System-dynamics modelling of the electricity-development nexus in rural electrification based on a Tanzanian case study

Abstract

The rural electrification-based literature reports a limited knowledge of the long-term socio-economic changes that electricity access can bring in remote contexts and the consequent feedback on electricity demand. Such lack of understanding causes an inefficient allocation of economic resources for rural energy projects and inappropriate sizing processes. We model the multifaceted dimensions of the rural electricity-development nexus by formulating a system-dynamics model based on a Tanzanian case-study and using 13-years of data for calibrating it. The modelled structure provides the first quantitative step in the research committed to develop an appropriate modelling framework for deriving policy insights regarding the electricity-development nexus and the evolution of electricity demand for rural areas of developing countries. The simulation results show and highlight the dynamics behind the structural behaviour of some socio-economic system variables (e.g. income and IGAs growth), the exogenous determinants (e.g. accessibility of the rural village), and the complementary activities (e.g. micro-credit at electricity access) that allow electricity access to foster local socio-economic changes, which in turn supports the growth of electricity demand. Our findings allow to increase the understanding on the complex electricity-development nexus and provide a novel modelling framework for projecting the electricity demand for rural settings.

Keywords: rural electrification, electricity-development nexus, electricity demand, system dynamics, energy modelling, Tanzania.

1. Introduction

With the Sustainable Development Goal 7 “Ensure access to affordable, reliable, sustainable and modern energy for all” (SDG7), the Agenda 2030 set by the United Nation in 2015 recognises the importance of the nexus between energy and sustainable development in all its economic, social and environmental dimensions. By 2030, the goal aims at ensuring access to electricity and clean fuels and cooking technologies to all the global population. Focusing on the electricity carrier, the International Energy Agency estimates that still 1 billion people lack access to electricity in developing countries (International Energy Agency 2018). Rural electrification is expected to largely contribute to the achievement of electricity access goals, since people still living without electricity will live predominantly in rural areas (International Energy Agency 2017). In this framework, the need to develop sustainable and appropriate approaches to electricity planning clearly emerges. In rural energy planning, the assessment of long-term electricity demand and the relation with local socio-economic improvements are the most critical and complicated steps. Indeed, wrong projections of electricity demand could negatively impact on local livelihood and socio-economic opportunities and cause an inappropriate sizing of local energy solutions, leading to supply shortages or cost recovery failure, as argued by (Riva et al. 2019c), Cabral et al. (Cabraal et al. 1996a, 1996b), Kivaisi (Kivaisi 2000). From the literature, it emerges a lack of understanding and research on this issue, which entails a little attention and consideration of the long-term evolution of electricity demand within rural electrification-based studies and models. One of the reasons is due the fact that the socio-economic complexities behind the evolution of the electricity demand in rural areas are far from being completely analysed, discussed and characterised.

A second reason which prevents a proper understanding and assessment of the long-term dynamics that determine the evolution of electricity demand in rural areas is the lack of appropriate quantitative models for characterising and formulating the *electricity-development nexus*. With this term, we mean the potential socio-economic changes that access to electricity and use bring about in rural contexts, and the reverse impact that such potential socio-economic improvements may have on increasing electricity consumption. The characterization of this nexus is a challenging task, since “the dynamics of growth and electrification are complex, involving many underlying [socio-economic] forces” ((Khandker et al. 2013), pg. 666). The presence of these complexities suggests that simple black-box regression models or predefined sets of relations of cause and effect are not appropriate to model the energy-development nexus and the dynamics behind the evolutions of electricity demand. Rather, models for projecting energy demand should involve detailed multidisciplinary analysis, which takes a wide range of factors into account (Sterman 1988). Thus, being able to provide an appropriate modelling framework for formulating the dynamics behind such electricity-development nexus can lead to more reliable electricity demand projections and reliable planning strategies for rural electrification.

These issues are linked with and subjected to many complexities, namely the low understanding of the socio-economic structure of local rural communities (*structural uncertainty*), the multifaced and multidimensional factors characterise the system (*structural uncertainty*), and the unknown impact and relevance of such factors on the electricity consumption, and vice versa (*parameter uncertainty*).

1.1. Objective and organization of the work

The considerations above set potential new challenges for the energy access- and energy modelling-related research, that is: (i) to assess the fundamental dynamics, variables, and exogenous policies that characterise the electricity-development nexus and (ii) generate long-term projections of electricity use to support rural electrification. This work represents the first stage for achieving these challenges, and its specific objective is to formulate and calibrate a simulation model based on a real case study, in order to provide a robust modelling framework for carrying out further policy testing activities on the electricity-development nexus and generate long-term projections of rural electricity demand.

The outline of this paper is as follows: Section 2 introduces the state-of-the art of the research on the electricity-development nexus and demand modelling for rural contexts of developing countries, and well as the novelty of the work and the rationale and methodology employed. Section 3 reports the system-dynamics modelling process, namely the conceptualisation of the problem and the boundaries of the analysis, the formulation of the model, its calibration with actual data and the uncertainty analysis. Section 4 reports the results and discussion. Section 5 draws the conclusions and indication for future research work to overcome the limitations of the approach.

2. Background – electricity demand and socio-economic changes

2.1. State-of-the art

A first step to dealing with and understanding all the possible complexities involved in the electricity-development nexus is offered by a previous work of the Authors published in (Riva et al. 2018a; Riva 2019). It undertakes a comprehensive and extensive analysis of the peer-reviewed literature on electricity access and its impact on rural socio-economic development, and vice versa. The analysis was carried out by developing graphical causal loop diagrams that allow to capture, visualise, and discuss the complexity and feedback loops characterising the multiple dimensions of the electricity-development nexus. In the analysis, a few of the factors in the energy-development nexus were identified to be exogenous, but the main part of the diagrams depicts the relationship of the factors through closed causal loops. This shows how factors identified in the energy-development nexus literature are interconnected, and in order to identify the system's behaviour and to capture the dynamics in the energy-development nexus, a simulation approach that takes feedbacks into account is needed.

In the field of energy modelling in developing contexts, Bhattacharyya and Timilsina (Bhattacharyya and Timilsina 2010) criticised most global energy models that project future residential energy demand based on relatively simple exogenous and deterministic relationships, since they neglect such specific socio-economic dynamics of developing countries and use aggregate macro-data. In this context, system dynamics (SD) represents an appropriate candidate approach for modelling the electricity-development nexus, since the latter is affected by high uncertainty, strong non-linear phenomena, complex diffusion mechanisms, time-adjustments of technology perceptions, time delays, and feedbacks. In addition to this, SD theory offers a modelling process which contributes to a more holistic understanding of a system and its relevant causalities. Despite being very limited, also the literature in the field of energy and development supports the suitability of

SD for modelling complex issues. Electricity production and use in developing countries are analysed in the Threshold 21 and iSDG models (Collste et al. 2017; Pedercini et al. 2018), two simulation tools based on SD developed by the Millennium Institute to support comprehensive, integrated long-term national development planning, and to investigate the interconnections between the 17 SDGs. Alam (Alam 1997) develops a SD-model for representing and simulating an integrated rural energy system for rural Bangladesh, suggesting that "System-dynamic methodology appears to be the most appropriate technique for handling complex systems (pg. 593)", due to the presence of many feedback loops in farming energy systems. Musango et al. (Musango et al. 2011) and Brent et al. (Brent et al. 2011) state that SD has the potential for assessing the sustainability of renewable energy technology in developing countries by accounting the economic, social, environmental and other factors that might influence the process of energy technology development. Steel (Steel 2008) develops a SD model to simulate the decision-making process of electricity consumers in rural Kenya, while choosing between grid and off-grid power options at national level. Jordan (Jordan 2013) uses SD to compute the electricity demand in a long-term power capacity expansion model for Tanzania, demonstrating that electricity demand should be treated as an endogenous factor in energy planning processes, rather than exogenous. Zhang and Cao (Zhang and Cao 2012) analyses the future energy supply mix for a rural Chinese region by using SD to simulate the nexus between rural economic growth, growth in population and energy consumption. Smit et al. (Smit et al. 2019) use Community Based System Dynamics modelling to investigate the issues that affect energy fuel choice and energy access as related to the introduction of a renewable energy solution in an informal settlement in South Africa. In their analysis regarding the appropriateness of Agent-Based Models and SD in modelling diffusion mechanisms of electricity connections in rural areas of developing countries, Riva et al (Riva et al. 2019b) suggest that SD can represent a more suitable method since it requires less quantitative data and it provides a more structural and holistic modelling framework for conceptualising and formulating in a the determinants and complexities affecting the evolution of electricity demand in unelectrified areas. Notable contributions are provided by Hartvigsson in investigating the main dynamics affecting the success of failure of micro-grid projects in rural Tanzania (Hartvigsson 2015, 2016, 2018, Hartvigsson et al. 2015, 2018). He modelled the interrelation between electricity uses, reliability, affordability issues, and local economy. He suggests that SD allows to make a holistic analysis of energy systems in rural contexts "where the introduction of new technological and social arrangements creates new interfaces between technology, people and their societal and natural surroundings ((Hartvigsson et al. 2015), pg. 2)".

