Decision Support Systems 57 (2014) 150–159

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

A decision support system for sustainable energy supply combining multi-objective and multi-attribute analysis: An Australian case study

Alessandro Mattiussi [a], Michele Rosano [b], Patrizia Simeoni [a,*]

[a] Dipartimento di Ingegneria Elettrica, Gestionale e Meccanica, University of Udine, via Delle Scienze 208, Udine, Italy
[b] Sustainable Engineering Group, Curtin University, Sarich Road, Bentley, Perth Western Australia, Australia

ARTICLE INFO

Article history:
Received 8 March 2013
Received in revised form 23 August 2013
Accepted 23 August 2013
Available online 31 August 2013

Keywords:
Eco-industrial park
MCDA
AHP
CHP

ABSTRACT

A framework for an energy supply decision support system (DSS) for sustainable plant design and production is presented in this paper, utilising an innovative use of multi-objective and multi-attribute decision-making (MODM, MADM) modelling together with impact assessment (IA) of the emission outputs. The mathematical model has been applied within an eco-industrial park (EIP) setting and includes three steps. First, an assessment of the total EIP emissions' inventory and impacts is conducted; the second step, focusing on the sustainability benefits of combined heating and power (CHP) plants and photovoltaic technologies, developed a multi-objective mathematical model including both economic and environmental objectives in a Pareto-frontier optimisation analysis. Four different scenarios involving combinations of CHP plants (internal combustion engine, gas turbine, micro-turbines and fuel cells) and two types of PV plant (monocrystalline and polycrystalline) were evaluated. The third step utilises a MADM methodology – the analytic hierarchy process (AHP) – for selecting the best alternative among the Pareto-frontier efficient solutions. This model has been applied to a case study of an EIP located in Perth (Kwinana Industrial Area—KIA), Western Australia.

1. Introduction

Day-to-day decision making requires both objective and subjective perspectives, utilising the former for rational, constrained modelling and the latter for adapting specific problem issues to the decision-making process. The combination of both formal and informal information in the decision-making process is the main focus of this paper, referring to typical multi-criteria issues such as energy production. A decision support system (DSS) is defined as a software-based tool assisting in the decision-making process by interacting with both internal/external users and databases while utilising standardised or specific algorithms for problem solving [5].

Power, D. [21] identified four main types of DSSs, depending on the main drivers guiding the decisional process:

- Model-driven DSSs: such DSSs require a limited amount of data because of the intrinsic composition of the system, used to evaluate quantitative data in a tailor-made structure that can be adapted to other external requirements. Initially developed for financial planning, this category of DSS was later used for multi-criteria decision making and spatially driven decisions such as logistics or distribution modelling.
- Data-driven DSSs: the database structure behind the DSS is emphasised, and the operations of data-warehousing and manipulation are the most relevant for such DSSs. Online – meaning interactive (such as the OLAP) – and offline applications can be found, and web-based data-driven DSSs currently represent the natural evolutions of such models.
- Communication-driven DSSs are used for exploiting the network and communicating capabilities of the system, which includes the use of groupware, conferencing or other computer-based communications. This category is directly related to group DSSs, developed to promote a participatory approach to the decision process, and their relation with model-driven DSSs has been studied, aiming to include the shared approach of the former with the structured modelling of the latter.
- Document-driven DSSs, also called “text-oriented DSSs”, are used for document retrieval, especially in large groups/organisations, to support the decision-making process. The advent of a Web-based system increased the possibility of such DSSs, allowing rapid access of documents distributed in worldwide databases.
- Knowledge-driven DSSs: these are specific, tailor-made systems used in a particular domain and developed for a particular person or group of people. Power [21] acknowledged the relationship with Artificial Intelligence systems, in which the DSS follows a series of rules to evaluate and eventually make decisions on the problem to be analysed.

Arnott & Pervan [2] reported a framework for DSS classification and sub-classification, identifying personal DSSs, group support systems, executive information systems, intelligent DSSs and knowledge-management-based DSSs. Each of such DSSs presents sub-branches

* Corresponding author.
E-mail address: patrizia.simeoni@uniud.it (P. Simeoni).

0167-9236/$ – see front matter
http://dx.doi.org/10.1016/j.dss.2013.08.013

depending on their specific features and temporal evolution. In particular, model-driven DSS represents the focus of this study. The modellisation stage, focusing on multi-criteria modelling, will be investigated in the following paragraphs.

Multi-criteria, multi-attribute and multi-objective analyses – while similar in their ultimate purpose of assisting with the final decision-making process [18] – differ in their defining concepts. Multi-criteria decision-making (MCDM) "deals with a general class of problems that involves multiple attributes, objectives and goals" [32]. Although MCDM represents the major class in decision-making support systems, multi-attribute (MA) and multi-objective decision-making (MODM) represent their subclasses, [20] related to more specific approaches in the decision-making model. Life cycle assessment (LCA) and impact assessment (IA) are tools used in industrial ecology [3] to quantify and evaluate the emissions (air, water and soil) from various parts of a production process and then evaluate their impacts on different elements of the ecological system (e.g., human health, ecosystem damage and resources) depending on the IA methodology chosen.

Optimisation with multiple conflicting objectives has no single best solution, but a set of solutions, named the "Pareto-set" for Villfred Pareto (1848–1923), who first studied them, which can be applied to social science, economy and game theory. Multi-objective optimisation techniques therefore identify a set of non-dominated solutions which represent the optimums for a given problem. The concept of domination can be illustrated as follows: an alternative a is non-dominated by b if a is better than b for at least one objective while not being worse than b for all of them.

