# Leveraging Machine Learning for Sustainable and Self-sufficient Energy Communities

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## Abstract

Community Energies (CEs) are the next-generation energy management techniques that empowers citizens to interact with the energy market as self-consumers or prosumers actively. Successful implementation of CEs will promote sustainable energy production and consumption practices; thus, contributing to affordable and clean energy (SDG7) and climate action (SDG 13). Despite the potential of CEs, managing the overall power production and demand is challenging. This is because power is generated, distributed and controlled by several producers, each of which with different, and potentially conflicting, objectives. Thus, this project will investigate the role of machine learning approaches in smartening CEs, increasing energy awareness and enabling distributed energy resources planning and management. The project implementation will be centered around proof of concept development and capacity development in Africa.

## 1 Problem

In recent times, vast portions of the world have witnessed rapid increase in energy use due to urbanization, economic growth and population increase. The rise in energy use is currently accounting for 40% of global Greenhouse Gas (GHG) emissions, which pose challenges to climate and sustainability [1]. To address this, the Paris Agreement set forth an objective to reduce energy-related GHG emissions by more than 70 percent by 2050 through massive deployment of Renewable Energy Sources (RES) [2]. The use of RES that goes along with efficient energy management strategies is likely to play a significant role in the heart of climate change mitigation and adaptation efforts [3].

Consequently, different countries adopt new approaches for the RES transition, focusing on engaging communities towards sustainable and clean energy systems. In this context, a wide range of community energy (CE) systems are currently being implemented worldwide with European countries at the forefront [4]. CEs are the next-generation energy management technique with distributed generation, storage, delivery, and consumption enabling proactive consumers (prosumers) to transact their energy as goods and services [5]. As decentralized and distributed RES-based systems, CEs promote sustainable energy production and consumption practices, enabling customers to access a wide range of alternative energy sources according to their preferences [6]. Simultaneously, CEs can provide various benefits such as creating a competitive energy market, reducing power outages and network loss, increasing the overall efficiency of power systems, and supplementing alternative energy sources according to user preferences [5, 7].

Tackling Climate Change with Machine Learning workshop at NeurIPS 2020.

Implementing CEs in Africa's rural areas will help meet Sustainable Development Goals (SDG) for climate action (SDG13) and affordable and clean energy (SDG7). Consequently, enhanced access to clean energy will help achieve equitable access to education (SDG4) and reduce inequality within and among countries (SDG10). Even though CEs implementation in Africa can be challenging, Africa presents a unique opportunity for proper planning and innovation, given the fact that there are not so many legacy systems to integrate.

It should be noted that, for efficient energy management and long-term reliable operation of the CEs, it is necessary to monitor and estimate the amount of energy demand and predict the amount of energy that will be generated. Efficient energy management has the potential of scaling down capital investment needed to provide sufficient and reliable energy supply, which is the necessary condition for facilitating the broad adoption of CEs and increasing the self-consumption of CEs. It will further enable prosumers to coordinate their energy usage and prepare the buy and sell to balance the CEs demand and supply. Managing the overall CE's power production and demand is more challenging since power is generated in a distributed manner and controlled by several producers. Moreover, power generation is highly unpredictable as it depends on RES that is affected by weather conditions. To this end, it is essential to investigate the role of data-driven and machine learning approaches in smartening CEs, increasing energy awareness, and enabling distributed energy resources planning and management.

## 2 Technical solution

In this project, we will focus on two specific objectives i) proof of concept development, ii) research capacity development and awareness creation in developing countries. In the first objective, the project will investigate the value-propositions of data-driven and machine learning approaches in smartening and enhancing energy-management practices in CEs. Specifically, we want to; understanding how different data sources, including individual appliance consumption, could be leveraged to maximize the self-consumption, reduce peak-demands while ensuring fair trading between the peers in CEs. Secondly, we will explore machine learning strategies that could facilitate knowledge transfer from CEs with quality data to CEs with poor-quality data, especially in developing countries. Ultimately, this will enable us to establish the minimum data requirements for developing data-driven solutions that can be deployed in resource-constraints environments.

In the second objective, the project seeks to build research capacity through knowledge transfer and awareness creation. Several initiatives like Deep Learning Indab, Data science Africa and Black in AI with support from big tech players like Google, Amazon, and Facebook are in place, focusing on increasing African participation and contribution to the advances in AI and ML. However, little emphasis has been given to the potential of these techniques in energy and climate change. Thus, in this project, capacity development and specific awareness rising will revolve around the values, capabilities, and limitations of the data-driven solution and machine learning techniques in energy and climate change. This is expected to increase the number of AI-aware stakeholders involved in energy research, decision-making, and policy-making from academia, government, and industry. We are confident that for effective and successful uptake of AI research outputs and innovations, the government, industries, and other relevant stakeholders in the energy sector must understand AI better.

