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Comparison of metaheuristic optimisation methods for grid-edge technology that leverages heat pumps and thermal energy storage

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ABSTRACT

Grid-edge technology can unlock flexibility from consumers to contribute to meeting the growing need for flexibility in European energy systems. Furthermore, power-to-heat technology such as heat pumps and thermal energy storage has been shown to both decarbonise heat and enable the cost-effective integration of more renewable electricity into the grid. The consumer's reaction to price signals in this context presents the opportunity to simultaneously unlock operational cost reductions for consumers and localised implicit demand-side flexibility to benefit grid operators.

In this paper, the prediction accuracy, run-time, and reliability of several (metaheuristic) optimisation algorithms to derive optimal operation schedules for heat pump-based grid-edge technology are investigated. To compare effectiveness, an optimisation effectiveness indicator OEI is defined. Particle Swarm Optimisation (PSO) and Genetic Algorithm (GA) were found to be most effective and robust in yielding quasi-optimal minima for the non-linear, multi-modal, and discontinuous cost function. GA optimisation with binary variables is 5–15 times more effective than with continuous variables. Using continuous variables, PSO is more effective than GA due to smaller optimisation error, shorter run-time, and higher reliability (smaller standard deviation). Simulated Annealing and Direct (Pattern) Search were found to be not very effective.

1. Introduction

For the transformation of energy systems towards systems that are dominated by large shares of renewable energy, flexibility must be harnessed in all parts of the energy system [1]. Flexibility is the key to operating energy systems securely and economically. This is especially the case for systems with large shares of renewable energy [2]. Such energy system flexibility can be gained from more flexible generation, sector-coupling, more storage, interconnection, grid-reinforcements, and more demand-side flexibility. The idea of sector-coupling is to provide flexibility to the energy system via power-to-heat (P2H), vehicle-to-grid (V2G), or power-to-gas (P2G) technologies. Electrical energy is converted and stored in the form of thermal, electrical, and chemical energy respectively. This flexibility is also a key concept of smart energy systems [3].

The latter applications can adjust their demand profiles based on price signals and thus decouple the timing of final energy (heat, electricity or chemical) demand from electricity supply. Power-to-heat technology has been proposed to decarbonise the heating sector and simultaneously enable the cost-effective integration of more variable renewable electricity generation [4].

Part of the required flexibility can be offered by energy flexible buildings [5]. For instance, decentralised demand-side flexibility can be offered to the grid by heat pump and thermal energy storage (TES) systems. A large number of heat pumps represent a significant flexible load. This offers flexibility to the grid at time scales ranging from minutes to days. Demand-side flexibility can be differentiated into explicit and implicit flexibility services. Explicit demand response (DR) is committed, dispatchable flexibility that can be traded on the energy market. This type of flexibility is generally provided by aggregators that control large aggregated capacities. Implicit demand response is defined as the consumer's real-time reaction to price signals while retaining autonomous control over their equipment. Both explicit and implicit demand response are necessary to accommodate different consumer preferences and to exploit the full spectrum of consumer and system benefits from demand-side flexibility [6]. A key enabler for implicit demand response has been included in the European Commission's Clean Energy for all Europeans package. Directive (EU) 2019/944 on Common Rules for the Internal Market for electricity entitles European citizens to request a smart meter and a dynamic price contract. This will allow them to be rewarded for shifting consumption to times when

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Nomenclature

Abbreviations

CPP	Critical-peak pricing
COP	Coefficient of performance [−]
DR	Demand response
DS	Direct Search (pattern search)
EU	European Union
GA	Genetic Algorithm
GW	Giga Watt
HP	Heat pump
HPTES	Heat pump and thermal energy storage
HVAC	Heating, ventilation and air-conditioning
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
LP	Linear Programming
MILP	Mixed Integer Linear Programming
OEI	Optimisation effectiveness indicator [−]
P2G	Power to gas
P2H	Power to heat
PSO	Particle Swarm Optimisation
Q	Heat [J]
RTP	Real-time pricing
SA	Simulated Annealing
SMP	Electricity system marginal prices [€/kWh]
SOC	State of charge [J]
TES	Thermal energy storage
TOU	Time-of-use
U	Thermal transmittance of the TES [W/m^2K]
V2G	Vehicle to grid
VRE	Variable renewable energy
WEF	World Economic Forum

Symbols

f(x)	Objective function
M	Number of equalities
N	Number of inequalities
$\mathbb{R}^n$	n-dimensional search space of real numbers
T	Decision variable type
x	Decision variable vector
μ_{err}	mean optimisation error [%]
μ_t	mean run-time [s]
σ_{min}	standard deviation of the optimisation errors [%]
$\phi(x)$	Equality constraint function
$\psi(x)$	Inequality constraint function

energy is widely available and cheap [7]. Since electricity storage is more expensive than thermal energy storage by approximately an order of magnitude, sector-coupling through power-to-heat has been extensively researched. Effectively, additional and flexible loads are made available to the grid through the electrification of thermal energy applications.

The combination of power-to-heat and implicit demand-side flexibility reflects one application of emerging grid-edge technology. Grid-edge technology based on heat pumps and thermal energy storage has the potential to provide thermal energy for heating with massively reduced emissions at low cost. Simultaneously, this enables distributed demand-side flexibility to help balance the grid and integrate large shares of renewables. Previous research points to operational cost reductions of more than 17% [8] and the potential to shift up to 100% of critical (peak) loads [9] compared to a load-following reference system.

Ensuring benefits for consumers and energy systems alike requires conveniently automated real-time optimisation of energy demand. The optimisation of the resulting scheduling problems is complex and computationally expensive. To avail of the potential benefits, system operational optimisation is required. The optimisation should consider day-ahead electricity prices, expected load, and other relevant variables to derive optimal schedules. The optimisation of these schedules requires the minimisation of non-linear, multi-modal, and discontinuous objective functions. As a driver of control equipment cost, there is a need to reduce computational complexity. The operational optimisation of such grid-edge technology must be performed quickly and effectively to enable fast response to changing grid conditions. Common optimisation approaches avoid nonlinearities and opt for linear programming (LP), mixed-integer linear programming (MILP) or quadratic programming for simplicity. However, using simplified algorithms might lead to suboptimal results [10]. Metaheuristic optimisation routines such as Genetic Algorithm or Particle Swarm Optimisation can tackle nonlinear or nonconvex optimisation problems with relatively low computing load compared to mathematical programming.

But how effective are these methods? How close do these algorithms come to the true optimum? How fast does the algorithm converge? And how reliably does the algorithm converge over multiple optimisation runs? With plenty of literature on metaheuristics emerging for various optimisation problems, only a few researchers attempt to address these questions which can be difficult to answer because determining a true global optimum is often intractable.

1.1. Aim of this study

The question must be answered as to which optimisation technique can reliably yield near global optima with the least computational effort for optimised grid-edge technology? This study investigates the effectiveness of various global optimisation techniques on the example of optimal operation schedules for a heat pump and thermal energy storage system. It quantifies optimisation effectiveness with a proposed optimisation effectiveness indicator (OEI) which is based on the optimisation error, run-time, and reliability of several metaheuristic optimisation methods. The system considered in this research consists of a residential 7 kW (thermal) heat pump and 1000-L sensible thermal energy storage. It is simulated in MATLAB R2018b and optimised using the MATLAB Global Optimisation Toolbox. Genetic Algorithm, Particle Swarm Optimisation, Simulated Annealing, and Direct (Pattern) Search are benchmarked against one another and an optimisation effectiveness indicator proposed. Furthermore, the effect of the decision variable type, resolution and length of the optimisation horizon is examined. As some of the tested algorithms contain pseudo-random events, each optimisation is performed repeatedly under identical conditions to establish statistical significance.

2. Literature review

The World Economic Forum (WEF) identifies three major trends affecting the electricity grid: electrification, decentralisation and digitalisation [11]. These trends are blurring the traditional boundaries between producers, customers, and distributors. Customers will produce, consume, store, and sell electricity aided by grid-edge technology that provides automation, analytics, and optimisation. The benefits of a smart, decentralised and more connected electricity system are increased reliability, security, and sustainability. Over the next decade, the WEF estimates the value from the transformation of electricity at $2.4 trillion, thus unlocking significant economic value for industry, customers, and society. However, this must be enabled by proper policy, market and regulatory frameworks. In Europe, the introduction of

Directive (EU) 2019/944 on Common Rules for the Internal Market for electricity presents an important step in that direction. It entitles European citizens to request a smart meter and a dynamic price contract that allows them to be rewarded for shifting consumption to times when energy is widely available and cheap [7].

