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Workflow-based architecture for optimal planning of integrated local multi-energy systems

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***Abstract*—Integrated local multi-energy systems are recognized as a promising option to achieve the ambitious energy and climate goals set by the European Commission for 2030. The nature of integrated systems requires a sound combination of interdisciplinary methodologies and complementary tools. Creating an efficient architecture capable of exploiting synergies between tools is therefore crucial for designing, analysing and operating integrated energy systems. The joint application of different tools needed for analysing a local system can be very demanding and time-consuming due to vastly different data structures and functionalities. To address the need for complementary tools, the aim of this paper is to establish and test an integrated modelling architecture allowing the interaction of tools into a modular toolbox for the optimal planning of integrated local multi-energy systems, and also present key preliminary outcomes.**

***Index Terms*—Integrated Local multi-energy systems, distributed energy resources, flexibility, demand response, optimal planning**

I. Introduction

A. Motivation and background

Meeting the ambitious energy and climate goals set by the European Commission (EC) for 2030 and beyond requires a commitment beyond the electricity sector. Providing decarbonization across different energy sectors through an integrated approach appears to be a viable path for the future energy supply as outlined in the ETIP-SNET's Vision 2050 [1]. Integrated local multi-energy systems are recognized as a promising alternative to centralized energy supply and distribution systems to meet local energy needs since they can promote efficient use of the available energy by exploiting synergies between heat and power technologies, storage and flexible demand. However, achieving the optimal configuration and operation of integrated local multi-energy systems requires a sound combination of interdisciplinary methodologies and complementary tools from different domains.

B. Related literature

For the planning and operation of complex energy systems at the local level, different models and tools need to collaborate for better effectiveness and scalability. The authors of [2], [3] provide an overview of models and tools relevant to this context. The relevant models are the island energy-system tools such as H2RES and the local community energy-system tools such as Integrate, BCHP Screening Tool, COMPOSE, MODEST, HOMER, TRNSYS.

In the past, to secure the optimal planning of multi-carrier energy systems, various approaches have been employed to couple different models with complementary features. Also, it is necessary to consider the exchange of data among them for further analysis beyond being used for tool integration.

These approaches can be categorized into three categories as follows.

1) **Chain the different models together through specialised code**. This approach has flexibility and efficiency for one specific pair of tools but expert users are needed and it has low modularity. For instance, the Renewable Energy Deployment System (ReEDS) is a long-term expansion planning model developed in the General Algebraic Modeling Language (GAMS) by the National Renewable Energy Laboratory (NREL) [4] and is using this approach to connect with other models. Although it does not refer to multi-carrier energy systems, it covers a wide variety of different renewables and storage systems such as pumped storage hydro and compressed air energy storage. The authors of [5] provide an interface based on Python for facilitating the co-simulation of commercial software tools that foster multi-carrier models simulation.
2) **Monolithic program** This approach means extending one tool by directly including one or more others. For the user, the resulting tool is easy to learn. However, creating such a tool becomes increasingly difficult as the complexity of the system increases. In the literature,

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examples of such approaches can be found in [6] where the Calliope framework is presented. Calliope is used to develop energy system models with high spatial and temporal resolution for planning multi-carrier energy systems. A Calliope model employs a collection of text files that fully define a model, with details on technologies, locations, resource potentials, etc. In [7], a planning tool for smart grids with storage and photovoltaics is presented for an electricity grid. The setup is using different models developed in commercially available tools that connect to each other through delimited (.csv) files. The authors have automated the process for better handling. [8] provides a toolbox where different models technical, business and societal are combined together for the optimization of multi-carrier energy islands. A combination of this and the previous approach is followed by the AnyMOD framework [9]. AnyMOD is a Julia programming framework for creating energy system models. It fosters multi-carrier energy systems and renewable integration. Individual models are defined by delimited files and can be run with a few lines of standard code. More advanced applications require advanced users.

