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Neural network metamodelling in multi-objective optimization of a high latitude solar community

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ABSTRACT

A solar community of 100 residential houses was optimized for Finnish conditions with the aim of achieving a 90% solar fraction for both space heating and domestic hot water. Optimization was done using a novel method based on neural network metamodelling and compared to the standard NSGA-II genetic algorithm. Compared to NSGA-II, the new method obtained a larger hypervolume by finding better solutions both in the center and edge of the non-dominated front. The combined non-dominated front of both methods was better than either one separately. The performance target was achieved as the optimal solar community designs had heating solar fractions ranging from 64% to 95%.

1. Introduction

Global solar energy capacity continues to increase (van der Hoeven, 2014). Unfortunately, a large penetration of solar generation capacity may cause problems with the electric grid due to the diurnal and undispatchable nature of solar energy (Denholm and Hand, 2011). Seasonal variability of solar energy is another major problem, which is especially significant in high latitudes, such as in the Nordic countries. To combat this problem, seasonal energy storage is needed. Except for pumped hydro facilities, large scale seasonal electricity storage is currently not economically feasible (Beaudin et al., 2010; Pierpoint, 2016). Thermal storage, however, is already a mature technology ready for deployment (Navarro et al., 2016).

A typical thermal storage system is a hot water tank in a house, for which the optimal size has been investigated before (Rodríguez-Hidalgo et al., 2012). Such a system can even be used to store excess electricity from solar panels to a limited degree (Hirvonen et al., 2016). Tanks are usually only used for short-term storage and additional systems may be needed for seasonal storage. Underground tank-based seasonal storage was used in the first practical Finnish solar community study (Lund, 1984), though the storage turned out to be undersized. Different storage technologies have been reviewed in Xu et al. (2014) and many real-life projects summarized in Schmidt et al. (2004) and Bauer et al. (2010)). One increasingly common seasonal storage type is the borehole thermal energy storage (BTES), where the heat is stored directly to the ground through boreholes drilled into rock or soil (Rad and Fung, 2016). Thermal storage efficiency scales with size, as heat losses get relatively smaller with increasing storage volume. Because energy generation capacity also gets cheaper with size, seasonal storage systems should be community solutions. A successful example is the Drake Landing Solar Community in Canada (Sibbitt et al., 2011), which has achieved a 98% solar fraction for space heating (SH) through seasonally stored solar energy, providing heat for 52 residential houses.

Such systems cannot be directly copied to other locations, but need to be adjusted to the local conditions (Flynn and Sirén, 2015). Properties such as ground conductivity and thermal capacity affect system performance. In this study, the Drake Landing design is modified to supply both space heating and domestic hot water (DHW) for a community in Finland (above 60°latitude). Due to the high latitude, the winter heating demand is high while seasonal solar variability is very large. There is practically no solar energy available during winter, making seasonal storage mandatory to achieve high solar fraction in heating. To help achieve higher temperatures required for DHW, a solar assisted ground source heat pump is included in the energy system. To maximize

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Nomenclature

Abbreviation	Explanation
ANN	artificial neural network
BTES	borehole thermal energy storage
DHW	domestic hot water
G	total incident solar radiation
HP	heat pump
LCC	life cycle cost
NSGA	non-dominated sorting genetic algorithm
PV	photovoltaics
SF	solar fraction
SH	space heating
SPF	seasonal performance factor
ST	solar thermal

the feasibility of the design, multi-objective optimization is used to minimize both external energy demand and life cycle cost (LCC).

Many different methods exist for energy system optimization. Recent storage-integrating district heating optimization studies have been reviewed in Olsthoorn et al. (2016). Typical single-objective optimization problems are about minimization of cost or energy/exergy consumption, often solved using mixed integer linear programming (MILP). For multi-objective optimization, genetic algorithms such as NSGA-II (Deb et al., 2002) are a common choice. A genetic algorithm was used to optimize the energy system of a pre-simulated zero energy building in Ascione et al. (2016) and also for optimizing the seasonal storage and solar heating system of a greenhouse (Durão et al., 2014). Other population-based methods such as particle swarm optimization have also been used for sizing solar power installations (Khare and Rangnekar, 2013). Simulated annealing has also been used for the same purpose (Ekren and Ekren, 2010). Linear programming with sparse revised Simplex was used to optimize the design for a hybrid renewable energy community (Wang et al., 2015). Interval-linear programming and chance-constrained programming were combined in Cai et al. (2009) to perform optimization under uncertainties, such as solar and wind availability. Similar interval-based optimization was used for scheduling optimization of renewable energy systems (Chen et al., 2015).

