Development of a multi-objective optimization tool for the reduction of energy cost and environmental impact in the industry sector

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Abstract: In the context of an increasingly renewable and volatile global energy landscape, our project introduces an innovative multi-energy optimization tool designed to minimize energy costs and environmental impacts in complex industrial plants. Leveraging advanced AI (Artificial Intelligence) techniques, including genetic multi-objective optimization with forecasted inputs, we developed and simulated a tool that dynamically allocates energy flows across plant systems, ensuring economic efficiency and ecological sustainability. Integrating predictive analytics for PV (Photovoltaic) production and electricity price forecasting, the model adeptly navigates the complexities of renewable energy sources and fluctuating market prices. The simulations elucidate that the optimization model exhibits enhanced efficacy within manufacturing facilities characterized by higher redundancy of energy systems, integration of intermittent renewable sources, and deployment of energy storage solutions. For an average energy-intensive facility, the model is projected to reduce the carbon footprint associated with energy consumption by up to 15% and facilitate a reduction in energy costs by up to 10%, demonstrating its substantial potential in promoting environmental sustainability and economic efficiency in industrial energy management. This work not only showcases the potential for AI in enhancing the efficiency and resilience of renewable energy systems but also sets a benchmark for future developments in the energy sector's transition towards sustainability. Moreover, this methodology's applicability extends beyond energy systems to all plant utilities, including water management, and can be adapted for production process management, offering a comprehensive approach to optimizing operational efficiencies across a broader spectrum of utility management and production processes. The main limitation encountered lies in the current cost and complexity of processes digitalization, which, however, is decreasing thanks to increasingly accessible communication technologies.

Keywords: energy, optimization, efficiency, algorithm, Ottimo

1. Introduction

The contemporary global energy landscape is marked by escalating demand, dwindling non-renewable resources and growing environmental concerns (IEA - International Energy Agency, 2023). The industrial sector, being one of the largest consumers of energy worldwide, is at the forefront of this challenge. It faces the dual pressure of reducing energy costs for economic viability and minimizing environmental impacts to meet increasingly stringent regulations and societal expectations (Armaroli and Balzani, 2007), (Kesicki and Yanagisawa, 2015). The situation is further complicated by the volatility of energy prices and the urgent need for transition towards sustainable energy sources (Rintamäki et al., 2017).

In response to these challenges, optimizing energy use in industrial plants has emerged as a critical necessity rather than a choice. Efficient energy management not only contributes to cost savings but also significantly reduces the environmental footprint of industrial operations (Borowski, 2021), (Li et al., 2020), (Rot et al., 2020).

We began our journey towards developing this idea by asking ourselves this question: "What is the best way to

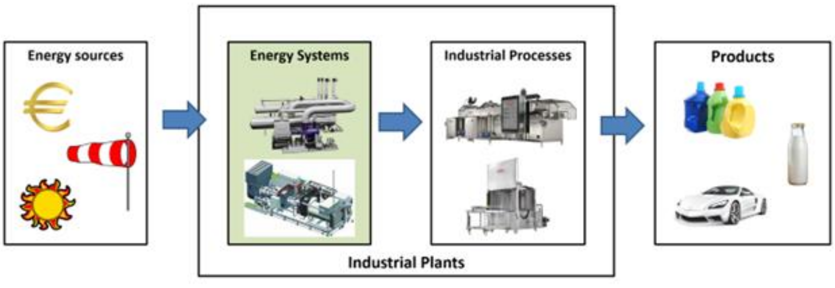

Figure 1.The boundaries of the system

manage the energy systems of a plant in a manner that is both economically and environmentally sustainable?”

This paper introduces an innovative multi-energy optimization tool designed specifically for the industrial sector. The tool explores computational models to identify optimal configurations of energy use that minimize costs and environmental impacts simultaneously. Artificial Intelligence (AI) stands at the core of our multi-energy optimization tool, enabling it to analyse vast datasets, predict energy demands, and simulate the impact of different optimization strategies under varying conditions.