3) **Workflow management.** This approach focuses on creating an interaction framework where different tools can communicate through a shared database by using standardized data structures. Once established, usage is relatively easy for regular users and offers flexibility and scalability options as well. Scenarios can be run in parallel modelling tasks whereas it is easy to develop and apply for several users. SPINE Toolbox [10] is a Python-based open-source energy system modelling framework for multi-carrier energy systems planning with high level of temporal, spatial and technological adaptability that adopts workflow architecture and supports data exchange among different models. It enables groups of users, that are developing local workflows, to collaborate as a team on large-scale problems that require data curation. It also facilitates multiple tools and models through version control of workflow routines and databases for data storage. One of the main advantages of the Spine Toolbox is that it is problem agnostic and allows for rapid development of new ad-hoc optimization and simulation models in Python, GAMS, or Julia. It can be used for modelling and simulating a wide range of complex energy systems, integrating electrified transport and variable renewable energy systems [11].

C. Contributions and organization

This paper has been developed within the framework of the Horizon 2020 project eNeuron [12]. The project aims to embrace the local multi-energy systems integrated approach by offering an innovative toolbox with functionalities for their planning and operational optimization. This ambition is explicitly designed and applied to energy islands and confined energy systems under the concept of Integrated Local Energy Community (ILEC), which is defined in the eNeuron project as a set of energy users deciding to make common choices to satisfy their energy needs to maximize the benefits derived from this collaborative approach based on the implementation of a variety of electricity and heat technologies and energy storage and the optimized management of energy flows.

The paper presents the preliminary key results from the development of the eNeuron toolbox with a focus on the optimal design and operational analysis phase of local multi-energy systems. The integrated nature of local multi-energy systems presumes a complex interaction of different aspects from various energy sectors, rather than considering each sector individually. Therefore, the optimal configuration, development, and operation of a local multi-energy system require an interdisciplinary knowledge base. One principal challenge is that existing analytical frameworks are fragmented in terms of methodologies and functional tools making integration between them very demanding.

Based on the literature review, numerous tools and models exist to tackle the optimal operation and planning of integrated energy systems. Such tools are having their distinct advantages and limitations and can be categorised as per the target energy network aggregation level such as international, national, regional, and micro grid levels. Their specific spatial and temporal resolutions are also important to consider. There is no established best practice for implementing workflow management approaches to foster collaboration of well-known and widely used planning tools. Hence, the contribution of this paper is to provide a toolbox concept through a workflow-based architecture that is modular and expandable. The proposed concept brings together a commercially available planning tool (Integrate) with other research tools to facilitate their interaction in a joint framework.

II. Methodology

This paper focuses on the architecture of system planning and operational analysis depicted as the upper part encapsulated by the SPINE Toolbox in fig. 1. The planning phase allows for the identification of the optimal configuration for a new system through a multi-objective approach and a discrete set of investment options as well as determining an optimal expansion plan for the system in the future. After the system planning phase, the operational analysis phase takes the given system design as input from the system planning tools and performs an in-depth analysis of the optimal dispatch of the system based on a selection of potential scenarios (stochastic approach), a day-ahead forecast, or using the raw historical time series data directly. Although these phases entail separate processes, they need to be consistently interlinked because the planning phase determines one or more system designs to be considered by the operational phase. There may also be a feedback link as the operational analysis might detect system designs that will be infeasible under some of the operational situations considered, and therefore should be excluded from the planning phase. Both phases involve multiple tools feeding information to each other.