2.2. Novelty of the work

In accordance with the system dynamics concept of *"learning"* as feedback loop (Sterman 1994), this work is based on the previous modelling findings provided in (Hartvigsson 2015, 2016, 2018, Hartvigsson et al. 2015, 2018; Riva 2019; Riva et al. 2019a), which set the basis for the use of the system dynamic theory in the field of rural electrification. As a novelty, this paper adds the following foci as for the use of system dynamics in this field:

1. as an approach for *characterising* the electricity-development nexus and its multifaceted dynamics;
2. for *projecting* long-term electricity demand scenarios;
3. from the perspective of the *energy planner*.

Moreover, standing on the previous work of the Authors (Riva et al. 2018a), this paper adds a quantitative formulation and calibration of the electricity-development nexus based on a real case study. In the energy access research field, the transparent formulation provided in this paper provides a novel modelling framework for carrying out further testing activities on the electricity-development nexus, and it is meant to contribute to the same effort of other researchers focusing on energy demand models and rural electrification. Concerning the SD research field, the modelling process followed and applied in the context of this research can provide a meaningful example on the potentiality and suitability of SD for approaching to modelling issues in the relative new field of energy access and rural socio-economic sustainability. New archetypes about some of the typical multifaceted rural socio-economic dynamics and complexities are also provided, as well as a new source of qualitative and quantitative data.

2.3. Rationale and methodology

By relying on a SD approach, this work is meant to provide a first step in the development of a model for analysing and understanding the electricity-development nexus for rural areas in developing contexts. The conceptualisation, formulation, and calibration methodological steps are followed and described. In the results section, the model structure is discussed by analysing some of the observed model behaviours over the simulation period. The model is based on a real case-study, i.e. a hydroelectric-based electrification programme implemented in the rural community of Ikondo, Tanzania, in 2005 by the Italian NGO named CEFA Onlus. This can be perceived as a limitation of the approach, since the results achieved by following this approach lack of immediate generalisation and applicability to different contexts. On the other hand, in the relatively new field on energy access many issues are still unsolved, the availability of data is scarce, and the investigation of the electricity-development nexus and the evolution of electricity demand are still involving exploratory research approaches. This explains the decision of the Authors to build the model based on a real case study, which allowed to ground the understanding of the modelled issue on actual observed dynamics and quantitative data, paving the way for simplifying and generalising the model.

3. Methodology

3.1. Model conceptualisation and introduction to the Ikondo case

3.1.1. The Ikondo case-study

Analysis of the context. CEFA Onlus is an Italian NGO founded in 1972 by a group of agricultural cooperatives based in Bologna, Italy. In Tanzania, the NGO has realised three mini hydro-electric power plants in the rural areas of Iringa and Njombe regions, which currently serve around 10 villages connected to the mini-grids. The village of Ikondo is the target context of this work. According to the latest 2016-data gathered by CEFA, Ikondo has a population of around 4000 people, divided in approximately 820 households (HHs). The village is characterised by an agriculture-based livelihood, with around 100-120 Income Generating Activities (IGAs) started after the electrification of the community in 2005, towards the installation of a run-of-river hydropower plant built in 2005 with a nominal power of 83 kW. In 2016, CEFA completed the upgrade of the power facility with an additional 350 kW turbine – achieving an overall generation capacity of 433 kW. The power plant is managed by a local utility, namely Matembwe Village Company (MVC), founded by CEFA and now independent. CEFA founded also a local micro-credit utility, namely SACCOS, which is also in charge of recording and collecting the monthly electricity bills in the village.

Data collection campaign. Data collection on the field was carried out in three timeslots by the team of the Sustainable Energy System Analysis and Modelling group of Politecnico, and the current Project Energy manager of CEFA. Table 1 reports the main information regarding the data collection campaigns. In the following, the rationale to deal with numerical data gathered from different time periods and villages is explained.

For *Ikondo*, which is the village used to calibrate the model, two data collection campaigns have been performed:

- With the surveys performed in January 2018, there were collected (1) the punctual time-series data of monthly electricity consumptions and electricity connections of the village used for calibrating the model (see Fig. 1 and Fig. 2), and (2) the information from the interviews as main references used for defining the search-space of the calibration (Appendix C of the Supplementary Material) and to assess if the model's output at simulation time corresponding to January 2018 are comparable with local assessment (Table 9).
- The data gathered with the surveys performed in September 2017 have been the second source of information for improving the definition of the optimisation search-space for the calibration parameters and for assessing if the model's output at simulation time corresponding to September 2017 are comparable with the local assessment.

The villages of *Nyombo and Kidegembye (2016), Ukalawa (2017), and Matembwe (2017)* were selected after the following considerations: these villages are relatively close to Ikondo, they show similar livelihood conditions, and they have been experiencing similar socio-economic dynamics after their electrification. For these villages, the data collected during the surveys were not used primarily for model calibration, but as "backup” data to improve the characterisation of the optimisation search-space of some parameters and to assess the model’s output when the Ikondo (2017 and 2018) data lacked and/or show limited specific references to some parameters and variables. Indeed, the extension of the dataset with these further data would add more confidence on the model output. From a SD perspective, omitting structures or variables known to be relevant because numerical data are unavailable is considered to be less accurate than using the modeller’s best judgment – or the most reliable and available proxy as done in this manuscript – to estimate their values. According to Jay Forrester, ‘‘To omit such variables is equivalent to saying they have zero effect—probably the only value that is known to be wrong!’’ (Sterman 2002). Moreover, Nyombo and Kidegembye (2016) and Ukalawa (2017) data have been considered where Ikondo (2017 and 2018) data reported a too much narrow range of values for some parameters, putting too many constraints to the optimization performed for model calibration. Moreover, it is important to highlight that, as it emerges from Table 1, the sample size of the people interviewed is not statistically representative of the total population. According to this, these data were not used for performing or deriving any descriptive statistics or statistical inferences, but they were used to evaluate the possible optimization search space of the calibrating parameters and assess the model’s output with the information available for 2017 and 2018. On the contrary, for the calibration itself, we relied on the full set of available electricity consumptions and number of connections data related to Ikondo.

Table 1. Main information concerning the on-field interviews.

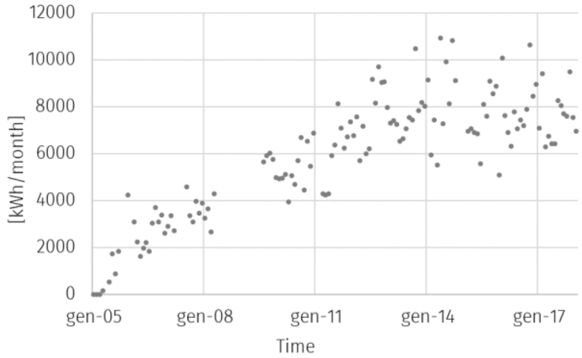
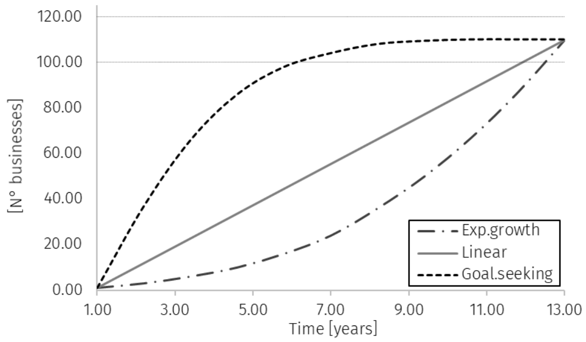
Period	Target	Villages	Aim
June 2016	***33*** Electrified HHs and ***18*** IGAs in electrified areas	Electrified villages of Nyombo (2'981 people) [1] and Kidegembye (4210 people / 842 HHs) [2]	- Defining ranges of income, expenditures; - Gathering information about the electricity use (n° and type of appliances, operation time, time windows, power).
September 2017	***38*** Electrified HHs and ***25*** IGAs in electrified areas	Electrified villages of Ikondo (4011 people, 821 HHs) [2] and Ukalawa (1766 people / 387 HHs)	- Defining ranges of income, expenditures; - Defining hours of working, farming, and for housework; - Defining ranges of connection cost; - Gathering information about the electricity use (n° and type of appliances, operation time, time windows, power).
January 2018	- ***6*** experts: (1) the Country Director of CEFA in Tanzania; (2) The Manager Director of MVC (the electricity utility of Matembwe); (3) the Manager Director of SACCOS (the micro-credit utility of Ikondo which is in charge also to collect the electricity bills); (4) (Ex)Manager Director of MVC; (5) MVC accountant; (6) The Manager director of the Bomalang'ombe Village Company (BVC) (the electricity utility of the village of Bomalang'ombe) and head of the electricians in Ikondo; - ***3*** IGAs: (1) one grocery, which was one of the very few activities which was set also before electrification; (2) one garage and (3) one carpentry, which are among the very few "electricity intensive" IGAs of the villages. - ***2*** farmers: (1) a land owner; (2) a poor farmer; - ***2*** women: (1) MVC accountant; (2) House keeper for CEFA and clothes seller; - ***2*** teachers: (1) Head of Matembwe primary school; (2) Head of Kanikelele's primary school; ***1*** physician at Matembwe dispensary.	Electrified villages of Ikondo (4011 people, 821 HHs) [2] and Matembwe (2879 people / 637 HHs) [2]	- Understanding the history of development of Matembwe-Ikondo; - Conceptualising (i.e. identifying the main variables and dynamics) the electricity-development nexus for Ikondo; - Discussing the structure of the model; - Gathering quantitative data about the variables and parameters formulated in the model (see model calibration); - Collecting the data of monthly electricity consumption for Ikondo consumers from 2005 to 2017 included.