2.1. The need for balance and flexibility

The key to securely and economically operating energy systems with large shares of renewable energy is flexibility [2]. For the transformation of energy systems towards systems that are dominated by large shares of renewable energy, flexibility must be harnessed in all parts of the energy system. The International Renewable Energy Agency (IRENA) defines flexibility as "the capability of a power system to cope with the variability and uncertainty that variable renewable energy (VRE) generation introduces into the system in different time scales, from the very short to the long term, avoiding curtailment of VRE and reliably supplying all the demanded energy to customers" [12]. The International Energy Agency (IEA) defines energy system flexibility more technology-agnostic as "the ability of a power system to reliably and cost-effectively manage the variability and uncertainty of demand and supply across all relevant timescales, from ensuring instantaneous stability of the power system to supporting the long-term security of supply". Energy system flexibility can be gained from more flexible generation, sector coupling, more storage, interconnection, grid-reinforcements, and more demand-side flexibility.

Lund et al. comprehensively reviewed available flexibility options to enable the integration of high levels of variable renewable electricity into the energy system [13]. They describe available and future flexibility measures sourced both from the supply-side and the demand-side including ancillary services and storage options. They postulate that large shares of variable power can already be handled using existing energy system-inherent flexibility capabilities without new investments. Taking a whole energy system view with integrated thermal and electric systems will yield major new opportunities for renewable power integration.

2.2. Flexibility from demand response and power-to-heat

The European Commission's Clean Energy Package, launched in November 2016, includes various measures that could unlock the European demand response potential on a large scale. Currently, European energy systems avail of approximately 20 GW of demand response-activated capacity whereas the current potential of 100GW is estimated to increase to 160GW by 2030 [14]. Gils previously assessed the theoretical demand-response potential in Europe and North Africa. They differentiate between minimum load reduction and minimum load increase potentials with estimated 61GW and 68GW respectively [15].

Torriti et al. examined European experiences with DR to understand factors that facilitate and impede its development [16]. The common reasons hampering the advance of DR were found to be limited knowledge, high-cost estimates and adverse policies. Nonetheless, they find that a wide roll-out of smart metering technology can create the platform for an informed consumer capable of responding to prompts from the supply side. This should help Europe to realise its full DR potential. A review of price-driven residential demand response by Yan et al. also predicts a major role for DR in the future smart grid that is enabled by smart metering infrastructure. Time-of-use (TOU) and critical peak pricing (CPP) tariffs have been shown to shift (peak) energy demand and are easily followed. However, only a real-time pricing (RTP) program can reflect the dynamic relationship between supply and demand [17].

The potential of Power-to-heat technologies for renewable energy integration was investigated by Bloess et al. [4]. They reviewed model-based residential power-to-heat analyses and found that power-to-heat technologies can cost-effectively contribute to fossil fuel substitution, renewable energy integration, and decarbonisation of both the electricity and heat sectors. However, it is required that such systems are sufficiently flexible to enable the effective coupling of electricity generation and the space heating sector. This argument is corroborated by Fischer and Madani in their review of heat pumps in smart grids [18]. They concluded that heat pumps, when controlled appropriately, can help to ease the transition to a decentralised energy system accompanied by a higher share of prosumers and renewable energy sources. They argue that it is critical to take a holistic view of both the energy system at a local level and on how it is integrated into the national energy system. A pure electricity grid perspective could negatively impact on the performance of the local heating system while a purely local focus may result in undesirable effects on the electricity grid. Thus, heat pumps must be operated to yield both consumer and power grid benefits. Regarding the integration and management of heat pumps in building energy systems, they suggest researching the design of optimal flexible systems including sizing, layout and control approach.

Kohlhepp et al. reviewed recent field studies to investigate the flexibility potential of demand response from P2H. They investigated whether the technology was sufficiently mature for mass usage regarding cost-efficiency, social attractiveness, and the capability of making key flexibility contributions. They conclude that while significant benefits such as effective congestion relief in distribution grids have been demonstrated, the current field-tested control and information technology and economic and regulatory frameworks do not yet meet the flexibility challenges of smart grids with a very high share (>50%) of intermittent renewable generation. Furthermore, questions are raised about whether monetary revenue from residential TES-based DR sufficiently encourages investment. As a limitation of the reviewed literature, they raise concerns over many field projects trying to fit flexibility services into existing electricity markets and regulation frameworks rather than envisioning new flexibility markets [19]. Good et al. provide comprehensive 'socio-techno-economic' review and classify barriers and enablers of demand response in smart grids into fundamental and secondary barriers within markets, society, technology, and policy. They also include key enablers to tackle these barriers. Metering, a fundamental barrier, can unsurprisingly be addressed by the installation of metering at a necessary resolution. Furthermore, they recommend real-time network pricing and decentralised optimisation to tackle distribution network constraints and complexity respectively [20].

2.3. Operational control optimisation in energy flexible buildings

Chen et al. review measures to improve energy demand flexibility from buildings for DR. They find that a more flexible system (building) can draw more economic and environmental benefits from a high penetration of renewable energy through advanced control strategies and measures. Such strategies include price mechanism, energy storage systems, energy management system (EMS) with optimal DR control algorithms, and passive and active HVAC peak load controls [21].

The control of heat pumps in energy flexible buildings was reviewed by Péan et al. [22]. They reviewed supervisory control of heat pumps for improving the energy flexibility provided by buildings. They found that the more complex and costly model predictive control outperforms the simpler rule-based control. Furthermore, they concluded that thermal storage was necessary for activating energy flexibility in buildings. Despite active thermal energy storage offering greater flexibility and passive storage inhibiting more restrictive temperature constraints, the authors conclude building mass to be the more promising solution as no prior investment is required. Nonetheless, it is unclear whether optimised scheduling and dynamic modelling of the coefficient of performance (COP) and losses were used to draw these conclusions. Shaikh et al. review the optimised control systems for building energy and comfort management of smart sustainable buildings [23]. They extend the optimisation focus from optimal heating control to optimal control of lighting, air quality, humidity, and/or plug load. Thus, multi-objective optimisation becomes a key tenet of their investigation.

While they do not particularly consider energy flexibility, they argue that Genetic Algorithm is the most recognised technique in building performance [optimisation]. They suggest that optimisation algorithms such as multi-objective genetic algorithm, simulated annealing, meta-analysis, and others require in-depth exploration.

Finn et al. optimised the operation schedules of an immersion heated hot water cylinder [24]. They showed a correlation between the day-ahead half-hourly price of electricity and real-time wind availability. Consequently, they suggest the use of price as an incentive for demand response. This would enable a larger amount of renewable energy on the electrical grid. Optimising for lowest operational cost with day-ahead electricity prices, they conclude that with decreasing energy losses from the optimised device, the financial savings and wind generation increase while conventional generation decreases. For simplicity, they solved the optimisation problem with linear programming. Fischer et al. used MILP to optimise the design and operation of an air-source heat pump with solar PV and varying electricity prices. MILP was used to avoid nonlinearity [25]. The effect of linearisation on the optimality of the results is difficult to gauge.

2.4. Metaheuristic optimisation

While significant contributions to the field of metaheuristic optimisation have been made since the 1950s, interest in the field has surged with the arrival of cheap and powerful ICT equipment. There is no shortage of new nature-inspired algorithms that are named after insects, fish, birds, insects, bacteria and many more.

Makhadmeh et al. comprehensively reviewed many of these metaheuristic (or approximate) algorithms alongside the deterministic (or exact) methods in studies on optimisation methods pertaining to the power scheduling problem in a smart home [26]. They found that the approximate methods were more efficient in addressing the problem due to their performance in exploring high-dimensional search space for which the exact methods were unsuitable. Genetic Algorithm was found to be the most commonly used algorithm for this type of problem followed by Harmony Search Algorithm, Bacterial Foraging Algorithm and Particle Swarm Algorithm. Hybrid metaheuristic optimisation algorithms such as genetic wind-driven algorithm or foraging and genetic algorithm were found to be especially promising. In their conclusions, the authors flag the lack of standard datasets to facilitate comparison studies.

A detailed description of various optimisation techniques for active thermal energy storage control is provided by Ooka and Ikeda [27]. They reviewed studies investigating optimisation techniques for TES operation. Categorising into mathematical programming and metaheuristic methods, they describe algorithm concepts and their applicability to the optimisation of active TES. They conclude that there is little information about the accuracy and the computational load of metaheuristic methods. The authors call for performance comparisons and benchmarks of optimisation techniques. Frangopoulos provides an overview of developments and trends in energy system optimisation including synthesis-, design-, and operation optimisation [28]. They find that global optimisation is computationally heavy and that the development of methods which are both effective and efficient is still a challenge.

