Modelling Framework for Intelligent Dynamic Energy Systems

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***Abstract*—This PhD project aims to develop a versatile modelling framework for dynamic energy systems, crucial for addressing fluctuations and uncertainties in energy demand and production, and achieving current climate goals. By exploring trade-offs between accuracy and computational efficiency, and leveraging advancements in artificial intelligence and machine learning, the project seeks to provide a robust tool for energy system design and control.**

I. Introduction

THE adoption of the Paris agreement by a large number of the world's industrialized nations has led to a call for action to drastically reduce greenhouse gas emissions, in order to achieve the ambitious goal of limiting the global temperature increase to 1.5°C above pre-industrial levels. Among the sectors involved, energy systems account for close to 75% of all emissions, as seen in figure 1, and represent one of the toughest challenges for the green transition, due to their historically heavy reliance on fossil fuels. Energy systems and their modelling represent therefore a hugely important and fast-growing area of research, as they must adequately incorporate the current demands in order to support good policy making.

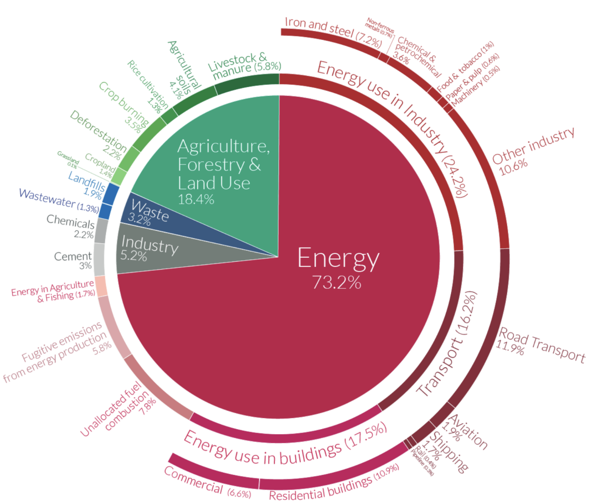

Fig. 1: Global greenhouse gas emissions in 2016 by sector [1].

Energy systems can be modelled as a large and diverse combination of sub-systems or components, forming an integrated complex multi-scale network [2]. These sub-systems can include energy storage, filling, production, consumption, transfer, and a system controller, as can be seen in figure 2. The behaviour of these components can become quite complex, and the optimisation of the system as a whole relatively challenging. It is therefore crucial to have an efficient and versatile model to ease both operation and design, allowing for the inclusion of generic sub-systems in the framework while providing useful information on the system state at every point in time. Additionally, these systems come in multiple scales, from small, such as autonomous underwater vehicles, through medium-sized installations, like temporary remote military bases, to large national and international electricity grids. This means that a robust energy system model must also be scalable.

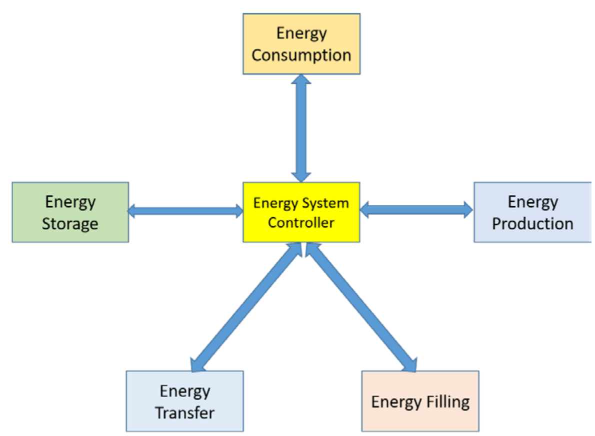

Fig. 2: Generic energy system and its respective sub-systems.

Energy systems are inherently dynamic, a characteristic that is especially prevalent in the energy conversion processes. For instance, energy production by means of renewable sources such as solar and wind energy is highly variable, and subject to fluctuations at all time scales. However, despite their relative instability compared to fossil and nuclear solutions, their use is expected to steadily increase as nations rally to achieve the current climate goals. Likewise, electricity demand is expected to undergo significant changes in the near to distant future [3]. The electrification of infrastructure, such as train lines, and the expansion of industries previously not reliant on electricity could result in increased global consumption. Additionally, the widespread establishment of power-hungry sectors, such as data centers, is expected to contribute to this spike in energy demand. This load increase will likely be combated through the inclusion of distributed energy resources in the systems themselves, and with the utilisation of demand side management. Lastly, an increasing interconnection to Europe will inevitably change the dynamics and management of Norway's own energy system.