## 3 Impacts

The project's medium to long-term goal is to introduce data-driven and machine learning innovation to leverage the potential of CEs. The improved energy productivity in CESs that goes along with efficient energy consumption will make the energy sector more affordable, reliable, sustainable, gender-inclusive, and climate-smart. The goal will be achieved by applying machine learning techniques to smarten CEs and improve their energy management and the development of human-capacity and awareness in the area of AI/ML and its application in energy and climate change.

Through-out the project life-cycle, it is expected that the expertise and knowledge from the North will reinforce the research and development capacity in AI/ML and its application in energy and climate change to African researchers. Consequently, it will improve the African partners' capability to carry out advanced research and stimulate energy innovation that addresses sustainable development (promoting SDG 17).

Moreover, knowledge transfer through capacity building in research and development will help attain universal quality higher education and increase international visibility (SDG 4). This is expected to establish a sustainable pipeline of talent and human development to meet the localized and global needs (promoting SGD 1 and 8). In the long-run, we expect partners in Africa to continue producing useful research for innovation in data-driven and machine learning solutions and their application to energy, climate change, and other sustainability challenges. The government, industries, and key stakeholders will support the effective up-scaling of current and future innovations and effectively use these innovations.

## 4 Project implementation plan

The implementation plan for this project is organized into four works packages (WPs):

**WP:1 Project preparation, baseline information, and stakeholder engagement.** This WP aims to identify existing approaches and initiatives (baseline information) and key stakeholders that will be engaged throughout the project life-cycle. The baseline information is needed to measure the output (immediate results) and outcome (Intermediate results). The qualitative and quantitative techniques will be employed to collect baseline data on the current skill level and available personnel with potential and interest of developing AI/machine learning skills, the type of infrastructure and the existing gap, the nature of academia-industry-government collaboration in AI/machine learning, especially in the energy sector in developing countries.

**WP:2 Development of innovative AI/ML solution for enhanced energy management in CEs.** This project seeks to use existing data sources from our partner in Europe and expand the existing research on robust machine-learning techniques for energy-disaggregation (Non-intrusive Load Monitoring (NILM)) [8, 9, 10, 11], demand-side management [12], and forecasting [13, 14, 15] to develop solutions that can work in constrained environments. The project will also incoparate human-computer interaction aspects as there is crucial gap between humans and AI [16].In Africa, where the project is expected to be carried out, different data sources such as weather and RES data will be used to validate the applicability of proposed techniques. Masters and Ph.D. students expected to be enrolled in this project will support the development of the innovative data-driven solutions for CEs.

**WP:4 Capacity development and awareness creation.** Building capacities of the research team and key stakeholders is central to this project. Capacities will be built through the following methods: (1) Curriculum development for Msc program 2) MSc, Ph.D., and Post-doc training. 3) Summer school and exchange program. Development of the new curriculum will place more emphasis on blending data-driven and machine learning concepts with RE and Energy Conservation so as to ensure sustainability of consumption through monitoring, prediction and forecasting of demand and production. The curriculum will also incorporate new delivery modes that harness skills development, soft skills, creativity and innovations. To build a well-trained workforce that meets local and international needs of AI with its application to energy conservation, the project seeks to support training of MSc, Ph.D and postdoctoral studies. Scholars from partnering institutions will participate in exchange programs to ensure development of holistic and climate-aware research ideas, innovations, and solutions. The project will extend research results to key stakeholders through demonstrations and presentations, social networks, websites, online learning platform, and local and national media. This will increase awareness, create interest, and facilitate easy uptake of innovation by the government, industries, and other relevant stakeholders.

**WP 4: Operationalization of AI/machine learning applications through academia-government-industry collaboration.**
In this WP the project shall focus on strengthening Academia-Government-Industry linkage. One of the many ways of ensuring this is enhanced mobility across the existing technological hubs, incubators and AI/machine learning labs, co-design and co-creation, and co-evaluation of the results. To this end, the project will use the following key methodological success factors: strong institutional commitment to collaboration in research and capacity building that is backed by policy and regulatory framework. North-South based knowledge sharing spirit that is expected to apply the best practices to capitalize on strengths from either side and minimize the weaknesses and risk factors.

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