Jordehi et al. reviewed and classified different research works on demand response optimisation problems and introduced the most common deterministic and metaheuristic optimisation methods [29]. The focus of the study was on the benefits of demand response optimisation and the effectiveness of the algorithms was not treated in particular. However, such criteria should be considered in the selection of optimisation methods as reported by Kheiri who extensively reviewed optimisation methods for energy-efficient building design [30]. Mahdi et al. reviewed optimisation strategies for the combined economic emission dispatch problem that seeks to simultaneously minimise cost and emissions. They found the advanced nature-inspired methods to be most suitable and successful with hybrid methods showing the best prospects. While identifying algorithm parameter selection and high computational time as problematic they emphasise the importance of reliability, robustness and computational efficiency when selecting a suitable optimisation technique. The significance of nature-inspired algorithms and their hybrids was further corroborated by Anoune et al. who reviewed optimisation techniques for the design and operation of stand-alone hybrid renewable energy systems based on solar and wind energy paired with battery storage [31]. They point to the algorithms' ability to search local and global optima, good calculation accuracy and faster convergence speed. Nazari-Heris et al. review, explain and apply a battery of (meta) heuristic optimisation methods to solve the combined heat and power economic dispatch problem [32]. The obtained optimal solutions were tabulated and compared regarding minimum cost and computational time. For the studied problem, the exchange market algorithm yielded the smallest minimum.

Little is known about algorithm effectiveness including their accuracy, run-time, and reliability because many of the studies compare one or more algorithms to a reference scenario. The determination of these effectiveness indicators is non-trivial. Ideally, the absolute global optimum would have to be known as a reference to quantify algorithm accuracy. For instance, Pillai and Rajasekar use analytic methods to identify PV parameters for PV panel performance prediction [33]. Then they review existing metaheuristic algorithms noting their accuracy and convergence speed amongst other characteristics. The hybrid Bee Pollinated Flower Pollination Algorithm performed best for their problem in terms of accuracy and convergence speed.

Investigating the pitfalls of commonly used optimisation algorithms in building energy optimisation, Si et al. apply four commonly used optimisation algorithms to the design optimisation of a reference building to investigate their (in)effectiveness and reasons for failure [34]. In their study, Particle Swarm Optimisation with inertia weight showed the best performance irrespective of initial position and control parameters. Contrarily, these parameters significantly affected the effectiveness of Discrete Armijo Gradient Algorithm and Hooke-Jeeves Algorithm. Particle Swarm Optimisation with constriction coefficient was found to be ineffective for all tests.

3. Material and methods

This study investigates the effectiveness of various global optimisation techniques to answer the question: Which optimisation technique can reliably yield near global optima with the least computational effort for optimised grid-edge technology?

Befitting to the fierce mild and windy Irish climate, we selected a power-to-heat application as an example for grid-edge technology. The optimisation problem was to derive a cost-optimal schedule for a heat pump (HP) and thermal energy storage system with implicit demand response. We quantified the effectiveness of the metaheuristic optimisation algorithms noting their optimisation error, run-time, and reliability.

3.1. Framework and definition of optimisation effectiveness

The optimisation framework, shown in Fig. 1, is erected around the model which is used to simulate the grid-edge technology under given boundary conditions. The heat pump and active thermal energy storage system based upon its operation schedule does or does not satisfy the required energy demand for the simulated day. Alongside the operational schedule, the model inputs include the boundary conditions: electricity prices, ambient air temperature, and thermal demand. The model outputs are the operational cost for the day and a binary variable that signals whether demand has been matched or not.

In the simulation/optimisation phase the optimisation algorithm interacts with the model to derive the operational schedule that satisfies the demand for the least operational cost for a set of static boundary

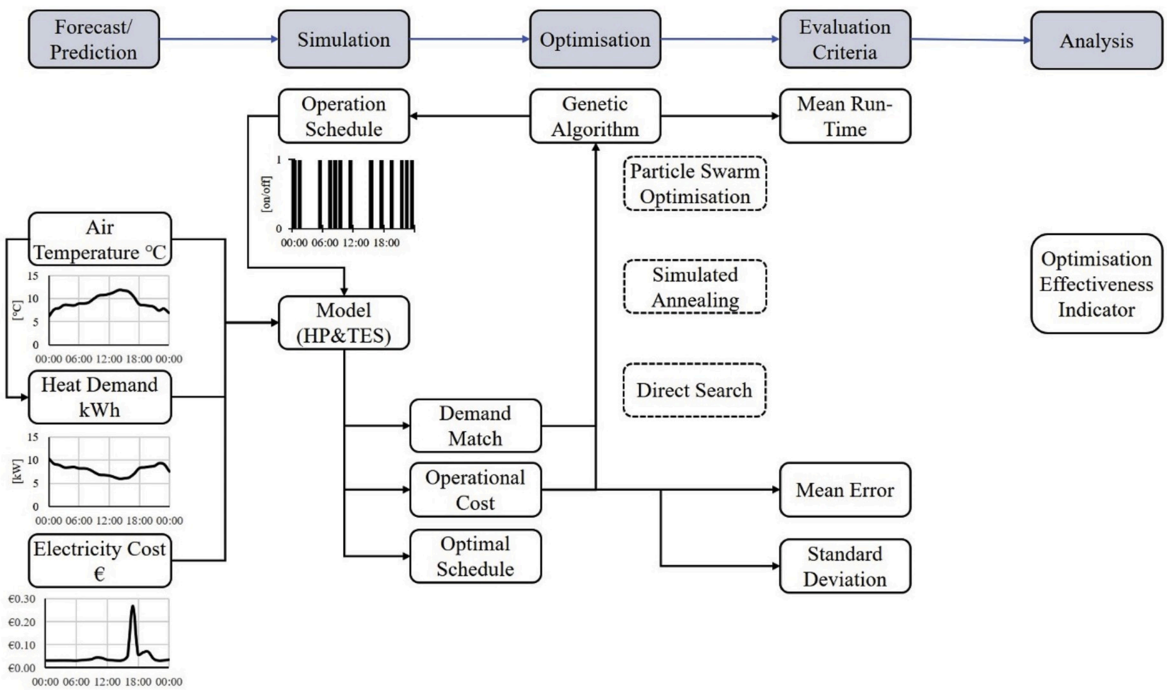

Fig. 1. Framework for comparison of metaheuristic optimisation methods for grid-edge technology leveraging heat pump and thermal energy storage.

conditions. The tested algorithms Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Simulated Annealing (SA), and Direct Search (DS) all contain pseudo-random events. Thus, each optimisation is performed repeatedly (n = 30) under identical conditions to establish statistical significance. The recorded data states the acquired quasi-minimum value for the objective function and the run-time until the algorithm reached stopping conditions. A value for the true minimum derived by brute-force calculation and statistical analysis enables the analysis of the optimisation effectiveness.

Si et al. characterise the effectiveness of optimisation algorithms [34]. They suggest that an effective optimisation algorithm should simultaneously (i) be able to deliver a satisfactory optimal solution, (ii) be able to complete the optimisation process within a given time constraint, and (iii) to demonstrate good reliability.

All optimisation algorithms tested in this study rely to different degrees on pseudo-random numbers. These numbers are pseudo-random because they are generated by a definite, non-random computational process using tables of random numbers rather than supposedly true random processes observed in the environment such as atmospheric noise or quantum phenomena. GA, PSO, and SA use random numbers to explore the search space. Direct (Pattern) Search requires an initial starting point which in this study is also created pseudo-randomly. Thus, different solutions are yielded for every optimisation run. Due to the variability of solutions multiple optimisation runs are performed in this study to assess the statistical population. Mean minima, mean run-time, mean optimisation error and standard deviation are then used to compare the effectiveness of all tested optimisation algorithms.

The true minimum can sometimes be obtained through exhaustive or brute-force calculation and is the ideal benchmark to verify satisfactory optimal solutions. However, the exhaustive enumeration can be impracticable due to extensive calculation run-times. Thus, multiple optimisation algorithms can be executed repeatedly to yield a quasi-global minimum. Then the optimisation error can be calculated as:

$$Optimisation\ Error = \frac{solution - (quasi)global\ optimum}{(quasi)global\ optimum} \tag{1}$$

Furthermore, optimisation run-time and reliability can be quantified using the mean optimisation run-time and the standard deviation of the optimisation error after multiple optimisations.

