle to supply waste to a central biodigester. Economic incentives, such as reduced fuel costs from biogas use or access to organic fertilizers, can encourage greater participation.

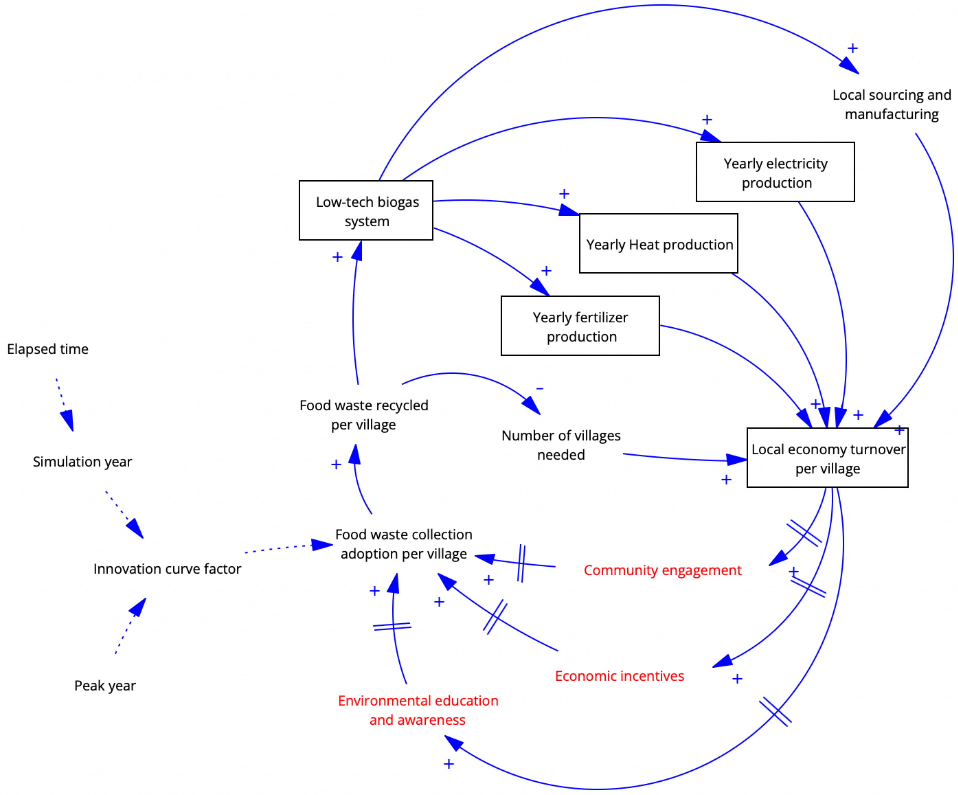

Figure 16 System Dynamics Low-tech biodigester model

The model primarily consists of positive feedback loops that drive growth, with one key exception: the number of villages that need to be involved in the waste collection process, a factor that can also be referred to as density. A lower number of participating villages leads to higher waste collection efficiency and reduces logistical costs, making the system more sustainable and cost-effective. Conversely, as the number of villages increases, collection becomes more complex, potentially decreasing efficiency and increasing associated costs.
External factors, highlighted in red within the model, play a crucial role in shaping different development scenarios. These factors include community engagement, the economic benefits of increased turnover, and financial incentives provided by policy programs. Additionally, education and awareness initiatives influence the long-term success of the system by encouraging participation and behavioural change within the community.
All these external influences are subject to delays, as indicated by the delay marks in the model. This means that their effects are not immediate but take time to materialize. Whether it is the impact of policy incentives, the gradual shift in community behaviour, or the economic response to new opportunities, these changes unfold progressively, reflecting the inertia inherent in social and economic systems.
As in model presented in the previous use cases, the dotted lines represent accessory variables, which are essential for assessing and comparing different scenarios. These variables serve as adjustable parameters that help explore how various factors influence the system under different conditions.

With an approach like the one presented in the nanogrid simulation, the adoption of food waste collection is modelled using the **innovation S-curve**, which follows a logistic function (I)**.** This sigmoid curve effectively represents the gradual adoption process, starting with slow initial uptake, followed by a phase of rapid growth, and eventually stabilizing.

$$I(t) = \frac{1}{1 + e^{-k\,(t - t_{inflection})}}$$

$$FW(t) = FW_{avg} * I(t)$$

Where:

- k is the growth coefficient, which controls the steepness of the curve. A low rate (k = 0,3) is selected to capture slow but eventual growth. This assumption aligns with case studies in other low-income regions where organic waste separation takes decades to scale, particularly in the absence of strong regulatory frameworks or financial motivators;
- $t\_inflection$ is the year when adoption accelerates the most. The model will simulate different scenarios which may be influenced by policy and regulation;
- $FW(t)$ is the food waste collection factor as a function of the average recycling rate in emerging economies, adjusted by the innovation factor, which evolves over time to reflect adoption dynamics and technological diffusion;
- FW_{avg} is the average recycling rate in emerging economies, 30% (McKinsey, 2016).

Figure 17 shows how the innovation curve shape changes across the different scenarios, with the inflection year gradually shifting in time.

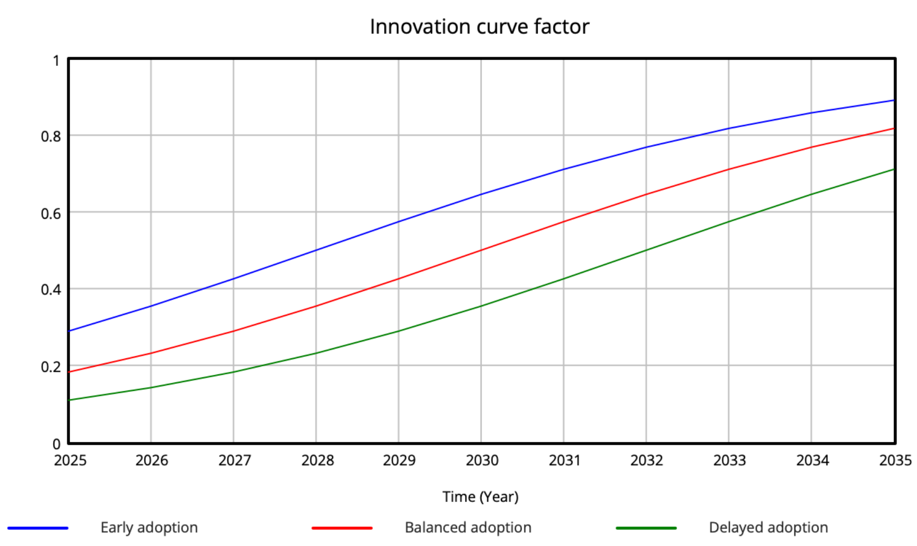

Figure 17 Innovation curve factor in different scenarios

Hence, the amount of **food waste recycled** is determined by multiplying the suitable food waste per village by the food waste collection adoption rate. Consequently, the model calculates the number of villages required for waste collection (N_V) to ensure the biodigester receives its nominal feedstock supply, in this case of 220 t/year. As food waste recycling efficiency increases within a single village, the total number of villages needed decreases, optimizing resource utilization and logistical efforts.

$$N_V(t) = \frac{F_N}{F_W \cdot FW(t)}$$

Where:

- $N_V(t)$ is the number of villages required to be involved in waste collection practices;
- F_N Is the nominal feedstock supply;
- F_W Is the annual food waste generation suitable for the biodigestor, derived from literature as 72,5 tons/year (IRENA, 2016);
- $FW(t)$ is the food waste collection factor as previously defined.

Figure 18 shows how the number of villages needed to meet the demand of food waste to be recycled decreases when the collection efficiency and adoption improves, as reported in Figure 19 instead.

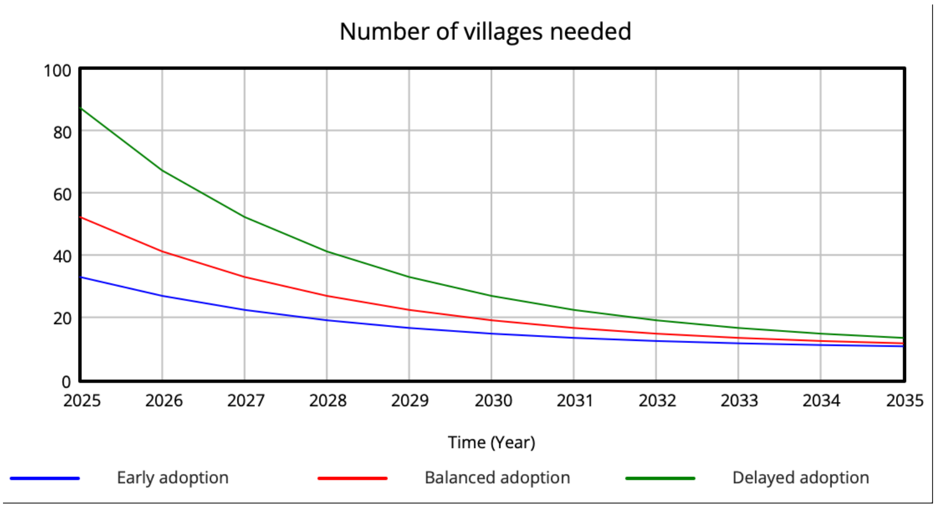

Figure 18 Number of villages needed for waste collection to operate the biodigester

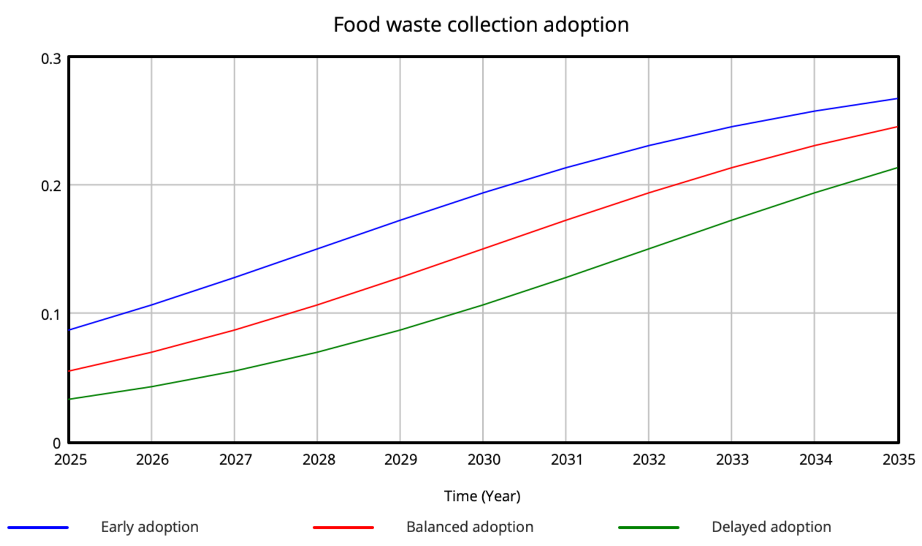

Figure 19 Food waste collection adoption in different scenarios

The results indicate that the number of villages required can be significant, even under the best-case scenario of early and efficient food waste management from medium-sized villages.

This highlights the importance of carefully selecting a suitable site for the biodigester. Ideally, it should be located near large business facilities such as supermarkets or hotels, which generate substantial amounts of food waste daily, often enough to sustain a single biodigester independently. This is the current strategy in the ENERGICA project for identifying initial locations, as it helps mitigating the challenge of aggregating non-pre-sorted food waste from multiple villages.

While biodigester applications remain an interesting solution for village waste management, offering environmental sustainability and economic benefits to communities, the business-oriented use case appears more viable. However, the high initial investment remains a significant challenge even for businesses. To address this, a "waste-as-a-service" model could be an attractive alternative, allowing for a gradual investment approach while enabling businesses to benefit from the revenues generated through electricity, heat, and fertilizer sales.

The technical specifications of the biodigester, along with its associated outputs, including electricity generation, heat production, and fertilizer yield, are sourced from the ENERGICA demonstrator's data book, whose data are summarized in the following table.
Although data are available for both 1AD and 5AD biodigester configurations, the system dynamics assessment will focus on the 1AD case as the reference option. This choice keeps the model structure clear and manageable while reflecting a modular solution that is generally more accessible and scalable from an investment perspective.

Technical input	1AD biodigester	5AD biodigester
Feedstock consumption	220 t/year	1095 t/year
Electricity output	53 MWh/year	292 MWh/year
Fertilizer output	197.465 liter/year	987.690 liter/year
Electricity sale tariff	40 $/MWh	40 $/MWh
Heat sales tariff	25 $/MWh	25 $/MWh
Fertilizer sales price	1,25 $/Liter	1,25 $/Liter

Table 3 Biodigester technical specification in the demonstrator

The **annual local economic turnover** (ET) is calculated for a single biodigester to assess its financial impact. To determine its influence on the broader community, this yearly turnover is divided by the number of villages involved, offering a clearer representation of its territorial impact and the effectiveness of community engagement.
However, in business-oriented use cases, this approach does not apply, as the annual turnover directly supports the financial viability of the biodigester investment, reinforcing the business case.
A higher turnover concentration per village enhances secondary benefits, such as improved access to purified water through electricity generation, expanded heating facilities for both domestic and industrial use, and increased agricultural productivity due to the availability of organic fertilizer. These positive spillover effects strengthen community engagement and trust, fostering long-term participation in sustainable waste management and renewable energy initiatives.
Additionally, the annual local economic turnover is further boosted by the active involvement of the local workforce in both the manufacturing and operation of the biodigester. However, due to the lack of reliable quantitative data to accurately measure its impact, this factor is incorporated qualitatively in the analysis rather than through numerical estimations.

$$ET_{tot}(t) = \frac{ET_E + ET_H + ET_F}{N_V(t)}$$

Where:

- ET_E is the yearly revenue for electricity sales;
- ET_H is the yearly revenue for heat sales;

- ET_F is the yearly revenue for fertilizer sales;
- N_V is the number of villages involved.

Figure 20 illustrates how local economic turnover evolves over time under the different scenarios: it ranges from about $2,900/year to $7,600/year in 2025 across the three cases, and rises to roughly $19,000/year to $23,000/year by 2035.