In simulation-based optimization, the actual simulations can often take a long time compared to other processes in the optimization. This makes it very important to minimize the number of simulations required. One method to achieve this goal is to do optimization in separate stages (Hamdy et al., 2013). This way, unreasonable variable combinations can be filtered out and partially optimized results used as inputs. Also, if some part of a system model is independent of the others, it may be possible to simulate it only one time and just use tabulated values for the rest of the runs, reducing the need for time-consuming simulations.

Another way to reduce the need for simulations is through metamodelling (or surrogate models) (Bornatico et al., 2013). A metamodel is a model of a model, meaning that it is generated out of output from another model. Metamodels are typically very fast to run compared to detailed simulation programs. Utilizing a metamodel can reduce function evaluation time from minutes or hours to a fraction of a second. One metamodelling technique is the use of artificial neural networks (ANN). The principles of ANN are explained in detail in Kalogirou (2000). In short, neural networks use linear equations to find relations between inputs and outputs and can be used to quickly simulate even phenomena that are not completely understood, as long as proper training data is available.

For example, ANN was used to make a metamodel out of a TRNSYS building model, which was then used with a genetic algorithm (GA) to do optimization (Asadi et al., 2014). First, parametric runs were done to generate a database for training the ANN. The ANN metamodel is very fast to use and allows quick optimization. Unfortunately, generating an adequate training set to ensure the accuracy of the metamodel requires a significant amount of simulations, so actual time saving compared to direct optimization is not guaranteed. Generally neural networks are trained with an extensive dataset and then used to completely replace the original model to complete optimization, as was done in Boukelia et al. (2016) and Magnier and Haghighat (2010). However, other methods such as kriging have also been used for parallel optimization and surrogate modeling (Hussein and Deb, 2016).

The novelty in this study is the introduction of a new neural network based optimization method for problems where the function evaluation takes a long time compared to other calculation processes. Instead of generating a complete training set before optimization, the optimization is started with a very small training set which is updated as the optimization progresses. The ANN is retrained as new samples are added after each optimization step, increasing the ANN accuracy and improving optimization results. Additionally, instead of a single neural network for the whole search space, several neural networks are trained in parallel, each representing a different section of the objective space. The optimization method will be applied to a solar community design problem, which will reveal new information about solar heating and seasonal energy storage in high latitude Nordic conditions in the community scale. The objective is to find a range of energy-economic optima for solar communities with a high solar fraction. An important subobjective is to find a configuration with over 90% solar fraction for heating.

2. Materials and methods

2.1. Energy system details and modeling

The study centers on a hypothetical Finnish solar community with a local heating grid, modeled using TRNSYS 17 and first introduced in ur Rehman et al. (2016). The solar community consisted of a 100 residential buildings, each with a heated area of 100 m^2. The design of the centralized heating system is shown in Fig. 1. Heat generated by the solar thermal collectors was stored in either the high temperature domestic hot water (DHW) tank at around 60 °C or the low temperature space heating (SH) tank at around 40 °C, depending on tank temperature levels and the chosen control algorithm. If the tank temperature rose 10 °C above the setpoint, the energy in the tank was discharged into the seasonal storage until the tank had cooled down enough.

The seasonal storage was a borehole thermal energy storage (BTES), which is a grid of boreholes drilled into the ground. Each borehole was fitted with U-tube piping which served as a heat exchanger between the ground and heat transfer fluid. Several boreholes could be connected in series so that the fluid exiting from one borehole could be pumped into the next one. In charging mode, hot fluid was pumped into the center of the storage and the cooled output flow was directed into the next borehole in series. Thus, a radial temperature distribution could be formed, where the center of the storage had the highest temperature and the edges had the lowest, minimizing heat losses to the surroundings.