We define an optimisation effectiveness indicator (OEI) to combine the mean error, mean run-time, and standard deviation. The relation between run-time, mean optimisation error, and standard deviation can be expressed as:

$$OEI = \frac{1}{\mu_{err}\mu_t\sigma_{min}} \tag{2}$$

where μ_{err} is the mean optimisation error of a sample, μ_t is the mean run-time, and σ_{min} is the standard deviation of the population of minima.

3.2. Optimisation

Optimisation is defined as to make something as good as it can be, or to use something in the best possible way. In mathematics, it is generally possible to determine a true optimum. In engineering, however, optimisation is subject to contemporary system understanding, underlying assumptions, available technology, and quantitative model. Thus, only an intermediate optimum can be obtained.

Real-world problems with explicit objectives can generally be formulated in generic form as nonlinearly constrained optimisation problems such that:

$$\min_{\boldsymbol{x}\in\mathbb{R}^n} f(\boldsymbol{x}),\quad \boldsymbol{x} = (x_1, x_2, \ldots, x_n)^T \in \mathbb{R}^n \tag{3}$$

where $f(\mathbf{x})$ is called the objective function. It maps n decision variables x_i into the solution space. The decision variable type T can be binary, discrete or continuous. Besides, the objective function can be constrained in terms of M equalities and N inequalities, pertaining to energetic, economic or regulatory system limitations:

$$\varphi_j(\boldsymbol{x}) = 0,\ (j = 1, 2, \ldots, M) \tag{4}$$

$$\psi_k(\boldsymbol{x}) \geq 0,\ (k = 1, 2, \ldots, N) \tag{5}$$

Some solvers such as Simulated Annealing or Particle Swarm Optimisation cannot accommodate constraint functions. Thus, a penalty function is included in the objective function to dismiss unfeasible alternatives. This technique enables solvers that do not normally accept non-linear constraints to attempt to solve a non-linearly constrained problem.

In engineering optimisation, it is generally desirable to maximise the performance of an artefact while minimising its cost at the same time. When performance refers to system efficiency, optimisation for cost implicitly optimises for performance. Nonetheless, it may be desirable to explicitly optimise multiple objectives simultaneously. In energy systems, such objectives could include renewable energy share, efficiency, energy use, user comfort, or emissions. As different objectives often conflict with one another, a compromise must be found using multi-objective optimisation. In the present study, optimisation for lowest cost simultaneously optimises for both grid benefits and user benefits optimising COP and TES losses while user comfort is ensured through demand match for every interval.

An exact solution for a global optimum can easily be found if the problem is simple. That is the case for linear and convex problems. However, the problem at hand is like many other engineering problems non-linear, non-convex and multi-modal. An exhaustive search through the calculation of all options would guarantee to yield the optimum. However, this requires time and resources and can thus be intractable as the optimisation problem evolves towards the combinatorial explosion. The complexity of optimisation and combinatorial explosion can be expressed as:

$$\mathbb{R}^n = T^n \tag{6}$$

where $\mathbb{R}^n$ is the search space or the total number of permutations, T is the number of values that the decision variable can take, and n is the number of optimisation steps. Thus, binary optimisation with 24 hourly intervals yields 2^{24} permutations. Changing the resolution to 48 half-hourly intervals with decision variables representing ten 10%-steps (e.g. for a variable speed heat pump) results in 10^{48} permutations. This means a difference of 40 orders of magnitude.

Optimisation approaches can be categorised into (i) search methods (heuristics), (ii) calculus methods (derivative-based), and (iii) stochastic or evolutionary methods. According to the “no-free-lunch theorem”, there is no one optimisation algorithm that works best for all optimisation problems. The effectiveness of either algorithm depends on the type of optimisation problem. In this study, Genetic Algorithm, Particle Swarm Optimisation, Simulated Annealing, and Direct (Pattern) Search are tested for their effectiveness in yielding quasi-global optima. A description of how these algorithms work is provided by Refs. [27].

3.3. Model description and objective function

The cost function quantifies the operational cost of the heat pump and storage system which is simulated over the optimisation horizon with dynamic COP. Here, the optimisation horizon is one day, and the aim is to determine the optimal heating schedule for the day ahead. The heat demand and electricity cost profiles depend on the type of day. This is also referred to as state of nature (i.e. ambient air temperatures, heat demand and electricity market cost).

3.4. Model description

The considered system consists of a $7kW_{TH}$ air-to-water heat pump which is paired with a sensible thermal energy storage tank (1 m^3 H_2O). The heat pump and thermal energy storage (HPTES) system supplies the space heating demand of a detached Irish family house with a floor area of 156 m^2. The C2-rated dwelling has a heat demand of 93 kWh/m^2/annum. A mathematical representation of the model can be found in Refs. [8,9] where cost benefits and load-shifting potential were investigated.

The model is designed sufficiently complex to capture dynamic nonlinearities in system response such as COP variations, but simple enough to maintain feasible optimisation run-times. To this end, the simulation boundary was drawn between the thermal energy supply side and the heat distribution system. It is assumed that the heating distribution system maintains comfortable room temperatures as long as sufficient energy is supplied with a minimum temperature of 45 °C. The COP is dynamically modelled using an artificial neural network trained with data supplied from the manufacturer.

The system, shown in Fig. 2, is simulated over the optimisation horizon using heat demand-, ambient air temperature-, and electricity cost vectors that represent the state of nature. A decision variable vector represents the states of the heat pump as either binary (on/off) or continuous (variable speed). Each permutation of the decision variable vector results in a unique energetic performance as TES temperature changes with energy content. This affects the COP of the heat pump and heat losses through the thermal envelope which are dynamically modelled in this study. The outputs of the model are the operational cost for the simulated timeframe and whether heat demand was matched.

The system was modelled over the optimisation horizon of 24 h with hourly time steps. This is consistent with input data resolution. However, longer optimisation horizons and higher resolution are possible, but such models also require longer simulation and optimisation run-times. Also, minimum heat pump run-times of generally 15 min must be accommodated.

3.5. Model calibration and input data

The model is sensitive to the simulation environment including technology, climate, and electricity price elasticity. Here it is calibrated to a detached home with an average (C2) energy rating in the temperate oceanic Irish climate. Price elasticity is modelled based on electricity system marginal prices (SMP) that is sensitive to the large share of wind energy generation (approximately 40%). The supervisory control retrieves data about the current state of charge of the TES, the forecasted ambient air temperature, the expected heat demand profile, the day-ahead electricity prices, and an operational schedule. Fig. 3 shows the input data profiles used in this study for a typical workday during the heating season in December in Ireland. The heat demand profile is synthetically created using the heating degree method. A representation of set-back temperatures during working hours or night-time could be represented through a different demand profile.

The temperature forecast is available through standard web-services from the meteorological service office and may be used to derive the expected heat demand profile and heat pump performance. Perfect forecast of ambient air temperatures was assumed using historical data from the Irish Meteorological Service (MET Éireann). The day-ahead electricity prices were derived using SMP. As Ireland has not implemented real-time electricity tariffs yet, these spot market prices were scaled to approximate more realistic end-user prices. An assumed electricity base-rate of €0.10/kWh was scaled with the ratio of instantaneous spot market price to the annual average price. At the time of conducting the study, €1 could buy £0.88 or $1.08.

3.6. Equipment

The testing platform was a Dell® Latitude Laptop E5570 with an Intel® Core™ i3-6100 CPU at 2.3 GHz and 8 GB RAM operating 64-bit Microsoft® Windows™ 10.