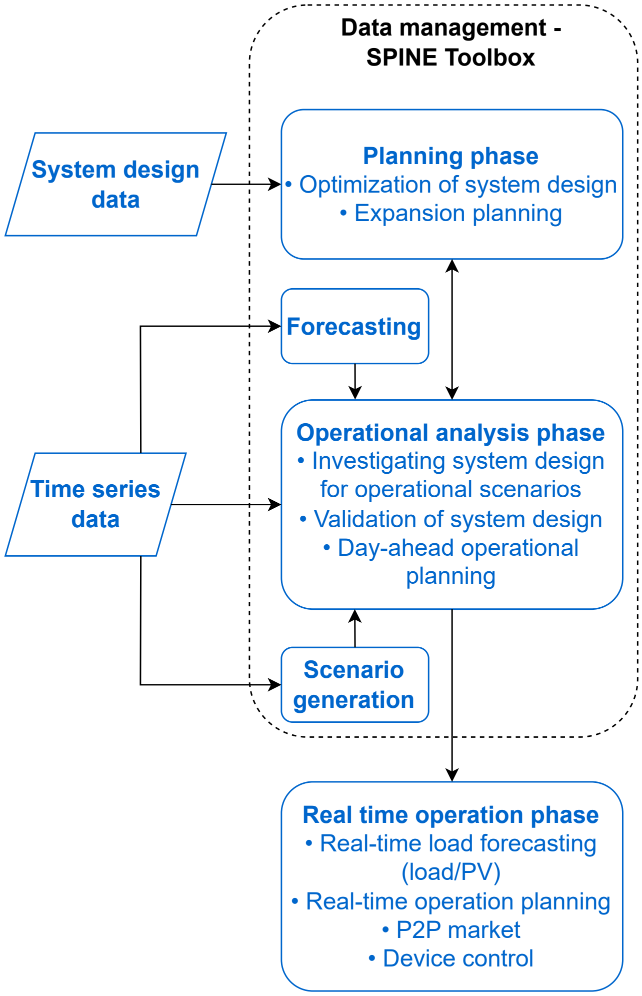

Fig. 1. High-level representation of eNeuron toolbox architecture.

Since the toolbox includes several tools with software legacies, restrictions based on intellectual property rights, and multiple users at different locations, it is not feasible to bundle them together to provide a single tool for all aspects of the multi-energy system design and operation. Hence, an architecture for tool interaction is warranted to coordinate and unify the data handling between the tools.

This paper builds on a workflow management tool, developed by the Horizon 2020 project SPINE [10]. By using SPINE it is possible to create repeatable workflows in a consistent manner such that different tools can interact through a common database.

A. Planning tool

One of the planning tools in the eNeuron toolbox is Integrate [13] (formerly eTransport [14]), a software system for the optimisation of integrated energy systems. The optimisation objective is to minimize net present costs, considering both investment and operational costs for the planning horizon. It can be used to optimise the development of an energy system while considering the projections in energy demand and the different technological possibilities for energy supply, conversion between energy carriers, distribution, storage, end-use measures and restrictions on CO2 emissions.

Integrate requires spatial data (e.g., system borders, location of system components), time aspects (planning horizon), energy needs, existing energy supply, energy prices and possible investment options.

As output, Integrate provides one or more expansion plans in ranked order along with the operation of the system for the defined representative days. Integrate can thus optimize the expansion planning of the local energy system by considering an existing system configuration.

B. Operational analysis tool

Based on the system design, technologies, and their characteristics derived from the planning phase, the operational analysis tool allows for the dispatch of the multi-energy system by pursuing economic and environmental objectives when analyzing the various operational scenarios or day-ahead dispatch. In detail, the “Operational analysis” tool is based on a multi-objective optimization problem formulated through mixed-integer linear programming (MILP), and aims to obtain the optimal expected hourly operation strategies of the technologies in the multi-energy systems by minimizing the weighted sum of total daily costs and CO_2 emissions. Therefore, by adopting a multi-objective framework, the tool determines the optimal operation scheduling of the multi-energy system on the Pareto frontier in the two following modes:

- Stochastic approach: in this case, the optimization problem is stochastic and allows determining the expected daily operation strategies of the multi-energy system, by considering uncertainties related to RES, users’ loads and energy prices through a scenario-generation procedure that defines a set of scenarios related to uncertain parameters with their related probability of occurrence that represent input data for the stochastic optimisation problem [15], [16].
- Deterministic approach: in this case, the optimization problem is deterministic and uses as input data for RES generation, users’ loads, and energy prices from the day-ahead forecasted data or historical time series.

The other input data that are common for both approaches are: (1) Structure of the multi-energy system in terms of installed technologies and energy flows among technologies within the system; (2) Technical data of energy technologies in the multi-energy system (average energy efficiency and installed sizes); and (3) Carbon intensity of input energy carriers.