To tackle this variability, it is therefore crucial to have in place good forecasts for the energy production and consumption profiles, in addition to robust models that can combine these different time scales and allow for the addition of intelligent control systems.

The main goal of this PhD is to define a general framework for the fundamental modelling of an intelligent dynamic energy system that can address significant fluctuations and uncertainties in energy demand and production. It must also be computationally fast enough to enable training of state-of-the-art machine learning control systems, while also being usable as a larger design tool. The trade-offs between accurate and fast numerical models, such as model-based vs data-driven algorithms, will be explored, as will the possible abstraction constructs for different sub-systems. The advent of Artificial Intelligence (AI) and Machine Learning (ML)/Deep Learning (DL) methods has allowed for the development of powerful processes that are capable of combining different scales and effectively approximate complex functions and relationships. These areas will therefore also be explored, as a possible way to strike a balance between robustness and tolerance to complexity. Specifically, the PhD project will begin by developing a modelling framework for a stand-alone power system, and proceed with applying it as a base model for energy installations and autonomous or large-scale vehicles.

II. Background and Scientific Basis

This project is a part of the Intelligent Dynamic Energy Systems (IDES) project, a collaboration between the Department of Technology Systems (ITS) of the University of Oslo, the Norwegian Defence Research Establishment (FFI), and the Institute for Energy Technology (IFE). Within IDES, two other PhD projects will address work packages related to AI-based forecasting, and AI-based control of dynamic energy systems. This PhD will focus on frameworks for improved numerical modelling of energy systems, serving as a base for the two other projects. With these work packages combined, a new understanding of how to design and operate scalable energy systems can be achieved, through a reimagining of model, forecast and control, turning the project into one of strategic importance for all of the involved parties.

In a classical sense, there are two types of numerical models used to simulate the dynamics of energy conversion within a system, namely first-principle and empiric models. First-principle, or equation-based models, rely on the physics that is inherent to the conversion processes, such as heat and mass transfer. These models, when correctly calibrated, can deliver highly accurate results, but are typically computationally expensive and have low-reusability due the the series of fixed assumptions made during their development [4]. On the other hand, empirical models employ empirical equations that describe the performance of the various technologies utilized in the energy system. This results in high computation speeds,

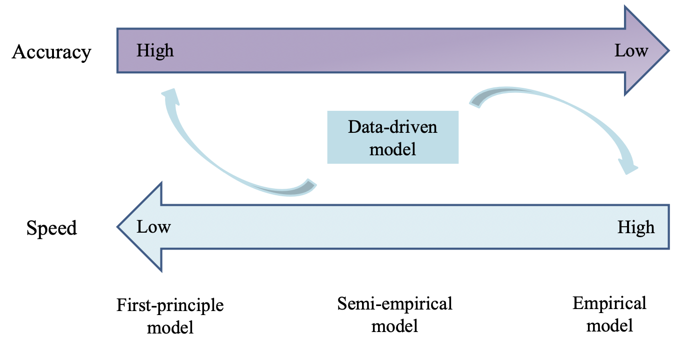

Fig. 3: Accuracy and computational speed of different modelling strategies [7].

due to the simplistic and generally linear nature of empirical equations, but low accuracy in the results, because of the lack of a physical foundation [5]. Between first-principle and empiric, there are also the semi-empiric models, which do include equations based on physical mechanisms, while also having key parameters specified by empirical values [6].

With the coming of the era of big data, data-driven models arrive as an alternative framework for energy system modelling. These approaches can reproduce the hidden algebraic relations between vast amounts of data sets without requiring a description of the physical processes inherent to the same data. This renders these models extremely versatile, and a shift from first-principle to data-driven modelling can already be observed in an array of fields of expertise [8]. Additionally, the creation of ML techniques adapted to different domains provides a new depth to data-driven approaches, due to its ability to handle high complexity and to adapt to the scale of the data [9]. The accuracy and computational speed of each type of model can be seen in figure 3.