4. Results & discussion

4.1. Brute force optimisation

Illustrating an excerpt of the 24-dimensional optimisation problem in two dimensions, Fig. 4 shows the operational cost of 100 24-bit schedules ordered in integer representation. The x-axis shows the binary operation schedule and the black line indicates the corresponding

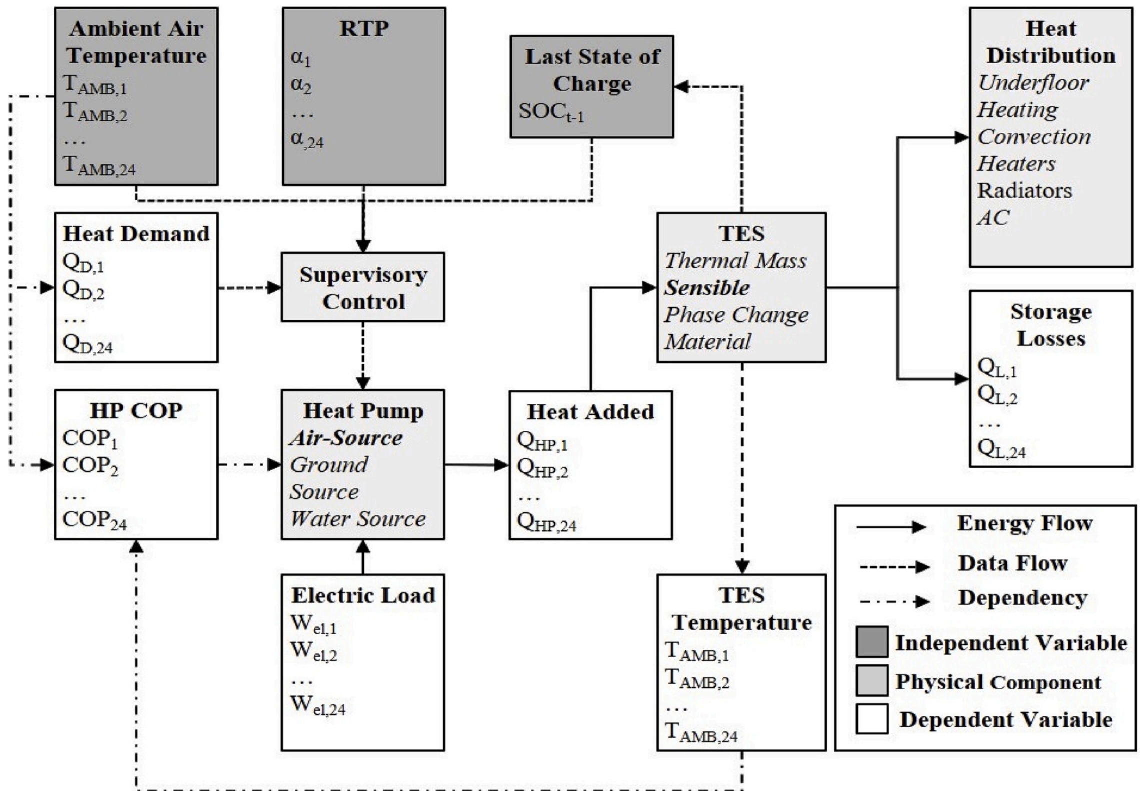

Fig. 2. Model schematic showing data flows, energy flows and system dependencies of optimal flexible.

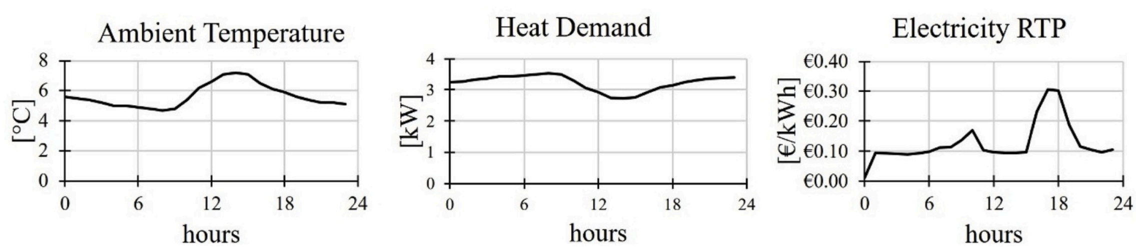

Fig. 3. Input Data: Perfectly predicted heat demand, ambient air temperature and electricity cost for the 24-h optimisation horizon.

cost. The feasible region where demand is matched is shaded in grey and represents the optimisation constraint. The represented simplest form of the scheduling problem indicates non-linear, non-convex, and discontinuous characteristics of the objective function that call for metaheuristic optimisation. For instance, the global minimum for this example occurs outside the displayed search space for the schedule: 111,011,100,010,010,101,010,110 (as an integer: 15, 607, 126).

Metaheuristic optimisation methods can provide sufficiently good, quasi-optimal solutions with relatively low computational effort. To determine how good "sufficiently good" is, a true global optimum is required to act as a reference. We simulated 2^{24} hourly on/off operation schedules to determine the operational cost for each decision variable vector permutation and whether it satisfied demand. This brute-force method is also known as exhaustive enumeration. It took 6 h and 27 min to yield the global minimum of € 2.887 which could then be used to benchmark metaheuristic optimisation methods.

Extending the optimisation problem to the use of integer or continuous variables renders brute-force methods intractable. Therefore, the quasi-global minimum that resulted from a total of 2070 optimisations with various algorithms was considered as the reference point for this study. Here, Particle Swarm Optimisation with a swarm-size of 100 (PSO100) yielded the quasi-global minimum of €2.855 (PSO100). Note, that in this example the computed minimum is merely 1.1% smaller using continuous rather than binary variables.

4.2. Binary versus continuous decision variables

Algorithm effectiveness is a function of accuracy, computation time, and reliability. Here, we investigate the algorithm effectiveness of genetic algorithm versus genetic algorithm – one using binary decision variables and the other using continuous decision variables. Furthermore, different population sizes - a key optimisation parameter - are tested to investigate its effect on effectiveness.

Binary decision variables can represent the on/off states of the controlled technology. Continuous or integer variables can be used where the controlled technology is operated at workloads between zero and 100% (e.g. variable speed heat pump). The ability to tune the workload, using continuous decision variables, enables greater load shifting flexibility. This should also lead to a lower operational cost.

As a rule of thumb, MATLAB suggests a population size of 50 for less than five, and 200 for five or more decision variables. Fig. 5 showcases how increasing population size affects the optimisation criteria: a) mean optimisation error, b) mean run-time, c) standard deviation and d) overall effectiveness. The results for continuous decision variable

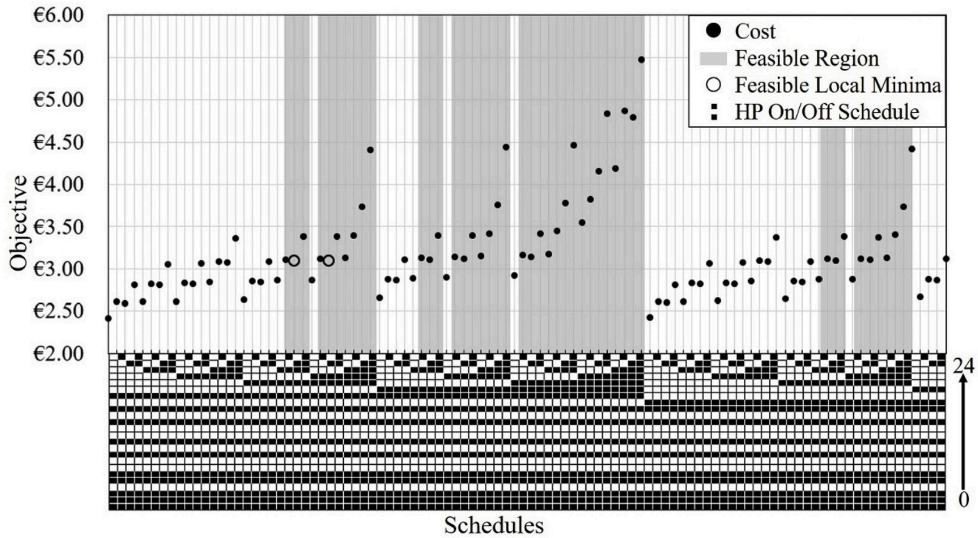

Fig. 4. The Non-convex, multi-modal and discontinuous objective function of the binary variable optimisation scheduling problem. The graph shows 100 of 17 million potential schedules to operate grid-edge technology based on a heat pump (HP) with thermal energy storage (TES).