C. Tool interaction

The tool interactions are implemented according to fig. 2. The implementation relies on separate but interlinked parts that together create an interlinked framework for connecting different tools. The framework is built utilizing the SPINE toolbox functionality as a building block to provide a system for data structures and workflow specifications. A local or

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remote database can be used for data interaction between tools. In this case, a shared remote database is utilized, facilitated through the SPINE toolbox, to exchange data between the decentralized tools.

Using section II-A and section II-B as a reference, the presented tools are located to the left in the figure. Each of the tools then has its own data import and export routines that are used by their individual workflows. The combination of these workflows then enables the interaction between the tools.

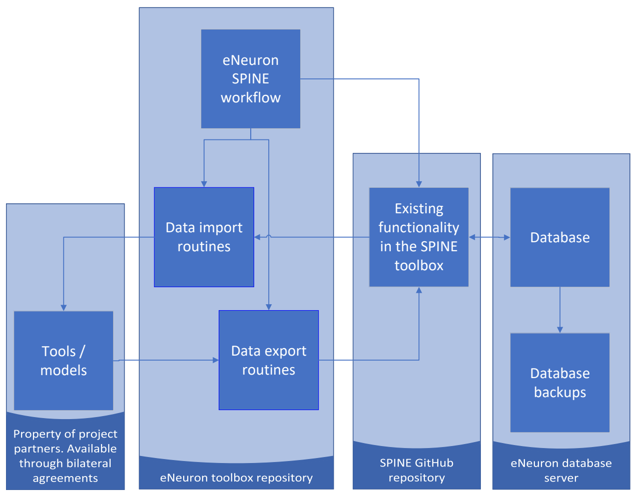

Fig. 2. Overview of the eNeuron workflow implementation architecture.

The git-based eNeuron toolbox repository hosts the SPINE workflows for the interaction between each tool and the database. Version control and collaborative development of the workflow specifications are possible because the specification of workflows is described using a text-based format (.json). Since each tool has its distinct data structures and formats, the eNeuron toolbox layer also includes data import and export routines to translate these structures and formats to the SPINE data structures. The tool-specific code for data import and export can then be executed as a part of the SPINE workflow.

Using the planning and operational analysis tools as an example, an energy system model is first specified in the Integrate tool. After the calculation of the optimal investment plans, the optimal system design and optimized representative days are exported from the tool and imported to the database through the workflow specification and specified data import routines. Once this part is completed, the system design can be specified for the operational analysis tool to conduct a more in-depth operational analysis of the system. The purpose of the operational analysis step is to investigate the feasibility of the proposed system designs and can also be used to determine the day-ahead optimal dispatch of a given system. If one or more of the provided system designs is found to be infeasible based on the outcome of the operational analysis, this information can be transmitted to the system planning part to exclude such system designs from the solution space.

III. Conceptual Application Example

A conceptual example of an application of the models and the information exchanged is described in this section.

A. System planning optimization

Figure 3 presents an example of a case study that is possible to model in Integrate. In this example case, hydrogen is considered as an investment option that can provide flexibility to the electricity grid and heat to the residential loads.

The overall objective of the Integrate model is to identify one or more investment plans that minimize the discounted net present value of all operational and investment costs. The results of the case would include the total costs (investment and operation based on representative days) of the energy system for the whole horizon for the cost-optimal solution and for a user-specified number of additional near-optimal solutions. In this simplified case, we can consider two alternatives: system topologies with and without investments in the hydrogen infrastructure, as well as the timing of the investment in the hydrogen system. The result would then describe the components in the system in each planning period and in each alternative as well as the costs, and operation of the system in each operating period. The operation of the resulting optimal system designs can then be analysed and improved in the next step.

B. Operational planning optimization

The optimal configuration obtained through the energy planning phase along with energy flows among the installed energy technologies to cover loads are used as the first input for the operational analysis tool. As previously mentioned, this tool is based on a multi-objective operation optimization problem with two objectives; (1) the economic and (2) the environmental objectives.