The rapid development of ML has sparked a paradigm shift in several traditional industries, especially when it comes to digitalisation. Regarding the energy industry, an IEA report states that "*digitally interconnected systems could fundamentally transform the current energy industry*" [10]. However, the same report points out that the design and operation methodologies of energy systems remain by and large unchanged, despite some isolated successful case studies, such as the development of ML algorithms for energy demand prediction for buildings [11] and transportation [12]. In general, ML algorithms employed in the context of energy systems include supervised, unsupervised, and reinforcement learning. In supervised learning, the input variables, or features, are labelled, meaning that the outputs are also provided, so known sets of inputs and outputs are used as training data to develop predictive models for unknown feature values. Supervised learning can be further divided into regression and classification problems, depending on whether the outputs are continuous or discrete/categorical. Most ML applications developed so far for energy systems have fallen under this classification [7]. In unsupervised learning, only the features are labelled, so the ML problem consists in finding hidden patterns in the feature space, through techniques such as clustering. Finally, reinforcement learning employs reward functions that allow for interactions between the software and the environment, enabling dynamic decision-making. It is thus an invaluable tool for optimisation under heavy uncertainty [13].

Optimisation goes hand in hand with the modelling of energy systems, and begins with the formulation of the envisioned objective in the form of a mathematical programming problem, with decision variables, an objective function that should be minimised or maximised, and the constrained variable space, typically written as

$$\begin{aligned} \min_{\boldsymbol{x}} \quad & f(\boldsymbol{x}) \\ \text{s.t.} \quad & g(\boldsymbol{x}) \leq 0 \\ & h(\boldsymbol{x}) = 0, \end{aligned} \tag{1}$$

where $\boldsymbol{x}$ is the vector of decision variables, f is the objective function, and g and h correspond respectively to the inequality and equality constraints. These optimisation problems can be further categorised into linear programming (LP), mixed integer linear programming (MILP), nonlinear programming (NLP) and mixed integer nonlinear programming (MINLP), according to the linearity of the equations employed and the domain and continuity of the decision variables. However, NLP and MINLP problems, though simple to formulate, do not have an easily reachable optimum through the algorithms available as of today [14]. They are therefore often linearised into respectively LP and MILP formulations, in order to improve efficiency. This demonstrates how challenging the choice and development of solution algorithms is, both for energy system design and operation, rendering it a promising focus point for this project.

Multiple-objective optimisation (MOO) poses also a formidable challenge during model development. When building scalable systems, these can be thought of as integrated complex multi-scale networks. In these cases, it is common that multiple objectives may arise (e.g. minimising both the cost and CO_2 emissions of an energy system). It is often the case that no single optimum exists, due to the conflicting nature of multiple objectives, so the goal becomes that of generating trade-off compromise solutions, also know as *Pareto-optimal* solutions. There are several available algorithms to deal with MOO, the most popular being population-based, that convert the problem into a set of single-objective subproblems, surrogate-based, where the objectives and constraints are approximated by comprehensible models, and combinations of the two. These methods have been employed to, among other cases, aid in thermal system design [15] and environmental economic power dispatch [16].

Modelling systems that display a high penetration of variable renewable sources present a whole new set of challenges, mainly regarding temporal resolution and planning horizons [17]. These are crucial aspects in both technical and economic analyses [18], and a review of current modelling solutions, including a categorisation in optimisation, equilibrium and alternative models, can be found in [19]. While there is a rich variety of modelling proposals to tackle these issues, scalability remains an issue, as design questions such as the derivation of the electrical energy storage capacity for Europe with adequate spatial resolution still have a limited answer [17].

Uncertainty regarding the long-term future is another challenging aspect of developing future-proof models when considering aspects such as price fluctuations in energy markets [20], [21] and the evolution of consumer behaviour. As of now, four main techniques have been identified to tackle this issue: Monte Carlo analysis, stochastic programming, robust optimisation, and modelling to generate alternatives [22]. Each of these have their unique set of advantages considering the parameter space of knowledge on the sources of uncertainty and the impact of the undesired outcomes. However, most studies employ only simple sensitive analysis or scenario studies to address sources of uncertainty, revealing room for improvement in this area.