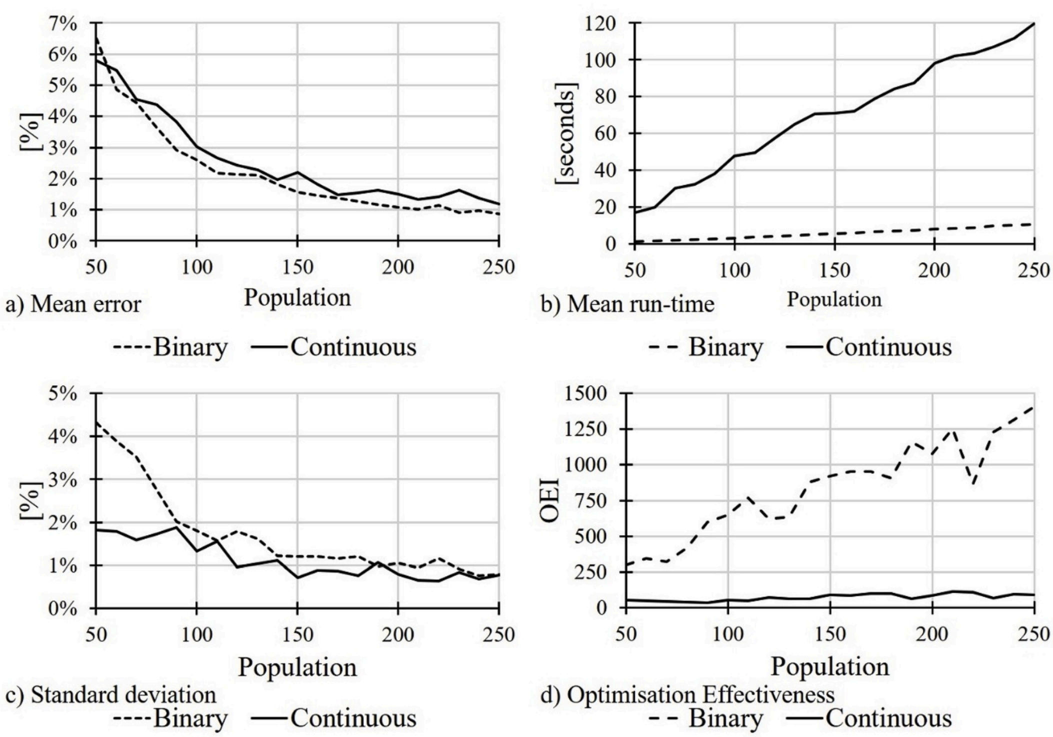

Fig. 5. Mean Error, mean run-time, standard deviation and optimisation effectiveness indicator using binary and continuous variables.

optimisation are represented by the continuous line whereas the binary results are represented by the dashed line. Mean optimisation error is used as a measure of optimisation accuracy. With increasing population size, the mean optimisation error decreases for both variable types and converges to approximately 1%. The mean optimisation error for binary optimisation is on average 0.5% lower than for continuous optimisation. This is the case for all population sizes bar the first one (50), that is recommended for less than five variables. The second factor affecting optimisation effectiveness is the run-time which signals computational complexity. Fig. 5(b) illustrates how increasing population size increases the run-time for both variable types. However, a larger toll is taken for continuous than for binary optimisation. Increasing the population by a factor of ten increases the run-times by factor 50 and five respectively. In the context of the results for mean error, it can be argued that the relatively small increase in run-time for binary optimisation can be tolerated to enhance optimisation error.

The third factor affecting optimisation algorithm adequacy is its reliability. Due to the stochastic nature of metaheuristic algorithms, any two optimisation runs yield different results. After multiple optimisation-runs under identical boundary conditions, the standard deviation of the mean error distribution is used to characterise the reliability of the tested algorithm. Fig. 5(c) shows how increasing population size reduces the standard deviation of the mean error and thus enhances reliability. Continuous variable optimisation loses its advantage with increasing population size where the standard deviations of the two variable types converge.

Combining the three optimisation effectiveness criteria in the optimisation effectiveness indicator yields the graph shown in Fig. 5(d). It reveals the superiority of binary optimisation to continuous variable optimisation using Genetic Algorithm. For binary optimisation using a population size of 160 and a sample size of $n = 100$, it can be stated with 99% confidence that the optimisation error is 1.0–1.7% above the true global minimum. The mean run-time was 6 s. This compares to 6 h and 28 min for exhaustive enumeration. A regularly optimised HP and TES system could thus react to changing real-time prices within seconds to minutes if minimum run-times for the HP are respected.

Summing up, optimisation for binary variables with GA is 5–15 times more effective than continuous variable optimisation. Increasing population size decreases optimisation error and enhances optimisation reliability at the cost of increasing computational complexity, i.e. run-time. This trade-off works better for binary optimisation where run-time increases at a lower rate. Furthermore, it can be speculated that increasing the population size beyond 150 cannot be justified as the mean error improvements are relatively small compared to the increase in run-time. However, this must be investigated on a case-to-case basis to find a compromise between leaning towards faster optimisation time and towards lower optimisation error.

4.3. Metaheuristic optimisation using continuous decision variables

While GA optimisation with binary variables displays a clear effectiveness advantage, applications like battery storage or variable speed heat pumps could benefit from the higher resolution that is offered by optimisation with continuous variables. In this study, switching from binary optimisation to continuous optimisation reduced the mean minimum by only 1.1%. This increased the run-time by a factor of approximately ten. But the simulated system was optimally designed using a similar optimisation framework. Thus, systems with spare capacity using a variable speed heat pump could enhance economic storage utilisation [9].

In this study, the assumptions about boundary conditions and technology capacities preclude any conclusions about whether binary on-off control may outperform continuous variable speed control. Consider for instance an oversized heat pump that can generate and store thermal energy in excess of the application's instantaneous heat demand during a low-cost period. However, when a high-cost period coincides with a non-shiftable demand, the system gains from increased flexibility due to its ability to regulate its power. Thus, the local crucial heat demand can be met while keeping power demand as low as possible. The outcome of such a comparison is highly dependent on system design (e.g. HP and TES capacities) and resolution (e.g. 1 h, 15 min, etc.). It shall be subject of a future study on simultaneous optimisation of operation and design.

Here, the algorithm effectiveness of Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Direct Search (DS), and Simulated Annealing (SA) is investigated and compared for continuous variables considering sensitivity to key algorithms parameters. The selected key parameters were population size for GA, particle swarm size and initial temperature for SA. Fig. 6 visualises the optimisation error distributions for a selection of the tested algorithms that performed most effectively in their category. GA210 (population size of 210) and PSO50 (swarm size of 50) play in a league of their own. Their mean optimisation errors of 2.0% and 2.1% are significantly lower than 15.5% and 27.1% for SA250 (initial temperature of 250) and Direct (Pattern) Search respectively. The same trend can be observed for the standard deviations. With 0.7% and 0.8%, GA210 and PSO50 are considerably more reliable than SA250 and DS with 3.1% and 22.3%. From the observed data, it can be stated with 99% confidence that Particle Swarm Optimisation (swarm size = 50) can yield a satisfactory quasi-optimal solution with a true mean error between 1.7% and 2.4% with 2.1% being the most likely. The results for Direct Search are not further considered in this study due to the prohibitive mean error and standard deviation.

Fig. 7(a) depicts the mean optimisation errors of the tested algorithms compared to the quasi-global minimum. The mean error using Genetic Algorithm, represented by the continuous line, decreases with increasing population size. The most rapid decrease can be observed for population sizes between 50 and 150 where the mean error reduces to below 2%. Using Particle Swarm Optimisation, the mean error also decreases with increasing swarm size. However, the decrease is less pronounced as PSO already achieves small errors of around 2% for swarm sizes of 50. The mean error measured for Simulated Annealing fluctuated around 7% above PSO and GA and is independent of the initial temperature.

The computational complexity, measured by mean run-time, is shown in Fig. 7(b). For GA and PSO, it increases linearly with increasing population and swarm-size respectively. For PSO this increase happens slower than for GA at rates of 0.4 and 0.5 respectively. SA wins in terms of computational complexity with a consistent mean run-time of approximately 3 s. In the context of the mean error, it becomes clear that GA must run 71 s to achieve the same 2% error that PSO can achieve in 14 s. A much faster result can be yielded in 3 s using SA at the cost of increasing the optimisation error to 16%.

Fig. 7(c) illustrates the reliability of the tested algorithms represented by their standard deviations from the mean optimisation error. PSO and GA indicate improving reliability with increasing values for population and swarm size. Analogously to the results for mean error, the standard deviation of PSO is consistently low for all swarm sizes whereas larger population sizes of above 150 are required for GA to achieve a similarly low standard deviation of below 1%. The standard deviation for all SA initial temperatures fluctuates around 4%.

The Optimisation Effectiveness Indicator graphed in Fig. 7(d) reveals PSO as the most effective optimisation algorithm for the studied problem. This is especially the case for small swarm sizes and thus short run-times. Here PSO can outperform GA and SA by factors 8 and 10.5 respectively. This advantage decreases with increasing swarm size but

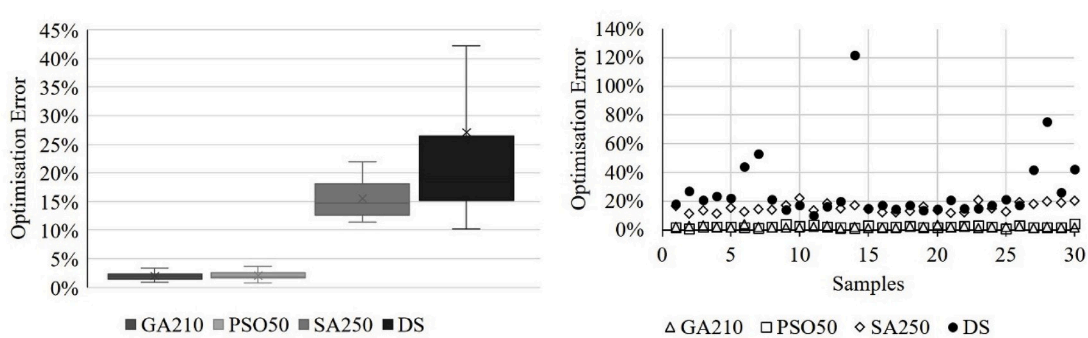

Fig. 6. Optimisation error distribution and reliability of selected algorithms GA (population = 170), PSO (swarm size = 120), and SA (initial temperature = 60). n = 30.

