Proceedings of BS2015:
14th Conference of International Building Performance Simulation Association, Hyderabad, India, Dec. 7-9, 2015.

MULTI-OBJECTIVE ROBUST OPTIMIZATION OF ENERGY SYSTEMS FOR A SUSTAINABLE DISTRICT IN STOCKHOLM

Cong Wang, Ivo Martinac, and Alessandro Magny
Royal Institute of Technology, Stockholm, Sweden

ABSTRACT

This paper applies a multi-objective robust design optimization approach to the energy system design of a sustainable district. The life cycle cost and the greenhouse gas emissions are the two objectives that are minimized. In order to investigate the possbility to implement a nearly zero energy district, the non-renewable primary energy consumption is kept below a certain value, handled as a constraint in the optimization. Through the proposed robust design optimization methodology, the robust Pareto optimal solutions are obtained, which are less sensitive than the deterministic ones to the uncertainties assumed in the selected most influential economic and technical paramers as well as design variables.

INTRODUCTION

The new recast of the European Energy Performance of Buildings Directive requires that all newly constructed buildings within the European Union reach nearly zero energy levels (nZEB) by the end of year 2020 (EPBD 2010). However, finding cost-optimal energy system solutions for nZEB is a challenging task, requiring intensive measures taken from both the consumption side and supply side. It is also considered to be difficult to achieve nearly zero energy at individual building levels, which motivates researchers to seek the potential solutions of nZEB for a group of buildings (Kayo et al., 2014). This extends nZEB to the district or community level and puts forward the concept of 'nearly zero energy community/district'.

In parallel to finding cost-optimal solutions of nZEB, another important issue is to minimize environmental burdens. The EU 20-20-20 targets, for instance, aim to reduce 20 percent of the greenhouse gas emissions by the year 2020. Therefore district planners often have to face trade-offs between cost saving and good environmental performance. The purpose of this study is thus to assist district planners in designing a district of both good economic and environmental performances. The annualized life cycle cost and the greenhouse gas emissions are herein adopted as two objectives to minimize, representing the economic and environmental performances respectively. The nearly zero energy level is handled as a constraint on the non-renewable energy consumption in this study.

Energy system designs, as many real word design issues, are susceptible to uncertainties. Uncertainties in energy systems might arise from inaccuracy of energy demand estimation, manufacturing errors and deviation from optimal operative performance of energy conversion technologies, unpredictability of renewable energy production due to intrinsically stochastic weather and climate conditions, and varying economic parameters, etc. Most of the existing studies that resolve district energy system design issues rely on deterministic approaches, assuming all system parameters are perfectly known and suffer no variability. Uncertain variables may have great influences on the final outcome, though they are most likely confined within an acceptable range. Thus the desirable optimal solutions should be robust to small deviations of optimization inputs. The robust optimal may not necessarily coincide with the global optimal. Figure 1 adapted from Yao et al. (2011) illustrates the concepts of deterministic optimal and robust optimal for a single objective optimization problem.

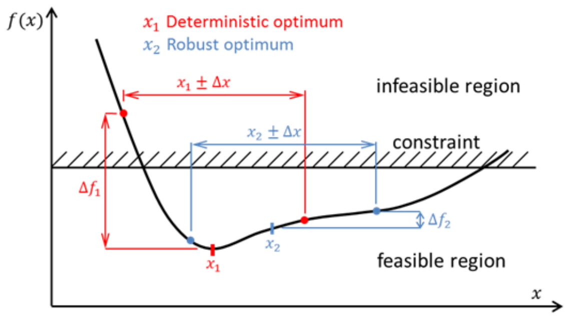

Figure 1 Illustration of a robust optimal solution (adapted from Yao et al. 2011)

A deterministic approach would conclude that solution x_1 is preferred to solution x_2 and is the global optimal. If the design variable is assumed subject to an uncertainty, however, solution x_2 is superior to solution x_1, as it implies a less risky attitude than solution x_1. Variations around the deterministic optimal solution x_1 might lead to a significant degradation of objective performance and could even cause a violation of the constraint in the worst case. Solution x_2 , on the other hand, has just slight performance deterioration.

Despite the deep root in structural design and aerospace engineering (Schüller and Jensen, 2008; Yao et al., 2011), only recently has optimization under uncertainty attracted attention in the building performance and energy community. Hopfe et al. (2012) proposed a Kriging meta-model based robust multi-criteria design optimization approach for building designs, with uncertainties imposed on the five most sensitive input parameters. The resulting Pareto solutions showed more robustness than the deterministic ones. Shi et al. (2008) studied the techno-economic performance of an autonomous PV-wind hybrid power system, and achieved a robust optimal system configuration which is insensitive to design variable variations. Rezvan et al. (2012) applied a robust optimization approach to determine the optimal capacity of distributed energy generation technologies under uncertainties in load demand. Moradi et al. (2013) applied a fuzzy programming approach to determine the optimal capacities for the CHP and boiler considering uncertainties in both energy demand and delivered energy prices.