A. Energy Installation Case Study

The IDES project has a goal of studying both medium and large energy installations. Medium-sized installations refer to installations with local power production such as on-site photovoltaic solar panels, local power storage like batteries for short-term and hydrogen for long-term, and local power consumption. In the context of collaboration with FFI, remote military bases are stellar candidates for a case study in this project. These bases can be thought of as microgrids, with localised interconnected energy resources and loads [23]. They are therefore a good starting point for testing potential modelling frameworks, as resilience and energy cost efficiency are the main goals of these scenarios. This can also test the framework's ability to include variable renewable energy sources [24], as they are an important source of self production for these facilities, and its robustness due to future uncertainty. There will also be extensive collaboration opportunities with the third work package of IDES, which focuses on forecasting of wind and solar energy production, the main energy sources in such installations. However, one of the greatest challenges of this case study will be the access to data, due to the classified nature of information in this sector, which could possibly hinder the project's ability to explore data-driven solutions.

On the other hand, large-sized energy installations refer to, for example, renewable power plants with some kind of storage solution, but that also interact with the national energy grid. This case can test the scalability of the developed framework in both time, space and complexity, and allow for the construction of a breadth of optimisation scenarios.

B. Vehicle Case Study

Modelling vehicles as energy systems is a field of interest in many aspects, such as the automatisation of transportation and the electrification of this industry. In the context of the collaboration with FFI, the first focus of IDES will fall upon energy management in Autonomous Underwater Vehicles (AUVs). These are relatively small but complex vessels, that require precise control systems to maximise their range. Energy management strategies have already been developed for other water-based vehicles [25], but this case will test the versatility of the modelling framework, as one must consider a variety of factors such as battery life, route planning, and sensor usage. The goal can be thus formulated as a multi-objective optimisation problem, and the model must employ general intelligent energy management techniques in order to solve it, while using forecasts as inputs, and control strategies to enforce the obtained scheduling.

In the later stages of IDES, this framework can be applied to larger systems such as commercial ships or heavy-duty transport applications. These are as of today huge sources of emissions [26], and are prime candidates for the use of hydrogen as fuel, given the possibility of on-board energy production and storage in a larger scale. This will considerably increase the complexity of the system, and further challenge the developed framework and its integration with the other work packages of IDES, while modelling a potentially crucial component of the roadmap towards an emissions-free world.

III. Research Questions and Scientific Challenges

This project will be based on three main goals within energy systems modelling. It will firstly build knowledge on existing standards and methods within system modelling and optimisation, then create a general integrated framework, and finally apply it to a set of case studies. To achieve the main goal of developing the framework, the following research questions must be answered:

- How can one create a flexible and scalable modelling framework for a generic energy system?
- Which new modelling techniques can be established to optimise the design and operation of energy systems?
- How to include advanced forecast and control systems within the design of a modelling tool in order to test and validate their efficiency?

This is crucial in order to attain a model that can be employed in both operation and design analysis. Additionally, a special attention has to be given to the issue of tackling uncertainty, such as in fluctuating prices, variable renewable energy generation, demand side management, and flexibility in production and storage alternatives [17]. The reusability of the proposed framework is also a focal aspect, as energy system solutions for synthesis, design and operation are widely available for a number of cases, but seldom reused.

The main challenge related to these goals will indubitably be data sourcing. Whether it is to be employed in model validation or creation of data-driven techniques, information is key for this project, but the field is of a sensitive nature. However, the cooperation with IFE and FFI might unlock some otherwise inaccessible data, such as renewable energy forecasting from the IFE side, and, although admittedly more complicated, possible information regarding consumption profiles of military bases or autonomous vehicles from FFI.

IV. Scientific Method

This project is naturally divided into two components: modelling and optimisation. Regarding the modelling section, a thorough comparison between developed frameworks and existing models will need to be carried out in order to obtain quantifiable metrics of improvement. Among others, these metrics will consist in the benchmarking of speed, considered and/or permitted scales, accuracy, and robustness, i.e. generalisation, of models. For this direct comparison to be possible, the same system configuration and associated data have to be used for the considered methods. However, given the distinct nature of the studied models, different types and quantity of data are to be used for each case. For example, empirical models tend to mostly rely on input from experimental data associated with the targeted technologies, while data-driven models might include a greater array of information, such as that of peripheral systems. It is therefore important to ensure that, for each test, the data used is a subset of a common dataset. As for the source of the data, it is expected that a large portion of it will lie outside of the public domain, as a result of the tight collaboration with IFE and FFI. It is thus crucial to ensure the creation of comprehensible documentation, so as to ensure reproducibility with non-local data.