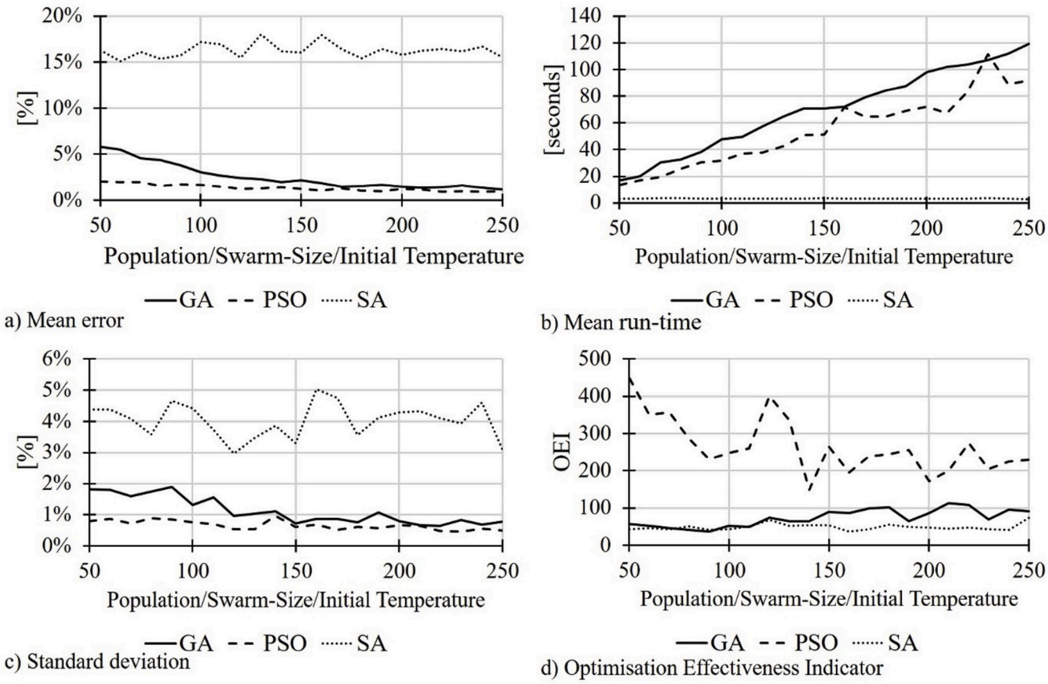

Fig. 7. Mean error, mean run-time, standard deviation, and optimisation effectiveness indicator (OEI) for continuous variables using Genetic Algorithm, Particle Swarm Optimisation and Simulated Annealing for grid-edge technology.

never goes below a factor of two and three respectively. The OEI values for GA and SA diverge for population sizes above 150 where GA becomes more effective. However, the OEI must be seen in the context of the mean error and the mean run-time. In the case of SA, a relatively large error combined with a relatively short run-time have a smoothing effect on one another. As a result, its OEI appears to be on par with GA. Application-specific weighting could be applied to achieve the desired effect. In the light of its overall superiority, the results of this study suggest the recommendation of PSO for optimising continuous variable grid-edge technology schedules.

4.4. Qualitative validation

The presented optimisation results are based on one specific case

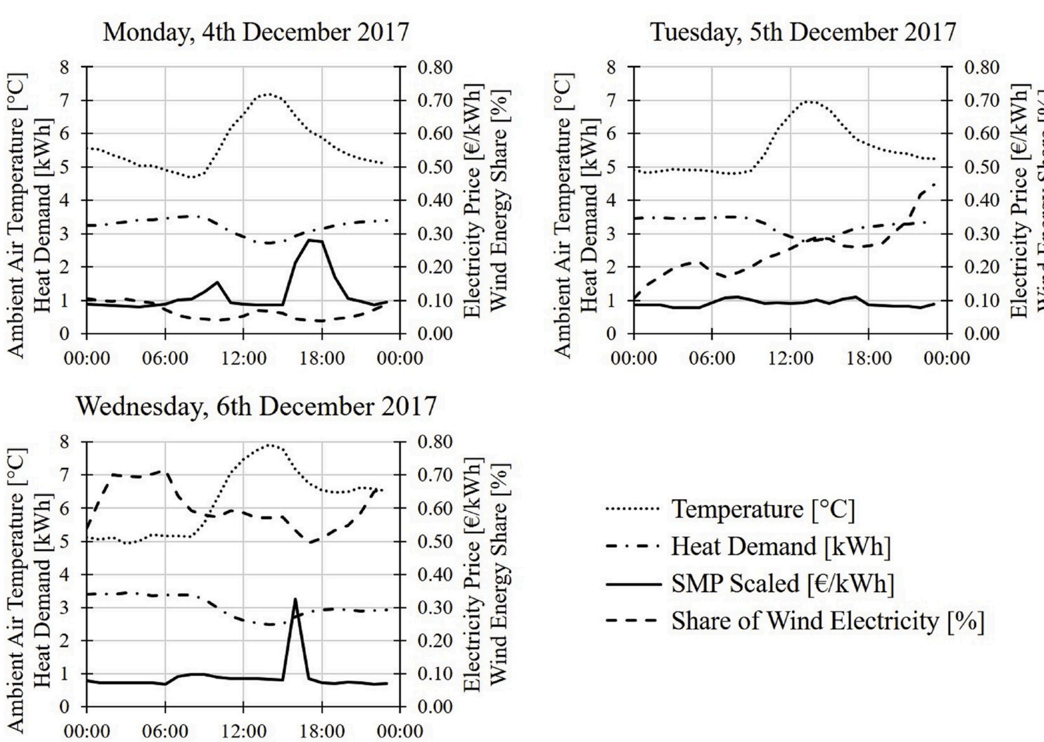

Fig. 8. Boundary conditions for the qualitative validation of optimisation effectiveness.

study characterised by the boundary conditions described in sections 3.3 and 3.4. To qualitatively validate the results, the two best-performing algorithms (PSO and GA) were tested again by applying three different sets of boundary conditions to the same system. Three consecutive working days during the heating season in Ireland, December 2017 were selected with similar thermal but varying electricity cost profiles. Fig. 8 displays the ambient temperature and resulting heat demand profiles with their corresponding electricity cost profiles. The electricity cost profiles are significantly affected by the share of wind energy on the grid which averaged at 6.6% on the first day, 24.7% on the second day and 60.3% on the third day.

Optimisations were performed for PSO and GA with swarm and population sizes increasing from 50-250 at increments of 25. Each optimisation was repeated multiple times to bring the sample size up to 30. The results for mean optimisation error, mean run-time and standard deviation of optimisation errors for the three different days are shown in Fig. 9. For all three days, PSO outperforms GA in terms of low mean optimisation error and short mean run-time. This is the case for all tested swarm and population sizes. With increasing swarm or population size, the run-times increase, and the optimisation error decreases.

While the difference in mean optimisation error may appear small, it should be noted that for GA to achieve the same optimisation error as PSO, it requires a population size (175) 3.5 times larger than PSO swarm size (50) with an increase of run-time factor of 4.8. The ability of the two algorithms to provide the indicated accuracies as measured by the standard deviation does not differ by much.

The optimisation effectiveness of the two algorithms for the three different scenarios with different algorithm parameters are graphed in Fig. 10. For all three scenarios, Particle Swarm Optimisation performs more effectively than Genetic Algorithm. This difference appears to be more prominent when the input profile, in this case, the electricity price profile, features stronger extrema. The first price profile, for instance, features a strong evening peak and a weaker morning peak. In the second scenario, the price remains almost constant with barely noticeable morning and evening peaks and the third scenario is characterised by a strong evening and weak morning peak. This observation indicates weakly that PSO may deal better with multi-modal features than GA.