However, little work has been found addressing the multi-objective robust optimization of district energy systems. This paper thus presents a multi-objective robust optimization approach for the design of a district energy system. A planned sustainable district in Stockholm, the Albano university campus, is used as a case study. The deterministic solutions are firstly found. Sensitivity analysis is then carried out to find the most sensitive parameters, which are assumed to be uncertain in the subsequent robust optimization. Finally, the robust Pareto solution are presented and compared to the deterministic ones.

METHODOLOGY

System modelling and definition

The district energy system is modelled as composed of three parts: the delivered energy sources, the energy conversion technologies, and energy load. Three delivered energy sources are assumed to be available: electricity from the grid (EG), biogas and biomass (wood pellets). Seven energy conversion technologies are available: biogas CHP, biomass boiler (BB), ground source heat pumps (GSHP) (one is reversible for space heating/cooling and the other for domestic hot water use only), absorption chiller (AC), on-site wind turbines (WO), PV and solar thermal collector (TC). These energy conversion technologies along with delivered energy sources are used to satisfy the four types of energy demand: electricity use ($E_{\mathrm{us,E}}$), space heating ($E_{\mathrm{us,H}}$), domestic hot water use ($E_{\mathrm{us,HW}}$), and cooling ($E_{\mathrm{us,C}}$). Figure 2 presents the sketch of the energy system, illustrating energy fluxes from energy sources to energy load through different types of conversion technologies.

The non-renewable primary energy consumption is calculated in agreement with the nZEB boundary definition (Kurnitski, 2013), following the equation,

$$E_{P,nren} = \sum_i E_{del,n,i} * f_{del,nren,i} - \sum_i E_{ex,n,i} * f_{ex,nren,i} \quad (1)$$

where i denotes the i-th energy carrier at the on-site boundary; $E_{del,n,i}$ and $E_{ex,n,i}$ are the annual delivered and exported energy respectively; $f_{del,nren,i}$ and $f_{ex,nren,i}$ are the corresponding non-renewable primary energy factors for delivered energy and exported energy respectively.

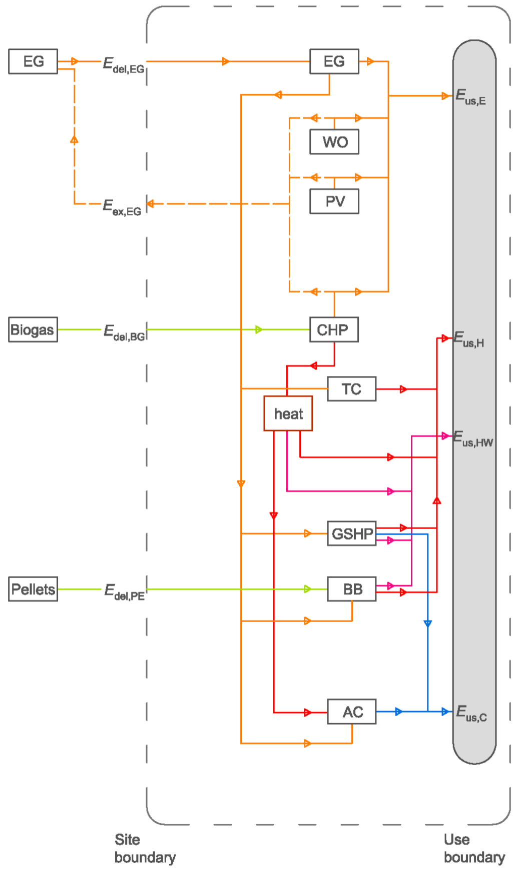

Figure 2 Energy system model with available energy technologies and energy flow

The greenhouse gas emission is expressed by the annual operational CO_2 equivalent emission, which is defined and calculated in consistence with the non-renewable primary energy calculation as follows,

$$m_{CO_2} = \sum_i E_{del,n,i} * K_{del,nren,i} - \sum_i E_{ex,n,i} * K_{ex,nren,i} \quad (2)$$

where $E_{del,n,i}$ and $E_{ex,n,i}$ are the same as above; $K_{del,nren,i}$ and $K_{ex,nren,i}$ are greenhouse gas factors for delivered and exported energy respectively, which convert the amount of energy consumed to the amount of equivalent CO_2 emitted with the unit $\mathrm{kg\,CO_2/kWh}$. As only electricity is exported to the grid, the corresponding greenhouse gas emission factor is assumed to compensate the grid mix.