As data-driven methods will also be studied, it is also relevant to comment on the testing method for machine learning models. These are generally tested by using a benchmarking of algorithms that compares speed and accuracy under the same conditions, by splitting the data into training and testing sets. The training set is used to train and optimise each model with a cross-validation technique, to assess the performance of different model configurations. The testing set is then employed to evaluate the accuracy of the trained models.

Regarding optimisation, different problem formulations and solution algorithms can be directly compared regarding the speed of the whole process and the quality of the final result. However, validation is a notoriously tough challenge in this domain, once again due to the classified nature of a variety of information related to the field. To tackle this, a close cooperation with experts is of the utmost importance to obtain the full picture of the value offered by the frameworks developed within this project.

V. Expected Impact

The motivation for this project is deeply grounded in the need for smart solutions to combat climate change and achieve an efficient green shift. By developing an effective framework for an intelligent and dynamic energy system, we can ensure smart distribution of available resources, and the widespread inclusion of variable renewable energy sources, along with their forecasts. This is likely to play a considerable role in the shift that is to come, in an age where demand-centric management is becoming increasingly crucial for achieving the proposed climate goals and ensuring the resilience of the systems themselves.

Regarding the area of energy systems as a whole, a recent push can be already observed towards the open-source world, which is inherently more transparent and collaborative – two key words often heard in the context of achieving ambitious climate goals. By developing an open-source based framework that is also general and modular in its design, it is the hope of this project to contribute to this transition and to an increased scientific collaboration within this field.

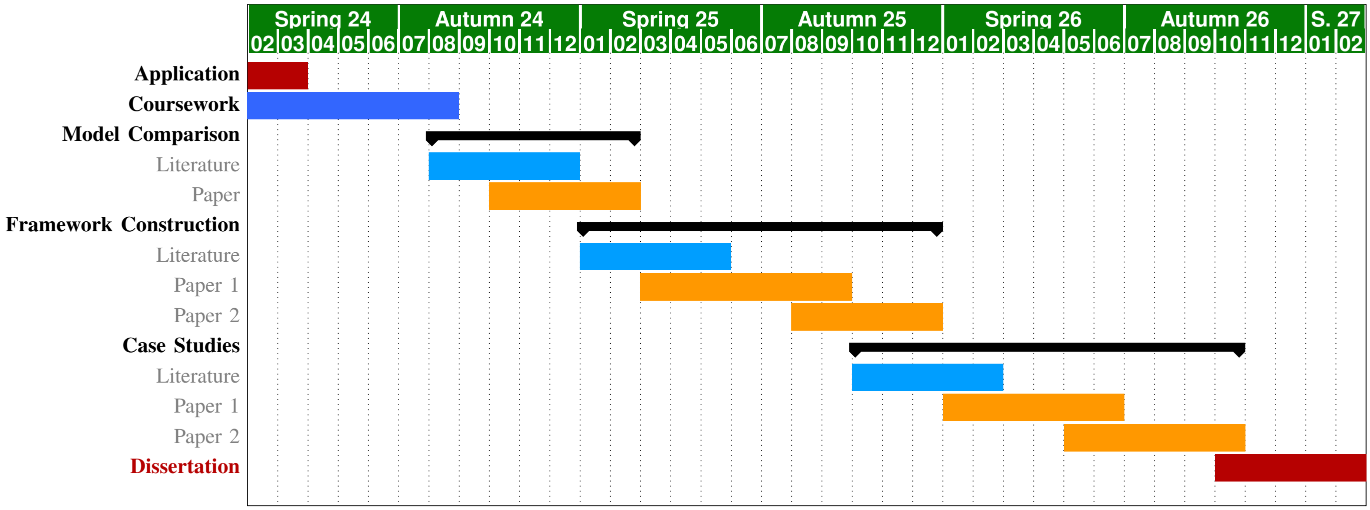

Fig. 4: Gantt chart with proposed timeline for the PhD project.

Furthermore, due to the targeted case studies, more accurate and widespread models may help explore society's options when it comes to shifting the heavy-duty transport and industry sectors to a zero-emissions paradigm, while the relevance in defence applications is apparent when considering robust models that can handle extreme weather scenarios and external interference in energy installations.