[1] Tanzania National Bureau of Statistic, 2002 National census. http://www.dataforall.org/tanzania/
[2] CEFA 2018 surveys.

3.1.2. Mapping key variables and dynamics

Reference modes and dynamic hypotheses. When dealing with rural electrification, a "long-term thinking" approach is advised (Riva et al. 2018b). The electricity-development nexus is affected by delays of years or even decades. Given the availability of data from the implementation of the Ikondo back in 2005, the time-horizon is set to 13 years. In this time horizon, data and surveys help to define potential reference modes of the system (examples in Table 2) (Sterman 2000).

Table 2. Examples of reference modes and insights.

	These are monthly data of the total electricity consumption of the Ikondo community. Electricity consumptions grew from 2005 to 2017. Moreover, this growth did not occur at a constant rate along all the horizon, and it shows a high level of short-term variability, confirming the presence of non-linear dynamics.
	These are the reference modes of the growth of business activities with electrification. The local experts stated that Ikondo had at most 2 business in 2005, while it now counts around 100/120 at the 13th year. According to this, one expert suggested an *Exponential growth* rate, while data related to the electrical connections of the local business suggest a *Goal seeking* behaviour.
"respect to the initial situation, the average income of the village is more than tripled (the manager director of the MVC)*"*	This indicates an expected substantial growth of income from the beginning of 2005 to the present days.
"People work more in the evening, while farmers can continue their work during the night (the manager director of the MVC / BVC / SACCOS /local workers / local farmers)"	This suggests an expected growth in the time spent for doing business and farming activities during the night hours.
"*Before electricity, 50% of students usually passed the exams at the end of the primary school, now 67%* (Dean of Kanikelele's primary school)	This indicates an expected increase in the educational attainments for the community after electrification.

Causal loop diagrams (CLDs). The identification of the key variables and dynamics for the Ikondo village are based on the CLDs drawn by the Authors et al. (Riva et al. 2018a) in their analysis of the electricity-development nexus, and modified according to the local surveys. Appendix A of the *Supplementary Material* reports the "modified" causal loop diagrams for Ikondo, and the related explanation.

3.2. Formulation and calibration of the simulation model

3.2.1. Structure formulation

The structure of the model is based on the qualitative dynamics described through the previous conceptualised causal loop diagrams. Its formulation is based on an iterative process based on the questionnaires implemented in the field and the information shared with CEFA's local experts. The formulation of the final structure of the model is based on 11 main sub-models: *IGAs formation and Income*, *Market demand, Market production and revenues, Agricultural revenues, Population, Time savings, Education, IGAs electricity connections, HHs electricity connections, Household appliances diffusion,* and *Electrical Energy consumption*.

The model is composed by around 80 levels (*viz.* integral equations), 260 auxiliary variables (*viz.* algebraic and differential equations), 140 constant parameters, and 8 look-up tables. For formulating individuals' behaviour, to deal with the classical SD-hypothesis of perfect mixing and homogeneity within the levels, the agents of the model are represented as households divided in two classes: low income households (LI HHs) (i.e. who rely only on agricultural-based activities) and high-income households (HI HHs) (i.e. who rely both on agricultural-based activities and work in an IGA). This assumption, discussed and reasoned with local CEFA's experts, does not consider a very small fraction of the population, viz. the very poor people who live on alms, and very rich traders or large-land owners.

The model simulates the impact of electricity access and consumption on the socio-economic changes experienced in Ikondo's community. It then evaluates the feedback on the community's electricity consumption by generating long-term evolutions of the electricity load of the entire community along the simulated time horizon. The model documentation of all the 11 sub-models and the stock-and-flow structure is fully reported in the Appendix B of the *Supplementary Material*.

3.2.2. Calibration with historical time-series

Model calibration is a fundamental step of the formulation of a SD-model, which does not aim at assessing the validity or confirming the model, but for building confidence in it. Accordingly, it is here employed for assessing the structure and the uncertainty of the model, since it aims at: (i) verifying the ability of the model to replicate the observed historical behaviour of the system; (ii) uncovering model flaws and hidden dynamics; (iii) identifying a reasonable set of parameters' values most consistent with relevant the knowledge of the system, that could be employed for further applications of the model.

The model calibration needs appropriate and reliable data. According to Jay W. Forrester (Forrester 1980), three types of data are necessary to develop the structure in models: *numerical* (e.g. time series), *written* (e.g. operating procedures, archival materials), and *mental data* (e.g. people's impressions, their perception of the system). In this study, numerical data are used for comparing model behaviour, while mental and written data are employed to set the search-space of the optimisation (see Appendix C of the *Supplementary Material*).

The lack of reliable and available data is one of the most critical challenges for tracking the progress and supporting the research and new investments in rural electrification. In this context, CEFA has been implementing a data recording system of electricity use information from the beginning of 2005, when the Ikondo plant started producing electricity. For accounting purposes, 2 main types of time-series data have been tracking for households and IGAs:

(1) Number of metered electricity connections;
(2) Monthly electricity consumptions of all the connected users.

Each data point contains the information (viz. "data items") resumed in Table 3. The villages of Isoliwaya, Kanikelele, Nyave, and Ukalawa were electrified through the extension of the transmission line implemented in 2016, and they are not considered in this work since they are outside the boundary of the system. Also CEFA's facilitates and cooperatives are excluded due to data scarcity, a different accounting mechanism of electricity use, and because their operations do not cope with the modelled dynamics of market supply (described in Appendix B of the *Supplementary Material*). Schools, churches, administrative offices are excluded as well since they are outside the boundaries of the analysis.

Table 3. Data items for CEFA's time-series data

Consumer type	Households
	IGAs
	(Public services)

Villages	Ikondo (Isoliwaya) (Kanikelele) (Nyave) (Ukalawa)

Raw data were processed to fix some issues observed in the main database – Table 4 reports the main problems and the implemented solutions. The final panel database contains 524 data points. Fig. 1 and Fig. 2 report the time-series data of monthly electricity consumptions and the number of metered electricity connections for both the HHs and the IGAs. The solid black lines, whose values vary from 0 to 100% (the holes in the lines indicate 0% of data availability), represent the percentage of data available each month after the data processing.

Table 4. Data processing rules of CEFA's database.

Issue	Condition		Solution
Missing data points	*> 1 consecutive missing datum*	→	*REMOVAL* of the datum
	= 1 isolated missing datum	→	*MEAN VALUE* between the first (two) preceding and the first (two) consecutive value(s)
Aggregated records	*data referring to 2 different months are recorded all in 1 month*	→	The aggregated records *SPLITTED IN HALF* in two monthly values
Monthly outlier	*the value of electricity demand for a month differs more than 75% from the first preceding and the first consecutive available value*	→	*REMOVAL* of that monthly datum

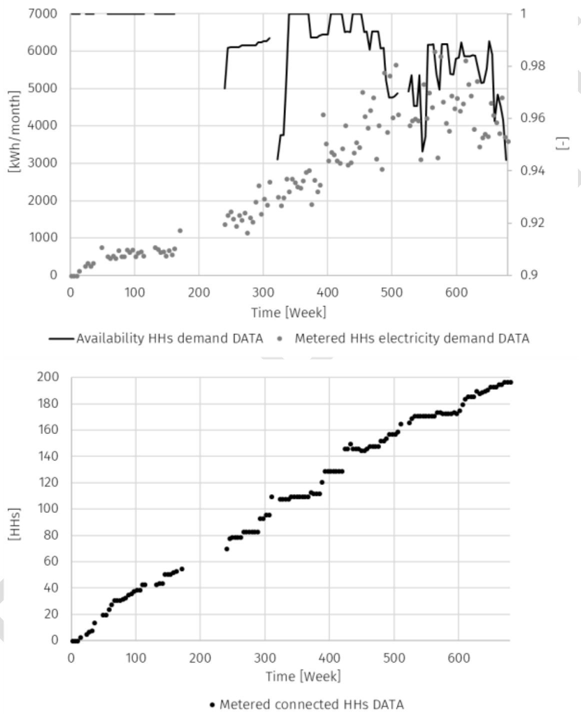


Fig. 1. Data on monthly electricity demand for HHs [*129 data points*] (top) and on the number of HHs connected to the mini-grid [1*31 data points*] (bottom).

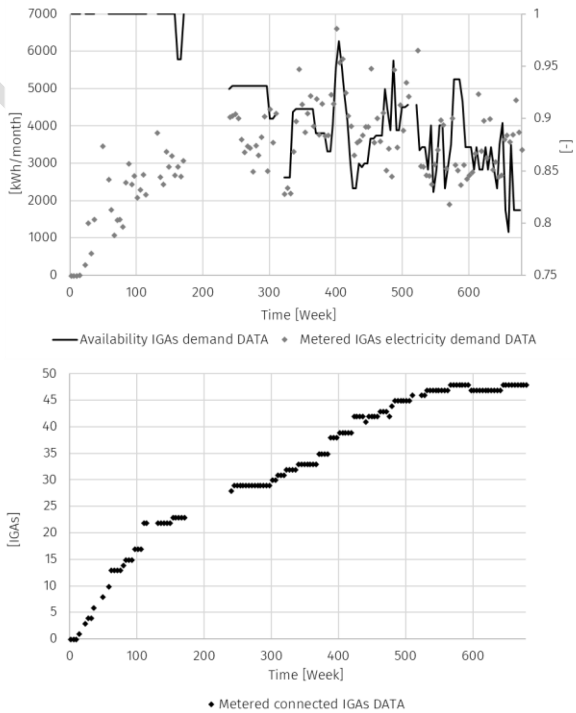


Fig. 2. Data on monthly electricity demand for IGAs [*131 data points*] (top) and on the number of IGAs connected to the mini-grid [133 data points] (bottom).