The life cycle cost (LCC hereinafter) covers over the entire life time the investment cost, operation and maintenance (O&M) cost, delivered energy cost, and compensation from selling electricity to the gird. The disposal and recycling cost, however, is not taken into account. LCC is expressed as annually interest rate leveraged cost, calculated as follows,

$$LCC = \sum_s C_{inv,s} * A_s + \sum_s C_{O\&M,s} + \sum_i E_{del,n,i} * P_{buy,i} - \sum_i E_{ex,n,i} * P_{sell,i} \quad (3)$$

where s stands for the s-th energy conversion technology, i stands for the i-th energy carrier, $C_{inv,s}$ for the corresponding investment cost, A_s for the annuity factor, $C_{O\&M,s}$ for the O&M cost, $P_{buy,i}$ for the purchased price with $P_{sell,i}$ representing the selling price of energy i. The selling electricity price to the grid is assumed to compensate one third of the purchased price from the grid, which is, compared to the current market situation, a rather conservative estimation with the grid fee, tax and transmission loss taken into account (E.ON Sverige AB, 2015).

For details regarding the non-renewable primary energy factors, greenhouse gas emission factors, and delivered energy prices as well as other cost parameters, readers are referred to Magny (2014).

The power produced from renewable energy sources by PV, solar thermal collectors, and wind turbines etc., is dependent strongly on weather conditions. Due to this intrinsic intermittency of renewable energy sources, the designed energy system should have the capacity to balance the energy demand at real time. The energy system in this study is thus simulated on an hourly basis, with all renewable energy production determined by real time weather conditions. The loss of power supply probability (LPSP) is a measure of the insufficiency of energy supplies, with positive values indicating the failure of the energy system in balancing the energy demand (Lu et al., 2014). LPSP is thus employed herein to indicate the sufficiency of the designed energy system, calculated as the ratio of failure time to the whole time length (Yang et al., 2003),

$$LPSP = \frac{\sum_{t=1}^{t=N} hour(P_{supply} < P_{demand})}{N} \quad (4)$$

Multi-objective robust design optimization

In multi-objective optimization, as the objectives usually conflict each other, a set of optimal solutions instead of a single one can be found, which is referred to as a Pareto front or Pareto optimal solutions. Similarly, deterministic Pareto solutions might not be robust, as small deviations in input parameters may probably cause serious degradations in the output. This raises the need for a robust design optimization, defined as a methodology to find the optimal that are insensitive to various variations.

Major approaches addressing uncertainty in robust optimization include fuzzy programming (Mavrotas et al., 2008), min-max regret analysis (Yokoyama and Ito, 2002), and sampling-based approaches etc. Monte-Carlo simulation (MCS) methods are a widely used class of sampling-based methods that obtain the statistical features of output by performing repeated sampling and computation. As MCS methods treat the deterministic simulation model as a black-box, a deterministic mode can be easily extended to robust optimization without extra modification. Traditional MCS methods require a large number of samples due to the random sampling technique, causing a high computational intensity. To overcome this, the Latin Hypercube sampling (LHS) is often employed, which reduces the number of samples while maintaining the sampling accuracy, by dividing each uncertain parameter into a number of equally probable intervals and selects a sample point within each interval (Helton and Davis, 2003).

In this study, the selected uncertain variables are perturbed by LHS to generate enough number of samples. A uniform distribution and no correlations between uncertain variables are assumed.

The formulation of the robust optimization approach used in this study is given below:

$$\begin{cases} find \;\; \boldsymbol{X} \\ min \;\; \tilde{f}_i(\boldsymbol{X},\boldsymbol{p}) = k\mu_{f_i}(\boldsymbol{X},\boldsymbol{p}) + (1-k)\sigma_{f_i}(\boldsymbol{X},\boldsymbol{p}) \\ s.t. \;\; g_j(\boldsymbol{X},\boldsymbol{p}) \le 0 \end{cases} \quad (5)$$

where **X** denotes design variables, and **p** represents system parameters, $\tilde{f}_i$ is the i-th effective objective function representing the weighted sum of the mean μ_{f_i} and the standard deviation σ_{f_i} of the i-th original objective values of the LHS samples, with k denoting the weighting factor, and g_j is the j-th constraint. Both design variables **X** and system parameters **p** can be assumed uncertain and are sampled based upon the specified distribution pattern.

The Pareto archive NSGA-II algorithm is employed to solve the multi-objective optimization problem, which has been reported to have good convergence (Hamdy et al., 2012). The optimization tool used is MOBO, a multi-objective building optimization software, developed by Palonen et al. (2013).

CASE STUDY

Case description

The Albano university campus, located in the northern part of Stockholm city, is planned to be built sustainably, ecologically and economically, using the best available technology for minimizing energy consumption and environmental impact (City of Stockholm, 2015). It is expected to host more than 10 000 students and staff as well as other inhabitants. The campus consists of both lecture and residential buildings with a total floor area of 100 000 m^2 at the first phase. The energy load profiles for each building are estimated and aggregated to obtain the total profiles of energy use for the whole district. The annual energy consumption and the peak power load are given in Table 1.