2. Literature Overview

The application of artificial intelligence is rapidly evolving across various fields of engineering and beyond, impacting every sector. When faced with decision-making problems that involve multiple decision drivers, the extensive use of multi-objective optimization algorithms (MOO) becomes prevalent. These are applied to a wide range of issues, including the sizing of energy systems, reduction of emissions, and cost minimization of energy. Among the optimization algorithms most frequently employed are those of the genetic type. GMO (Genetic Multi-objective Optimization) techniques mimic natural selection processes to solve complex optimization problems that involve competing objectives (Karami and Dariane, 2022). The review in (Cui et al., 2017) offers a comprehensive overview of 28 applications. GMO algorithms are employed in 9 out of the 28 studies reviewed, targeting very specific applications, primarily for sizing purposes and the development of solutions to static problems. Other similar applications are presented in (Liu et al., 2022), (Zhang et al., 2022), (Moretti and Panzieri, 2013), (Hajinezhad et al., 2023), (Alzahrani et al., 2023). In (Liu et al., 2022), an interesting resolution approach is featured, as it combines the forecasting of renewable resources with optimization. In our work, building on the previously cited studies, we have introduced a dynamic algorithmic framework for the use of GMO combined with predictive methods, which, according to our best researches, has not been documented in the available literature.

2.Materials and Methods

The proposed methodology is articulated through a structured, three-phase approach: Plant Virtual Modeling, Energy Forecasting and Optimization. Each phase is intricately designed to transform empirical observations into a comprehensive mathematical model, facilitating the application of heuristic algorithms for effective problem-solving.

2.1. Plant Virtual Modelling

The initial phase, plant virtual modelling, constitutes the core foundation of our algorithmic design. This intricate process involves the mathematical encapsulation of the physical plant operations, focusing on converting the complex dynamics of industrial processes into quantifiable models. So, to effectively model the energy system of a plant or a specific segment of it, a comprehensive set of equations is imperative. These equations originate from the analysis of energy inputs (energy sources) and the corresponding outputs required to meet the operational energy demands (energy loads) of the business. The objective is to ensure that the energy requirements of the business activities are fully met by the capabilities of the energy plants. Each energy system is characterized by distinct operational features and efficiency levels. The primary energy demand is influenced by both the configuration of the energy system and the specific demands of the business operations.

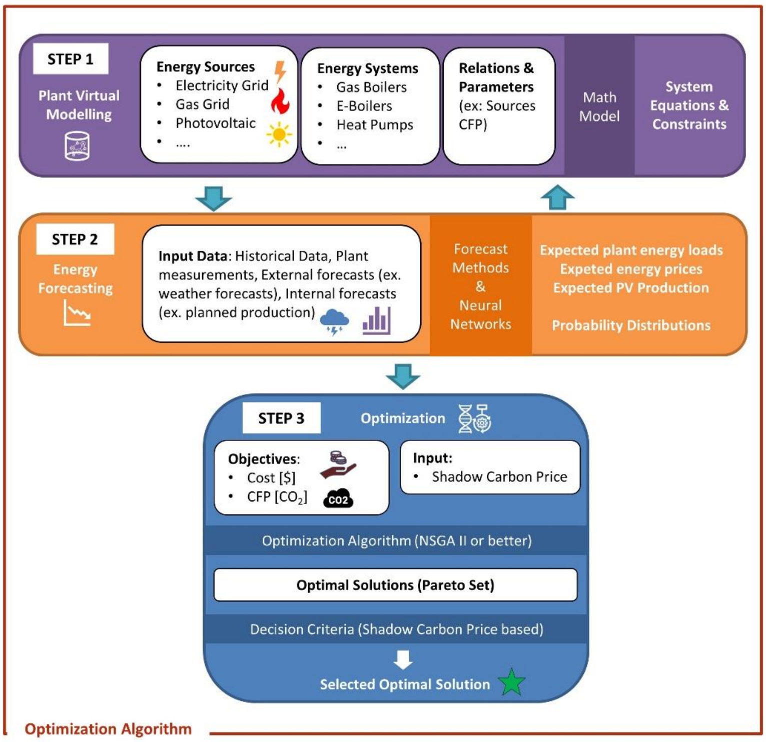

Figure 2.Conceptual algorithm structure

To mathematically represent a generalized plant energy system, it is essential to develop a suite of equations that include:

Energy carriers balance equations: these equations account for the supply and demand balance within the energy system of the plant, ensuring that the generated power meets the operational needs without significant surplus or deficit. As an example, electrical and thermal balance equations are normally necessary.