3.2.3. Calibration set-up

Model calibration is a mathematical optimisation, which finds the combination of the parameters, which minimises the difference between model output and historical data. Two are the main controls set in order to perform an appropriate optimisation: the *Optimiser* and the *Search-space*.

Optimiser. The settings of the optimiser define the mathematical procedure to employ in Vensim DSS ® in order to search the optimal solution. The Powell's algorithm is used, based on a numerical procedure proposed by Michael J. D. Powell (Powell 1964).

Search-space. The definition of the search-space for the optimisation guarantees that the final solution is found within feasible values of each parameter to calibrate. The model counts 139 constant parameters, 123 of which are calibrated through the definition of an appropriate search-space based on the literature, local interview, modeller's choice. For each calibrated parameter, the Appendix C of the *Supplementary Material* reports the search-space and the related source and reference. The acronyms *LB* and *UB* stand for "Lower Bound" and "Upper Bound", respectively.

In the calibration process, the payoff was defined according to Eq. (26):

$$payoff_k = -\sum_{t=1,\ dt}^{T} \sum_{v=1}^{4} \left[\frac{\left(model\ vaue_v(t) - datum_v(t) \right)^2}{weight_v} - a_v \right] \tag{1}$$

where *t* is the simulation time, *T* is the simulation horizon, *v* represents the model variables to compare with data (Table 5). The *weight* and the likelihood term *a* are formulated in the way described in Eq. (27), which makes it possible to estimate the weight as a calibration parameter.

$$\begin{cases} weight_v = \dfrac{StdDev_v^{\ 2}}{2} \\ a_v = \ln\left(StdDev_v \right) \end{cases} \tag{2}$$

where the *StdDev* is standard deviation of the measurement error for the variable *v*, which is estimated by the model itself during the optimisation process.

Table 5. Data and variables used for the definition of the calibration payoff.

Data used	compared to **Model variable**
Metered IGAs electricity demand DATA (Fig. 2-top)	Since the availability of IGAs electricity demand data is not always 100%, data are compared to the time-dependent variable *Partial IGAs electricity demand* obtained by the product between the *Total IGAs electricity demand* variable (*Supplementary Material*, Eq.(32)) with the time-series *Availability IGAs demand DATA* (as clearly visible in Fig. 2-top) containing the values of data availability for electricity demand of local businesses.
Metered connected IGAs DATA (Fig. 2-bottom)	Local surveys pointed out the presence of shared meters for business. The *Metered connected IGAs DATA* time-series is therefore compared to the time-dependent variable *Metered IGAs* obtained by multiplying the variable C*onnected IGAs* (*Supplementary Material*, Eq. (24)) with the calibration parameter *fraction of sharing meter*.
Metered HHs electricity demand DATA (Fig. 1-top)	Since the availability of HHs electricity demand data is not always 100%, the data are compared to the time-dependent variable *Partial HHs electricity demand* obtained by the product between the *Total HHs electricity demand* variable (*Supplementary Material*, Eq.(30)) with the time-series *Availability HHs demand DATA* (as clearly visible in Fig. 1-top) containing the values of data availability for electricity demand of local households.
Metered connected HHs DATA (Fig. 1-bottom)	Local surveys did not point out the presence of shared meters for residential connections. Data are compared to the *Total Connected HHs* (see *Supplementary Material,* Eq. (27)) variable.

3.3. Parameters uncertainty towards Monte-Carlo Markov-Chain

According to Rahmandad et al. (Rahmandad et al. 2015), Markov-chain Monte-Carlo (MCMC) is a mathematical approach to explore the appropriateness of the calibration of a model and to assess potential good proxies of the confidence bounds of calibrated parameters. In this study, MCMC was employed to characterize the payoff distributions around the calibrating parameters without making any assumption on their mathematical properties (van Ravenzwaaij et al. 2018). To perform MCMC in the appropriate way, the autocorrelation of the residuals shall be evaluated, since it can bias the results of the MCMC and the confidence bounds on the parameters. Fig. 3 reports the residuals evaluated on the 4 payoff functions employed in the calibration, and the related Durbin-Watson (DW) test used for assessing the autocorrelation (Durbin and Watson 1950, 1951).

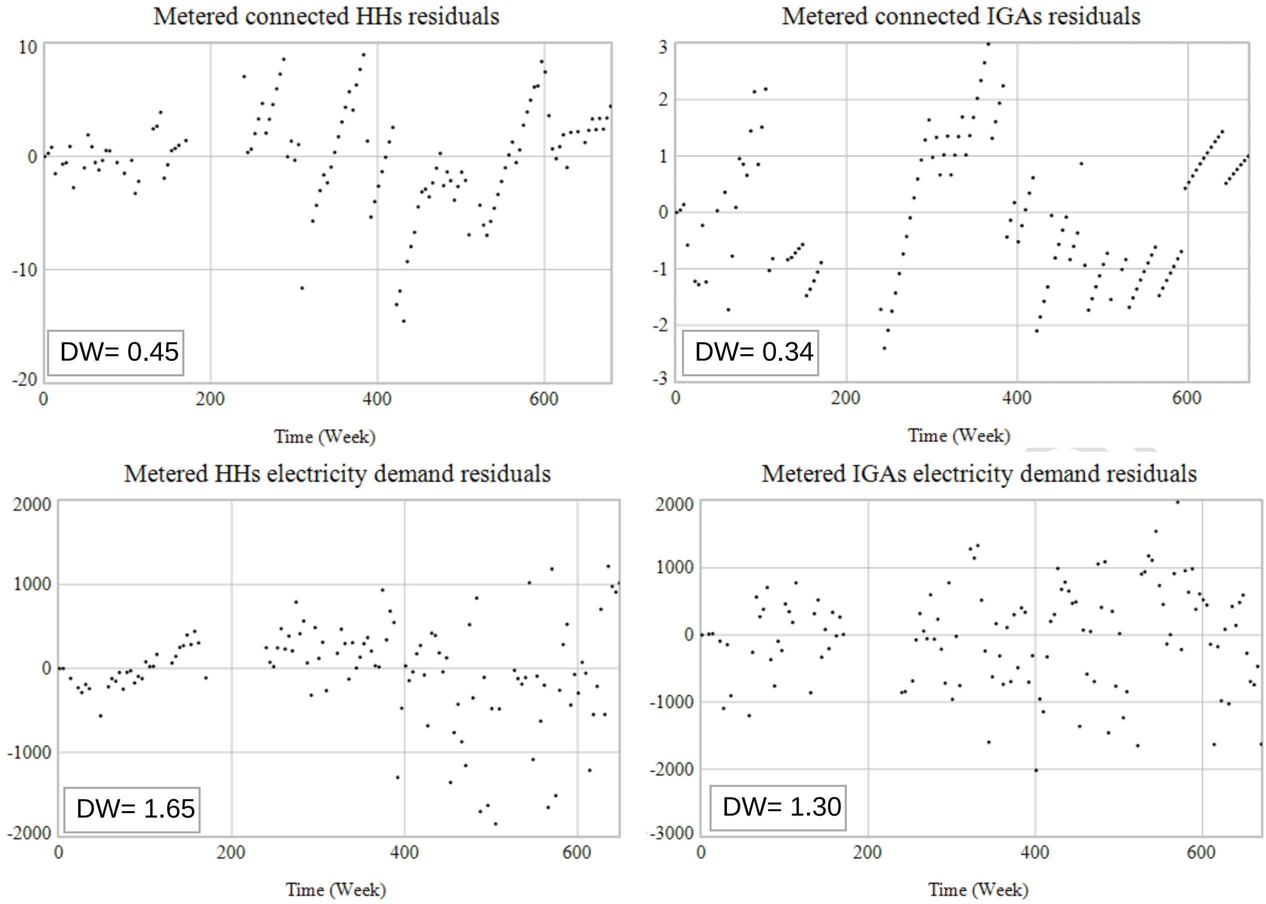


Fig. 3. Residuals and Durbin-Watson test for the variables used for defining the payoff.

According to (Field 2013), as a very conservative rule of thumb, values less than 1 or greater than 3 of the DW test definitely confirm that the residuals are affected by autocorrelation. This information, together with the plot of the residuals, was considered sufficient for considering just the residuals of *Metered connected IGAs* and *Metered connected HHs* as clearly autocorrelated. It is worth nothing that also the graph of the residuals of the *Metered HHs electricity demand* suggests an initial sign of autocorrelation, due to the inability of the model to estimate properly the household demand in the first weeks of the simulations (as seen in Table 8 in the statistics applied to calibration results).

Given these results, the payoff sensitivity was carried out by relying just on the payoff evaluated on the *Metered IGAs electricity demand* and *Metered HHs electricity demand* variables, whose calibration is not affected by significant levels of autocorrelation. This modelling decision avoids implementing the MCMC on the potentially biased likelihood surfaces specified by the payoff function of the *Metered connected IGAs* and *Metered connected HHs*, since the related residuals are clearly affected by autocorrelations. Moreover, this choice does not prevent the definition of the confidence bounds on all the calibrating parameters, since also the parameters more related to *Metered connected IGAs* and *Metered connected HHs* have a direct or indirect impact on the *Metered IGAs electricity demand* and *Metered HHs electricity demand*. On the contrary, this choice gives more large confidence bounds and more preventive estimations.

