A methodology to integrate Artificial Intelligence with energy and water Management Systems to improve sustainability.

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Abstract. The paper introduces a generic methodology to integrate artificial intelligence with energy and water management systems to drive continuous improvement and achieve sustainability in their operations. The methodology consists of five steps, but only two are described in more detail in this paper. Specifically, the second one is where a key performance indicator (KPI) system is used to assess the methodology impacts in different use cases. The KPIs are structured hierarchically to effectively determine the impact of use cases at different operational levels. The hierarchical levels defined are related to the energy and production systems facing sustainability. The fifth step, where a methodology for the AI model development is developed, is centered around the strategy of minimum viable solution (MVP). This provides the simplest AI solution for sustainability as soon as possible. Once the solution is built, then iterates over it towards more significant results are found.

Keywords: Sustainability, resource management, artificial intelligence

1. Introduction

Artificial Intelligence (AI) is one of the most disruptive technologies in this century, which has started transforming business organisations and societies in ways we could not have envisaged a few years ago [1]. Specifically, AI is a powerful instrument that can assist us in our quest for environmental sustainability [2]. Integrating AI in energy and water management systems presents a transformative opportunity for increasing sustainability in several sectors. AI can enable more precise control of different sys-tems, optimising energy use and water consumption. It can also predict maintenance needs, reducing downtime and prolonging equipment life. In energy and water man-agement, AI can assist in monitoring usage, identifying leaks, and optimising recycling processes. These advancements contribute to cost savings and align with the global drive towards more sustainable and environmentally friendly production practices.

To maximise the impact of these innovations, it is critical to ensure that they are guided and managed by a solid methodology. This approach ensures that AI-driven initiatives are not static solutions but active parts of the continuous improvement practices in place. Therefore, a consistent methodology is provided to ensure that the impact of water and energy resource efficiency is aligned with operational and sustainability goals in a continuous improvement environment.

The general methodology is introduced in the following sections, and the second and fifth steps are outlined in the third and fourth sections. The third section presents a Key Performance Indicators system that allows the sustainable indicators to be fulfilled in the use case and, therefore, orient the AI techniques to work correctly. The fourth sec-tion is devoted to the AI model development methodology. This methodology involves developing and fine-tuning AI models for each AI task identified to improve sustaina-bility in each use case. Finally, the conclusions are presented in section 5.

2. Methodology

A methodology is defined as the union of (i) a global and generic reference procedure which shows the structure of the existing and projected system and (ii) the description and control of the activities which lead, step by step, from the existing system to the future one; it takes into account the evolution and specific limitations and

12th International Conference on Interoperability for Enterprise Systems and Applications (I-ESA24), April 10th-12th, 2024, Chania, Crete, Greece.
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CEUR Workshop Proceedings
CEUR-WS.org/Vol-4167/paper15.pdf

presents evaluation criteria about the behaviour of the system in relation with several prospects (economy, quality, etc.) [3].
The AI-driven Continuous Improvement Methodology (AICIM) aims to implement AI-driven initiatives in a structured and effective manner, ensuring that the impact of water and energy resource efficiency is aligned with operational and sustainability goals and with other ongoing continuous improvement initiatives. This methodology outlines a systematic approach to identifying, implementing, and refining AI solutions within an organisation so they can be applied to other organisations seeking to leverage the potential of AI in continuous improvement.

This methodology ensures that each step is optimised for maximum performance and efficiency, from the initial identification of the AI task to continuously monitoring and updating AI models. This section will delve into each methodology step, providing in-sights into how businesses can leverage AI to drive continuous improvement and achieve sustainable success in their operations.

The methodology consists of the following steps:

Step 1.- Use case definition and Characterization: Begin by clearly defining the use case and, within the use case, clearly define the AI task(s) involved. The specific problems or functions addressed using AI in each case include anomaly detection, prediction, or forecasting. This step consists of understanding the use case in detail (related to water and energy resource efficiency), how AI can be applied to address it and how the results of different AI techniques or optimisation techniques must be combined to handle the use case.

Step 2.- Expected Impact: Clearly define the Key Performance Indicator and define a target impact for the use case.

Step 3.- AI task analysis: This step involves a comprehensive analysis of the AI and optimisation techniques used in the different use cases, encompassing the problem definition and literature review to identify potential candidate solutions. This step will also determine the metrics that will effectively measure the success of each candidate's AI solution.