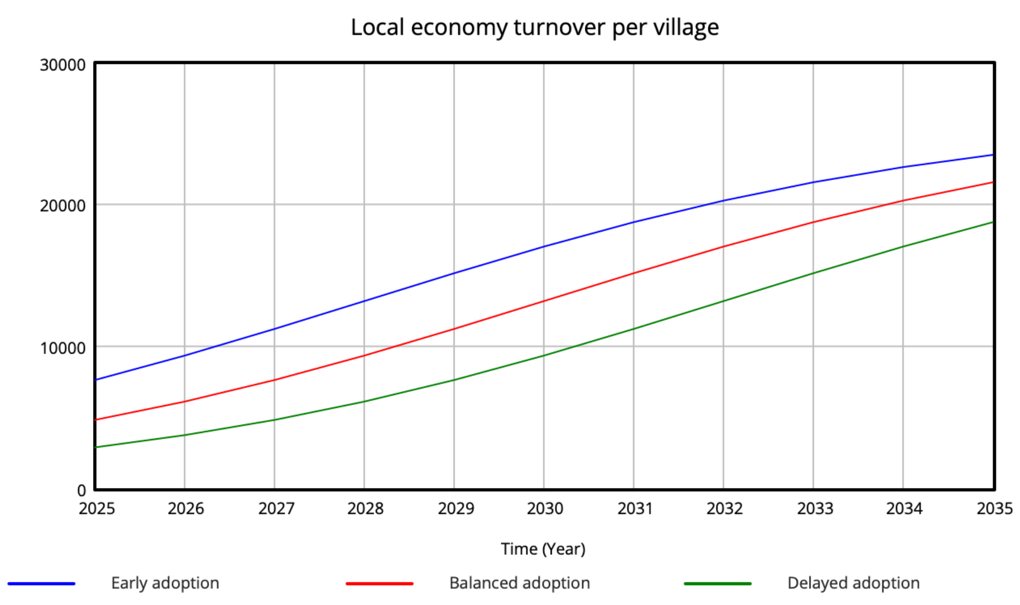

Figure 20 Local economy turnover in the different scenarios

As a conclusion, the key factor in the model is the **approach to food waste management**, where environmental education and awareness play a crucial role in driving positive change. Increasing public knowledge on sustainable waste practices can significantly improve participation rates. Additionally, economic incentives for proper waste management can further encourage communities to adopt and maintain efficient food waste collection and recycling practices, reinforcing long-term engagement and sustainability. These factors, highlighted in red in the model as qualitative variables, close the feedback loop, by reinforcing or adjusting the initial assumptions on the effectiveness of food waste management.

2.4.3 Solar powered e-mobility solution for motorcycle taxis in urban areas in Kenya

The electrification of local mobility offers numerous benefits, spanning environmental, social, and economic advantages. However, as seen in more developed countries, the transition to electric mobility often encounters challenges related to market and social acceptance, typically beginning with skepticism and reluctance to change.

This chapter investigates the System Dynamics of adoption of electric boda bodas in Kenya.

Figure 21 introduces the main drivers behind the adoption of electric boda bodas, including proven operational cost savings, better air quality, and improved comfort in day-to-day use. Awareness and social acceptance strongly shape riders' willingness to invest, while government policies and incentives help lower entry barriers. Flexible financing schemes can further enable uptake by making electric mobility more affordable and accessible.

Education and training initiatives can also speed up acceptance by strengthening peer effects and word-of-mouth diffusion. In this context, the innovation curve remains a useful lens to interpret the expected growth path of electric mobility, influenced by different levels of investment readiness and openness to adopting green technologies.

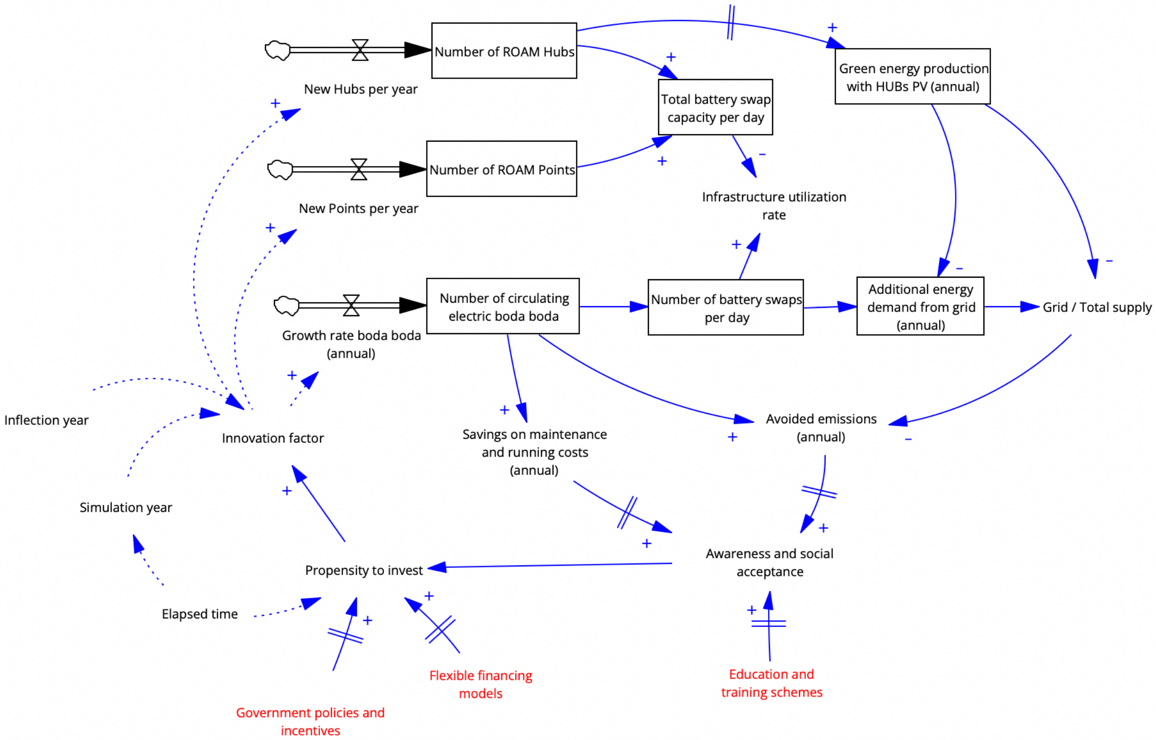

Figure 21 System Dynamics Electric Boda-boda electrification model

The model features three main flows: one representing the growth of electric boda bodas in the market and the other two related to charging infrastructure development, specifically the expansion of ROAM Hubs and Points.

These flows are interconnected, as they influence each other in a classic chicken-and-egg problem: while the adoption of electric vehicles depends on the availability of charging infrastructure, the expansion of infrastructure is often driven by growing demand for electric vehicles. However, in most cases, infrastructure needs to be established first to encourage the widespread adoption of electric boda bodas.

In the System Dynamics model, the first element modelled is the annual growth rate of boda bodas, which is represented by a decreasing innovation curve.

As seen in vehicle electrification trends in Europe, the market can experience rapid growth during the early adoption phase. However, as the market matures and approaches saturation, the growth rate typically slows down, reflecting the natural shift towards a more stable growth trajectory (IEA, 2025).

Figure 22 illustrates how the innovation curve changes across scenarios, with the inflection year shifting over time. Figure 23 shows the resulting impact on the growth rate of electric boda bodas, which varies accordingly across the scenarios.

$$I(t) = 1 - \frac{1}{1 + e^{-k\,(t - t_{inflection})}}$$

$$Gr_B(t) = Gr_{B_{avg}} * I(t)$$

Where:

- k is the growth coefficient, which controls the steepness of the curve. In the boda boda model, this is defined by the propensity to invest, which increases over time from 0.3 to a plateau of 0.8 as adoption increases (Aderiana Mutheu Mbandi et al, 2023);
- $t_{inflection}$ is the year when adoption accelerates the most. The model will simulate different scenarios which may be influenced by policy and regulation;
- $Gr_B(t)$ is the growth rate of boda bodas, as a function of the average growth rate, adjusted by the innovation factor, which evolves over time;
- $Gr_{B\,avg}$ is the average growth rate of boda bodas of 50% per year, as reported in ENERGICA data book.

The following table outlines different adoption scenarios, highlighting key factors that shape the inflection points and growth trajectories of electric boda bodas motorcycles in the coming years.
Leveraging the data from the ENERGICA data book from ROAM, the initial years are projected to see rapid growth, with annual increases reaching up to 50%. The growth rate decreases over time, following the rates defined by the innovation curves of the three different scenarios, presented in Table 4.

Scenario	**Inflection point**	**Key factors influencing adoption**	**Growth rate**
Early adoption	2032	Government incentives, affordable financing models, charging infrastructure expansion, strong awareness campaigns, and early adopters driving peer influence	Rapid growth
Balanced adoption	2030	Moderate policy support, growing but limited charging infrastructure, small-scale financing options, increasing awareness, and gradual social acceptance	Steady growth
Delayed adoption	2028	Lack of financing options, insufficient charging infrastructure, weak government incentives, low awareness, and social reluctance to transition	Slow growth

Table 4 Boda-bodas' growth scenarios

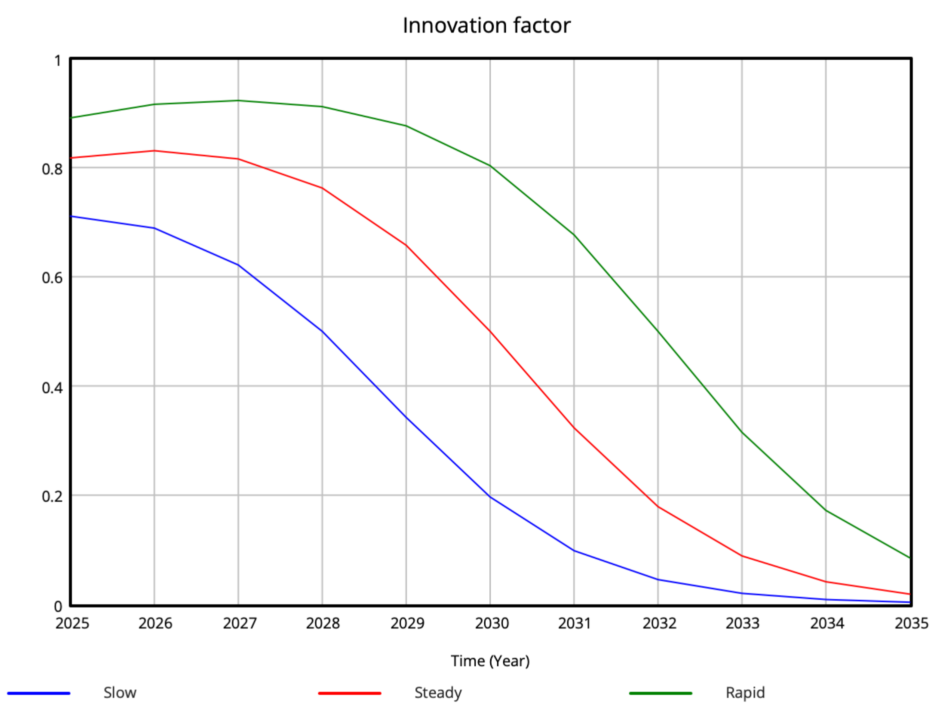

Figure 22 Reversed innovation curve shape for boda-bodas' growth

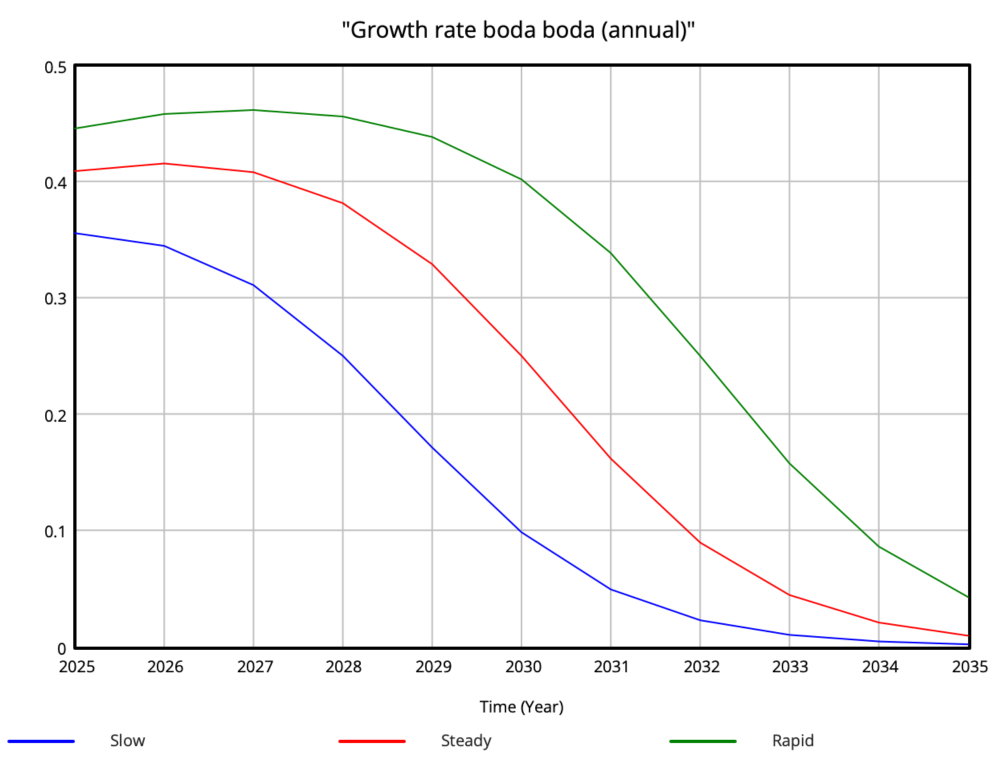

Figure 23 Boda-bodas' growth rate in different scenarios

The **total number of circulating boda bodas** is determined by integrating the annual growth rate over time, beginning from an initial baseline of 1000 bikes, as reported in ROAM data. This approach accounts for cumulative growth and provides a dynamic estimate of fleet expansion.

$$B(t) = B(0) + \int_{o}^{t} Gr_B\,(t) * B(t)\,dt$$

Where:

- $B(0)$ is the initial number of circulating boda boda, 1000 bikes;
- Gr_B(t) is the growth rate of boda boda as previously introduced;
- $B(t)$ is the number of circulating boda boda at time t, as the circulating fleet will increase.

Figure 24 depicts the projected growth of circulating electric boda bodas from 2025 to 2035 under the three different adoption scenarios. The **Slow Growth** scenario (blue line) shows a gradual increase, reaching slightly above 4000 by 2035, indicating a more conservative adoption rate. The **Steady Growth** scenario (red line) follows a moderate trajectory, surpassing 8000 by the early 2030s before tapering off towards 2035. In contrast, the **Rapid Growth** scenario (green line) demonstrates exponential expansion, with numbers exceeding 18000 by 2035, reflecting accelerated adoption due to factors like policy incentives, infrastructure expansion, and cost reductions.

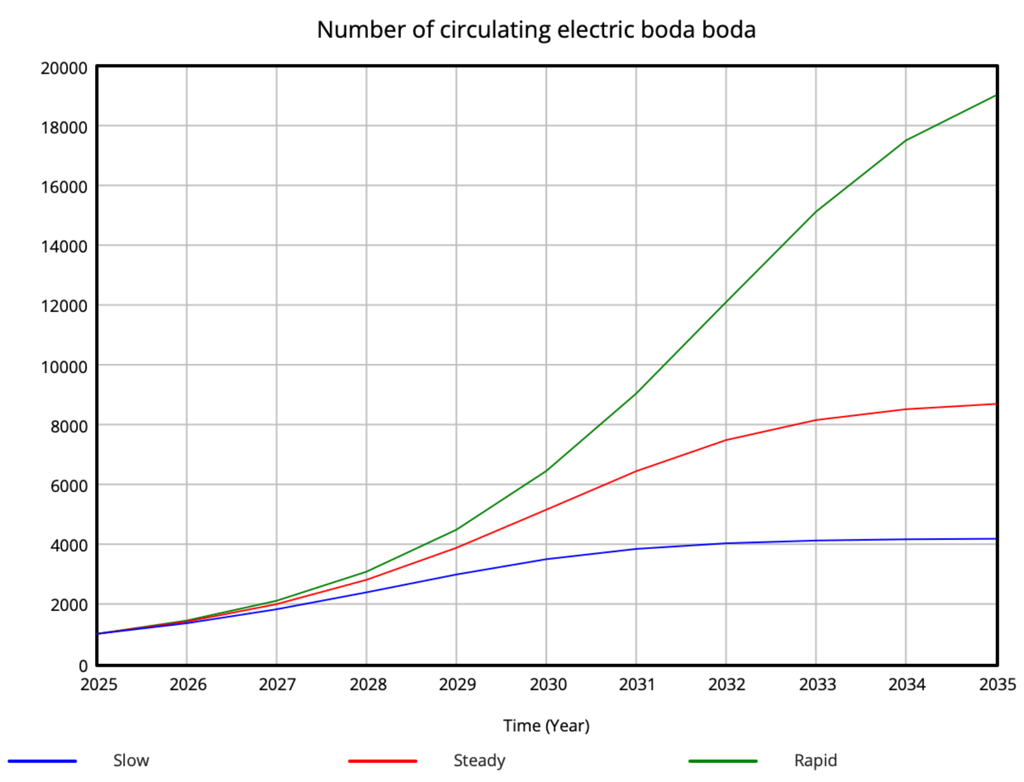

Figure 24 Number of circulating electric boda boda in the different scenarios

As the adoption of electric Boda Bodas increases in Kenya, there is a growing need for a robust battery-swapping infrastructure to support this transition. Given that each electric boda boda requires approximately **1 -2 battery swaps per day**, ROAM Hubs and ROAM Points should handle the demand efficiently.