For the sake of transparency and replicability, the main MCMC settings implemented in Vensim DSS ® are listed in Table 6.

Table 6. MCMC options set in Vensim DSS ®.

Setting	Value	Explanation
:MC*LIMIT*	20000	The maximum number of iterations to perform
:MC*BURNIN*	500	The number of iterations, which identifies the *burn-in* or *convergence* period, to allow the chain to converge towards the "right" values of the parameters.

		Since the MCMC is implemented after the Powell calibration, the *burn-in* is set very short since it is potentially superfluous
:MC*NCHAINS*	2	Number of Markov Chains to run per parameter
:MC*INITMETHOD*	Hybrid	It represents a hybrid strategy for initializing each chain, through which a random direction is chosen. Then, the move in such direction is scaled iteratively by half or doubled until the largest possible move with a reasonable chance of acceptance (at least 5%) is found.

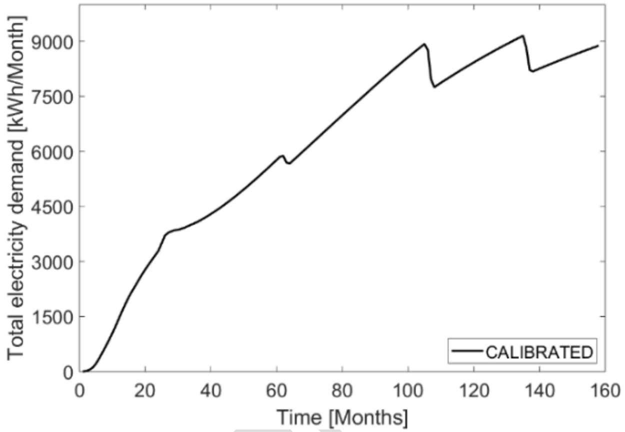
The MCMC process returns the list of all the accepted points (i.e. the accepted set of $\bar{\theta} = \{\theta_1, \theta_2, \dots, \theta_{123}\}$ values of the parameters). The confidence bounds of each parameter were evaluated at 90% of confidence by considering the 0.05 and 0.95 percentiles of the list of all the accepted points $\bar{\theta} = \{\theta_1, \theta_2, \dots, \theta_{123}\}$. Complete results are reported in the Appendix E of the *Supplementary Material*.

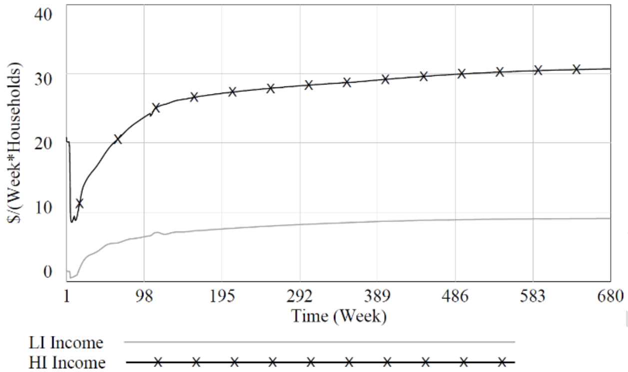
4. Results and discussion

4.1. Discussing relevant model behaviours

This section introduces a discussion about how the detailed model structure drives some of the observed model behaviours over the simulation period, and the potential tipping points the model structure can generate. This analysis is performed by evaluating the behaviour of some of the variables simulated with the calibrated set of parameters.

Table 7. Comparison between model's output, local data and experts' assessment.

Variable	***Graphical representation***	***Discussion***
Total electricity demand [kWh/Month]	 **Fig. 4. Trend of the *Total electricity demand* variable.**	The simulation output reports the calibrated output of the *Total electricity demand* variable, which represents the total monthly consumption of electricity by the Ikondo community. The growing trend of electricity consumption is in line with other theoretical and empirical studies from the literature: Mustonen (Mustonen 2010) uses LEAP model to investigate possible developments and growth paths for electricity demand from 2006 to 2030 for a rural village in Lao People's Democratic Republic. Xiaohua et al. (Wang et al. 2006) indicate that the rural households in the Shouyang County in China have experienced a growth of electricity use especially due to increased ownership levels of electrical appliances. Zomers suggested that in the case of developing countries, rural electricity demand can increase "at more than just a few per cent per annum ((Zomers 2003), pg. 71)". Gustavsson (Gustavsson 2007b) presents data from a case-study of a photovoltaic-Energy Service Company (PV–ESCO) project company in Lundazi, rural Zambia, indicating that the clients of the system have purchased and used a growing number of appliances over time. Muñoz et al. (Muñoz et al. 2007) report monthly data of electricity consumption in two different Moroccan villages, showing a positive trend of electricity load from 2002 to 2006. Morante and Zilles (Morante and Zilles 2001) and Reinders et al. (Reinders et al. 1999) report that in the village of Sukatani, in the Province of West Java, Indonesia, households have experienced was a large increment of electricity consumption between 1992 and 1997, from 4.65 to 7.65 kWh/month. Habtetsion and Tsighe (Habtetsion and Tsighe 2002) investigate the electrification rate of 13 rural villages in Eritrea, finding that an annual growth of connections of 17%, and an annual consumption growth rate of 54% Beside the growing trend, novel interesting considerations about the model behaviour and growing dynamics can be reported from the results of the simulations: 1. The initial months show the trend typical of a S-shape diffusion curve, but with a short *early-stage* of adoption. This suggests that electricity access is not perceived as an actual innovation by people, but something that they already know, desire, and are willing to pay for. This conclusion is supported also by the relatively high calibrated values of *awareness effect* parameters, as discussed in Appendix D of the *Supplementary Material*. 2. The change in the trend after the first 20/25 months caused by the change of the tariff scheme of the electrical connections has a significant impact on the electricity consumption. This indicates the importance of connection cost on the diffusion of the connections. This in in line with the literature, which suggests that electrification projects must be accompanied by sustainable "cost of connection" policies, such as international "smart" subsidies or cost-sharing mechanisms (Sovacool et al. 2013) for covering initial investments (Zomers 2003; Baldwin et al. 2015). 3. The electricity tariff emerges to be definitively a significant determinant of the electricity demand, as visible with step-changes in the figure. In accordance with (Hartvigsson 2018), this confirms the importance of affordability when planning rural electrification strategies.

HI Income *[$/Week/HHs]* LI Income *[$/Week/HHs]*	 **Fig. 5. Trend of the *HI and LI Income* variables.**	In accordance with causal-loop diagrams of sub-section 3.1.2, the growing trend of the electricity demand displayed in the figure is driven by the growing trend of the income-based variables, which confirms the direct causal relationship between the economic growth of the local community and the impact on electricity demand. Fig. 5 reports the trend of the Income variable for the HI and LI HHs, which shows a goal seeking behaviour characterised by an initial more rapid growth, followed by a smoother approach to a constant value. From the figure, it emerges an initial phase of sudden decrease of the income, which is not a model initialisation problem, but it is due to the initial high level of unsatisfied market demand, which creates a backlog of perceived needed new IGAs. To set-up all such initially desired IGAs, the initial level of debt that people take out with the micro-credit utility, or the savings needed to set-up the business, is high. Once reduced the backlog, income starts increasing. This confirms that electricity itself does not bring economic growth, but its provision must be necessary complemented with financial instruments that generate an initial reduction of economic resources. This is in line with the literature, since facilitating access to credit and finance is the most common recommendation (Biswas et al. 2001; Bastakoti 2006; Adkins et al. 2010; Kooijman-van Dijk and Clancy 2010; Gurung et al. 2011; Peters et al. 2011; Brass et al. 2012; Baldwin et al. 2015), since it allows people to set-up new IGAs, and facilitates a regular cash-flow, which in turn helps build financial capital (Bastakoti 2006). Fig. 5 suggests also that the economic benefits electricity access have limits. This is confirmed by the trend of the HI and LI Income variables that show an initial exponential growth approaching to a limit. This can be explained by the second causal-loop diagram displayed in **Errore. L'origine riferimento non è stata trovata.**. At the beginning of the simulation, the reinforcing loops R1a and R1b are prevalent, since the level of unsatisfied market demand of the people is high due to few available IGAs. With access to electricity and micro-credit, more activities are developed and start satisfying the local market demand as long as the effect of the market competition and the related balancing loop B1 becomes relevant, and no more IGAs are developed (Fig. 7). Evidence of this situation of market saturation can be found in the empirical literature, where the creation of new IGAs as a result of electrification can be even followed by stagnation or a reduction of wages due to an abundance of labour supply over labour demand (Dinkelman 2011).

IGAs *[IGAs]*

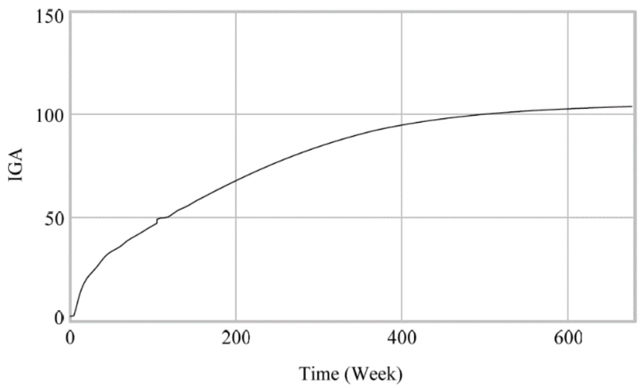


Fig. 6. Trend of *IGAs* variable.