Constraints equations: in addition to balance equations, these constraint equations play a pivotal role in accurately depicting the operational limitations and regulatory requirements that the energy system must adhere to.

To obtain a comprehensive and functional model of a plant's energy system, balance equations and constraint equations must be integrated into a cohesive mathematical system. Solving this system is essential for deriving a complete solution that accurately represents the operational dynamics of the energy system. For the mathematical model to be solvable and meaningful, it is mandatory to ensure the system's feasibility. Achieving feasibility involves structuring additional equations or relationships that align the variables and parameters within the system.

The endeavour is twofold: (i) Mathematical modelling employing both linear and nonlinear equations, derived from historical data and trend analyses, and (ii) Statistical modelling through neural network training and forecasting methodologies.

Mathematical modelling is initiated by defining pertinent variables and parameters that accurately represent the system's operational characteristics. Through methodical data interpolation, graphical representations were constructed, which are then extrapolated to develop functional relationships. This approach not only minimizes computational demands but also ensures precision and determinacy in the resulting models. For interpolation of data Microsoft Excel interpolation function was used.

However, despite the efficacy of mathematical modelling in encapsulating the dynamism of industrial operations, this approach is not devoid of significant limitations. Primarily, the accuracy and reliability of mathematical models hinge on the depth of understanding of the system's mechanisms and the precise definition of operational variables and parameters. This complexity necessitates a comprehensive study and expertise in the system being modelled, imposing a steep learning curve and demanding considerable human input for equation development. Secondarily, a critical limitation of using linear and nonlinear equations lies in the prerequisite for data correlation and the ability to interpolate functions without significant deviations. The models are predicated on the assumption that empirical data can be accurately represented through mathematical equations, a condition not always met. For the interpolation to be considered of "quality," it must closely mirror the operational realities without introducing substantial errors or variations. However, not all datasets satisfy this constraint, limiting the applicability of mathematical modelling across different industrial scenarios.

On the other hand, neural network-based modelling represents a significant shift from "traditional" mathematical approaches. At its core, a neural network is a computational system inspired by the structure and functional aspects of biological neural networks in the human brain. It consists of interconnected layers of nodes or "neurons," each designed to process inputs and generate outputs based on learned patterns. This architecture enables neural networks to learn from and make predictions about data in a way that mimics human cognition (Basheer and Hajmeer, 2000).

The principal advantage of employing neural networks lies in their ability to model complex, nonlinear dynamics without the explicit need for defining underlying mathematical equations. Unlike mathematical modelling, which relies on a deep understanding of the system's mechanics and precise variable definition, neural networks learn directly from data, identifying patterns and relationships through iterative training processes. This capability allows for modelling of systems with high degrees of uncertainty and variability, where traditional equation-based approaches might falter due to the intricacies of the system's behaviour or when the relationships between variables are not clearly defined or understood. However, this advantage is not without its challenges and limitations. The "black box" nature of neural networks, where the decision-making process is not transparent, makes it difficult to interpret how inputs are transformed into outputs. Furthermore, neural networks require large amounts of data for training to achieve high accuracy and generalizability. This dependency on extensive datasets can be a hurdle in scenarios where data is scarce, expensive to acquire, or contains significant noise. In addition, the training of complex neural networks is computationally intensive and time-consuming.

Neural networks are readily accessible through various Python libraries, which offer powerful tools for building and training custom neural network models with extensive support, "democratizing" access to advanced predictive modelling and analysis tools. In this algorithm, TensorFlow and Keras libraries have been used (Abadi et al., n.d.), (François Chollet, 2015).