Figure 25 shows how the number of battery swaps evolves across the different scenarios.

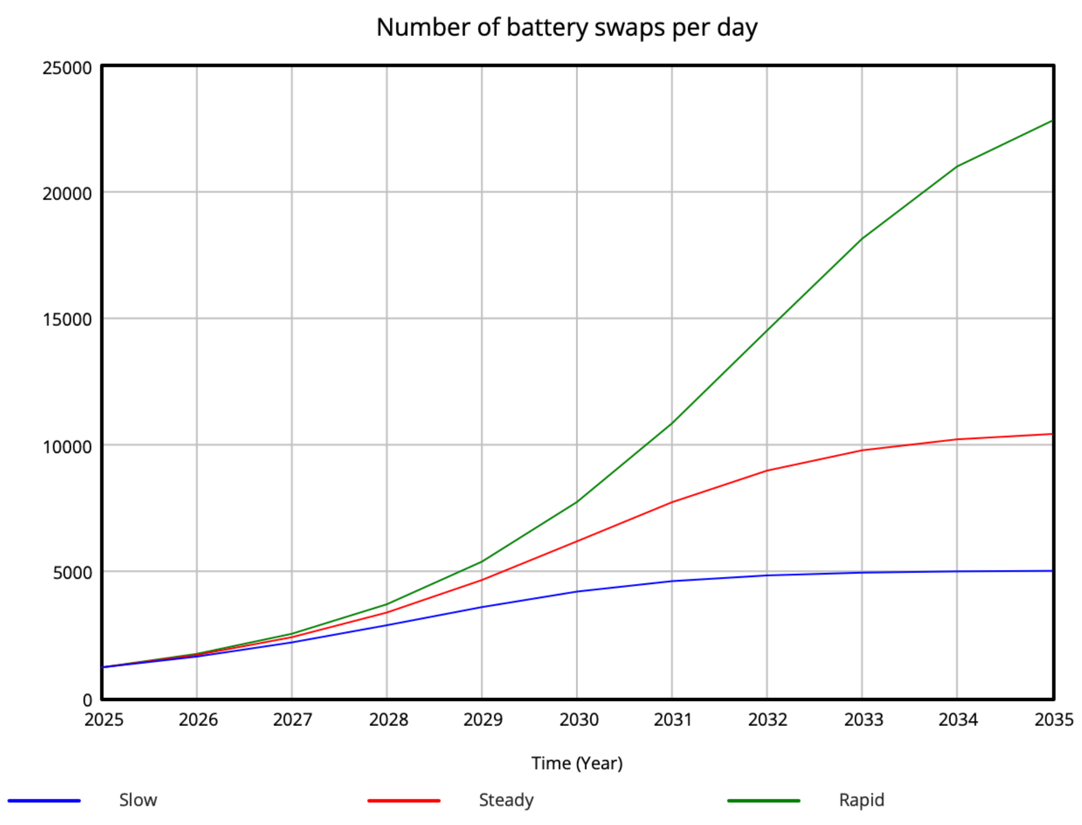

Figure 25 Number of battery swaps in the different scenarios

ROAM Hubs and **ROAM Points** serve different roles in supporting the electric boda boda ecosystem. **ROAM Hubs** are large, centralized facilities that offer battery swapping, charging, maintenance, and customer support, capable of handling hundreds of swaps per day (**200-500 swap/day**). In contrast, **ROAM Points** are smaller, decentralized stations primarily focused on quick battery swaps, allowing riders to exchange batteries efficiently without extensive services (**50-150 swap/day**). Average data is used as the basis for the simulation.

Figure 26 shows a standard ROAM Hub installation, serving as the central focus of the ENERGICA demonstrator.

Figure 26 ROAM Hub in Kenya

A well-developed charging network is essential for mass electric bikes adoption, yet its expansion often lags behind vehicle growth due to investment constraints, policy delays, and uncertain demand projections. At the same time, electric bikes adoption itself is hindered by the lack of visible and accessible charging stations, as potential users hesitate to switch without confidence in a reliable charging network.

In the data book, ROAM establishes the minimum annual installation rate for new Hubs and Points, setting a baseline of 6 Hubs and 12 Points per year. As of 2024, the network has already expanded to include 10 Hubs and 2 Points, marking an initial step toward scaling the infrastructure.

However, beyond just the number of installations, the effectiveness of the charging network also depends on strategic placement, accessibility, and visibility of these hubs. A poorly located hub, even if available, may not effectively serve users or encourage EV adoption. This model does not account for these spatial and behavioural factors, which are critical in determining how well the infrastructure supports real-world usage and confidence in electric mobility.

To model a realistic growth trajectory for the infrastructure, the same innovation curve used for boda bodas is applied to Hubs and Points. This results in a plateau-shaped growth pattern across the three different scenarios, capturing the initial rapid expansion phase followed by a gradual stabilization as the system matures, as shown in Figure 27 and Figure 28.

Initially, most swaps are handled by hubs, as early adoption requires strong infrastructure, centralized technical support, and rider education. However, as electric motorcycles become more widespread, the demand for convenience and accessibility increases. Over time, the network of ROAM Points expands, reducing the dependency on centralized hubs. This shift enables a faster, more flexible battery-swapping system, where riders can access a swap station almost anywhere, similarly to how fuel stations currently operate. Eventually, a wide portion of swaps occur at Points, ensuring a dense, easily accessible network, while hubs focus on servicing, repairs, and high-demand urban centres.

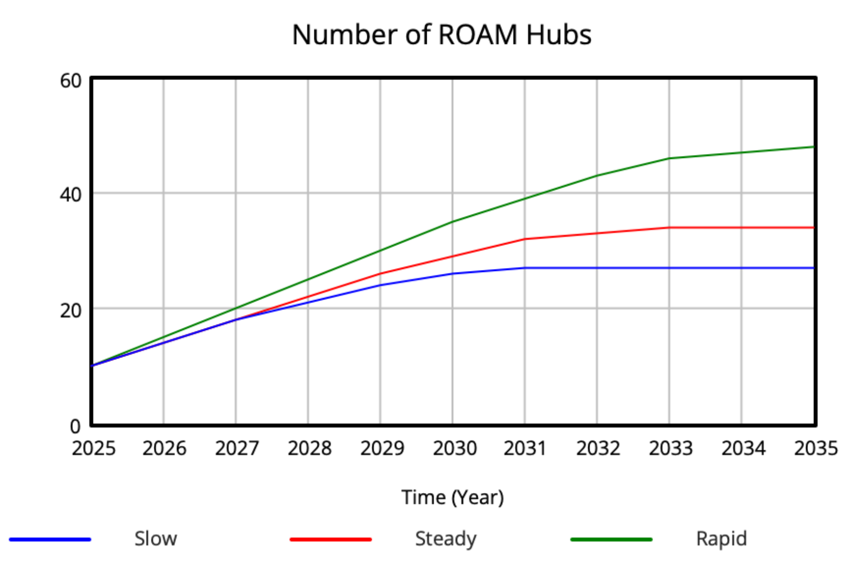

Figure 27 ROAM Hubs growth in different scenarios

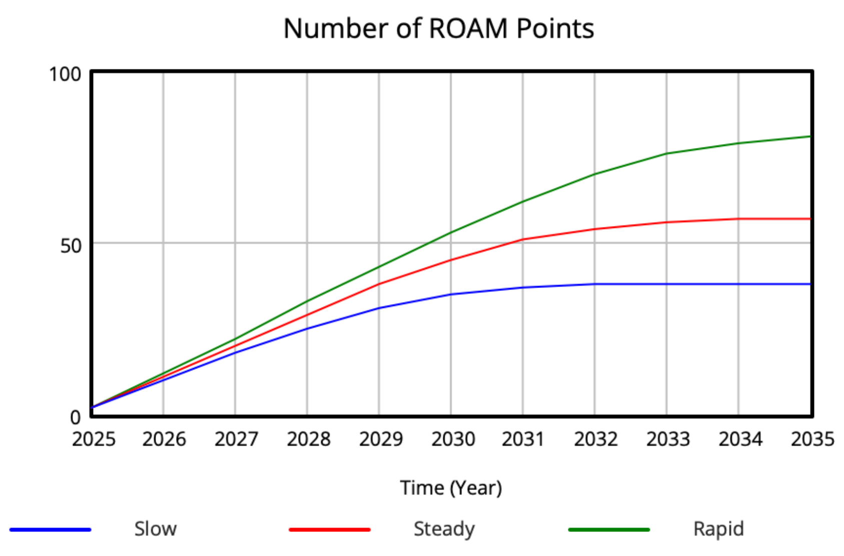

Figure 28 ROAM Points growth in different scenarios

By considering the total battery swap capacity per day provided by Hubs and Points, the **infrastructure utilization rate** can be determined. This is calculated by dividing the daily number of battery swaps by the total daily swap capacity, indicating how effectively the infrastructure meets users' needs.

$$U_R(t) = \frac{S_d(t)}{S_{tot}(t)}$$

Where:

- U_R is the infrastructure utilization rate;
- $S_d$is the daily number of battery swaps changing according to the growing circulating boda bodas' fleet;
- S_{tot} is the total daily swap capacity, growing as more swapping hubs and points are installed.

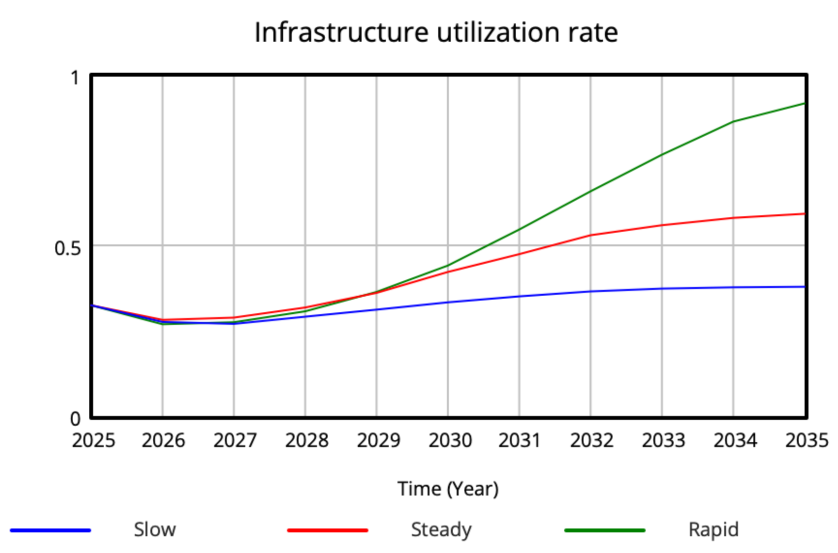

Figure 29 Infrastructure utilization rate in different scenarios

The infrastructure utilization rate trends, shown in Figure 29, highlight the delicate balance between expanding battery-swapping infrastructure and the adoption of electric boda bodas. Initially, all scenarios show a slight decline, suggesting that early infrastructure investments may outpace demand. However, as electric boda bodas adoption increases, utilization rates rise, with the Rapid scenario demonstrating the highest growth, while the Slow scenario risks underutilization and bottlenecks. The Steady scenario offers a balanced approach, preventing both overuse and inefficiencies.

These findings suggest that ROAM's infrastructure growth rate suits the Rapid scenario but may require adjustment if boda boda adoption is slower than expected. A flexible, data-driven approach, considering not just the number but also the placement, accessibility, and visibility of hubs, is crucial to ensuring sustainable EV growth.

ROAM Hubs are designed to incorporate **solar photovoltaic** (PV) systems to lower electricity costs, enhance sustainability, and ensure uninterrupted operation during blackouts. Each hub integrates a 6 kWp solar PV installation, capable of generating approximately 10 MWh per year, which supplements the primary electricity supply from the national grid.

Figure 30 shows how green energy production can grow over the years in the different scenarios, reaching a plateau of 270 MWh/year in the slow scenario, growing to 480 MWh/year in the rapid scenario.

This solar setup helps alleviate the load on the grid but is insufficient to fully meet the energy demands of electric mobility. While each swapping station operates on a regular three-phase grid connection, it must be located where the grid is stable and, ideally, equipped with a diesel generator as a backup to ensure continuous service. This hybrid energy approach optimizes efficiency, minimizes operational costs, and strengthens the reliability of the charging infrastructure.

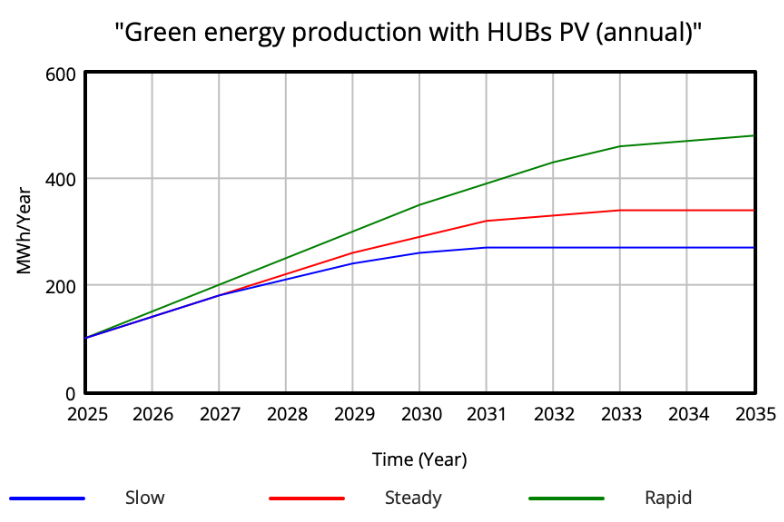

Figure 30 Green energy production from PVs in HUBs

The electric motorcycles used in the Kenyan demonstrator are equipped with a 2.7 kWh swappable lithium-ion battery, providing an estimated range of 90 km per charge. These modular lithium-ion batteries were selected for their higher lifespan and efficiency. The **additional electricity demand** is estimated by multiplying the battery capacity (2.7 kWh) by the average number of swaps per day (1.2 swap/day), providing an approximation of daily energy consumption (ROAM Motorcyles, 2025).