Design variables, objectives and constraints

Ten design variables are selected based on the availability of energy sources and energy conversion technologies. Seven of them are continuous variables representing the size of energy conversion technologies, and the other three are discrete or binary variables denoting the existence or the number of energy conversion technologies. Table 2 presents the ten design variables as well as their ranges and/or acceptable values. Two limits are imposed on the design variables: one is to limit the total area of solar thermal collectors and PV panels based upon the total available roof area, and the other is to limit the size of ground source heat pumps with the maximum capacity estimated based upon the borehole capacity.

Table 1 Estimated peak power and energy load of the Albano campus

	Peak Power [kW]	**Energy Load** [MWh]
Heating	1100	2107
Hot water	180	1187
Cooling	1300	470
Electricity	770	3888

Table 2 Design variables for the Albano case

Decision variables	**Range**
Heat pump size [kW]	[0, 2000]
Heat pump size (hot water) [kW]	[0, 2000]
PV panel area [m^2]	[0, 11000]
Solar thermal collector area [m^2]	[0, 11000]
Biogas CHP size [kW]	[10, 3000]
Biogas CHP existence [-]	{0; 1}
Biomass boiler size [kW]	[100, 2000]
Biomass boiler existence [-]	{0; 1}
Absorption chiller size [kW]	[100, 2000]
Absorption chiller existence [-]	{0; 1}
On-site wind turbines number [-]	{0; 1; 2; 4; 5; 6; 7; 8; 9; 10}
On-site wind turbines size [kW]	{2.2; 4; 13.1; 25.4; 30; 60}
Limit	
Total size of heat pumps [kW]	< 2000
Total area of solar devices [m^2]	< 11000

As the purpose of this study is to investigate the possibility to realize a nearly zero energy district, the non-renewable primary energy consumption is taken as the first constraint to be kept below a certain limit. The EPBD recast requires that the non-renewable primary energy use should be no more than a national limit value which is determined by each member state. However, the process of defining Swedish nZEB is still ongoing. One reference is the current Swedish building code, which requires that the annual delivered energy use for residential buildings in Stockholm without electric heating be under 80 kWh/m^2 and commercial buildings 70 kWh/m^2. Therefore the smaller value of 70 kWh/m^2 is adopted in this study.

As the energy system is designed to sufficiently satisfy the energy demand on the campus, LPSP is included in the optimization as the second constraint. In this case study, LPSP is kept zero, which implies that the energy demand is always met solely by the designed energy system over the whole year.

RESULTS AND DISCUSSIONS

In this section, we illustrate the capabilities of our modelling and optimization framework. The results obtained with the deterministic model are firstly presented in order to shed light on the inherent trade-off between economic cost saving and environmental performance. Sensitivities to economic and technical parameters are then analysed on two solution cases selected from the deterministic Pareto front. Finally robust Pareto solutions achieved under the robust optimization framework are presented and compared.

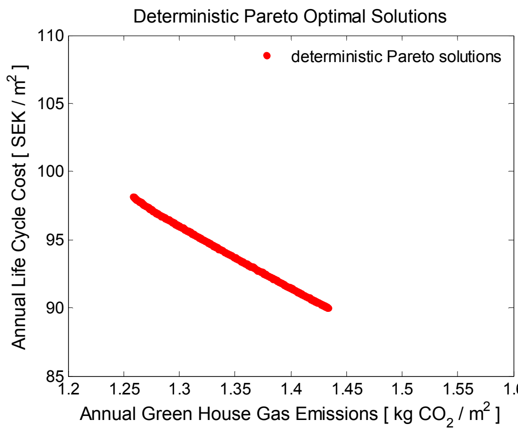

Figure 3 Deterministic Pareto optimal solutions that trade off life cycle cost and greenhouse gas emissions

Deterministic results

Optimal solutions obtained through the deterministic optimization approach are presented in Figure 3, appearing as a Pareto front. A clear trade-off can be observed between the economic and environmental performance measured by specific annualized life cycle cost and greenhouse gas emission respectively. Neither the biogas CHP nor TC appears in this set of solutions. Instead, BB serves to supply the heat for space heating and domestic hot water use which cannot be fully covered by GSHP. The electricity is supplied collaboratively by EG, WO and PV, with excess electricity exported to the grid. The cooling demand is satisfied by GSHP working at the cooling mode. The best economic performance solution shows an annualized economic cost of 90 SEK/m^2 and an annual greenhouse gas emission of 1.43 kg CO_2 / m^2. In contrast, the economic cost of the minimum greenhouse gas emission solution rises to 98 SEK/m^2 with a drop of greenhouse gas emission to 1.26 kg CO_2 / m^2. Intermediate solutions starting from the best economic performance extreme curb the greenhouse gas emissions by gradually replacing GSHP for domestic hot water use with BB and by increasing the installed area of PV to limit the net non-renewable primary energy consumption.

Sensitivity analysis

In order to identify the most sensitive parameters, the two extreme solutions are selected for the sensitivity analysis, with the best environmental performance solution marked as case 1 and the best economic performance solution case 2. The adopted analysis is a one-at-a-time local sensitivity analysis, analysing the outcome by adjusting only one parameter at a time while keeping other parameters fixed. Although a global sensitivity analysis that examines sensitivity with regards to the entire uncertain parameter space provides much richer information, the local analysis method employed here is found sufficient to identify the most influential parameters.