Identifying the Pareto-frontier means also satisfying the following requisites for the solutions identified while minimising the total elaboration time, as reported in [1]:

- Spread: To find a set of solutions that "capture the whole spectrum" of the true Pareto front;
- Accuracy: To find a set of solutions as close to the real Pareto front as possible;
- Diversity: To find a set of solutions as diverse as possible.

Weise [30] provided a broad taxonomy of evolutionary algorithms, defined as "*population based metaheuristic optimization algorithms that use biology-inspired mechanisms like mutation, crossover, natural selection and survival of the fittest in order to refine a set of solution candidates iteratively*". First, metaheuristics is defined as a "*method for solving general problems, combining objective functions in an abstract way, treating problems as a black box*".

According to [30], the five main stages of evolutionary algorithms involve the following:

- Initial population, which allows the initial sample for analysis to be created from the possible set of candidate solutions;
- Design evaluation, which computes the objective value from the candidate solution;
- Fitness assignment, which, depending on the objective, determines the fitness of the candidate solution relative to a fitness criterion (weighed sum of objective values, Pareto ranking, etc.) which evaluates the suitability of the candidates to the optimisation required;
- Selection: based on the fitness of the candidate solution, at this stage the population (the group of candidate solutions) to be maintained is selected, while the remaining solutions are discarded.
- Reproduction: selected candidate solutions are reproduced by different mechanisms such as partial mutation, crossovers, or complete change.

As a class of MO techniques, the family of evolutionary algorithms includes, among others, evolution strategies (ES), genetic algorithms (GA), genetic programming (GP) and learning classifier systems (LCS) [30]. Among GA techniques, the non-dominated sorting algorithm (NSGA) represents an increasingly used method for the design stage. NSGA and its variant NSGA-II, first developed by Srinivas and Deb [25][26], are population-based metaheuristics encompassing seven steps for design optimisation [30], i.e., population initialisation, non-dominated sorting, crowding distance, selection, genetic operators, recombination and selection. Having defined the initial population based on problem constraints or user design of experiments (DOE), sorting is performed by assigning a priority value ("rank") to non-dominated designs, selecting designs for further explorations based on rank and crowding distance, i.e., higher fitness is assigned to individuals located on a sparsely populated part of the front [16]. Genetic operators, mainly "recombination", "crossover" and "mutation", are used for exploring the design space, which is then selected, maintaining a range of best-performing designs ("elitism") for the next fitness assessment, until the last generation of designs is assessed or the end criterion is reached.

To overcome the shortenings of lateral diversity in Pareto front determination of NSGA-II, Jeyadevi et al. [12] developed a modified NSGA (MNSGA-II) including a controlled version of elitism for improving the exploration stage and the lateral distribution of the Pareto Front, used in reactive power dispatch modelling. Guo et al. [10] used a modified version of NSGA-II to solve scheduling issues in production planning, relating scheduler utilisation to a production process simulator. Panda [19] used NSGA-II for electrical noise reduction in controller designs.

Yusoff et al. [31] reviewed the application of NSGA-II in machining design, concluding that such an algorithm represents a reliable and popular tool in MO machining setup, allowing the inclusion of multiple performances and variables. There are numerous published applications of MCDM in plant design. Multi-objective (MO) analysis has been broadly used in designing product components, but limited research has considered the environmental impacts of the process. Vince et al. [29] assessed the design installation of a Reverse Osmosis plant for desalinated water production, including both economic and environmental criteria. However, in this analysis, the environmental impact was limited to a quantitative environmental assessment of water discharges, considering electricity production and the water recovery rate as the environmental criteria. Mirzaesmaeeli et al. [15] treated environmental emissions as a constraint in a mixed integer linear programming (MILP) optimisation of a Canadian power producer, while the optimisation model proposed in [22] included environmental emissions considered as externalities, i.e., those externally generated but unaccounted for in the costs. Harkin et al. [11] used MO optimisation to design CO_2 capture systems retrofitted in coal power stations. They took into account the percentage of CO_2 captured (maximised) and the energy input to the process (minimised), evaluating results as a function of the input parameters. Guillén-Gosálbez [9] applied MO optimisation, discussing its validity when assessing multiple objectives such as environmental outcomes, and introduced a mixed MILP-MO model, which they then applied to heat exchanger designs and petro-chemical supply chains. Environmental impacts within LCA typically include acidification, eutrophication, global warming and eco-toxicity. Bernier, Maréchal, & Samson [4] used both thermo-economic and environmental objectives for a carbon dioxide capture plant design, integrating LCA (in terms of global warming potential) into the optimisation model. Applied evolutionary algorithms were used in [7] for power plant capacity estimation, considering only technical (maximise exergy efficiency) and economic (minimising total costs) criteria in identifying Pareto-optimal solutions.

Most MCDM methodologies provide a unique utilisation of MO *or* MA analysis. This paper aims to establish a framework for including both MO *and* MA decision-making modelling and introduces a general methodology for DSS in sustainable energy plant design (§ Section 2.x). The proposed framework has been developed to assess both individual companies and EIPs, in which the summations of each individual company's emissions can be aggregated to provide an emissions figure for the entire EIP. Such a framework has then been applied to a specific case study in the Kwinana Industrial Area (KIA, Perth, Western Australia): the three specific stages of data assessment (§ 3.1) are related to the whole