2.2. Energy Forecasting

Following the complex phase of plant virtual modelling, the next critical step in developing the algorithm involves energy forecasting. This phase is pivotal in predicting the future availability of energy from renewable sources, specifically photovoltaic (PV) systems installed on rooftops, and forecasting energy prices in relation to national prices. To tackle these forecasting challenges, two distinct neural networks aimed at providing rapid estimates of both energy availability from PV systems and future energy prices were designed. The first neural network focuses on forecasting the energy output of PV systems. By leveraging historical data on sunlight exposure, weather conditions, and the performance characteristics of the PV installations, this model is trained to predict the amount of energy that can be generated over future periods (Laudani et al., 2020). The second neural network is tasked with predicting future energy prices, taking into account various factors such as market trends, demand and supply dynamics that could influence the PUN (Italian National Price) (Basso Alice, 2020).

The topic of energy forecasting, particularly the prediction of energy production from photovoltaic (PV) systems and the forecasting of energy prices, is well-documented in literature and supported by numerous commercial services offering detailed insights via API connections ("Solar panels energy prediction - OpenWeatherMap," n.d.), (Kohl, n.d.), ("Electricity Price Forecasting Software Services Solutions," n.d.). While recognizing the importance and the established base of knowledge in this area, our work primarily focused on the development and refinement of the plant virtual modelling and optimization phases.

2.3. Optimization

The optimization phase of our algorithm represents the final moment where the mathematical system of the plant is dynamically calculated at every timestep (t). This process is meticulously evaluated through a multi-objective genetic optimization algorithm, leveraging two critical fitness functions: the environmental fitness function (*OME-Ottimo Model Environment*) and the economic fitness function (*OMC – Ottimo Model Cost*). The environmental fitness function assesses the carbon footprint associated with the plant's energy consumption, aiming to identify solutions that minimize environmental impact. Concurrently, the economic fitness function evaluates the cost implications of energy usage, seeking to optimize financial efficiency. This dual-focus approach allows for a balanced consideration of both sustainability and economic viability in the plant's operations.

$$OME = \sum_{t=1}^{n} OME(t)$$

$$OMC = \sum_{t=1}^{n} OMC(t)$$

Multi-objective optimization is an advanced method used to solve problems involving several conflicting objectives. Unlike single-objective optimization, which focuses on finding a single optimal solution, multi-objective optimization aims to identify a set of optimal solutions, considering that improvements in one objective may lead to compromises in another. This approach is particularly suited to complex systems where trade-offs between different goals, such as cost and environmental impact, must be carefully managed.

Genetic algorithms (GAs) are a family of computational models inspired by natural selection and genetics (Cui et al., 2017). They are particularly effective for solving optimization problems in complex and dynamic systems. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a highly regarded version of GA, renowned for its efficiency in handling multi-objective optimization problems (Deb et al., 2002). NSGA-II operates by generating a population of potential solutions, evaluating them based on the defined fitness functions, and then using selection, crossover, and mutation processes to evolve these solutions over successive generations. Through Python language, is it possible to implement *GAs* through many available libraries. In Ottimo Algorithm Pymoo Library has been used (Julian Blank, 2020).

The culmination of the NSGA-II's optimization process is the identification of the Pareto set, which contains the optimal solutions discovered through the algorithm's iterations. Named after economist Vilfredo Pareto, the Pareto set comprises solutions that are considered Pareto optimal, meaning that no other solutions are superior in all objectives (Karami and Dariane, 2022), (Deb et al., 2002). Each solution within this set represents a possible strategy for managing and operating the plant's energy systems, illustrating different trade-offs between cost and environmental impact. The Pareto set serves as a crucial decision-making tool, providing stakeholders with a range of optimized solutions that balance economic and environmental considerations.

To select the most appropriate solution from the Pareto set for implementation, a decision-making process (*DMP*) must be set. In Ottimo Algorithm *DMP* is performed by implementing a weighted optimal solution approach, which leverages a configurable parameter: the shadow carbon price. The shadow carbon price assigns an economic value to carbon emissions, effectively quantifying the cost of CO2 emissions in financial terms (Fawson et al., 2019). By integrating the shadow carbon price into our optimization framework, we are able to give CO2 emissions an economic weight, making environmental and economic considerations directly comparable.