Table 5 shows a comparison of the key features of electric and traditional gasoline boda bodas.

Feature	Gasoline boda boda	Electric boda boda
CO_2 emissions (g/km)	120	0 if solar powered 23 if grid powered
NO_x emissions (g/km)	0.2 - 0.5	0
PM emissions (g/km)	0.05 - 1	0
CO emissions (g/km)	1 – 5	0
Operational lifespan	5-7 years	7 –10 years
Noise pollution	High	Low
Maintenance (M)	0,05 USD/10km	0,035 USD/10km
Running costs (R)	0,288 USD/10km	0,08 USD/10km

Table 5 Electric vs gasoline Boda-boda comparison table

Reports estimate that annual CO_2 emissions from the whole Nairobi's transport sector are approximately 4.80 $MtCO_2$, emphasizing the need for sustainable mobility solutions (Aderiana Mutheu Mbandi et al, 2023).

Nairobi's high vehicle density, severe traffic congestion, and dependence on fuel-powered transport make the sector a significant source of emissions. The adoption of electric boda bodas presents a promising solution for improving air quality by reducing both long-term CO_2 emissions and immediate pollutants such as nitrogen oxides (NO_x), particulate matter (PM), and carbon monoxide (CO). While CO_2 reductions have broader environmental benefits, the decrease in NO_x, PM, and CO directly enhances urban air quality, leading to reduced smog, improved respiratory health, and lower overall pollution levels.

However, transitioning to electric boda bodas does not equate to a zero-emission shift, as indirect emissions from electricity generation depend on the energy mix used for charging.

To quantify this impact, the System Dynamics model estimates the **avoided CO_2 emissions** from the adoption of electric boda bodas, as shown in Figure 31.

The model calculates the emissions avoided by replacing gasoline-powered motorcycles with electric ones while also incorporating the residual emissions from grid electricity use. The local grid's emission intensity is factored into the analysis, ensuring a more accurate assessment of the net environmental benefits of electrification (Energy and Petroleum Biannual Statistics Report, 2025).

$$AE(t) = B(t) * \ Average\ km\ range * (AE_G - AE_E * E_G)$$

Where:

- AE are the avoided CO_2 emissions;
- B is the number of circulating boda bodas;
- $Average\ km\ range$ is given by ROAM data;
- $AE_G\ and\ AE_E$ are respectively the CO2 emissions from gasoline boda boda and from electric boda boda powered from grid;
- E_G is the % of energy taken from the grid for boda boda operations, which is the total energy demand minus the energy locally produced by PV installed on ROAM Hubs.

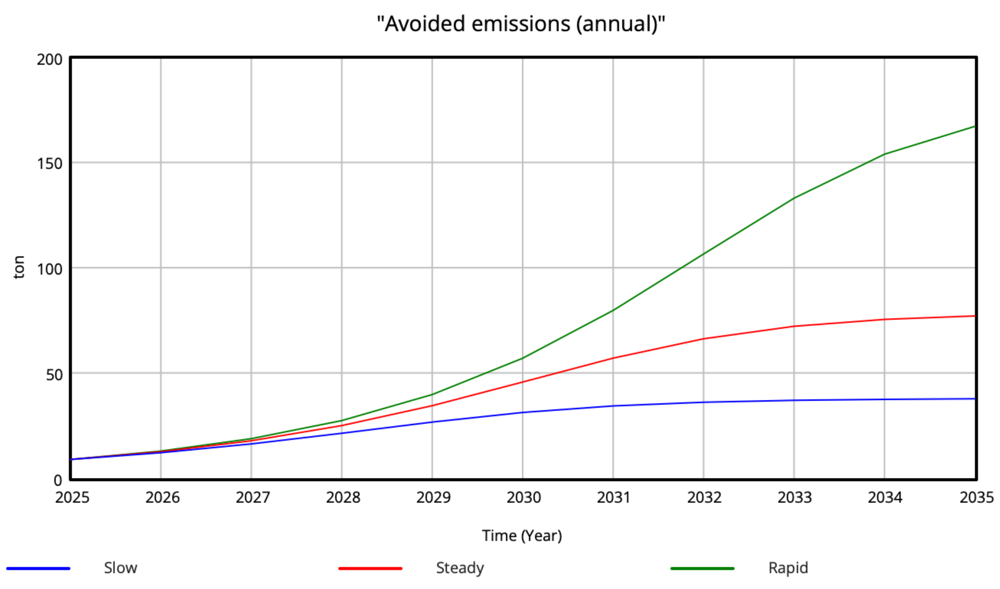

Figure 31 CO2 avoided emissions with boda boda electrification

Electric boda boda also present significant **advantages in terms of maintenance and operational costs,** offering riders a compelling way to offset the higher initial purchase price compared to traditional gasoline-powered models. With lower fuel and servicing costs, electric motorcycles become more cost-effective over time. This gradual reduction in the price gap provides long-term financial benefits, making the switch to electric increasingly attractive. Figure 32 shows the savings curve under the different scenarios.

Insights gathered by ROAM at the local level indicate that cost savings are the primary driver behind the shift to electric mobility, even more than environmental considerations. The financial benefits of electric boda bodas not only encourage individual riders to make the transition but also strengthen word-of-mouth advocacy, further propelling the shift to electric transportation.

Reference data are taken from the ROAM table previously presented.

$$S(t) = B(t) * \left(\left(M_{gasoline} - M_{electric} \right) + \left(R_{gasoline} - R_{electric} \right) \right)$$

Where:

- B is the number of electric boda-bodas as previously defined;
- $M_{gasoline}$ and $M_{electric}$ are the maintenance costs respectively for gasoline and electric motorcycles;
- $R_{gasoline}$ and $R_{electric}$ Are the running costs respectively for gasoline and electric motorcycles.

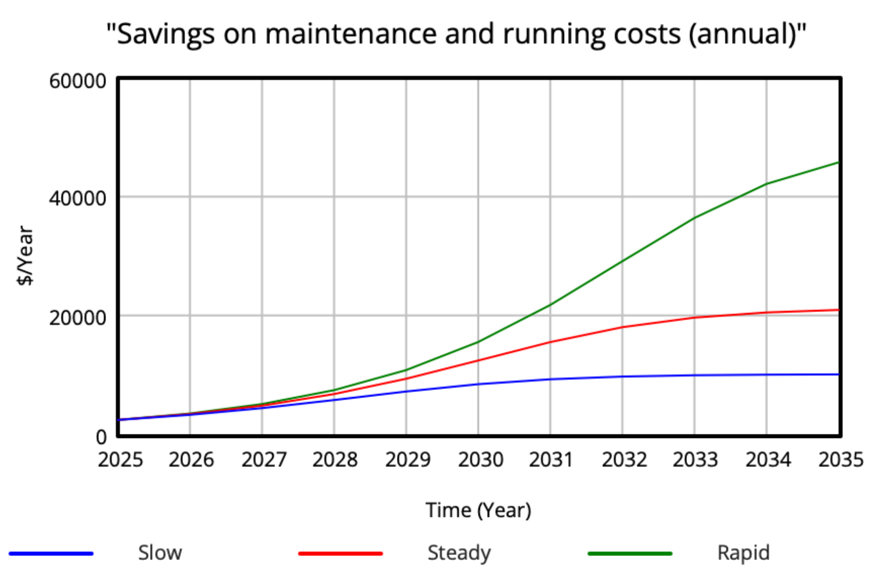

Figure 32 Maintenance and running cost savings in the different scenarios

As awareness of the economic and environmental benefits of electric boda bodas grows, **social acceptance** also improves. Boda bodas' riders, highly sensitive to daily operating costs, are primarily driven by financial savings, as lower fuel and maintenance expenses directly increase their profits, making affordability a key motivator for adoption. In contrast, while air pollution reduction benefits the whole population, it is less immediately perceptible to individual riders. A cleaner urban environment improves public health over time, but it does not offer instant personal financial gains, making it a weaker initial driver of adoption.
Additionally, while concerns over air pollution and emissions are rising, economic survival remains the top priority for most riders. Since respiratory health improvements and smog reduction take months or even years to become evident, environmental benefits alone are not enough to drive mass adoption.

By integrating **education and training programs** with **robust policy support**, such as targeted **incentives and flexible financing models**, the willingness to invest in electric boda bodas can be greatly enhanced. Government-backed initiatives like subsidies, tax incentives, or reduced import duties can help offset initial purchase costs, while financing options such as affordable monthly rental rates, which can be covered by the savings on fuel and maintenance, make the transition more accessible. As the number of electric motorcycles on the road increases, heightened visibility and awareness will reinforce the shift towards electric mobility, creating a positive feedback loop that drives further adoption.

2.5 Results discussion and conclusion

The system dynamics assessment across the three demonstrators confirms that technology performance alone does not determine uptake. In all cases, diffusion is primarily shaped by reinforcing feedback loops that link affordability, user experience, and peer effects, while balancing loops emerge from infrastructure constraints, limited access to capital, and institutional barriers. As a result, the transition dynamics are nonlinear: early-stage interventions have disproportionate impact, and small shifts in the timing of "tipping points" can materially change adoption trajectories over the full simulation horizon. Across the three demonstrators, three recurring patterns stand out:

- **Adoption is constrained by “entry conditions” rather than long-term potential.** Even when the long-run benefits are positive, uptake remains slow if users face high upfront costs, limited financing, low awareness, or uncertainty about reliability and after-sales support. Once early barriers are reduced, reinforcing loops accelerate diffusion through learning effects, trust building, and word-of-mouth.
- **Infrastructure readiness acts as a system bottleneck.** In each demonstrator, supply-side capacity and operational readiness determine whether demand converts into sustained adoption. When infrastructure scales too slowly, unmet demand dampens social acceptance and reduces willingness to invest, delaying the inflection point and flattening growth.
- **Policy and financing are high-leverage variables.** Scenario comparisons consistently show that targeted incentives, risk reduction mechanisms, and flexible financing have a larger effect than marginal improvements in technical performance. Policies are most effective when designed to reduce early uncertainty and lower the initial investment hurdle, rather than only rewarding late-stage scale. The scenario set highlights that the main difference between pathways is often **the timing of the inflection year**, not the ultimate direction of change. Shifting the inflection year earlier triggers faster growth rates and earlier realization of benefits, while delayed inflection results in slower uptake and a longer “valley of hesitation.” This is consistent with innovation diffusion dynamics: changes in awareness, willingness to invest, and enabling conditions translate into different curve shapes, which then propagate through linked variables such as local economic activity, service availability, and environmental impacts.

In practical terms, this means that interventions that appear incremental at the individual level can be decisive at system level if they move the system past critical thresholds (for example, minimum service coverage, minimum reliability levels, or minimum affordability).

The system dynamics approach is most valuable for comparing trajectories and identifying leverage points. At the same time, results depend on parameter assumptions, proxy variables, and the representation of delays. The most important uncertainties typically relate to financing conditions, policy stability, and operational performance in real-world settings. A pragmatic next step is to use the demonstrator evidence to iteratively calibrate the model, and to expand sensitivity testing around the variables that most strongly shift the inflection year.

Overall, the combined results support a clear strategic takeaway: the fastest pathway is the one that reduces early uncertainty and upfront barriers, while scaling the enabling ecosystem in parallel with demand. This aligns technical deployment with the social and economic conditions required for sustained adoption across all three demonstrators.

3. RISK ASSESSMENT

3.1 Introduction

3.1.1 Background

Despite ongoing efforts, achieving the Sustainable Development Goals (SDGs) by 2030 requires increased investment to meet the ambitious targets set for this agenda and beyond. In line with SDG 7 (Affordable and Clean Energy), the International Energy Agency (IEA) estimates there is a need to increase renewable energy (RE) investments to approximately USD 600 billion worldwide by 2030 to ensure universal energy access while meeting climate change targets, with a substantial contribution expected from the private sector (IEA, 2023 and Donastorg et al., 2017). However, limited RE investments may be attributed to capital intensity and unattractive risk-return profiles, where *risk* is understood in accordance with ISO 31000 as the effect of uncertainty on an organisation's ability to meet its objectives (Abba et al., 2022). Energy projects, particularly in development contexts, operate within complex structural and institutional environments that generate uncertainties and risks affecting the sustainable execution of project activities and the delivery of envisaged outputs (Abba et al., 2022):

i) Risks in RE projects are complex and necessitate multidisciplinary perspectives for their management, which implies evaluating different dimensions such as environmental, social, technical, regulatory, and economic etc.

ii) RE risks are not independent but they interact and feedback with other risks, actors, and their actions. This translates into assessing the bilateral character of a project in constant interaction with its environment, not only exposing the project towards risks from its environment but as well exposing the environment to risks originating from the project activities, and

iii) RE investment decision risks, their occurrence, and impact to the project are associated to high uncertainty given the capital and technology intensive character and the lack of information about the market history.

The assessment of risks, understood in line with ISO 31000 as the systematic analytical process to identify, analyse and evaluate risks, is a critical component of energy project management to ensure project viability, safety, and sustainability. Furthermore, risk assessment allows investors to make better informed decisions which is crucial to increase adoption rates and implementation of RE technologies.

3.1.2 Aim and scope

In the context of the ENERGICA project, three demonstration sites provide empirical insights into the complexities of implementing different renewable energy-powered solutions, providing the basis for the development of an adequate risk assessment approach. These technologies have significant potential to contribute to energy development in the regions where they are implemented, as well as in regions with similar social and environmental characteristics. The aim of the following analysis is to conduct a holistic and replicable risk assessment for investment decisions, envisaged at each of the three activities on the sites:

- Nanogrid development and implementation to provide effective access to electricity and support productive uses of energy in rural Madagascar
- Low-tech efficient biogas system in Sierra Leone
- Solar powered e-mobility solution for motorcycle taxis in urban areas in Kenya

To this end, the assessment adopts the perspective of investors or other decision-making entities evaluating the business activity under investigation in terms of its investment attractiveness. Notably, the methodology is limited to assessing risk threatening the business and energy activity, rather than emerging from the activity itself, such as potential environmental impacts (e.g. risks related to e-waste disposal). These latter risks are captured in a separated analysis, namely the Life Cycle Assessment, which will be reported in a separated Deliverable (D8.1).

To present the methodology and results of this analysis, the report is structured as follows. Section 3.2 describes how the risk assessment framework was defined, drawing on insights from the literature review and initial assumptions that focus the assessment on developing countries and RE projects. Moreover, this section outlines the approaches used for risk identification, analysis and evaluation. Here, the seven different clusters are introduced as environmental, social, technical, political, regulatory, market and financial. Later, the applied combination of semi-quantitative methods is explained, specifically the DEMATEL (Subsection 3.2.2.1) and Analytic Network Process (ANP) (Subsection 3.2.2.2) methods. Section 3.3 presents and discusses the results for each demonstration site obtained from workshops with experts and survey data, including the prioritisation of risks and the analysis of interdependencies. Finally, Section 3.4 synthesises the main findings, discusses their implications for investment decision-making, and highlights limitations and directions for future applications of the risk assessment framework.

The framework aims to ensure replicability and comparability of results. Nevertheless, risks are inherently context-specific, and projects must therefore be reviewed on a case-by-case basis.