Step 4.- Kaizen definition: This step aims to define specific, actionable Kaizen (continuous improvement) initiatives based on the insights gained from the AI task analysis. This involves identifying areas where processes can be optimised, reducing inefficiencies, and enhancing overall performance using AI solutions.

Step 5.- AI Model Development: This step involves the actual development and fine-tuning of AI models for each of the AI tasks identified. The AI model development is synced with the KAIZEN definition and planning to ensure that the models are not only technically sound but also aligned with the specific operational objectives of the com-pany. It encompasses selecting appropriate algorithms, preparing datasets, training the models, and validating their performance against the defined metrics. This iterative phase involves testing, feedback, and adjustments to ensure that each AI model effectively addresses its respective task and contributes positively to the overall use case.

3. Key Performance Indicators system

Enterprises widely use performance measurement systems (PMS) to manage and make strategy-based decisions. A PMS defines a group of strategic objectives and associated performance indicators (KPIs) that provide information on whether the upstream objectives are being reached but with no further details on the causes [4].

In our proposal, the KPI system used to assess the impact of the different use cases is structured in a hierarchical organisation so that we can effectively determine the impact of use cases at different operational levels. The hierarchical levels defined are (in this case, at the enterprise level KPI related to the energy system (freezing installation), and the production systems (Table 1) have been chosen as an example:

1. **Environment:** This is the highest level in the hierarchy and encompasses the overall external conditions and factors that impact the organisation. KPIs at this level would measure how the enterprise's operations interact with and affect the broader environment, including sustainability practices, carbon footprint, and overall ecological impact. **Enterprise:** This level focuses on the factory as a whole. KPIs at the enter-prise level track the overall efficiency and sustainability of all production activities.

    1.1. **Enterprise**: This level focuses on the factory as a whole. KPIs at the enterprise level track the overall efficiency and sustainability of all production activities.

        1.1.1. **Freezing Installation**: This level is specific to the infrastructure used for freezing processes. KPIs would measure the freezing installations' efficiency, effectiveness, and reliability, including energy consumption, operational uptime, and maintenance costs.

            1.1.1.1. **Refrigerant Liquid Closed Circuit**: A subset of the Freezing Installation, focusing on the system used for servicing specific cooling needs. KPIs at this level monitor the performance and efficiency of an independent section of the freezing installation, including performance, energy efficiency, and system pressures.

        1.1.2. **Production System**: This level looks at the broader production system within the enterprise. KPIs here would assess the overall efficiency and productivity of the production operations, including throughput, yield rates, and production costs.

            1.1.2.1. **Process Segment:** This level focuses on specific segments or stages within the overall production process. KPIs would measure the efficiency and effectiveness of each segment, such as processing time, waste levels, and segment-specific operational costs.

                1.1.2.1.1. **Equipment**: Similar to the Equipment level under Freezing Installation but focused on the machinery and tools used in the production system. KPIs here would track the performance and maintenance of equipment specific to production, like operational downtime, efficiency, and lifecycle costs.

Each level of this hierarchical KPI system allows for targeted measurement and management, ensuring that high-level strategic goals and detailed operational objectives are aligned and monitored effectively

Level	KPI	Method
1	**CO2 Equivalent Emissions (CO2eq)** Total amount of carbon dioxide emissions, along with other greenhouse gases expressed in terms of CO2 equivalence	Conversion of C02 equivalent of total energy consumption using GWP factors
1	**Total Equivalent Warming Impact TEWI (CO2eq)** TEWI calculates the global warming impact of the energy freezing installation, considering both direct emissions from refrigerants and in-direct emissions from energy consumption.	Direct emissions (from refrigerants) + Indirect emissions (from energy consumption). Direct emissions are measured in CO2 equivalent, from the refrigerant liquid charge. In-direct emissions are calculated from energy consumption data.
1.1	**Energy Efficiency EnP(t) (Kwh/Ton)** Energy efficiency of the entire enterprise, de-fined as the amount of electric energy used to achieve the total production over a given pe-riod of time (eg monthly, annually)	Ratio of the electric consumption (considering all equipment, both freezing installation and production equipment) and the total production over a specified period (e.g. monthly, annually)
1.1.1	**Coefficient of Performance (COP)** (%) The COP measures the efficiency of the refrigeration equipment.	Ratio of the sum of the freezing energy provisioned by every section, and the sum of the electric energy consumed by every section of the freezing installation
1.1.1.1	**Actual Coefficient of Performance (COPA)** (%) COPA measures the actual performance of a refrigerant closed circuit section.	Ratio of the freezing energy provisioned, and the electric energy consumed in a closed circuit of a freezing installation
1.1.2.1	**Energy Efficiency EnP(p)** (Kwh/Ton) Energy efficiency of the process segment, de-fined as the amount of electric energy used to achieve the total production over a given pe-riod of time (eg monthly, annually)	Ratio of the energy consumed in the pro-cess segment and the production of the segment in a given period of time