VI. Ethics

As previously stated, the nature of the data referent to the field of energy systems is inherently classified, which directly contradicts the philosophy of scientific research and validation. It is therefore crucial to ensure the reproducibility of methods and results, as this research field becomes more vital by the minute. Reproducibility here refers to the ability to replicate the settings of a scientific study in order to verify the invariance of results. This can be achieved through data sharing, ensuring detailed documentation, and in some cases making the developed code openly available. Due to the involvement of parties that have an interest in maintaining the privacy of certain data and techniques, this becomes a striking ethical challenge. Possible workarounds can be for example the development of comprehensive documentation, the description of a framework rather than actual code, and the utilisation of dummy data-sets that can be used for validation purposes. However, a constant evaluation of the methods employed for development and scientific communication must be undertaken in order to ensure the satisfaction of the involved parties, while safeguarding the scientific quality of the project in terms of its transparency, accessibility and availability.

Furthermore, one of the project's stakeholders is the Norwegian Defence Research Establishment (FFI), that conducts research directly geared towards defence. Military related projects present inherent ethical challenges that must also be addressed [27]. While the project's findings should in principle be exclusively used in ways that are beneficial for society as a whole and for the security of the Norwegian state, one must also consider the potential misuse of developed technologies. A preliminary evaluation must be therefore undertaken prior to the execution of each case study, in order to assess their potential ethical ramifications.

VII. Project Timeline

The first semester is to be dedicated to knowledge building through coursework and a general literature review. A total of 25 study points are to be completed within this time, with the remaining 5 planned to be obtained in a summer school the same year.

Regarding the project subdivision, this can be done keeping three broad goals in mind, each contributing and building up to the following one. This way, they can be scheduled in a sequential manner that can also be efficiently made parallel, as seen in figure 4. The first task will be to select the modelling approach intended for the project, with a goal of performing comparisons both at a global and at a case study level. Secondly, a modelling framework is to be built and documented, and a demonstration of its functionalities to be performed on a case study that allows for the integration of the AI forecasting work package. Lastly, there is the goal of exploring the case studies specific to the IDES plan description, regarding the military base installation and the vehicle system. An ample timeslot has also been allocated for writing the final dissertation.

According to current considerations, working titles for the proposed articles in each focus block include:

- Model Comparison
  - "A comparison of empirical, first-principal, and data-driven models for electrolyser technologies in standalone power systems"
- Framework Construction
  - "A framework for data-driven modelling and optimisation of generic energy systems"
  - "Optimisation of hydrogen production in solar farms using data-driven modelling and AI-based forecasting"
- Case Studies

– "Modelling the feasibility of robust military bases reliant on variable renewable energy"
– "Optimising maritime decarbonisation with onboard hydrogen production"

VIII. Project Organisation and Cooperation

As previously mentioned, this project is a part of IDES, a collaboration between ITS, IFE, and FFI. Each party will be represented by means of a supervisor.

Øystein Ulleberg (IFE) will take the main supervisor role in this project, and will be able to provide invaluable directional insights, with his expertise lying in hydrogen technologies, simulation modelling, and energy systems as a whole. The co-supervisors will be Tareq Abou-Qassem (FFI), with a strong competence in battery management systems and mathematical modelling, and a full-time ITS professor that will be selected at a later stage. Additionally, Isabel Llamas-Jansa (IFE) will act as a close mentor, with expertise in the modelling of hydrogen systems and experience in Monte Carlo simulations, while Paal Engelstad (ITS) is the designated head project manager for IDES. This team of experts lays the foundation for a strong collaborative environment between the three institutions, and facilitates a vibrant scientific stage with a breadth of perspectives, fully apt to tackle this highly interdisciplinary project.

Finally, IDES as a whole will create a long-term round table for collaborative discussions, with the potential of including an unlimited number of mentor positions, thus ensuring the project's continuity in the event of a member having to vacate their role.

IX. Cooperation with External Parties

All three parties involved in the IDES project share the goal of contributing to a rich spread of knowledge and competence between all partners. This collaboration serves not only the purpose of working on a specific project, but also that of creating a starting point for a long-lasting scientific partnership. This is the reason why all work packages associated to the project are being supervised by a team composed of members from all involved institutions. All in all, it is a cooperation expected to yield valuable competence from its collaborative nature, with a potential for development of highly impactful innovations in the field.

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