While some of the identified risks may be influenced by strategic decisions and their respective impact can be quantified with scenario or sensitivity analysis, others cannot be influenced and are unpredictable or very uncertain. Statistical analyses, such as Monte Carlo simulation, are a suitable tool to understand the potential impact of changing key aspects on the outcomes of the project. Therefore, results presented on this report connect to those of deliverable D7.3, where a thorough scenario analysis was carried out to evaluate the impact that fluctuations on economic parameters may have on the financial sustainability of the project activity.

3.2 Methodology

According to ISO 31000, risk management is a systematic and iterative process aimed at addressing the effects of uncertainty on objectives, within which risk assessment plays a central role by identifying, analysing, and evaluating risks to support informed decision-making. Effective risk management includes (i) establishing the context, (ii) risk assessment, (iii) risk treatment, (iv) monitoring and review, and (v) communication and consultation (ISO, 2009). Risk assessment is conceptualised as a three-step process that includes (i) risk identification, identifying sources of risk, events, causes, and potential consequences that may affect objectives; (ii) risk analysis, examining the nature of identified risks, including their likelihood and impact; and (iii) risk evaluation, comparing analysed risks against predefined criteria to determine their significance and to support prioritisation and decision-making.

Risk assessment is not an end in itself, but a means to inform risk treatment options such as mitigation, transfer, acceptance, or avoidance. Figure 33 illustrates selected methods available in scientific literature for risk identification, analysis, and evaluation, with the methods applied in this study highlighted in orange:

Risk assessment methods are diverse and can be combined in different ways depending on the specific context of the project, information available and means to collect it. Figure 34 summarizes key elements that were part of the main stages of this assessment, namely the identification and analysis that are to be thoroughly explained in the next subsections.

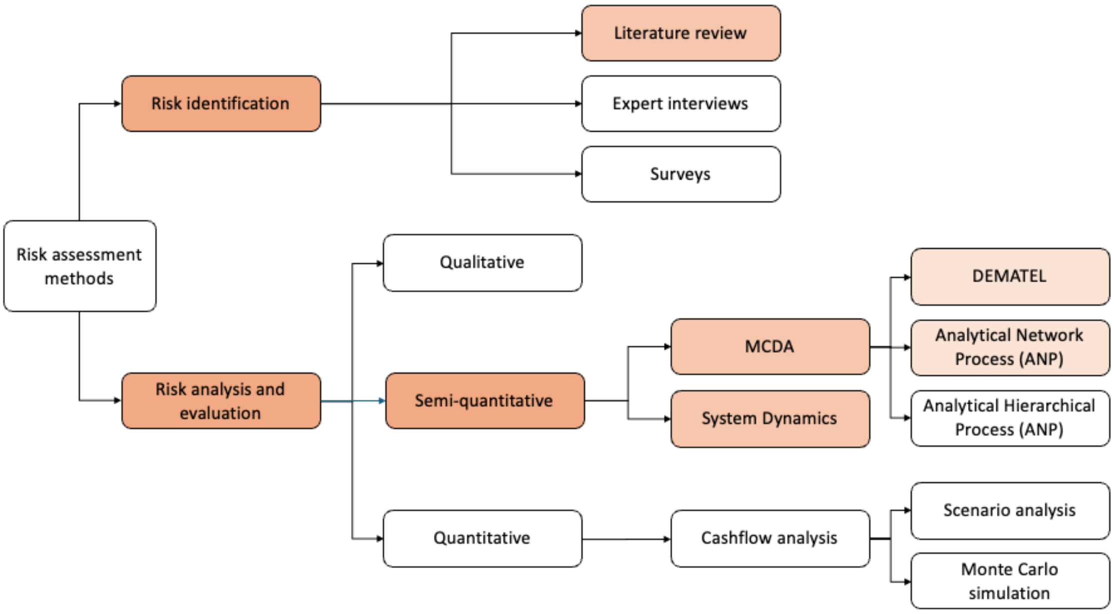

Figure 33 Overview of renewable energy project risk assessment methods in the reviewed literature

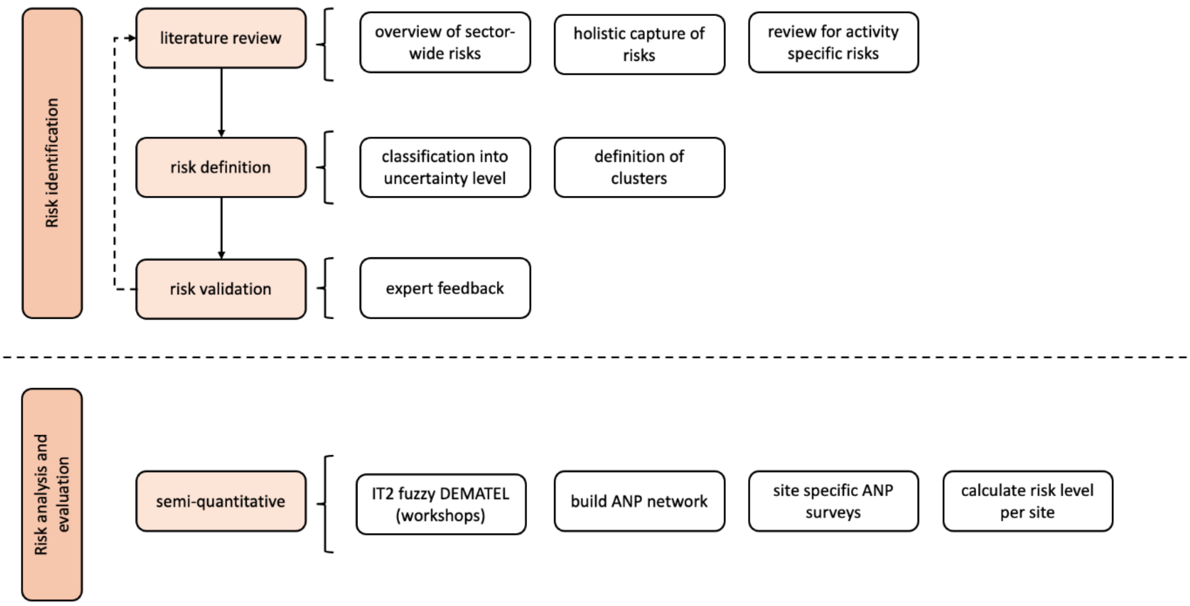

Figure 34 Summary of methodology applied in this analysis.

3.2.1 Risk identification

To bring forward a holistic risk assessment framework that would fit the context of the three projects, the literature review included interdisciplinary studies where different methods were used for identifying sources of risk, events, causes, and potential consequences that may affect investment decisions and success of business activities.

Various approaches to risk identification have evolved within the literature. Painuly (Painuly, 2001) suggests that popular approaches to risk identification include literature review, expert interviews or workshops, and site visits. As an efficient way to gather evidence on potential risks of RE investment, and in the challenge of not missing any potential risks, while at the same time incorporating national, regional or even local specialities, we applied a three-stepped literature review:

a) First step was focused on getting an overview of sector-wide risks. We consulted literature that provides a general overview of RE investment risks in developing context. Such papers were found via consulting the scientific database “Science direct” and conduct a rapid review based on various combinations of the key words “renewable energy”, “energy system”, “energy system planning” AND “risk”, “risk management”, “investment risks”, “barriers”. During this review, we focused on papers that at least to a significant extent present the results of a literature review in the respective field. We only considered papers written in English, and which are not older than 2020, given the dynamic character of RE investments and their environment. We further applied a geographical filter and only considered papers focusing on markets in the Global South.

b) Secondly, we snowballed the identified papers to capture all possible risks within the given project timeline. Data from the relevant papers was structured on Excel according to the information required, such as dimension and level of uncertainty. We found that most studies used a techno-economic approach, we decided to implement a holistic approach to consider other dimensions of risk that are usually overlooked. This provided a base for our list of clusters and classification of risks. All potential risk factors that were found during the literature review were listed and in combination with experience in demonstration sites we obtained a total of 96 risk factors grouped in 7 clusters

c) While the first two steps aimed to capture risks on the energy sector level, the third step relied on a more specific semi-structured review on energy using key-words specific to the activity of the projects, i.e. electric vehicle charging, or rural electrification. This, in combination with expert feedback and the System Dynamics tool presented in the first part of this report, allowed to narrow down the list of risks to be considered in this study to a total of 33

Prominent examples propose different classifications of risks, for example the one by Bhattacharyya (Bhattacharyya, 2018), who defined technical, policy, financial, revenue, and political risks as factors impacting mini-grid implementation to scale in developing countries. Wu et al. (Wu et al., 2020) proposed technical, political, economic, resource, social/environmental and China context-specific risks for evaluating RE projects investment risk at a national level. Schmidt et al. (Schmidt et al., 2013) additionally considered risks according to barriers that stem from stakeholders at local, national, and international levels along revenue sources.

For the purpose of this study, we adjust a classification of risks formulated by Abba et al. (2022) to fit the context of the three demonstrators and distinguish risks within 7 categories:

- Technical risks: risks arising from factors related to the type of technology and its specificities, including technology maturity, resource capacity and factors that can affect the technical design, implementation and performance
- Policy and regulatory risks: refer to uncertainties in meeting project objectives due to legal frameworks, policies, or regulation changes
- Political risks: Refer to potential barriers to achieve objectives posed by the political context. This includes political instabilities, embargoes, corruption, political change or events resulting from specific actions of the government or society or from changes in law, policy, regulation, or the economic environment experienced in host countries
- Economic and financial risks: economic or financial factors that impact the project value or deployment. These can include changes in the economic environment on the macro level, e.g., currency fluctuation, uncertainties in accessing appropriate financing, revenue uncertainty
- Social risks: Risks emerging from unexpected social aspects, or the changes in social conditions, including e.g. public resistance, lack of social acceptance and lower technology adoption
- Market risks: the potential for financial loss arising from broad market factors that affect the dynamics of the market environment of the business
- Environmental risks: risks occurring from changes in environmental conditions, including climate disaster and climate events

3.2.2 Risk analysis and evaluation

RA involves understanding the causes, probabilities of occurrence and impact of risks. Several methods have been developed for RA (see an overview in Abba et al., 2023), broadly to be classified in qualitative and quantitative, or semi-quantitative methods.

Qualitative RA methods build on subjective methods and assessments to assess the probability and impact of risks. This often includes the combination of literature review, and exploratory interviews. In contrast, quantitative RA methods use statistical data and probabilities to determine risk levels, consequence analysis and risk reduction via numerical or computer-based models. Prominent methods that have been used to assess risks in RE projects, include Monte Carlo simulation (MCS), Sensitivity analysis (SA) combined with techno-economic (TE)/ cashflow analysis, and agent-based modelling (ABM).

- Techno-economic assessments, as conducted in Deliverable D7.3, aim to capture the economic potential of a project by thoroughly combining technical parameters and financial metrics. KPIs are used to quantify the potential in terms of financial viability. To strengthen the robustness of techno-economic assessments, the effect of fluctuations of certain paraments are often tested via sensitivity analysis, which varies these inputs within a certain defined corridor amongst the reference value. Alternatively, Monte-Carlo simulation (MCS) is a method that allows for uncertain input parameters and can be employed to produce probabilistic valuation models which incorporate risk.
- ABM is a dynamic model consisting of agents with an ability for learning. It allows representation of behaviours of agents such as investors, consumers and policymakers and their interactions over time. In literature, ABM is mainly used to determine the effectiveness of risk mitigation approaches.

Conversely, semi-quantitative methods assess have the flexibility to consider statistical and non-statistical risks. Risk analyses with these methods are typically characterised by interviews and placing numerical values to risk levels and priorities. Tools used for such semi-quantitative RA include exploratory and structured interviews, MCDA, and System Dynamics approach.

- Structured interviews in RE investment RA have been used to validate, and to prioritize risks. For example, Egli (2020), aiming to identify and refine findings on the most important risks, applied structured interview to collect perceived importance of priorly identified risks The authors applied the Borda count method to rank the risks and estimate their relevance. Other scholars (Mozuni, 2017) applied the Delphi expert method to estimate the importance of a set of risks.
- With a similar goal, to establish a ranking out of a set of alternatives, multi-criteria decision analyses (MCDA) are commonly applied to establish a plausible ranking of the severity, or occurrence of risks to RE investments. MCDA are a family of methods for decision support that can incorporate multiple actors' opinions to elucidate relationships such as priority and outranking between risk factors. They include methods such as Analytical Hierarchical Process (AHP) and Analytical Network Process (ANP), which allow to identify dependencies between risk factors and present flexibility when combined with interviews.
- To identify risks and influencing factors towards a defined indicator, System Dynamics (SD) has been used in RA. SD is characterised by feedback loops and time delays to model complex system behaviours. The method can be used for sensitivity analysis and scenario simulations. For a more detailed explanation of the SD approach, we refer to Section 2.2 above.

To account for interdependencies between risks, and according to suggestions from several studies, semi-quantitative methods, specifically the MCDA are an adequate option to conduct our risk analysis.

Specifically, we combined

a) Decision making trial and evaluation laboratory (DEMATEL) is a semi-quantitative method used to model directional cause-effect influences among factors by conducting pairwise comparisons between them. It has been used by several scholars for risk assessment due to the advantage of showing causality relationships between variables (Qiu, 2020) IT2 fuzzy DEMATEL was considered to find significance levels of the systematic risk criteria.

b) Analytical Network Process (ANP) is an extension of the Analytical Hierarchy Process (AHP) and are both part of the many different Multi-Criteria Decision Making (MCDM) methods. ANP was deemed suitable for our risk analysis because it is capable to deal with relationships among or within groups of criteria. The DEMATEL method was used in combination with ANP to effectively build the causal relationship of criteria. ANP can provide benefits in calculating criteria priorities and their relations Büyüközkan, 2016).

c) Techno-economic assessment including Monte-Carlo simulation. For complex uncertainties, not to be influenced by strategic decision making of the business, MCS is a useful method to feed techno-economic assessment with a plausible set of scenarios and investigate their impact. While the MCS provides possible input parameters, the techno-economic assessment will finally produce results of the impact on economic KPIs as defined within the techno-economic calculations (see Deliverable D7.3).

3.2.2.1 DEMATEL method

An overview of the DEMATEL approach is given in Figure 35. With this technique, it was possible to distinguish between cause-and-effect factors and to quantify the strength of influence between them. The values were gathered through two structured expert workshops conducted within the tream of the Department of Community Energy and Adaptation to Climate Change (CEACC) of the TUB. Participants were selected based on their experience in projects with similar characteristics to the ENERGICA project and its demonstration sites.

The workshops were organized in the following steps:

1. Predefinition of pairs: Previous analysis of the possible interlinkages was carried out to reduce pairwise comparisons by eliminating negligible influences. The influences between risk factors and clusters were assumed similar for all three site demonstrators, therefore the workshops were aimed to collect the general investment perspectives for RE projects.

2. Introduction and instructions: Presentation of the study objectives, and shared definition of the risk factors under consideration.

3. Questionnaire and discussion: Experts individually evaluated the degree to which one factor influences another using a predefined influence scale. Experts make evaluations comparing the relative influence of risks on the project success, and they are converted into the fuzzy sets. (Qiu, 2020). The comparison scale consists of the following levels: no influence (0), low influence (1), some influence (2), high influence (3), very high influence (4). Experts are asked to compare the criteria pair wise in terms of influence and direction. Joint discussions were held upon strong disagreement to reduce uncertainty in the final results. These evaluations are used to construct a matrix with the dimensions 33x33, called the direct-relation matrix A. Here, aij stands for the degree to which the criteria i affects the criteria j.