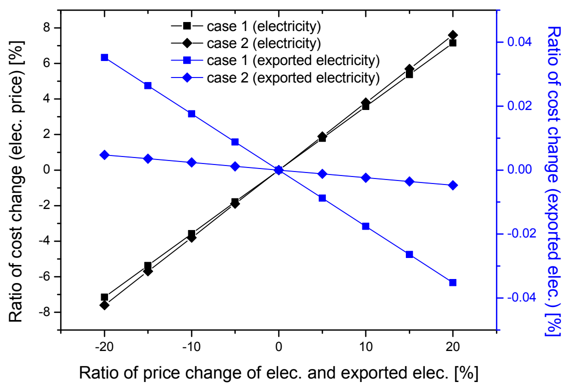

Figure 4 Sensitivity of life cycle cost to the price change of electricity and exported electricity

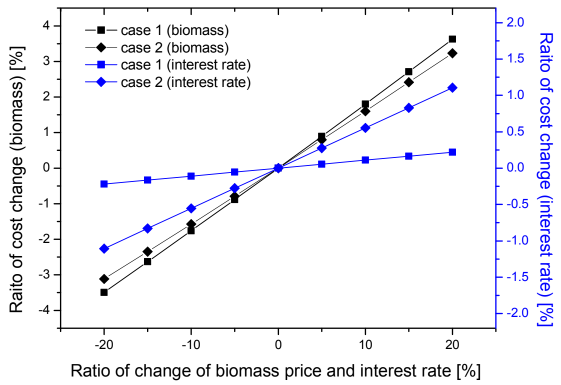

Figure 5 Sensitivity of life cycle cost to the change of biomass price and interest rate

Figure 4 and Figure 5 present the sensitivities of case 1 and case 2 to four economic cost parameters. The selected economic parameters include the electricity price, biomass price, the real interest rate, and the price of exported electricity. They are assumed to vary between -20 and 20 percent deviation from their current values. As expected, LCC varies linearly with the changes of energy prices and interest rates. The electricity price is found to be the most sensitive economic parameter, which is also proved by the large portion of delivered electricity cost in the total cost.

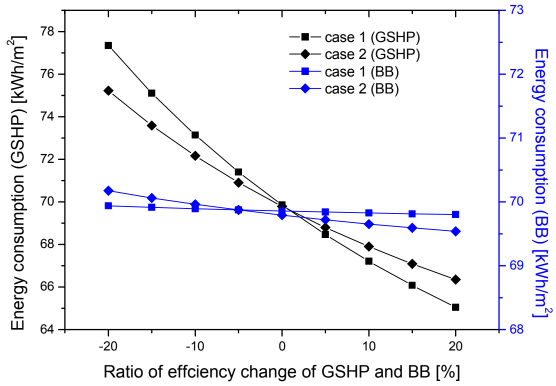

Figure 6 Consumption of non-renewable primary energy against the efficiency deviation of the ground source heat pumps (GSHP) and the biomass boiler (BB)

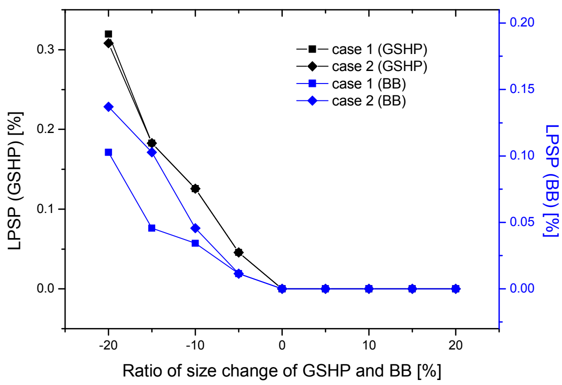

Figure 7 Loss of power supply probability (LPSP) against the size deviation of the ground source heat pumps (GSHP) and the biomass boiler (BB)

Further glances at the non-renewable primary energy consumption (referred to as NRPE hereinafter) reveal that the obtained results are almost at the edge of the constraint of 70 kWh/m^2. Therefore it is necessary to examine how the operative performance of energy conversion technologies affects NRPE. Figure 6 shows NRPE under different efficiencies of GSHP and BB respectively. The efficiencies are assumed to vary from 80% to 120% of their nominal values. The slight performance deterioration of GSHP causes a significant increase in NRPE. The influence of operative efficiency of BB on NRPE is small, due to the low non-renewable primary energy factor of wood pellets, but it is still probable that the constraint is violated.