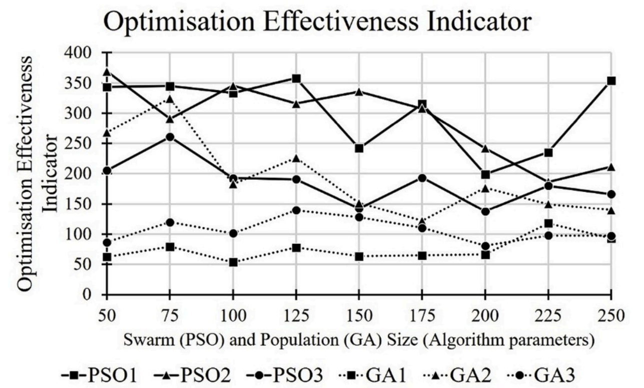

Fig. 10. Optimisation Effectiveness Indicator (OEI) for three scenarios with different optimisation algorithm parameters.

Overall, the quantitative validation reinforces the trends discussed in the previous section.

4.5. Limitations

The findings of this study must be placed in the context of the design of this study and its assumptions – choice of the optimisation problem, model, optimisation algorithms, optimisation objective, and algorithm parameters.

This study aimed to identify and assess metaheuristic optimisation algorithms for their effectiveness to optimise grid-edge heating technology. Since power-to-heat options offer great potential to decarbonise the heating sector and to simultaneously integrate more renewable

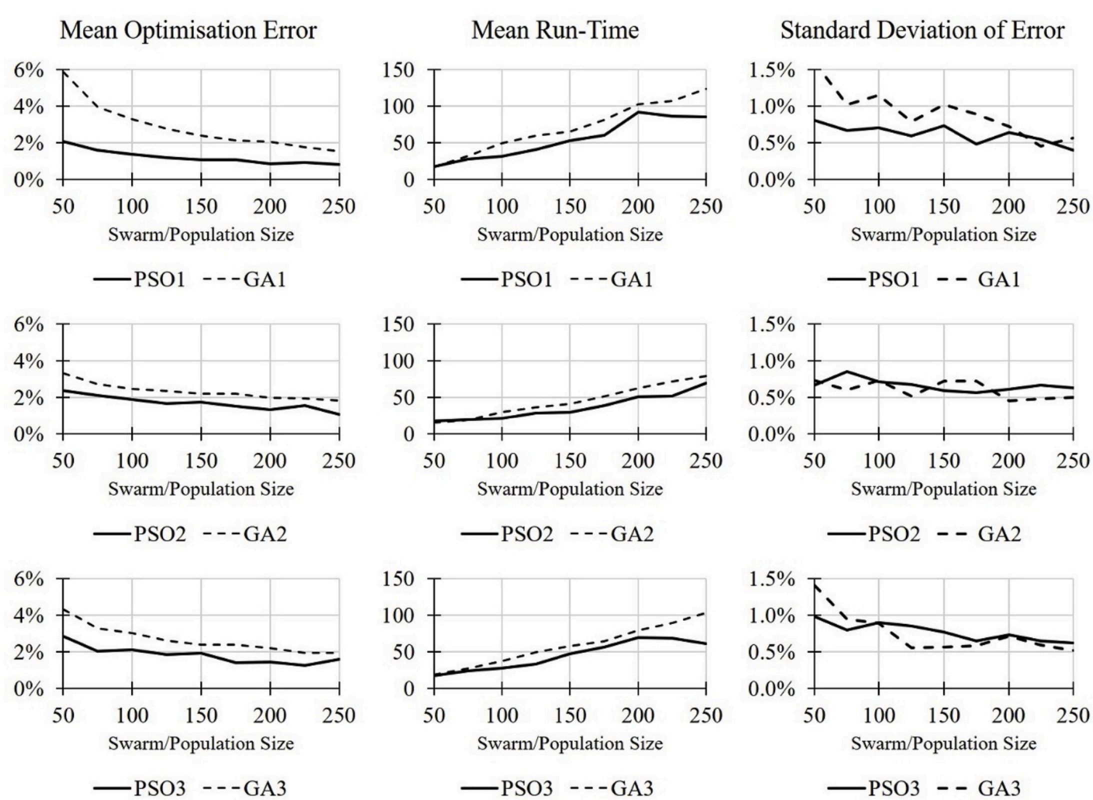

Fig. 9. Optimisation Results for three consecutive days with different boundary conditions for the same system.

energy, heat pumps with thermal energy storage, paired with implicit demand response, occurs to be a valuable tool for energy grids with large shares of renewables.

The optimisation for lowest operational end-user cost generates benefits to grid operators and the consumer. Nodal electricity pricing is instrumentalised to balance supply and demand. The optimisation takes seconds to minutes depending on controller, algorithm, and model complexity. Thus, the technology lends itself to real-time, intra-day, and day-ahead balancing of the grid. Grid events that require an instantaneous response including frequency and voltage events must be handled by other means (e.g. flywheels or batteries). Unlike with grid-level optimisation, this distributed optimisation makes it difficult to quantify demand response capacity beforehand. A learning-by-doing approach is required that may be too adventurous for conventional grid operators that depend on switchable capacities.

The simple model keeps optimisation time low. More complex models increase run-time per iteration. Run-time and iterations are strongly correlated in this study with PSO outperforming GA. But GA required just nine iterations where PSO required 200. As a result, increased model complexity could swing the advantage to algorithms that use fewer iterations.

The simplicity of the model in this study can be attributed to three assumptions. The simulation boundary is drawn between the thermal energy supply side and the heating distribution system. To satisfy thermal comfort constraints, a quantity of thermal energy at a temperature appropriate for the heating distribution system must be supplied at every time step. Here, a self-learning heat demand predictor is envisioned to determine the heat demand. The thermal energy storage is modelled as a fully mixed body of water with thermal losses through its envelope. The heat pump COP is modelled dynamically based on ambient air and TES temperatures using an artificial neural network trained with data from the heat pump manufacturer's performance surface maps.

Finally, there is no "one size fits all" optimisation algorithm. Algorithm performance is problem specific. This study was geared to use "out-of-the-box" MATLAB optimisation solutions. Algorithm-specific tuning parameters were not explored in depth. These parameters can significantly affect optimisation performance. Thus, the use of bespoke optimisation algorithms is likely to achieve increased effectiveness. Given the stochastic nature and pseudo-random number generation of the tested optimisation algorithms, a larger sample size would be beneficial to enhance the power of the statistical analysis. Moreover, in order to strengthen the generality of the findings presented in this article, further qualitative validation could be achieved through additional sensitivity analysis. This can be achieved by varying values of input and internal energy system model parameters such as heat pump and TES performance data, climate, heat demand, electricity price and wind energy share data.

5. Conclusion

Grid-edge technology can unlock flexibility from consumers to contribute to meeting the growing need for flexibility in the European energy systems. Furthermore, power-to-heat technology (e.g. heat pumps and thermal energy storage) has been shown to both decarbonise heat and enable the cost-effective integration of more renewable electricity on the grid. The consumer's reaction to price signals in this context presents the opportunity to simultaneously unlock operational cost reductions for consumers and localised implicit demand-side flexibility to benefit grid operators.

In this paper, the prediction accuracy, run-time, and reliability of several (metaheuristic) optimisation algorithms to derive optimal operation schedules for heat pump-based grid-edge technology were investigated. To compare effectiveness, an optimisation effectiveness indicator (OEI) was defined. Particle Swarm Optimisation and Genetic Algorithm were found to be most effective and robust in yielding quasi-optimal minima for the non-linear, multi-modal, and discontinuous cost function. GA optimisation with binary variables is 5–15 times more effective than with continuous variables. Using continuous variables, PSO is more effective than GA due to smaller optimisation error, shorter run-time, and higher reliability (smaller standard deviation). Simulated Annealing and Direct (Pattern) Search were found to be not very effective.

With optimisation run-times from 6-60 s, a regularly optimised HP and TES system could swiftly react to changing grid conditions. Such a tool could offer value to grid operators and consumers alike and contribute to the grid flexibility needed to integrate large shares of renewables.

To the best knowledge of the authors, this study is the first endeavour in quantifying optimisation algorithm effectiveness for optimised operation schedules of grid edge technology – in this case for heat pump and thermal energy storage systems under implicit demand response control. The results of this study may aid developers of grid-edge technology with the selection of appropriate optimisation methods and encourage more research to determine how optimal results are.

CRediT authorship contribution statement

C. Schellenberg: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft. **J. Lohan:** Writing - review & editing, Supervision. **L. Dimache:** Writing - review & editing, Supervision.

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