This section of the article outlined the integration of plant virtual modelling, energy forecasting, and optimization within a comprehensive framework. Employing mathematical and neural network-based modelling, we forecast energy needs and prices, subsequently leveraging a multi-objective genetic algorithm (NSGA-II) with a weighted optimal solution approach to balance economic and environmental objectives, ultimately guiding strategic plant energy management decisions.

3. Results

The simulation environment was meticulously designed to replicate the complex dynamics of industrial energy systems, as outlined in materials and method section. It incorporated variables such as energy demand fluctuations throughout the day, variable energy production from renewable sources like solar PV, and fluctuating energy

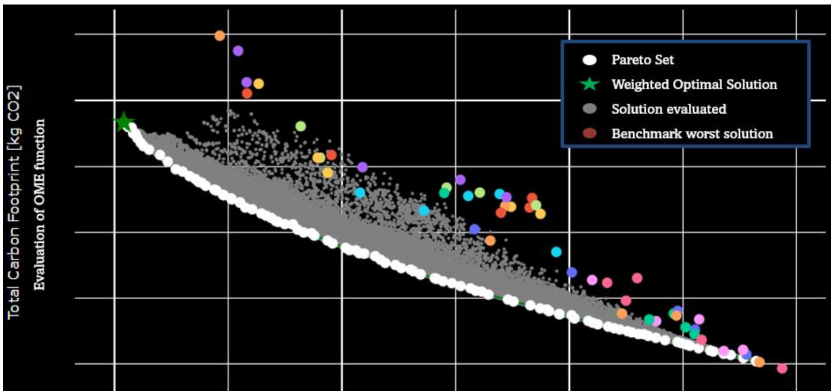

Figure 3. Pareto set: output of optimization process

prices for the energy grid (both for electricity and fuels consumption). The simulation parameters were defined by taking as an example a large manufacturing plant located in Northern Italy. This setup allowed for a comprehensive assessment of the optimization tool's performance under realistic industrial conditions.

Table 1. Simulation parameters

Simulation Parameter	Value
Natural Gas Boiler Size	25 MW
Photovoltaic Plant Size	10 MWp
Heat Pumps Size	7 MW
Eletric Boiler Size	12 MW
Yearly High Temp. (120°C) Thermal factory demand	200 GWh
Yearly Low Temp. (60°C) thermal factory demand	25 GWh
Yearly Direct (No Heat Generation) Electrical factory demand	100 GWh

We tested the two operative models ("manual" vs optimized genetic) with the above simulation parameters (Table 1) and with the hourly energy requirement trend from different yearly seasonal periods (February, June, September) and with the hourly market energy prices (electricity and natural gas) from 9 different weeks of the past three years (Table 2). The "manual" operative model was structured to reproduce the current non-automated plant management example plant.

Table 2. Simulation timeframes and IDs

Energy Price Simulation Year	Energy Price Simulation Week	Simulation ID
2020	February 10th-16th	***1***
	June 15th-21th	***2***
	September 14th-20th	***3***
2021	February 15th-21th	***4***
	June 14th-20th	***5***
	September 13th-19th	***6***
2022	February 14th-20th	***7***
	June 13th-19th	***8***
	September 12th-18th	***9***

For each week, the relevant simulation was performed, comparing the performance achieved by the genetically optimised management system with the fixed management system normally implemented in a manufacturing plant and the savings achieved were noted, both in terms of carbon footprint and energy supply costs. Also, the simulation parameters were modified to model different future scenarios. In particular, the photovoltaic system size was changed to 40 MWp (over 400% of the initial size) to study the effect of the increase renewable energy availability on the possible attainable savings.