The trend of the variable confirms the dynamics discussed above: an initial rapid growth of IGAs, due to the initial high level of unsatisfied market demand and accessibility to micro-credit, and therefore a backlog of needed IGAs. Once reduced the backlog, the process of IGAs formation follows a smoother path in accordance with the smother growth of the village income. The increase of IGAs as a result of electrification is suggested also in the empirical literature: R. Kumar Bose et al. (Kumar Bose et al. 1991) report that access to electricity led to a 20% increase in business activities in three villages in Eastern Uttar Pradesh. B. Bowonder et al. (Bowonder et al. 1985) show that access to electricity led to the creation of repair and serving shops and village entertainment enterprises such as movie tents and community televisions (TVs) in eight rural communities in India. Cabraal et al. (Cabraal et al. 2005) indicate that 25% of households with electricity operated a home business in Philippines, compared to about 15% of households without electricity. Bastakoti (Bastakoti 2006) reports that the Nepalese areas served by the Andhikhola Hydroelectric and Rural Electrification Centre (AHREC) experienced the creation of 54% more rural industries after electrification, allowing 600 more employees to have an income.

Fr income for food HI *[-]*

Fr income for food LI *[-]*

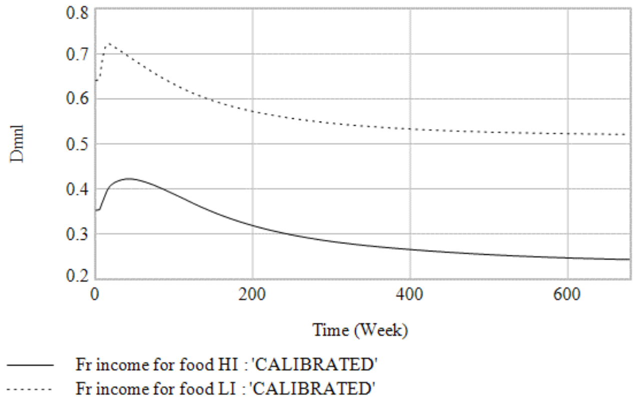


Fig. 7. Trend of *Fr income for food HI* and *LI* variables.

The initial phase of sudden decrease of the income variables (Fig. 5) at the beginning of the simulation horizon has a feedback on the variable representing the income spent for food. In the initial timeframe, in order to keep the demand for food at the same initial level, HHs increase their fraction of income for food expenditures at the expense of lower market expenditures. It then starts decreasing due to the gradual increase of HHs' expenditures for new and/or improved goods (the feedback *Electricity demand → Product innovation/improvements* displayed in the CLDs and in Fig. 8) and services at the expense of lower relative food expenditures. The relative greater increase of non-food expenditures over food expenditures is also suggested by the empirical literature: Khandker et al. (Khandker et al. 2012) indicate that electrification in India increased household per capita food expenditure by 14%, non-food expenditure by 30%. Zhang and Samad (Samad and Zhang 2016) report lower results, suggesting that gaining access to the grid in India is associated with an 8.4% increase in households' per capita food expenditure, a 14.9% increase in per capita non-food expenditure.

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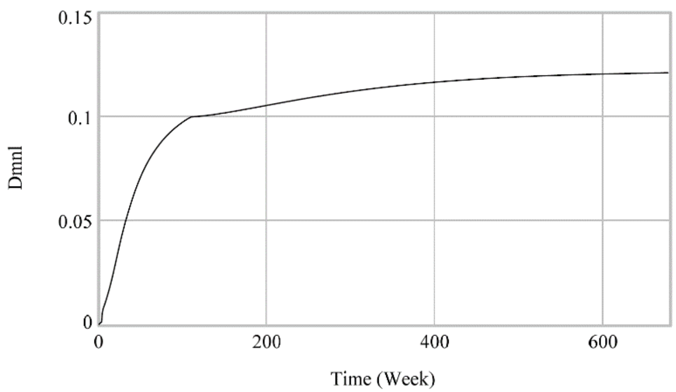

Fig. 8. Trend of *Electricity effect on expenditures* variable.
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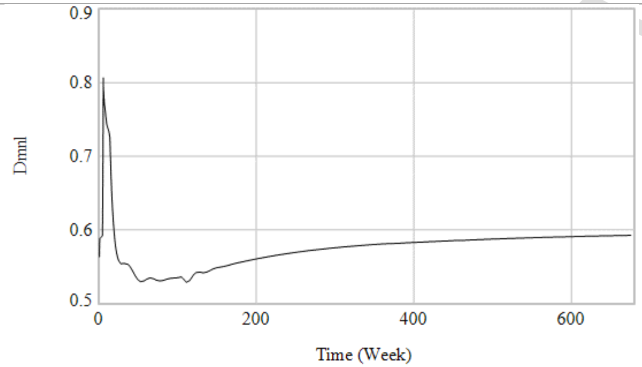
<tr>
<td>Fraction of external/internal farming revenues *[-]*</td>
<td>


Fig. 9. Trend *Fraction of external/internal farming revenues* variable.
</td>
<td>This variable represents the ratio between the farming turnover from the external and internal customers. As shown in Fig. 9, the external demand of agricultural products represents around 80% the total demand. At the beginning of the simulation horizon, HHs experience a drop in their expenditures to take out the debt with the micro-credit and save money to invest in IGAs. In this timeframe, the external demand for food product is therefore largely predominant. It then decreases below the initial level, due to an increase of the HHs' income per effect of the improvement in the socio-economic conditions triggered by electricity (see discussion for Fig. 5) that increase the internal expenditures for food by local inhabitants. It then starts increasing again due to the gradual increase of HHs' expenditures for more goods and services at the expense of lower relative food expenditures (Fig. 8).</td>
</tr>
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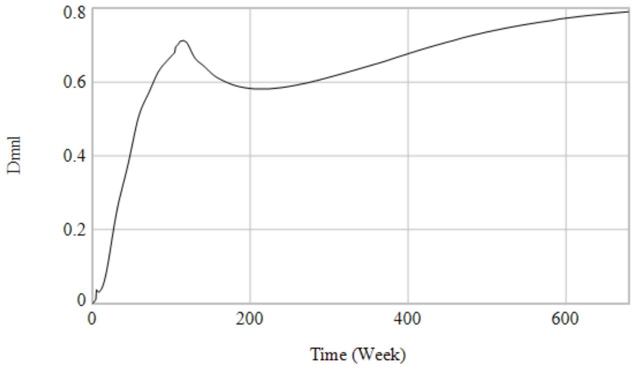
fr of connected IGAs *[-]*	 **Fig. 10. Trend of *fr of connected IGAs* variable.**	This variable shows an interesting behaviour. It initially increases rapidly due to the affordable cost of the connection – viz. IGAs get connected almost at the same time they set-up. With the change of the connection tariff, the process of IGAs connection become slower than the process of IGAs creation, causing the negative trend displayed in the figure. As soon as the number of IGAs reaches the plateau, the backlog of IGAs to connect starts reducing, inverting the sign of the derivative.

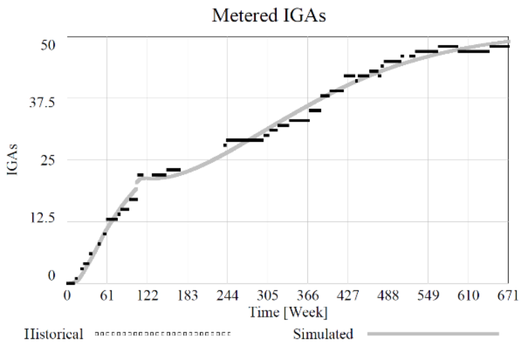
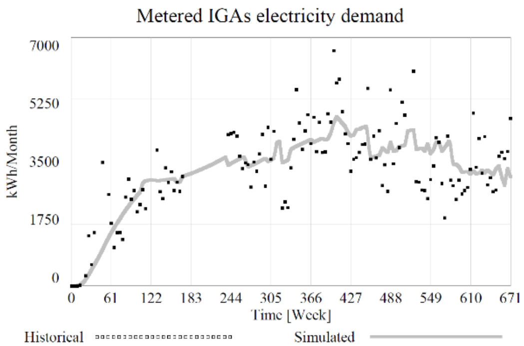
4.2. Behaviour consistency with data and experts' opinion

This sub-section aims at assessing the ability of the model to qualitatively and quantitatively reproduce the actual behaviour of the system, in order to build confidence in the model results, and uncover hidden dynamics and model flaws. The SD-based literature (Sterman 1984, 2000; Bala et al. 2017) proposes various statistical measures for assessing the correspondence between model and data of the calibration. In this work, two approaches were followed:

i. *Descriptive statistics* to assess the point-by-point fit: many common metrics (Sterman 1984) exist for measuring the error between a data series on *n* observations and the model output over the relevant time horizon. In this study, the *Coefficient of determination (R2),* the *Mean Absolute Percent Error (MAPE),* and the *Mean Square Error (MSE)* decomposed through the Theil Statistics are employed and calculated for the 4 variables used for defining the payoff. The results are discussed in Table 8, which indicates a good statistical fit between model and data, increasing the confidence in model output. All the calibrated values of the parameters are reported and discussed in the Appendix D of the *Supplementary Material*, which are the results of an iterative optimisation process.

ii. *Experts and data assessment*, by comparing the end-time values of some simulated variables with the experts' opinion and data: Table 9 reports the variables analysed and the potential range of values indicated by the experts at the end of the simulation time and in September 2017.