The economic objective is to minimize the expected total daily energy cost, that in this case corresponds to the cost of buying electricity from the distribution grid. The environmental objective is to minimize the expected total daily CO_2 emissions, which in this case correspond to the total CO_2 emissions associated with the electricity taken from the distribution grid that depends on the carbon intensity of the external power grid supplying the modeled multi-energy system. With the economic and environmental objectives defined above, the operation optimization problem has two types of objective functions to be minimized. To solve this multi-objective optimization problem, the weighted-sum method is used to have a single objective function formulated according to eq. (1) where c is a constant scaling factor to keep the two objectives at the same order of magnitude, and ω is the weight for the total daily cost varying in the range of 0-1. When the weight is 1, it is to find the solution that minimizes the total daily energy cost of the system (C^{TOT}), and when the weight is 0, it is to find the solution that minimizes the total environmental impact of the system (Env^{TOT}). When varying the weight in the range of [0, 1], the Pareto front between economic and environmental objectives is found.

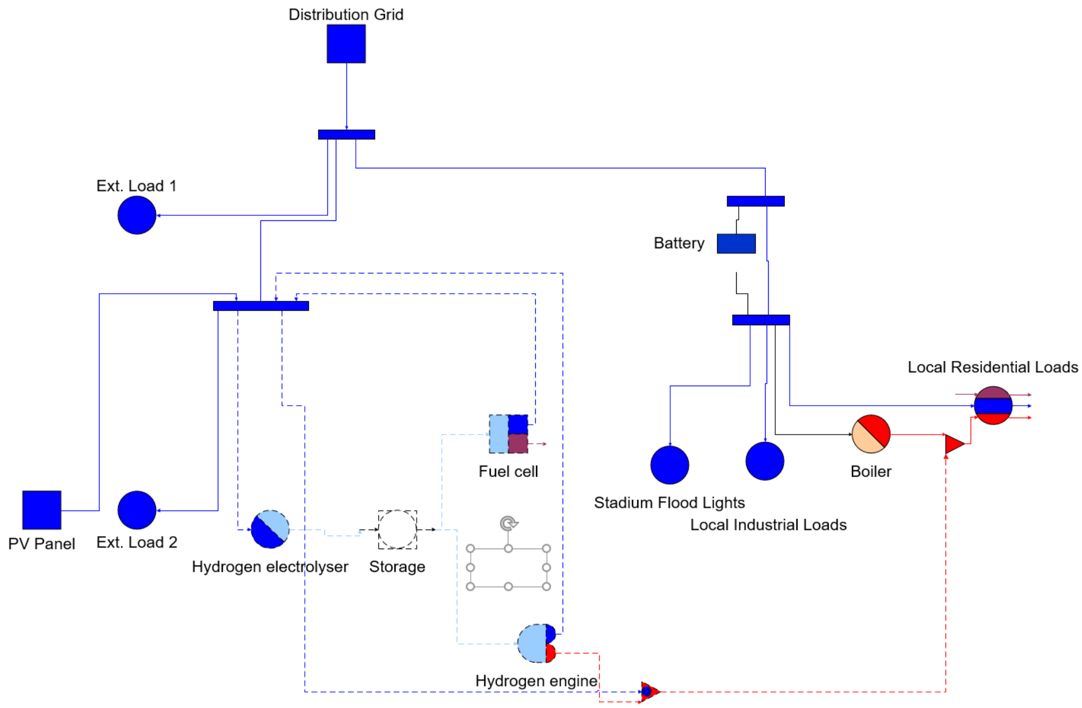

Fig. 3. Example of a case in the Integrate model. The local energy system of an area is modelled where the main energy carriers in the area are electricity (dark blue) and heat (red), while hydrogen (light blue) is considered for future investments. The system drawn in full lines represents the state of the system at the beginning of the planning horizon while the dashed line corresponds to the investment options.

$$Fobj = c\omega C^{TOT} + (1-\omega)Env^{TOT} \tag{1}$$

The total expected daily cost in the case study is the cost for buying electricity from the upstream grid, formulated in eq. (2).

$$C^{TOT} = \sum_{s_{sup}} \sum_{s_{dem}} \pi_{sup}\pi_{dem} \sum_{t} (Pr^{grid}_{s_{sup},t} P^{grid}_{s_{sup},s_{dem},t}) Dt \tag{2}$$

π_{sup} is the probability of occurrence for scenario s_{sup} in the set of supply-side scenarios, obtained through combining scenarios of solar irradiance and electricity prices; π_{dem} is the probability of occurrence for scenario s_{dem} in the set of demand side scenarios related to the electrical loads; $\mathrm{Pr}^{grid}_{s_{sup},t}$ is the price of electricity at time t in scenario s_{sup}; $P^{grid}_{s_{sup},s_{dem},t}$ is the power bought from the grid at time t in scenarios s_{sup} and s_{dem}; and Dt is the length of the time interval (1 hour).