Although the size of energy conversion technologies are design variables and optimized, the realized size may not be exactly equal to the desired size, due to various uncertainties in the manufacturing process, power generation process, and aging process. Figure 7 presents the effect of such a deviation on LPSP. The size of GSHP and the size of BB are selected to range from 80% to 120% of their optimized values. As can be observed from the figure, a smaller realized size than designed leads to the failure of the energy system to fulfil the energy demand. In particular, a 20% smaller size of GSHP leads to a LPSP of above 0.3%, which means that there would be 26 hours in the year when either the cooling or heating demand cannot be adequately satisfied.

Robust results

Based upon the sensitivity analysis, the electricity price is selected as the first uncertain economic parameter. Despite the absence of biogas in the deterministic Pareto solutions, uncertainty in its price is also taken into account, as the biogas market is getting volatile due to the concurrently increasing demand and supply. The sizes and efficiencies of ground source heat pumps, biomass boiler and biogas CHP are the six technical parameters that are considered to be uncertain. In total, there are eight parameters assumed subject to uncertainties.

The parameters are further assumed to independently follow a uniform distribution with equally probable values within specified ranges. Both economic parameters are assumed to range from 80% to 120% of the given values, whereas different uncertain ranges of six technical parameters are specified in the robust optimization. The weighting factor between the mean and standard deviation of objective values is also varied. Robust optimization is carried out on three scenarios, classified by different ranges of technical parameters and different weighting factors. Table 3 summarizes the robust setup of the three scenarios.

In the robust optimization process, each deterministic system configuration obtained from the output of the optimization algorithm, is perturbed with an LHS sampling. The sampling size should on the one hand be large enough to accurately mimic the stochastic distribution of uncertainties, and on the other hand be small to avoid high computational intensity. In this paper, where eight uncertain variables are taken, 192 samples are generated for each system evaluation. The result of robust Pareto solutions under the setup of 3 robust scenarios is presented in Figure 8, along with the previous deterministic result for comparison.

It can be seen from Figure 8 that the robust sets of Pareto solutions shift away from the deterministic one toward the less optimal direction, which is logical that the loss of performance is compensated by the increased robustness. The uncertain range of technical parameters seems to have the most significant impact on the locations of the robust Pareto front, as a big leap occurs when the uncertain range increases from 5% in scenario A to 10% in scenario B. This is because the biogas CHP together with the absorption chiller has to appear to guarantee the sufficient cooling power supply in scenario B, where GSHP alone fails to balance the cooling demand due to its uncertain size. The impact of the weighting factor on the solutions is negligible, as the cost and emission variations caused by uncertainties are small compared with that of NRPE and LPSP.

Table 3 Three scenarios of setup for the robust optimization approach

	scenario A	scenario B	scenario C
Elec. price	20%	20%	20%
Biogas price	20%	20%	20%
GSHP Size	5%	10%	10%
CHP Size	5%	10%	10%
BB Size	5%	10%	10%
GSHP efficiency	5%	10%	10%
CHP efficiency	5%	10%	10%
BB efficiency	5%	10%	10%
weighting factor	0.8	0.8	0.5

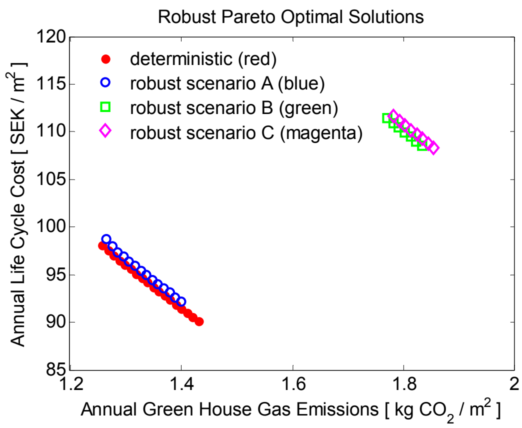

Figure 8 Robust Pareto optimal solutions that trade off life cycle cost and greenhouse gas emissions

The best environmental performance cases of each robust scenario are selected and the sensitivities of those cases are compared with the two deterministic cases, with results shown in Figure 9. Specifically, case 3, case 4, and case 5 are the least emission solutions of scenario A, scenario B, and scenario C respectively. The left three subfigures in Figure 9 show how LPSP is affected by the size change of CHP, GSHP, and BB respectively. The size deviation of GSHP seems the most influential. As expected, in case 4 and case 5, LPSP keeps zero within 10% deviation. The influence of efficiency variations of CHP, GSHP and BB, on NRPE consumption is given in the three subfigures in the middle, respectively. Similarly, the performance of GSHP has the most significant impact on NRPE consumption. Both two deterministic cases break the limit of 70 kWh/m^2 under an adverse efficiency variation, whereas all the three robust cases remain 'nearly zero energy'. The upper two subfigures in the right column of Figure 9 present how LCC varies to the price change of electricity and biogas respectively. The influence of energy price changes on LCC is linear and small. All five cases suffer from a similarly rising LCC with an increasing electricity price. Only case 4 and case 5 are affected by the biogas price variation, as CHP appears only in these two cases. Robust solutions have shown more robustness and higher reliabilities than deterministic ones, especially under uncertain technical parameters. Despite the observations made from a local sensitivity analysis, a global sensitivity analysis which gives quantitatively more reliable evidence would still support the robust solutions.