Mathematical processing of results require the following steps:

Step 1. Construct the direct relation matrix. Experts' assessments were aggregated using it2 triangular fuzzy sets to account for uncertainty in linguistic answers and weighed according to their own perception of expertise in the different dimensions that the survey is focused on. Sets were 'defuzzified' after aggregation

$$A = \begin{bmatrix} 0 & a_{12} & a_{1n} \\ a_{21} & 0 & \dots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}$$

Step 2. Normalize the direct-relation matrix. The direct-relation matrix A is used to calculate the normalized direct relation matrix M, using the formulae:

$$M = 1/k * A$$

$$k = max\left(max\sum_{i=1}^{n}|a_{ij}|, max\sum_{j=1}^{n}|a_{ij}| \right) i\,, j \in \{1,2,3,\dots n\}$$

Step 3. Calculate the total relation matrix. Once the normalized direct-relation matrix M is obtained, the following formula is used to compute the total relation matrix T, in which I is the identity matrix. T captures both direct and indirect effects among factors.

$$T = M + M^2 + M^3 + \cdots = \sum_{i=1}^{\infty} M^i = M(I - M)^{-1}$$

Step 4. Calculate influence dispatcher and receiver groups from T to identify key drivers and affected factors. The sums of all vector rows (D) and columns (R), give information about the influence degree [qiu] For each factor, the following indicators were derived:

$$D = \sum_{j=1}^{n} t_{ij} \qquad R = \sum_{i=1}^{n} t_{ij}$$

- Prominence (D+R): Indicating the overall importance of a factor within the system
- Relation (D-R): Distinguishing cause factors (positive values) from effect factors (negative values)

The resulting cause-effect diagram served as a key input for the subsequent ANP model development

Step 5. Set a threshold value and construct the network structure for ANP.

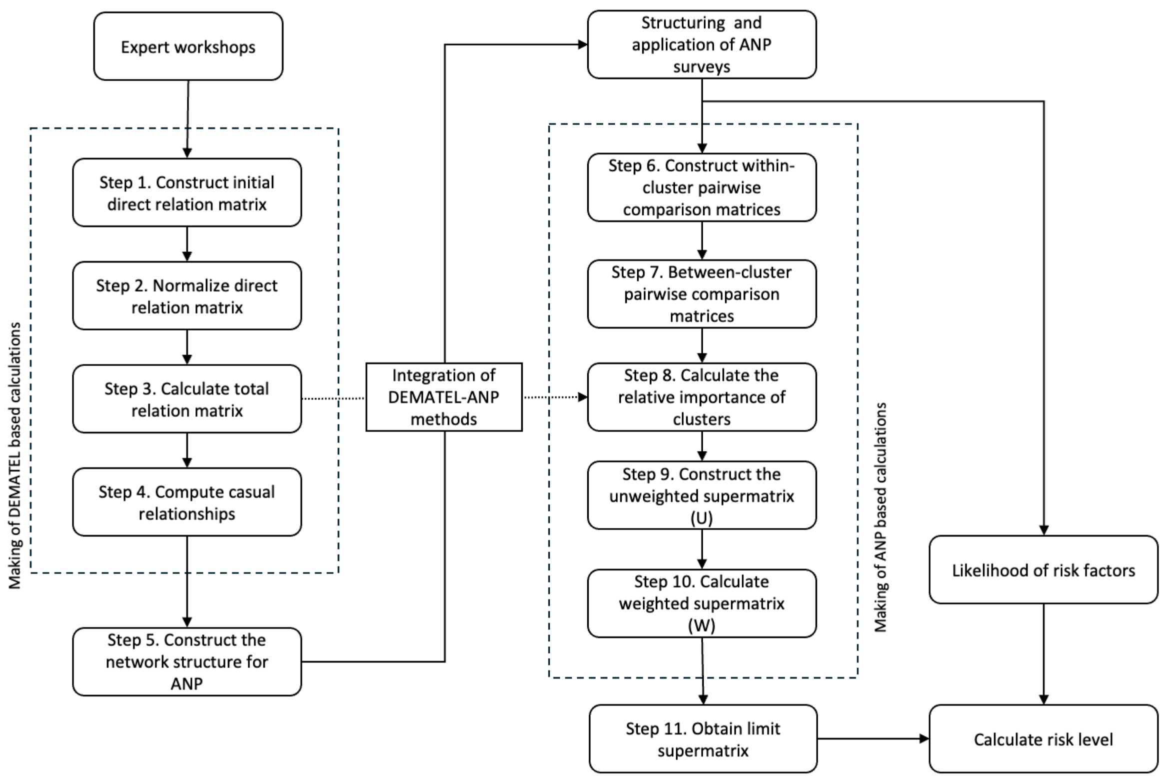

Figure 35 DEMATEL-ANP approach description

3.2.2.2 Analytical Network Process (ANP) method

ANP was used to prioritize the identified risk factors while explicitly accounting for interdependencies revealed by the DEMATEL analysis. Three surveys were designed to collect expert perspectives from each of the demonstration sites. The ANP survey aimed to elicit expert judgments on the relative importance of elements within and across clusters. An overview of the method can be found on Figure 35.

The questionnaires, distributed to the demonstration partners, were structured as follows:

The ANP questionnaire was structured on a digital form according to the network model obtained from DEMATEL results analysis (see Figure 35), consisting of 7 clusters and 21 elements for each site. Pairwise comparison questions were formulated to compare: a) elements within the same cluster; b) elements across different clusters, where relevant

Experts were asked to compare risk factors relative importance for the core business using Saaty's fundamental 1–9 scale. This scale from 1-9 represents pairs of equal importance (1), up to extreme inequality of importance (9). An expert can declare relative dominance between each pair of elements verbally as: equally important, moderately more important, strongly more important, very strongly more important, and extremely more important. These judgments can be transformed into numerical values of 1, 3, 5, 7, and 9. Reciprocals of these values are used for the corresponding transpose judgments. They were also asked to rate the likelihood of occurrence of all factors independently according to their experience.

Later, the results were processed considering the following steps:

Step 6. Within-cluster dependencies were modelled by conducting pairwise comparisons of cluster elements with respect to each element in the same cluster. The principal eigenvector of each matrix provides the local priority weights of the compared elements.

Step 7. Within-cluster and between-cluster dependencies were elicited and processed independently, as they represent distinct conditional relationships. Separate pairwise comparison matrices were constructed for each dependency type, and priority vectors were also obtained.

Step 8. Cluster weights were derived from the DEMATEL total influence matrix by aggregating element-level influences to the cluster level. The prominence values (D+R) of each cluster were normalized to obtain relative cluster weights, which were then used to weight the ANP supermatrix.

Step 9. Construction of the unweighted supermatrix. The resulting local priority vectors from Step 6 were placed as columns in the diagonal blocks of the unweighted supermatrix, ensuring that each column represents a conditional influence distribution. The resulting local priority vectors from Step 7 were embedded into the corresponding blocks for the unweighted supermatrix.

Step 10. Weighted supermatrix calculation. To ensure column stochasticity, the unweighted supermatrix is weighted by the relative importance of clusters, obtained from DEMATEL. The weighted supermatrix represents how the influence of element j is distributed across the system.

Step 11. Limit supermatrix. The weighted supermatrix is raised to powers until convergence is achieved. Because the weighted supermatrix is column-stochastic, the resulting limit supermatrix preserves column stochasticity and contains the global priority distribution of all elements. These final weights represent the relative importance of each risk factor within the network, accounting for both direct importance and indirect influences.

Excel and Phyton were used as tools for the mathematical development of the method.

3.2.2.3 Limitations of the DEMATEL-ANP method

Despite their strengths, both DEMATEL and ANP present methodological limitations that should be acknowledged.

First, both methods rely heavily on expert judgment, making results sensitive to expert selection, experience, and potential biases. While structured elicitation and consistency checks help improve reliability, subjectivity cannot be fully eliminated.

Second, the cognitive burden on participants is relatively high, particularly for ANP surveys involving numerous pairwise comparisons. This may lead to respondent fatigue and affect judgment quality, especially in complex networks with many interdependencies.

Third, DEMATEL assumes linear additive influences between factors, which may oversimplify non-linear or context-dependent interactions present in real-world risk systems.

Finally, the integration of DEMATEL and ANP requires methodological decisions (e.g. threshold selection, dependency inclusion) that can influence results. Transparency in these choices is therefore essential for result interpretation.

3.3 Results

In this Section, we present the results of the risk assessment following the above detailed methodology. Subsection 3.3.1 presents the set of identified risks, while Subsection 3.3.2 and Subsection 3.3.3 present findings from their assessment, DEMATEL analysis and ANP respectively. Subsection 3.3.4 shows the results from a likelihood assessment of risks to occur in the specific demonstrator context. Combining the impact of risks towards the project achieved by the ANP analysis, and the likelihood of risk occurrence, we scale the overall risk in Subsection 3.3.5.

3.3.1 Risk identification

As a result of iteration between literature review, risk definition and risk validation, the final list of risk factors contained 33 elements that were clustered into 7 categories as presented in Table 6. Each of the elements include a description, which allowed the experts participating in the subsequent workshops to align understandings in the right direction. In turn, each of the element were assigned a code for a systematic interpretation of results.

Table 6 Set of identified risks.

Cluster	Risk	Description	Code
Technical	technology maturity and performance risk	Maturity is the term used to describe whether the technology has reached its theoretical efficiency limit Progressiveness relates to the impact of increased productivity and new features on efficiency and quality This uncertainty connects to the expected performance of the service in the long term considering that these technologies have not been broadly used before (are they safe, stable, efficient?)	T1
	availability of qualified staff and capacity	Expenses for the research and development of technologies (possibility for improvement on the field), availability of local qualified staff and capacity including service and maintenance. Training, R&D activities, and capability to design, construct and operate.	T2
	grid reliability and capacity*	Redundancy of the power grid, grid capacity and management and electrical losses are uncertainties that may limit the ability to transmit and distribute generated power effectively *only Kenya and Sierra Leone	T3

	grid expansion and encroachment risk*	Mini grid coverage, traceability of service and uncertainties regarding grid expansion need to be considered to avoid stranded assets and loss of revenue *only Madagascar	T4
	logistics and site access	Availability of transportation infrastructure and distance to local markets can significantly increase operational costs, cause delays and pose challenges in maintenance	T5
	resource variability and estimations	Uncertainties in estimating power potential and its variability, but also fluctuations that can lead to deviations in expected energy yields.	T6
	project management and implementation disruptions	Possibility of schedule overrun, cost overrun, the interruption of construction, and supply chain disruptions	T7
	cybersecurity and data management	Developer's IT structure and data management capabilities, access control to physical assets	T8
	demand/load profile uncertainties	Estimations of customer base and demand, population distribution pattern changes and other variations in demand patterns	T9
Environmental	resource use intensity and environmental damage	Emissions, waste generation and disposal (e.g., hazardous waste from manufacturing, operational by products), resource use intensity (water for cooling, rare earth minerals for components). May cause habitat and ecosystem disturbance	N1
	extreme weather and natural disaster risk	Force majeure: floods, storms, earthquakes or wildfire risks etc.	N2
	climate change vulnerability	Changes in resource availability due to new weather patterns. Infrastructure vulnerability to extreme and more frequent climate events	N3
Economic	increasing capital costs	Changes in capital costs and high initial costs	E1
	operational costs uncertainties	Cost structure, operating costs, maintenance and technical visits, development and transaction costs, labour costs	E2
	access to capital	Access to affordable debt finance and loans, domestic investor capital and funding of the sector	E3
	debt structure and financing uncertainties	Interest rate, refinancing risk, financing scheme, unpredictable rates in borrowing, lending and returns; includes lender experience in RE projects	E4
	off-taker risks	Revenue uncertainty due to default by off-taker, potential customers with insufficient financial track records, unwillingness to pay, low affordability, seasonal income; includes customer churn rate	E5
	liquidity and general economic conditions	Region/Nation development, price volatility, possible operational liquidity issues arising from revenue shortfalls	E6
	foreign exchange fluctuations	Currency fluctuations risk	E7
Market	market growth potential	Market expansion opportunities, market share can affect competitiveness and the growth of projects. Market information and data availability; includes market readiness (reputation and appropriate local partners)	M1
	price sensitivity and unregulated competition	Price sensitivity to other energy sources, including conventional ones. Unregulated competition	M2
	market requirements and industry standards	Market distortion issues, eligibility requirements, license, approval and industry standards	M3
	speculative markets	External markets, land, commodity and foreign exchange markets, dependence on imports	M4
Social	community engagement and alignment	Reconstruction of social relationship network, cultural fit and behavioural adoption	S1
	public resistance	Public opposition to implementation. Characterised by insecurity or violence against workers, theft of components, damage and vandalism of infrastructure	S2

	social unrest caused by unpredictable events	Social instability caused by unpredictable events, inter-group, religious or ethnic tensions	S3
Political and governance	bureaucracy and land acquisition challenges	Institutional challenges, barriers due to complex institutional structures with overlapping responsibilities, regulatory and licensing complexity for commissioning, approvals and grid connection. Also, high costs or intervention of the government	P1
	bribery and corruption	High levels of corruption, weak rule of law and poor governance within administrative and business sectors can lead to unfair competition, increased unofficial costs, arbitrary decision-making, and a lack of legal recourse.	P2
	political will and geopolitical context	Political will to diversify into clean energy, management of the energy sector, including involvement of relevant experts in energy decision making and fostering relationships with private and public actors in the sector stabilise the operating environment. Insecurity of infrastructure, expropriation risk, political events that adversely impact the value of investments	P3
	legislative changes and enforcement of regulation	Policy maturity and enforcement of regulation regarding the implementation of this kind of projects	P4
Regulatory and policy	policy, regulated tariffs and taxation risks	Uncertainty in existence and variations in long term legal policy frameworks (e.g. access policy, price policy and industry regulation) Regulated tariffs, taxation	R1
	incentives and subsidies availability	Availability of incentives, subsidies to these technologies but also conventional alternatives. May affect financial attractiveness of the project and competitiveness.	R2
	conditions for supply	Definition of conditions of energy supply as the promise of service, codes and standards for effective control may affect the expectations of investors, developers and consumers and cause lower adoption of technology and financial underperformance	R3

3.3.2 DEMATEL

The aim of the DEMATEL analysis is to identify the most relevant risks to be assessed, based on the hypothesis that interrelated risks – risks that are influenced by others or have an influence on others – are the most important ones. This fulfills two goals: first, the set of risks to be assessed via pairwise comparison via questionnaires is reduced. Second, after having compared risks to identify their relative impact within the ANP process, the DEMATEL results inform us to apply weights when calculating the final impact.

Hence, to limit the burden on experts within the available time frame, the number of pairwise comparisons was reduced to the most relevant dependencies, which were identified beforehand using a direct influence matrix template. Interactions deemed negligible were assigned value 0 from the 0-4 scale. This allowed to reduce possible 1156 combinations to 192, a reduction of 84%.

Two identical workshops, with the participation of eleven experts in total, were organized to collect contributions to this stage of the risk assessment process. During the workshops, participants were asked to indicate their level of confidence across the different assessment areas, and their responses were weighted accordingly in the construction of the direct-influence matrix. To account for subjectivity and uncertainty in expert judgments, triangular fuzzy sets were employed to represent linguistic assessments as value ranges rather than single-point estimates. In cases where substantial disagreement among participants was observed, targeted discussions were conducted to clarify perspectives and support a more robust interpretation of the results. They were also asked whether they considered other relevant links could be identified among the ones that were excluded from the selected set of pairwise comparisons. Given the time constraints of the expert workshop, consensus-building was limited to one iteration.