Table 3. Base scenario: cost simulation results

Simulation ID	Cost SAVING [k€]	Relative Cost SAVING [%]
1	8	- 5,5%
2	7	- 6,7%
3	12	- 5,6%
4	10	- 4,1%
5	16	- 4,8%
6	30	- 3,7%
7	30	- 3,8%
8	50	- 4,5%
9	85	- 4,1%

Table 4. Base scenario: enviromental simulation results

Simulation ID	Environmental SAVING [tonCO2eq]	Relative Environmental SAVINGS [%]
1	80	- 8%
2	90	- 12%
3	90	- 11%
4	80	- 10%
5	80	- 11%
6	80	- 10%
7	70	- 8%
8	80	- 11%
9	110	- 14%

Discussion

A comparative analysis was conducted to highlight the optimization tool's advantages over traditional energy management approaches. The genetic model achieved an average cost reduction of 10% across various energy scenarios, alongside a 15% decrease in carbon footprint, compared to the reference management model.

The analysis of the simulation results demonstrated the multi-energy optimization tool's effectiveness in reducing energy costs and minimizing environmental impacts. For instance, in a scenario with high renewable energy availability, the tool dynamically shifted energy consumption patterns to capitalize on lower-cost renewable energy, resulting in significant cost savings and a reduction in carbon emissions. Conversely, during periods of low renewable availability or high demand, the tool strategically utilized energy storage or drew from the grid to maintain operational efficiency without compromising cost savings or environmental benefits.

Furthermore, in the scenario where the size of the photovoltaic plant was increased, the optimisation model proved to be even more effective when compared to the standard plant management model. This confirms that as complexity increases (i.e. number of plants to be controlled, variability of energy prices, large availability of renewable sources), rigid plant management is no longer efficient, when compared to new optimised models such as the one presented in this study.

Table 5. Enviromental savings: 9MW vs 40MW scenario

Simulation ID	10 MW PV Relative Environmental SAVINGS [%]	40 MW PV Relative Environmental SAVINGS [%]
1	- 8%	- 12,5%
2	- 12%	- 24,6%
3	- 11%	- 13,5%
4	- 10%	- 14,3%
5	- 11%	- 27,5%
6	- 10%	- 17,3%
7	- 8%	- 17%
8	- 11%	- 29%
9	- 14%	- 22%

5. Conclusion

This research underscores the significant potential of artificial intelligence (AI) and optimization algorithms in aiding the industrial sector to meet sustainability targets by optimizing energy use from both economic and environmental perspectives. Our findings reveal that these technological advancements not only enhance energy efficiency but also contribute to a more sustainable operational framework.

However, the high initial costs for digitalization, heavy reliance on data quality, and significant computational resource requirements are notable limitations. Customization might be necessary due to the specific configurations of different industrial plants, affecting the tool's generalizability.

Future research should focus on integrating emerging technologies like IoT and novel machine-learning models

for better data acquisition, transparency and manipulation. Expanding the optimization models to other utility management systems and enhancing predictive analytics through machine learning can further optimize energy usage and cost reductions.

Table 6. Cost savings: 9MW vs 40MW scenario

Simulation ID	10 MW PV Relative Cost SAVING [%]	40 MW PV Relative Cost SAVING [%]
1	- 5,5%	- 7,0%
2	- 6,7%	- 16,0%
3	- 5,6%	- 8,9%
4	- 4,1%	- 7,2%
5	- 4,8%	-13,7 %
6	- 3,7%	- 6,0 %
7	- 3,8%	- 5,9%
8	- 4,5%	- 12,2 %
9	- 4,1%	- 7,3%

Developing user-friendly interfaces will facilitate broader adoption, and conducting long-term impact studies can provide robust evidence of the tool's benefits, identifying areas for improvement in operational efficiency and sustainability

Building on this foundation, we are in the process of developing a product named "*Ottimo - AI Energy Advisor*." By harnessing the power of AI techniques outlined in our research, "Ottimo - AI Energy Advisor" seeks to make sustainable energy management accessible and actionable, breaking down the complexity of AI integration and driving forward the sustainability agendas of industries and companies alike.

ottimo A.I. for the industrial management optimization

Figure 4. Ottimo logo

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