CONCLUSION

This paper has investigated the feasibility of applying a multi-objective robust optimization approach to the design of an energy system for a sustainable district towards a nearly zero energy level. The optimization approach tries to simultaneously minimize the life cycle cost and the greenhouse gas emissions, while limiting the non-renewable primary energy consumption below a specified level. The Albano university campus in Stockholm is used as a case study to test the methodology. The optimal solutions are firstly obtained under deterministic conditions, where a clear trade-off can be seen between economic and environmental objectives. Further analyses show that the deterministic solutions are sensitive to uncertainties in certain parameters and design variables, which can even cause a loss of power supply. Therefore, the robust optimal solutions are obtained through the proposed robust design optimization approach. Robust optimal solutions sacrifice optimality in objectives for the robustness of the system. The results show that the more robustness in the energy system is wanted, the more compromise has to be made on the optimality of objectives. In this case study, the uncertainties in technical parameters including the sizes and efficiencies of energy conversion technologies prove to be the most influential, as a slight deviation from the designed value might lead to either a violation of the constraint for the non-renewable primary energy consumption or an insufficiency of power supply. In contrast, the economic parameters have shown less importance in the robust energy system design. This is because of the limited available types of energy conversion technologies, which results in very few options in meeting the energy demand.

The proposed multi-objective robust optimization methodology can assist district planners in several aspects. The methodology allows them to choose the trade-off between economic and environmental concerns while conforming to the nearly zero energy regulation. Also the methodology makes it possible for decision makers to identify the most influential parameters that might deteriorate the performance of the system. Finally district planners are provided with an opportunity to compromise between system robustness and the optimality of the objectives.

In future work, the uncertainties existing in energy load profiles and renewable energy productions, due to the stochasticity of weather or climate conditions, will be analysed and modelled in the optimization. More realistic distribution patterns like the Gaussian normal distribution and correlations among uncertain variables will also be considered. Electricity and thermal storage equipment will be introduced into the district energy system, which can be expected to have a significant influence on the optimal solutions.

REFERENCES

EPBD. 2010. Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings (recast), Official Journal of the European Union (2010) (18.06.10).

City of Stockholm. 2015. Albano Stockholms nya universitetsområde gestaltningsprogram. (In Swedish) http://insynsbk.stockholm.se/ accessed on August 2, 2013.

E.ON Sverige AB. Ersättning och avgifter, Sverige. http://www.eon.se/privatkund/Produkter-och-priser/Elnat/Producera-dinegenel/Ersattning--avgifter/ (In Swedish) accessed on May 1, 2015.

Hamdy, M., Palonen, M., & Hasan, A. 2012. Implementation of pareto-archive NSGA-II algorithms to a nearly-zero-energy building optimisation problem. *Proceedings of Building Simulation and Optimization, Loughborough, UK*, 118-125.

Helton, J. C., Davis, F. J. 2003. Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. *Reliability Engineering & System Safety*, *81*(1), 23-69.

Hopfe, C. J., Emmerich, M. T., Marijt, R., Hensen, J. 2012. Robust multi-criteria design optimisation in building design. *Proceedings of Building Simulation and Optimization, Loughborough, UK*, 118-125.

Kayo, G., Hasan, A., Siren, K. (2014). Energy sharing and matching in different combinations of buildings, CHP capacities and operation strategy.*Energy and Buildings*, *82*, 685-695.

Kurnitski, J., 2013. nZEB technical definition and system boundaries for nearly zero energy buildings. REHVA Federation of European Heating, Ventilation and Air Conditioning Associations, pp. 4-16, 2013. Brussels, Belgium.

Lu, H., Alanne, K., Martinac, I. 2014. Energy quality management for building clusters and districts

(BCDs) through multi-objective optimization. *Energy Conversion and Management*, *79*, 525-533.

Magny, A. A. A. 2014. Optimization of Energy Systems for a Sustainable District in Stockholm Using Genetic Algorithms: The case of Albano. Master thesis. Royal Institute of Technology, Stockholm, 2014.

Mavrotas, G., Diakoulaki, D., Florios, K., Georgiou, P. 2008. A mathematical programming framework for energy planning in services' sector buildings under uncertainty in load demand: the case of a hospital in Athens. *Energy Policy*, *36*(7), 2415-2429.

Moradi, M. H., Hajinazari, M., Jamasb, S., Paripour, M. 2013. An energy management system (EMS) strategy for combined heat and power (CHP) systems based on a hybrid optimization method employing fuzzy programming. *Energy*, *49*, 86-101.

Palonen, M., Hamdy, M., Hasan, A. 2013. MOBO a new software for multi-objective building performance optimization. In *Proceedings of the 13th Internationcal Conference of the IBPSA* (pp. 2567-2574).