3.3.2.1 Cause-effect analysis between factors

Table 8 was obtained after execution of steps 1-4. Here, an overview of the influence given and received by each factor is provided. Figure 36 shows how the risks are distributed according to their strength of influence and role as dispatcher or receiver of risk, relative to other risks. Connections were summarized in the form of cluster interactions map on figure 36.

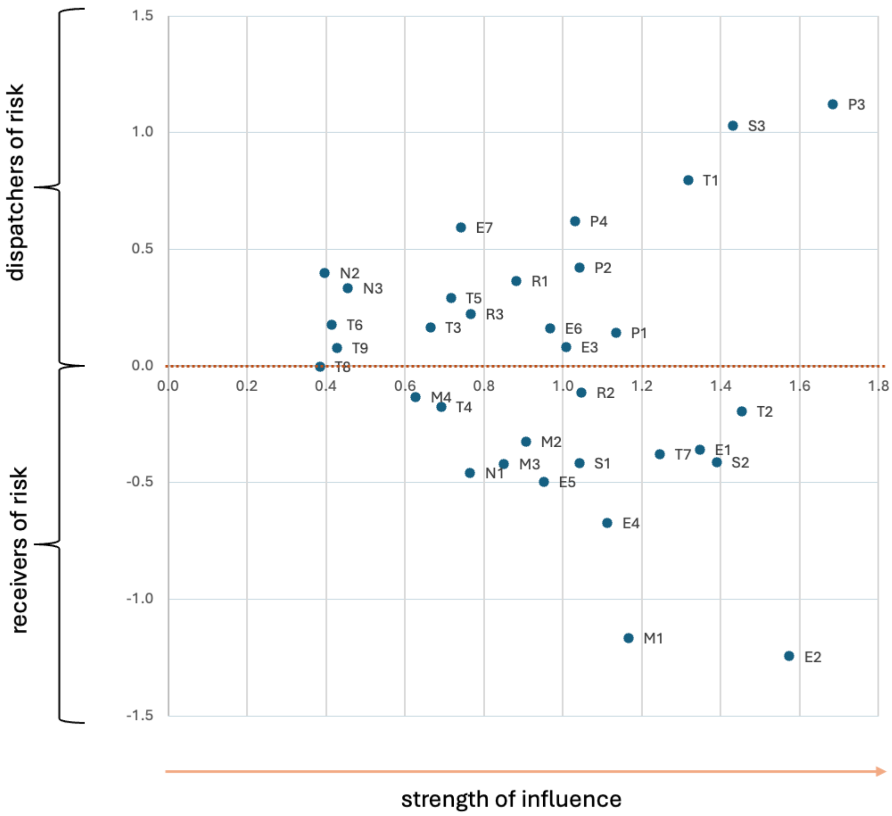

Figure 36 Results of the cause-effect analysis

P3 - political will and geopolitical context, S3 - social unrest caused by unpredictable events, and T1 - technology maturity and performance risk were found to be the top risks that interact mainly as drivers, meaning that other risks may increase likelihood and/or impact due to an increase in key indicators that define them. This result aligns with expected considerations, particularly in the context of developing countries, where investment decisions from private actors are oftentimes based on contextual factors such as governance, and political stability indicators which provide a sense of security of investment provided by international standard measurements. On the other hand, technology maturity and performance (T1) plays a key role to make a positive decision given that it is priority for most investors to ensure long term return. All three indicators are mostly external to the project and consider broader aspects that depend on the local context.

E2 - operational costs uncertainties, M1 - market growth potential, and E4 - debt structure and financing uncertainties are the most relevant receivers of risk. These factors have in common that they are highly dependent on internal conditions and their uncertainty can be significantly amplified by changes in other risk factors, which make them hard to predict, model and therefore make an informed decision.

Once the cause effect relationships were obtained, the threshold value was set at percentile 90 to complete step 5, which means that only 10% of more relevant and influential risk factors were to be considered for the ANP network construction. The most interlinked factors are presented on Table 7. We argue that addressing these highly interactive indicators during advanced stages of risk management, such as risk treatment, would have the largest impact on the risk level of the project. Therefore, investment decisions would in turn, be highly conditioned to the risk level of these indicators. The results from the total influence matrix above the threshold value allowed us to construct the ANP network summarized on Figure 37. The direction of the arrows represents the direction of influence between interacting factors.

Table 7 Most interlinked risk factors

Code	Risk
E1	increasing capital costs
E2	operational costs uncertainties
E4	debt structure and financing uncertainties
E5	off-taker risk
M1	market growth potential
M2	price sensitivity and unregulated competition
M3	market requirements and industry standards
N1	resource use intensity and environmental damage
N2	extreme weather and natural disaster risk
P1	bureaucracy and land acquisition challenges
P3	political will and geopolitical context
P4	legislative changes and enforcement of regulation
R1	policy, regulated tariffs and taxation risks
R2	incentives and subsidies availability
S1	effectiveness of community engagement and alignment
S2	public resistance
S3	social unrest caused by unpredictable events
T1	technology maturity and performance risk
T2	availability of qualified staff and capacity
T7	project management and implementation disruptions
T3	grid reliability and capacity (Kenya, Sierra Leone)
T4	grid expansion and encroachment risk (Madagascar)

3.3.2.2 Cause-effect analysis between clusters

The matrix calculated the total influence that each cluster exerts on other clusters, as well as on itself. For example, the 'Economic' cluster has an influence of 0.196430 on itself, and 0.000803 on the 'Environmental' cluster. This matrix helps understand the direct and indirect relationships between different groups of factors. Table presents a summary of these results by showing the overall influence of each cluster. The table is to be read as follows:

- D (given): Represents the total influence a cluster exerts on all other clusters. We observe the risks from the political cluster (0.89) to be influence other clusters the most, while the market cluster (0.18) seems to have the least impact on others.
- R (received): Represents the total influence a cluster receives from all other clusters. Risk factors from the economic cluster (0.97) receive most influence from other clusters, while the environmental cluster (0.16) receives the least.
- Prominence (D+R): This is the sum of 'D (given)' and 'R (received)', indicating the overall importance or centrality of each cluster within the system. For instance, 'Economic' (1.39) and 'Technical' (1.23) clusters have high prominence, suggesting they are very active in influencing and being influenced. In contrast, the environmental cluster (0.48) is of least importance.
- Cluster weight: This is the normalized prominence, showing the relative importance of each cluster as a proportion of the total prominence across all clusters. The 'Economic' cluster has the highest weight (0.20), indicating it is the most prominent cluster. Risks grouped in the environmental cluster (0.07) are of the least prominence.

Table 8 Cause-effect and influence between clusters

Cluster	**D (given)**	**R (received)**	**Prominence**	**Cluster weight**
Economic	0.411541	0.975252	1.386793	0.200067
Environmental	0.314946	0.162265	0.477211	0.068846
Market	0.18749	0.597075	0.784565	0.113186
Political	0.899076	0.309495	1.208571	0.174356
Regulatory	0.527585	0.235	0.762585	0.110015
Social	0.677153	0.406108	1.083261	0.156278
Technical	0.448023	0.780619	1.228642	0.177252

Figure 37 visualizes the risk network. While interdependencies exist on a risk factor level, in order to allow for a visual representation, the figure is a reduced summary showing interdependencies on a cluster level.

Among the most relevant interdependencies at the factor level, a feedback relationship between political and regulatory risks was identified, with experts attributing a stronger influence on political factors. This indicates that bureaucracy, political will, and governance quality (P1 and P3) play a central role in shaping investment decisions, due to their close connection with incentive structures and policy stability (R1 and R2). In turn, this interaction affects market growth potential (M1) and financing conditions (E4).

Uncertainty in operational costs (E2) emerges as a major effect of risk interactions and is primarily driven by technology maturity and performance (T1). As investment decisions are largely based on economic indicators such as operating expenditures (OPEX) and revenues, these variables can be interpreted as indirect measures of system performance and efficiency.

Social and technical risks are also strongly interconnected. For instance, the availability of qualified workers (T2) influences community alignment (S1), while social unrest (S3) can increase the likelihood of disruptions in infrastructure development and implementation (T7), and reinforces risks related to workforce availability (T2).

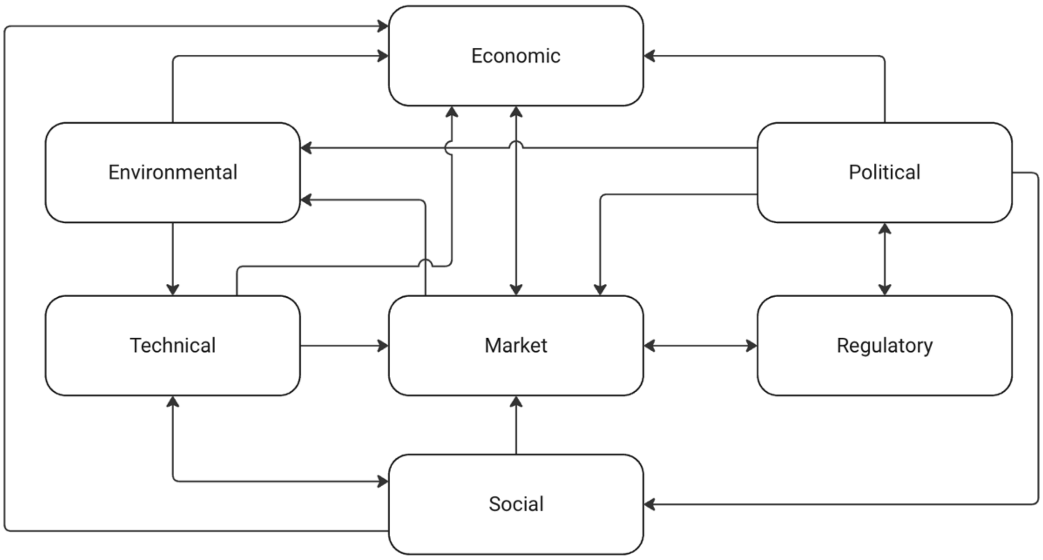

Figure 37 Structure of the ANP network

3.3.2 ANP

The ANP analysis aims to calculate the impact on the project activity a risk would have when materializing. Below, we summarize the results from the ANP analysis, which resulted from a relative comparison of risks. As of the highly contextual character of the risks, the ranking was conducted by the local demonstration partners. Within the surveys the respondents were asked to evaluate the risk factors relative importance by pairwise comparison. Processing the results according to the methodology detailed in Section 3.2 results in a relative scale of importance of each risk factor in regards to the project activity, which can be understood as an impact of the risk factor. Table 8 summarizes the normalized scores and visualizes a relatively higher impact of a risk factor by applying a color code, with a fainter red color expressing less impact, and deep red expressing higher impact. The reported values represent normalized ANP weights, expressing the relative impact of each risk factor on overall project risk within each national context. Higher values indicate a stronger influence of the corresponding risk factor, taking into account interdependencies among all dimensions.

Table 8 Results of the ANP analysis (impact of risks)

	Kenya	**Madagascar**	**Sierra Leone**
Technology maturity and performance risk	0,03228	0.00865	0.01765
Availability of qualified staff and capacity	0,03660	0.03494	0.02840
Grid reliability and capacity	0,04241	Not applicable	0.05549
Grid expansion and encroachment risk	Not applicable	0.10536	Not applicable
Project management and implementation disruptions	0,10455	0.04128	0.07851
Resource use intensity and environmental damage	0,00696	0.01981	0.02257
Extreme weather and natural disaster risk	0,02026	0.02625	0.03697
Increasing capital costs	0,07802	0.05196	0.09569
Operational costs uncertainties	0,18976	0.28929	0.19888

Debt structure and financing uncertainties	0,13590	0.03119	0.06260
Off-taker risks	0,10767	0.10240	0.10145
Market growth potential	0,06564	0.05847	0.05507
Price sensitivity and unregulated competition	0,05382	0.07284	0.11812
Market requirements and industry standards	0,05887	0.00802	0.03037
Community engagement and alignment	0,01323	0.03291	0.00568
Public resistance	0,01003	0.02879	0.01418
Social unrest caused by unpredictable events	0,00569	0.00728	0.00284
Bureaucracy and land acquisition challenges	0,00166	0.02192	0.00754
Political will and geopolitical context	0,00032	0.00601	0.00176
Legislative changes and enforcement of regulation	0,00051	0.00327	0.00160
Policy, regulated tariffs and taxation risks	0,00299	0.01850	0.02693
Incentives and subsidies availability	0,03284	0.03083	0.03771

Across all three countries, financial and operational risks emerge as the most influential categories, although their relative importance differs by context. Operational cost uncertainties represent the dominant risk factor in all cases, particularly in Madagascar (0.289) and Sierra Leone (0.198), and to a slightly lesser extent in Kenya (0.189). This highlights the critical role of cost volatility, efficiency of operations, and long-term cost predictability for energy projects in these markets. Closely related financial risks, such as increasing capital costs and debt structure and financing uncertainties, are also highly ranked, especially in Kenya and Sierra Leone, underscoring the sensitivity of projects to financing conditions and macroeconomic constraints. These are further analyzed in Deliverable D7.3.

By studying the table, clear country-specific risk profiles can be observed. In Kenya, in addition to operational and financing risks, project management and implementation disruptions (0.104) and off-taker risks (0.108) are particularly prominent. This suggests that contractual performance, counterparty reliability, and execution-related challenges play a decisive role in shaping project risk, alongside a comparatively strong exposure to financing structure considerations.

In Madagascar, the risk profile is more strongly influenced by the relation with the national utility and country-wide national electrification plans, reflected in grid expansion and encroachment risk (0.105). This reflects the importance of national regulations in infrastructure development for rural electrification with decentralized and private-sector led electrification projects. At the same time, off-taker risks (0.102) and price sensitivity and unregulated competition (0.073) indicate significant market-related uncertainties, while regulatory and policy-related risks, though present, remain of moderate relative importance.

In Sierra Leone, the results point to a pronounced exposure to cost-related and market risks, including increasing capital costs (0.099), price sensitivity and unregulated competition (0.099), and off-taker risks (0.104). Additionally, grid reliability and capacity (0.058) and extreme weather and natural disaster risk (0.040) carry higher relative weights than in the other countries, reflecting structural infrastructure constraints and vulnerability to climate-related events.

Social and community-related risk factors exhibit comparatively low normalized ANP weights across all three countries, indicating that, within the scope of the assessment, they are perceived to exert a more limited direct impact on overall project risk. Factors such as community engagement and alignment, public resistance, and social unrest caused by unpredictable events consistently rank among the lower-impact risks in Kenya, Madagascar, and Sierra Leone. This pattern suggests a generally favorable level of social acceptance of the assessed energy projects, likely reflecting the strong alignment of such projects with local development needs, including improved energy access, employment opportunities, and broader socio-economic benefits.

Overall, the results underline the context-specific nature of energy project risk in partner countries, while also identifying common high-impact risk drivers that can inform targeted risk mitigation strategies, financial instruments, and policy support measures.