Table 8. Statistics applied to calibration results

<table>
<tr><th>Graphical fit</th><th>Statistics</th><th>Comment</th></tr>
<tr><td rowspan="5">
</td><td>R^2 = 0.99</td><td>The model explains almost all the variability of the response data around its mean.</td></tr>
<tr><td>MAPE = 4.4%</td><td>The model presents a high level of accuracy, since the variability of data around the mean of the model output is very low.</td></tr>
<tr><td>U^M = 0.00</td><td>NO bias
The model output and the data series have the same mean.</td></tr>
<tr><td>U^S = 0.00</td><td>NO unequal variation
The model output and the data series have the same trend.</td></tr>
<tr><td>U^C = 1</td><td>ONLY unequal covariation
The error term is exclusively attributable to an error term with zero mean, which makes the model output and the data series to differ point by point. In particular, the model is not able to reproduce the “step-trend” of data that in this case is probably due to the process of IGAs formation that is not continuous in time.
It is an UNSYSTEMATIC error since the purpose is not to study cycles in the data.</td></tr>
<tr><td rowspan="5">
</td><td>R^2 = 0.61</td><td>The model explains more than half of the variability of the response data around its mean.</td></tr>
<tr><td>MAPE = 21.2%</td><td>The model presents a quite low level of accuracy, since the variability of data around the mean of the model output is not negligible. This means that the model is not able to capture the variability of data. This issue can be solved by (i) introducing and calibrating a random error term, or (2) by formulating the dynamics that can explain such variability. Potential reasons of this variability can be:
– Intra-season variabilities, due to the dependency of people financial availability with the harvesting period;
– Daily load variability, due to the unpredictability of people’s habits and use of electricity within the 24 hours.
This high level of variability is not a systematic error, since the purpose is not to study such variabilities in the long-term forecast.</td></tr>
<tr><td>U^M = 0.01</td><td>NO bias
The model output and the data series have the same mean.</td></tr>
<tr><td>U^S = 0.04</td><td>NO unequal variation
The model output and the data series have quite the same trend.</td></tr>
<tr><td>$U^C = 0.95 \cong 1 – U^S$</td><td>ONLY unequal covariation
The error term is exclusively attributable to an error term with zero mean, which makes the model output and the data series to differ point by point.
It is an UNSYSTEMATIC error since the purpose is not to study cycles in the data.</td></tr>
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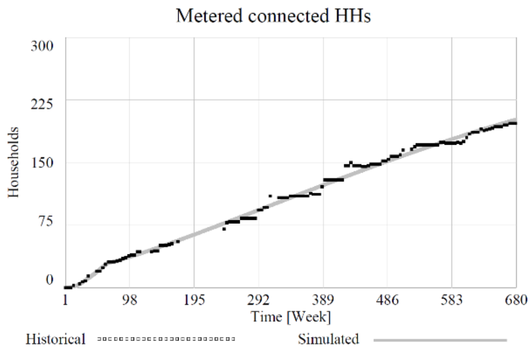
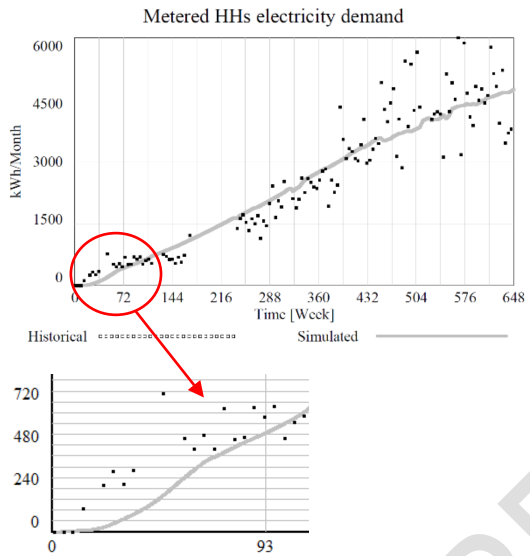
	$R^2 = 0.99$	The model explains almost all the variability of the response data around its mean.
	MAPE = 3.6%	The model presents a high level of accuracy, since the variability of data around the mean of the model output is very low.
	$U^M = 0.00$	*NO bias* The model output and the data series have the same mean.
	$U^S = 0.00$	*NO unequal variation* The model output and the data series have the same trend.
	$U^C = 1.00$	*ONLY unequal covariation* The error term is exclusively attributable to an error term with zero mean, which makes the model output and the data series to differ point by point. In this case, the "step-trend" in the data is probably due to the fact that the physical process of grid extension – viz. the constructions of further junction boxes in unelectrified areas of the village – is obviously not continuous in time. Once a junction box is built, the houses in its surroundings can start asking for a connection (if they can afford it). The other households that live farther have to wait that a new junction box is built, and this probably creates a wait with no further connections (viz. the flat side of the steps). It is an UNSYSTEMATIC error since the purpose is not to study cycles and short-term trends in the data.
	$R^2 = 0.88$	The model explains much of the variability of the response data around its mean.
	MAPE = 20.3%	The model presents a quite low level of accuracy, since the variability of data around the mean of the model output is not negligible. This means that the model is not able to capture the variability of data. The potential reasons and solutions are the same mentioned for electricity demand of IGAs. Moreover, the model underestimates the household demand in the first weeks of the simulations. Although this does affect the total electricity demand of the community (the IGAs demand is much higher) and the purpose of the model, the causes of this deviation respects to data are worth to be investigated. The problem is probably intrinsic to the perfect-mixing hypothesis of system dynamics, which cannot capture the presence of some actors (e.g. very rich people) who behave differently from the average. Although these actors represent a very small fraction of the population, at the beginning of the simulation their different behaviour could be predominant since they are reasonably the first people to be connected and to consume electricity. On the other hand, the hypothesis of perfect-mixing remains reasonable over the entire simulation horizon.
	$U^M = 0.00$	*NO bias* The model output and the data series have the same mean.
	$U^S = 0.09$	*NO unequal variation* The model output has almost 10% different trend.
	$U^C = 0.90 \cong 1 - U^S$	*ONLY unequal covariation* The error term is attributable to an error term with zero mean, which makes the model output and the data series to differ point by point. It is an UNSYSTEMATIC error since the purpose is not to study cycles in the data.

Table 9. Comparison between model's output, local data and experts' assessment.

	t=665.75		*t=679.25*	
Variable	***Range from data***	**Simulated**	***Range from experts' opinion***	**Simulated**
Total daily farming hours for LI HHs *[Hours/day]*	*[3 - 8]*	6.85		
HI Income *[$/Week/HHs]*	*[3.1-133.8]*[3]	30.66		
LI Income *[$/Week/HHs]*	*[0.9 - 15.4]*	9.08		
IGAs *[IGAs]*			*[40 - 120]*	104
Fraction of HI HHs *[-]*			*[0.28 - 0.42]*	0.36
Fraction of LI HHs *[-]*			*[0.52 - 0.78]*	0.64
IGA income ratio HI HHs *[-]*			*[0.40 - 0.95]*	0.73
farming income ratio HI HHs *[-]*			*[0.05-0.50]*	0.24
farming income ratio LI HHs *[-]*			*[0.75 - 1]*	1.00
Fr income for food HI *[-]*			*[0.05 - 0.30]*	0.24
Fr income for food LI *[-]*			*[0 - 0.7]*	0.52
Fraction of external/internal *[-]* farming revenues			*[0.5 - 0.9]*	0.59
fr of connected IGAs *[-]*			*[0.67-0.80]*	0.79
Fraction of market expenditures HI *[-]*			*[0.05 - 0.60]*	0.35
Fraction of market expenditures LI *[-]*			*[0.1 - 0.6]*	0.15
fr of HHs close to the grid *[-]*			*~ 50%*	**27%**

The comparison confirms that the model output is in line with the CEFA experts' judgment. Indeed, just one simulated variable does not reflect the value suggested by the one expert, namely the variable representing the fraction of HHs close to the distribution grid who could potentially afford the electrical connection. This could be due to two main reasons:

1. A bias in the expert judgment, since it refers to the comment of only one person, namely the head of the electricians and manager director of the local utility of another local mini-grid;
2. There are hidden dynamics not captured by the model and not emerged from the local surveys, other than the distance from the grid, which prevents a fraction of the population from obtaining the electrical connection.

Since the final objective of the model is not to understand the barriers to household connections, this inconsistency between experts' opinion and model output does not weak significantly the confidence in the model.

4.2.1. Surprising and interesting parameter values

In this sub-section, some of the optimised values of the parameters are reported and discussed in Table 10. All the calibrated values are reported in the Appendix D of the *Supplementary Material*. The calibrated values are the results of an iterative optimisation process. Indeed, the deterministic Powell algorithm does not prevent the possibility to find local minima, which are numerically sound, but not coherent with the reality, although this issue has been partially prevented for some parameters by the definition of precise search-space. This set of

[3]According to S. Pachauri in (Filippini and Pachauri 2004), data of households' expenditure is considered more representative of the economic activity of people than households' income: income data are hard to obtain for developing countries, since poor households do not pay income tax, many subsistence activities are not monetised and during surveys people often hide part of their income. Moreover, this is in line with the modelling hypothesis such that on a weekly basis, households' expenditures are equal to their income inflow.

values does not pretend to represent the actual value of the parameters, since other possible combinations of value may fit in a similar way. Rather, they represent the starting point for analysing the uncertainty of the model, assessing the ability of the model in describing an observed historical behaviour, uncovering hidden dynamics and model flaws, determining the prevalent and weak dynamics, and finally obtaining a set of values that could be used as a reliable starting point for the application of the model to further case studies.