Rezvan, A. T., Gharneh, N. S., Gharehpetian, G. B. (2012). Robust optimization of distributed generation investment in buildings. *Energy*, *48*(1), 455-463.

Schuëller, G. I., Jensen, H. A. 2008. Computational methods in optimization considering uncertainties-an overview. *Computer Methods in Applied Mechanics and Engineering*, *198*(1), 2-13.

Shi, J. H., Zhong, Z. D., Zhu, X. J., Cao, G. Y. 2008. Robust design and optimization for autonomous PV-wind hybrid power systems. *Journal of Zhejiang University Science A*, *9*(3), 401-409.

Yang, H. X., Lu, L., Burnett, J. 2003. Weather data and probability analysis of hybrid photovoltaic–wind power generation systems in Hong Kong. *Renewable Energy*, *28*(11), 1813-1824.

Yao, W., Chen, X., Luo, W., van Tooren, M., Guo, J. 2011. Review of uncertainty-based multidisciplinary design optimization methods for aerospace vehicles. *Progress in Aerospace Sciences*, *47*(6), 450-479.

Yokoyama, R., & Ito, K. (2002). Optimal design of energy supply systems based on relative robustness criterion. *Energy conversion and management*,*43*(4), 499-514.

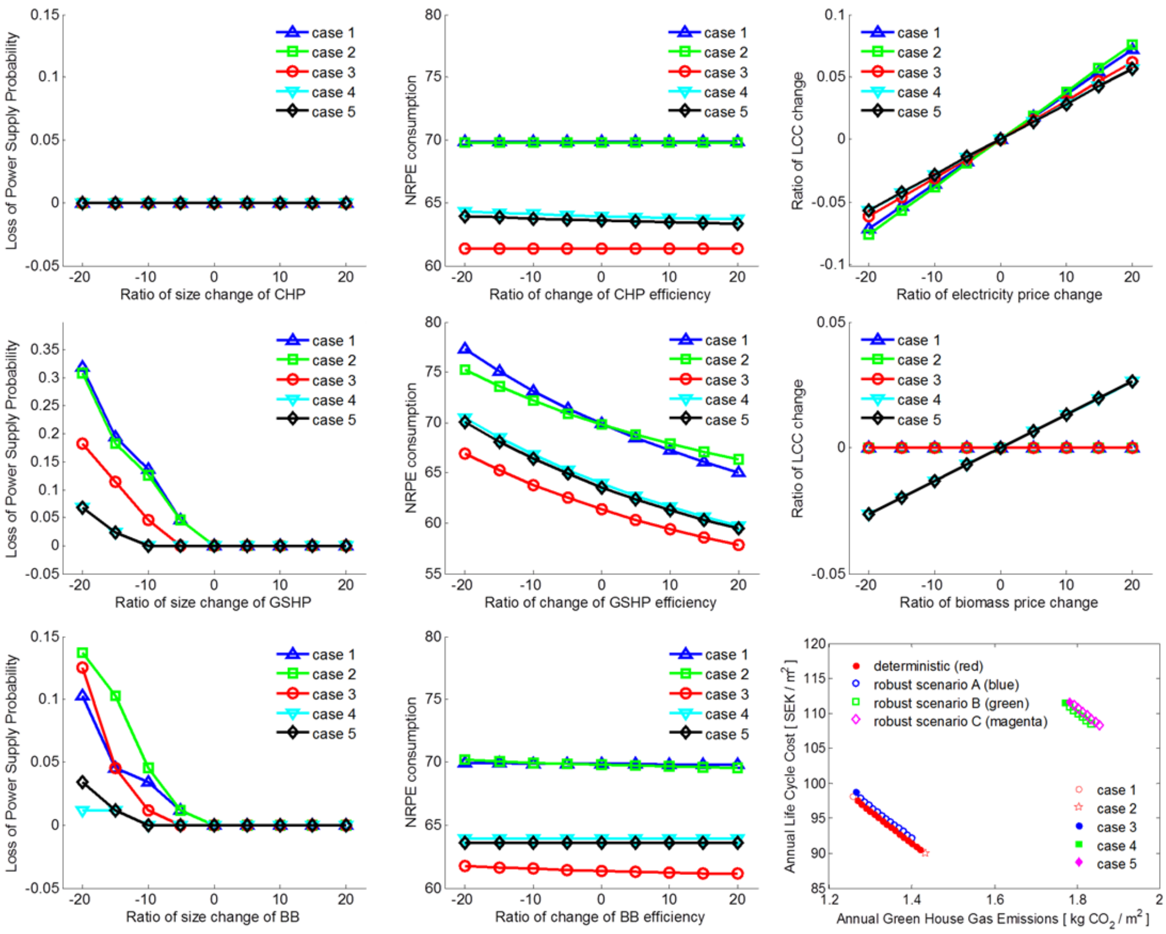

Figure 9 Sensitivity comparisons of five selected cases