3.3.3 Likelihood of risk occurrence

While the ANP process informed our study on the impact of risk factors on a project activity, the demonstrator partners subsequently rated the likelihood of occurrence of all factors independently according to their experience. Table 9 summarizes the estimated likelihood of risk occurrence in each demonstration site compared to other risk factors. The numbers are normalized, with higher values representing a higher likelihood of risk materialization. The table follows the same color code as above.

Table 9 Estimated relative likelihood of risk occurrence

	Kenya	Madagascar	Sierra Leone
Technology maturity and performance risk	0,02703	0,04651	0,07895
Availability of qualified staff and capacity	0,02703	0,06977	0,07895
Grid reliability and capacity*	0,05405	Not applicable	0,05263
Grid expansion and encroachment risk**	Not applicable	0,00000	Not applicable
Project management and implementation disruptions	0,02703	0,06977	0,05263
Resource use intensity and environmental damage	0,05405	0,04651	0,05263
Extreme weather and natural disaster risk	0,05405	0,06977	0,05263
Increasing capital costs	0,05405	0,06977	0,07895
Operational costs uncertainties	0,08108	0,06977	0,07895
Debt structure and financing uncertainties	0,05405	0,06977	0,05263
Off-taker risks	0,05405	0,02326	0,05263
Market growth potential	0,02703	0,02326	0,05263
Price sensitivity and unregulated competition	0,02703	0,02326	0,05263
Market requirements and industry standards	0,05405	0,04651	0,05263
Community engagement and alignment	0,02703	0,02326	0,02632
Public resistance	0,02703	0,02326	0,02632
Social unrest caused by unpredictable events	0,05405	0,04651	0,02632
Bureaucracy and land acquisition challenges	0,08108	0,06977	0,02632
Political will and geopolitical context	0,05405	0,04651	0,02632
Legislative changes and enforcement of regulation	0,05405	0,04651	0,02632
Policy, regulated tariffs and taxation risks	0,05405	0,04651	0,02632
Incentives and subsidies availability	0,05405	0,06977	0,02632

Overall, the results indicate that political, institutional, financial cost-related and operational risks are perceived as the most likely to materialize across the three country contexts, although their relative importance varies. In Kenya, the highest likelihood weights are associated with operational cost uncertainties (0.081) and bureaucracy and land acquisition challenges (0.081), suggesting that administrative processes and cost dynamics are expected to pose recurrent challenges. Several other risks, including grid reliability, financing uncertainties, and regulatory aspects, exhibit moderate likelihoods, pointing to a broadly diversified risk landscape.

In Madagascar, likelihood assessments show a more uniform distribution across multiple risk factors, with relatively high values assigned to availability of qualified staff and capacity, project management and implementation disruptions, extreme weather and natural disaster risk, and financial risks such as increasing capital costs and financing uncertainties (all at approximately 0.070). This pattern suggests that risks in Madagascar are perceived as systemic and interrelated, reflecting structural capacity constraints and exposure to external shocks. Notably, grid expansion and encroachment risk is assessed as not likely to materialize in the current project context. This reflects the specific geographical and infrastructural context of the chosen project sites, being located in very rural areas where grid extension is currently neither planned nor economically foreseeable within the project timeframe.

In Sierra Leone, likelihood weights are comparatively high for technology maturity and performance risk, availability of qualified staff, increasing capital costs, and operational cost uncertainties (all around 0.079). This points to a risk environment where technical readiness and human capacity, alongside cost volatility, are expected to be key determinants of project performance. By contrast, institutional and political risks, including legislative changes and policy-related factors, are assigned lower likelihood weights, suggesting a more predictable regulatory environment from the perspective of project implementers.

Across all three countries, social risk factors, such as community engagement challenges, public resistance, and social unrest, consistently receive lower likelihood weights. This indicates that, based on local expert judgment, social opposition or community-related disruptions are not expected to materialize frequently, reinforcing the observation of generally favorable social acceptance of energy projects.

3.3.4 Overall risk level

Combining the impact (ANP) and likelihood of a risk by multiplication, we can calculate an overall risk level presented in Table 10/Figures 38-40. The resulting values represent normalized composite risk scores, allowing for a comparative assessment of risk intensity across countries and risk categories.

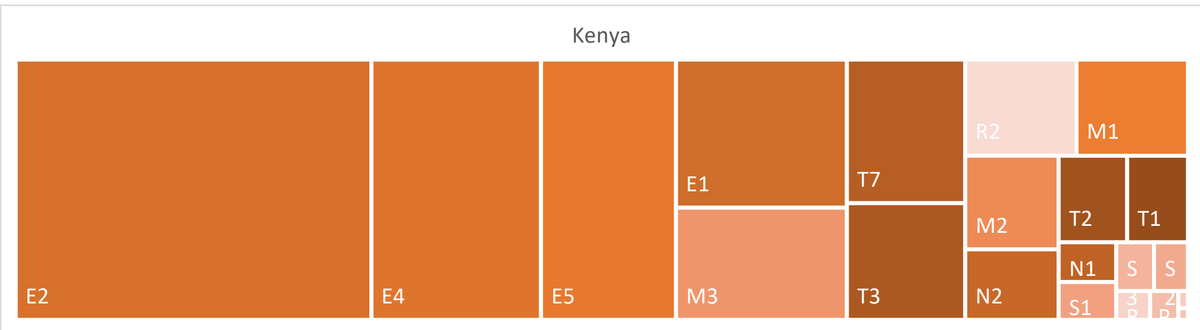

Figure 38 Overall risk level results - Kenya

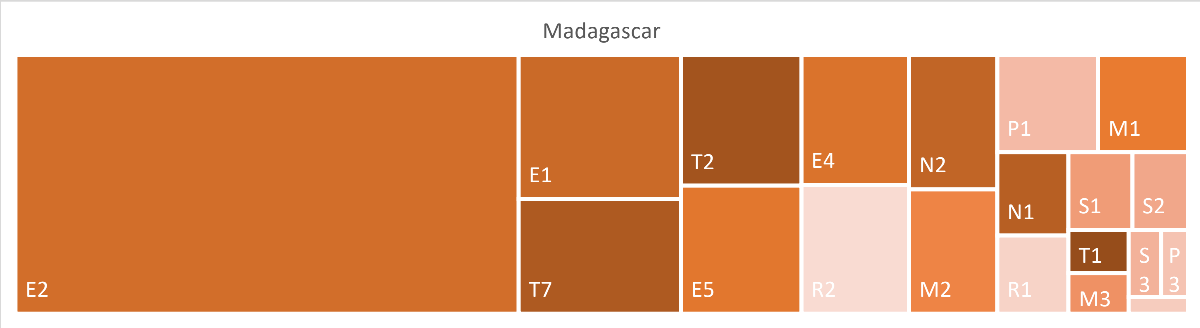

Figure 39 Overall risk level results - Madagascar

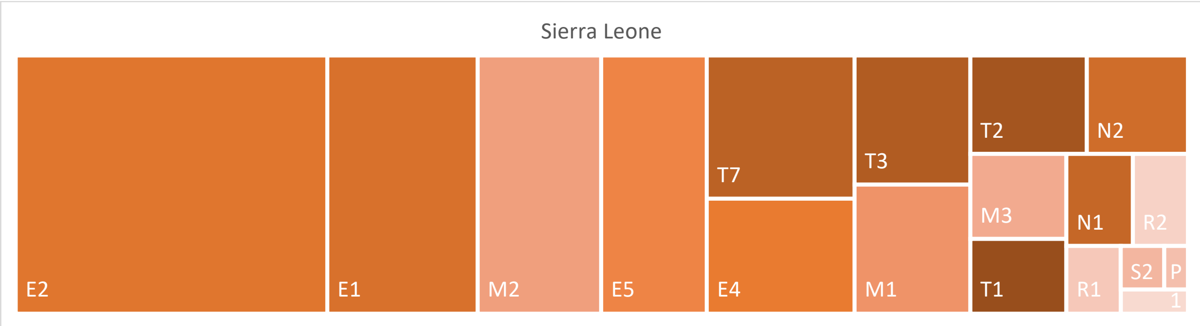

Figure 40 Overall risk level results - Sierra Leone

Table 10 Results of the overall risk level

	Kenya	Madagascar	Sierra Leone
Technology maturity and performance risk	0,01722	0,00856	0,02481
Availability of qualified staff and capacity	0,01952	0,05185	0,03998
*Grid reliability and capacity**	0,04523	Not applicable	0,05214
*Grid expansion and encroachment risk***	Not applicable	0,00000	Not applicable
Project management and implementation disruptions	0,05575	0,06126	0,07270
Resource use intensity and environmental damage	0,00742	0,01960	0,01796
Extreme weather and natural disaster risk	0,02161	0,03896	0,03529
Increasing capital costs	0,08321	0,07711	0,13286
Operational costs uncertainties	0,30357	0,42932	0,27164
Debt structure and financing uncertainties	0,14494	0,04629	0,05713
Off-taker risks	0,11483	0,05066	0,09243
Market growth potential	0,03500	0,02892	0,04395
Price sensitivity and unregulated competition	0,02870	0,03603	0,08814
Market requirements and industry standards	0,06278	0,00794	0,02212
Community engagement and alignment	0,00705	0,01628	0,00275
Public resistance	0,00535	0,01424	0,00726
Social unrest caused by unpredictable events	0,00607	0,00720	0,00142
Bureaucracy and land acquisition challenges	0,00265	0,03253	0,00374
Political will and geopolitical context	0,00034	0,00594	0,00087
Legislative changes and enforcement of regulation	0,00054	0,00324	0,00079
Policy, regulated tariffs and taxation risks	0,00318	0,01831	0,01334
Incentives and subsidies availability	0,03503	0,04576	0,01868

Across all three countries, operational cost uncertainties clearly emerge as the dominant overall risk, significantly outweighing other factors. This risk accounts for the highest composite scores in Madagascar (0.429), Kenya (0.304), and Sierra Leone (0.272), indicating a convergence of both high impact and high likelihood. The prominence of this risk highlights the central role of cost predictability, efficiency of operations, and exposure to price volatility in shaping project viability across diverse national contexts.

A second cluster of high-priority risks is formed by financial factors, though their relative importance varies by country. Increasing capital costs rank among the most significant risks in all three cases, and are particularly pronounced in Sierra Leone (0.133). Similarly, debt structure and financing uncertainties represent a major risk driver in Kenya (0.145), reflecting sensitivity to financing conditions and capital market access. Off-taker risks also remain consistently relevant across countries, underlining the importance of counterparty reliability and revenue security for renewable energy investments.

Distinct country-specific risk profiles can be observed. In Kenya, financial structure–related risks and off-taker performance combine with project management and implementation disruptions (0.056) to form a multifaceted risk environment. This suggests that, alongside cost-related concerns, execution capacity and contractual arrangements may play a critical role. Grid reliability and capacity (0.045) further contribute to the risk profile of operating the bidirectional charging hubs.

In Madagascar, the risk landscape is more concentrated, with a small number of risk factors accounting for a large share of overall risk. In addition to operational cost uncertainties, project management and implementation disruptions (0.061) and increasing capital costs (0.077) stand out. The elevated risk associated with availability of qualified staff and capacity (0.052) indicates that human and institutional capacity constraints materially affect project outcomes.

In Sierra Leone, overall risk levels point to a stronger influence of market-related and cost-related risks, including price sensitivity and unregulated competition (0.088) and off-taker risks (0.092), alongside increasing capital costs. Grid reliability and capacity (0.052) and project management disruptions (0.073) further contribute to the risk profile, indicating exposure to both infrastructure limitations and implementation challenges.

Across all three countries, social risks remain consistently low in terms of overall risk level. Factors such as community engagement, public resistance and social unrest uncertainties exhibit minimal composite scores, suggesting that their limited likelihood and/or impact reduces their prioritization relative to financial and operational risks. While these factors should continue to be monitored, the results indicate that they are unlikely to constitute binding constraints on project implementation under current conditions.

3.4 Conclusions of the risk assessment

This Chapter developed and applied a holistic, replicable risk assessment framework for renewable energy investment decisions in developing contexts, using the three ENERGICA demonstration sites in Kenya, Madagascar, and Sierra Leone. By combining risk identification with DEMATEL-based interdependency mapping, ANP-based impact prioritization, and expert-elicited likelihood estimates, the assessment enables a structured comparison of risk drivers across sites. Across all three contexts, financial and operational risks—most notably operational cost uncertainties, increasing capital costs, financing structure uncertainties, and off-taker risks—dominate the overall risk profile, while social risks are consistently assessed as comparatively low, suggesting generally favorable community acceptance under current conditions. At the same time, the results confirm that risk profiles remain strongly context-specific, reflecting infrastructure constraints, market dynamics, institutional capacity, and project design.

Moreover, project management and implementation disruptions was identified as relevant across all demonstration sites, in line with the System Dynamics analysis presented in this report. The risk analysis further indicates that infrastructure conditions are strongly influenced by interactions among multiple factors. Taken together, the results from both the System Dynamics models and the risk assessment suggest that political and regulatory measures should aim to mitigate this risk in order to support investment decisions in favor of renewable energy projects.

Key limitations relate to reliance on expert judgment and associated subjectivity, as well as the bounded project scope (focusing on risks threatening the business activity rather than impacts generated by the activity); future applications should expand expert sampling where feasible, revisit likelihood assumptions over time, and triangulate results with quantitative scenario and sensitivity analyses (e.g. as in D7.3) to strengthen robustness and support risk mitigation planning and investment de-risking.

4. CONCLUSION

This report applied an integrated analytical framework to assess the performance, diffusion dynamics, and risk profile of three renewable energy demonstrators within the ENERGICA project: solar nanogrids in rural Madagascar, low-tech biogas systems in peri-urban Sierra Leone, and electric two-wheelers with bi-directional charging in urban Kenya. By combining System Dynamics modelling with a structured, semi-quantitative risk assessment, the analysis captures both temporal system behavior and context-specific investment risks under uncertainty.

The System Dynamics analysis shows that technology adoption and scaling are primarily governed by feedback structures linking affordability, infrastructure availability, access to finance, and user acceptance, rather than by technical performance in isolation. Across all three demonstrators, adoption trajectories are highly sensitive to initial conditions and delays, with the timing of inflection points exerting a disproportionate influence on long-term outcomes. Infrastructure capacity, financing availability, and institutional readiness consistently act as balancing constraints, while policy support, learning effects, and cost reductions form reinforcing mechanisms that can accelerate diffusion once threshold conditions are met.

The risk assessment further clarifies the constraints identified in the dynamic analysis. Financial and operational risks—most notably operational cost uncertainties, capital cost increases, financing structure constraints, and off-taker risks—emerge as the dominant contributors to overall risk across all sites. Social and political risks are consistently assigned lower relative importance and likelihood, indicating that they are not expected to constitute binding constraints within the assessed project contexts. At the same time, the results confirm that risk configurations are strongly context-dependent, shaped by differences in infrastructure maturity, market structure, human capacity, and institutional arrangements.

Overall, the combined results demonstrate that the viability and scalability of decentralized renewable energy solutions depend on the interaction between system dynamics and risk exposure. The replicable framework presented allows for the systematic identification of high-leverage variables, critical uncertainties, and risk concentrations, and provides a consistent basis for comparing heterogeneous projects under uncertainty. As such, it supports rigorous evaluation of implementation pathways and complements techno-economic and scenario-based analyses by explicitly accounting for interdependencies, feedbacks, and expert-informed risk prioritization.

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