The total expected daily CO_2 emissions in the case study are the emissions associated with the electricity taken from the distribution grid, formulated in eq. (3) where CI^{grid} is the carbon intensity of the power grid, which the multi-carrier system is connected to.

$$Env^{TOT} = \sum_{s_{sup}} \sum_{s_{dem}} \pi_{sup}\pi_{dem} \sum_{t} (P^{grid}_{s_{sup},s_{dem},t} CI^{grid}) Dt \tag{3}$$

The Pareto frontier consists of the best possible trade-off solutions between the economic and environmental objectives, thereby leaving the choice to the decision-maker to select the preferred solution according to economic and environmental priorities.

The optimization problem is mainly composed of two types of constraints that are operation constraints for the technologies in the planned configuration, such as capacity constraints, and energy balance constraints (electricity and thermal energy balances in this case) that ensure that loads are satisfied at each time-step. The problem is based on linear energy models for the technologies present in the planned configuration and the optimization is carried out on an hourly basis. The problem can be solved with a (1) stochastic or (2) deterministic approach, the first considering uncertainties related to solar irradiance, loads and electricity prices and the latter with day-ahead forecast data on solar irradiance, loads and electricity prices. Therefore, according to the approach (1) or (2) used, the output will be (1) the expected daily operation strategies of the multi-energy system; or (2) the day-ahead scheduling of the multi-energy system, on the Pareto frontier.

The multi-objective optimization problem is implemented by using IBM ILOG CPLEX Optimization Studio V.12.10 and can be solved within 10 minutes with a zero mixed integer gap using a computer with 2.60 GHz (2 multi-core processors) Intel(R) Xeon(R) Silver 4214R CPU and 64GB RAM.

C. Information exchange

Table I describes the main information exchanged by the planning and operation tools described in this article.

The system planning phase defines one or more investment strategies. In each investment strategy, the corresponding system topology is described, and the topology may evolve through time as the investment timing is also considered. In our simplified example described in section III-A one possible strategy would include the hydrogen system, and the other strategy would be to not invest in the hydrogen system. These different system topologies can be represented in the workflow management software by the use of available data structures such as objects and relationships between objects.

TABLE I
EXAMPLE OF INFORMATION EXCHANGED THROUGH WORKFLOW PROCESS

Name	Data structure	Description
System design	Relationship classes for connected object instances	Included network components and the connections between them for each investment strategy and planning period
Optimal operation strategies	Array (time series) for each parameter for each object instance in each investment strategy, planning period and representative periods	Operation of available energy assets
Loads, prices and availabilities	Array (time series) for each parameter for each object instance in each planning period and representative period	Input data on loads to satisfy, available market prices, and resource availabilities

In addition to information to describe the overall system topology, data for each component in the system is also exchanged. The optimal operation strategies represent the optimal operation of the system for the representative days considered by the system planning tool. Therefore, the operational strategies will depend on the input data specifications provided, and also on the system design because components that are not part of an investment strategy cannot be included in the corresponding operational optimization. Hence, different operational strategies will exist for the various investment plans.

IV. CONCLUSIONS

This article describes the design and application of a workflow-based architecture to connect multiple energy system analysis tools in an integrated approach. The presented architecture paves the way for the next steps in eNeuron project while also providing a general architecture that can be adapted to other situations with other sets of tools that need to exchange information.

Based on the current findings, the main characteristics of the proposed workflow architecture are:

- Modularity and flexibility to meet the needs of different systems by employing the tools and functionalities that are needed.
- Blueprints for how to implement tool interaction giving scalability to include more tools, unlocking more functionalities in the future.
- Enhanced interoperability for different tools integration in the workflow.
- Builds on existing frameworks and is therefore relatively easy to maintain.

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