Table 10. Reporting and discussion of the values of the calibrating parameters.

Parameter	Search-space	Calibrated value	Relevant comments
awareness effect HI HHs *[1/Week]*	[0.000029 - 1]	0.976	These relatively high values reflect the fact that electricity access is not perceived as an innovation by people. Also the local interviews capture this dynamics, since also people that do not have electricity they are aware of its benefits and desire it.
awareness effect IGAs *[1/Week]*	[0.000029 - 1]	1	
awareness effect LI HHs *[1/Week]*	[0.000029 - 1]	0.021	
BETA – el *[-]*	[0 - 1]	0.897	Electricity has a relevant impact on local market productivity, especially due to the electrification of EE-reliant IGAs (e.g. Mills). This has empirical evidence also from the literature. E.g. Dijk (Kooijman-van Dijk and Clancy 2010; Kooijman-van Dijk 2012) indicates that, when the market-demand is high, tailors that used electric sewing machines were able to increase the productivity by two to three times more than the average, while grain millers reported processing larger volumes of grains per day.
EffectOfHomeElectricity *[-]*	[0 - 0.1]	0.0003	As suggested by the teachers in Ikondo primary school, electricity at home is not as much relevant as electricity at school for improving the pupils' educational attainment. This result is in line with a non-negligible part of the literature reports limited or very little positive impact of electricity use on educational attainment. Gustavsson (Gustavsson 2007a) reports no evidence of actual improvements of school children's marks as a consequence of access to solar services in the surveyed Eastern Province of Zambia (Gustavsson 2007a). Bastakoti (Bastakoti 2006) and Komatsu (Komatsu et al. 2011) find that in rural western Nepal and Bangladesh respectively, children reported an overindulgence in watching TV that limited their willingness to complete their homework in time.
Electricity-Income elasticity HHs *[-]*	[-1 - 0]	-0.09	This low value confirms what stated by the experts regarding this parameter: electricity is very cheap for households, and they do not change significantly their consumption patterns based on changes in the electricity price. The literature reports different results on this matter based on the context under study: Tiwari (Tiwari 2000) analyse the income elasticity to electricity demand for the city of Bombay, estimating values ranging from 0.28 to 0.40 based on income group. On the contrary, Moharil and Kulkarni (Moharil and Kulkarni 2009) suggest that despite the higher cost of electricity, people living on Sagardeep Island in West Bengal demanded more power for entertainment, comfort and developing job opportunities irrespective of their income level, suggesting very low levels of demand elasticity. Similarly, Alkon et al. (Alkon et al. 2016) use nationally representative household data from India, 1987–2010, and suggest that household income is not a primary determinant for willingness to pay for high-quality modern energy.
fr increase of market expenditures *[-]*	>0	0.90	The fractional increase in the market expenditures is almost proportional to the increase in IGAs connection. In the literature, Kirubi et al. (Kirubi et al. 2009) and Kooijman-van Dijk (Kooijman-van Dijk 2012) suggest that electric appliances allow for improvements in products' quality and production and/or selling of new products which can attract more consumers or increase the demand per-capita.
fraction of external source of LI income *[-]*	[0 - 0.05]	0.00	LI people are also the ones with no social networks outside the village.
fraction of initial HI HHs to be connected *[-]*	[0 - 1]	0.83	The initial HI HHs are the ones already willing to be connected since they have the resources to afford the connection.
GAMMA – edu *[-]*	[0 - 0.1]	0.002	It confirms that market productivity is inelastic respect to primary education attainments – viz. changes in the primary educational levels do not impact significantly on the market productivity.

housework reduction given by electricity *[Hour/Day]*	[0 - 1.3]	0.1	Electricity does not significantly impact on the burden of housework; indeed, the local women interviewed who confirmed a reduction in the housework confirmed that it was due to the electrical rice cooker, a technology that very few people can afford. The savings of time especially for cooking was also reported by Kumar (Kumar et al. 2009) in their study in 5 centres in Sagar Dweep Island in India, 38% of households stated a benefit from time savings for cooking.
internal migration effect *[-]*	≥ 1	1.004	This value indicates that the practice of moving the house close to the electrified area is not common, despite one expert mentioned it.
Max time for night housework *[Hour/Day]*	[0 - 4]	0.6	Households do not dedicate much time for night housework.
Max time for night working *[Hour/Day]*	[0 - 4]	3	It confirms that night-time for working is largely exploited by IGAs connected to electricity. This result confirms other empirical studies in the literature (Alazraki and Haselip 2007; Mishra and Behera 2016). E.g. (Peters et al. 2009) declared working longer thanks to lighting that extended their daily operating hours in Copargo (Benin). Jacobson (Jacobson 2007) suggest that lighting in the evening can benefit and positively impact teachers' income in rural schools in Kenya, enabling them to grade papers, plan evening lessons at home and earn some extra money.
maximum fraction of income for debt repayment *[-]*	[0 - 1]	1	This value suggests that when people plan to ask for a loan, they consider all their income for payback the loan. This is also suggested by the manager of the micro-credit, who indicated that when people obtained the loan, they want to pay it back as soon as possible.
Time to perceive decrease in operating hours *[Week]*	≥1	241015	This shows that people are hesitant in reducing time spent at work, seeking to use all the time available for trying to sell their goods and services.
Time to perceive electricity benefits *[Week]*	≥1	1	People are already aware of the benefits of electricity, as expected.
Time to perceive increase in operating hours *[Week]*	≥1	2.7	Contrary to parameter *Time to perceive decrease in operating hours [Week]*, if available, people are very willing to use all their time available for working and trying to sell their goods and services. In the literature, Meadows et al. (Meadows et al. 2003) state that the introduction of battery-operated lamps in rural Bangladesh allowed tailors to work for four more hours and thereby increase their revenue by 30% in Hosahalli village (India).

5. Conclusion and further work

Despite many investments in the rural electrification sector in the last decades, the scientific literature reports only fragmentary and sometimes controversial results regarding the impacts of electrification programmes, and most of the times the causes are attributable to the inappropriate planning of the off-grid power system capacities. In this context, wrong projections and assessments of the long-term electricity demand contribute to the over- and under-sizing of electricity systems and related infrastructures, especially in off-grid areas. This is caused by a limited knowledge and modelling of the long-term impact of electricity access on local socio-economic conditions and the consequent feedback on electricity demand. The lack of models and approaches for investigating and understanding the determinants of rural electricity demand, and making long-term reliable projections represent an informational and research gap that the present work contributed to fill by pursuing the following specific objective: to conceptualise, formulate, and calibrate a simulation model based on a real case study, in order to provide a robust modelling framework for carrying out further testing activities on the electricity-development nexus.

The *conceptualisation* phase was carried out based on a real case-study used as reference and for going further in the next stages of the modelling process, i.e. a hydroelectric-based electrification programme implemented in the rural community of Ikondo, Tanzania, in 2005 by the Italian NGO named CEFA. Considered a "successful case of rural electrification" by locals, practitioners, and academics, an important element of originality and contribution of this work was the improved characterisation of the electricity-development nexus and the main determinants of the electricity demand based on a real case. In the *formulation* phase, the formulation of quantitative and bottom-up white-box (i.e. causal-descriptive) relations that characterise the electricity-development nexus sets a novel modelling reference for further investigations on this research topic, providing the first step in the research and modelling work committed to develop more general, flexible, and customizable energy demand models. The model *calibration* contributed to highlight the presence of further determinants of the rural electricity demand that did not emerge from the analysis of electricity-development nexus but worth to be further investigated: intra-season variabilities, due to the dependency of people financial availability on the harvesting period, and daily load variability, due to the unpredictability of people's habits and use of electricity within the 24 hours. Then, the calibration process indicates the appropriateness of system dynamics in modelling the complexities behind the evolution of rural electricity demand. Still, it also revealed the need to investigate further modelling techniques to improve and/or overcome the SD hypothesis of perfect-mixing which caused a mismatch between data and model output in the first time-steps of the simulations. Finally, the discussion on some of the most relevant model behaviours identifies some fundamental dynamics that characterise the electricity-development nexus and that can be supported by exogenous activities as access to micro-credit.

From a SD perspective, new archetypes about some of the typical multifaceted rural socio-economic dynamics and complexities are also provided, as well as a new source of qualitative and quantitative data. Finally, the modelling process followed and applied in the context of this research provides a meaningful example on the potentiality and suitability of SD for approaching to modelling issues in the field of rural energy and socio-economic sustainability, paving the way for new multidisciplinary research opportunities and applications.

This work represents the first step towards an increased understanding on the electricity-development nexus in rural areas. Future activities will so include model and policy testing, as well as the sensitivity analysis, in order to assess the most critical and fundamental dynamics and parameters, generate the behaviour of other instances in the same class as the model were tested for different contexts than Ikondo, and finally assess the robustness of the conclusions on varying the assumptions over a plausible range of uncertainty.

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