4. AI model development methodology

The methodology for the AI model development is centered around minimum viable solution (MVP): provide the most straightforward solutions as soon as possible. Once the solution is built, iterate over it towards more significant results. That way, at any given point in time, once the first solution is delivered, there is always a viable product to deliver. The methodology is defined in 10 different steps:

1. **Taking the AI task** (for instance, anomaly detection) defined in the general methodology in step 3.

2. **Select the key performance metrics** from the ones determined in the general methodology (step 2) that must be used to evaluate solutions.

3. **Set evaluation metric target**. Based on the use case requirements, establish a target value for the metric or metrics selected for evaluation.

4. **Identify open-source implementations**. Identify open-source implementations that solve the problem and identify the models these open-source implementations use. 4.1. Investigate open-source libraries like sci-kit learn or Pycaret, which implement different algorithms for the same core task. 4.2. Look for research papers with open-source code available for the same core AI task and domain (for instance, anomaly detection in energy equipment), exploring catalogues like arxig.org.

5. **Rate the difficulty of implementation**. For each candidate solution, assess the level of difficulty of developing a solution with each candidate solution, considering if it is well documented, if it is low code or autoML, or if it requires adaptations or fine-tuning. Use a rating system on a scale from 1 – 5 to rate the difficulty level.

6. **Rate the difficulty of training dataset preparation.** For each candidate solution, and based on available data, rate the difficulty of preparing available data for the training dataset.

7. **Rate the potential performance.** Rate the potential performance that could be achieved with each candidate solution (for instance, an LSTM deep neural network can perform better than a random forest for time forecasting).

8. **Select candidate solution(s) for implementation.** Select candidate solutions based on the difficulty and potential performance ratings. Frameworks like PyCaret may al-low the implementation of different solutions simultaneously.

9. **Start experimentation.** Start development and use tools like MLFlow to track the evaluation metrics.

10. **Selection.** If a model achieves the target performance, select the deployment model. If not, continue experimenting with the model; if no experiment achieves target performance, return to 8 and select the next candidate model.

11. **Monitoring.** Track the performance of the model and issues like concept drift.

12. **Control.** Ensure the performance meets expectations; otherwise, return to 8 and select the next candidate solution.

13. Update evaluation target and go back to 2.

5. Conclusions

This paper has introduced a generic methodology to integrate artificial intelligence with energy and water management systems to drive continuous improvement and achieve sustainability in their operations. Regarding the different methodology steps, the paper focuses on two steps. Specifically, the second one is where a key performance indicator (KPI) system is used to assess the methodology impacts in different use cases. In this case, the KPIs have been structured hierarchically so that they can effectively determine the impact of use cases at different operational levels. The hierarchical levels defined are related to the energy and production systems facing sustainability. In the example, seven KPIs have been described regarding the energy system (freezing installation) and the production systems. These KPIs define a target impact, a key aspect of developing AI systems. The methodology for the AI model development (focus on the KPI target) is centered around the minimum viable solution (MVP) strategy. This provides the sim-plest AI solution for sustainability as soon as possible. Once the solution is built, then iterates over it towards more significant results are found. The results must be used by practitioners in several use cases that look to improve sustainability based on AI and by researchers who can develop several AI systems using the proposed methodology.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

1. Soumyadeb, C.; Pawan, B.; Prasanta, K.; Sian, J.; Amelie, A.: "AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework", Journal of Business Research,Vol: 144, 31-49 (2022). \

2. Chaudhary, G. "Environmental sustainability: Can artificial intelligence be an enabler for SDGs? Naturen environment and Pollution Technology. Vol. 22 N° 3 pp1411-1420 (2023).

3. Ortiz, A,; Lario, F. and Ros, L "Enterprise Integration - Business Processes Integrated Man-agement: A proposal for a methodology to develop Enterprise Integration Programs". Com-puters in Industry. Vol. 40, N°: 2,155-171. (1999)

4. Rodriguez Rodriguez, R. and Alfaro Saiz, JJ and Ortiz Bas, A., "Quantitative relationships between key performance indicators for supporting decision-making processes", Computers in Industry. Vol.: 60, N° 2, 104-113 (2009)