# Distributed optimisation of decentralised energy systems under uncertainty on HPC systems

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Nowadays, there is a decentralisation of the German energy sector driven by fluctuating renewable energy sources (RES) that are subject to non-negligible uncertainties. Stochastic modelling techniques enable an adequate consideration of manifold uncertainties in the investment and operation process of decentralised energy systems. However, their mathematical formulations lead to large-scale programs that are not feasible on one computer. The program is therefore decoupled and distributively optimised on high-performance computing (HPC) systems. Thus, robust-sufficient setup decisions for decentralised energy systems can be provided that are expected to be optimal.

## 1 Introduction

In the German energy sector, we are nowadays faced with the trend from a centralised to a decentralised energy supply (see e.g. [1, 2, 3, 4]). The decentralisation is mainly driven by fluctuating renewable energy sources (RES) which requires a high temporal resolution when real energy systems are considered. Moreover, RES are subject to weather-related uncertainties that cannot be neglected in the modelling process to achieve optimal decisions. Stochastic modelling techniques enable the optimisation of decentralised energy systems with an adequate consideration of these uncertainties (see e.g. [5, 6, 7, 8] for details), but typically lead to large-scale programs that are not feasible on one computer. The program is therefore decoupled into many smaller sub-programs that are distributively optimised on high-performance computing (HPC) systems.

This paper is structured as follows. The problem and its mathematical formulation are described in Section 2. The distributed optimisation process on HPC systems is presented in Section 3 and computational results are shown in Section 4. Finally, Section 5 gives a conclusion of the work and indicates needs for further research.

## 2 Problem description

The economic profitability of decentralised energy systems mainly depends on the investments at the first stage and their operation at the second stage. While the investments at the first stage can be considered as here-and-now decisions without uncertainty, the operation at the second stage is subject to uncertain conditions: such as energy supply and demand or electricity prices, which can occur in scenarios with different probabilities. Stochastic programming considers uncertainties by optimising the investment and operation decisions not for one specific, but for all possible scenarios with respect to their stochastic nature.

In [9], stochastic programming is used to optimise heat storages of a residential quarter in combination with a photovoltaic (PV) system and heat pumps. The quarter is modelled as a so-called two-stage stochastic mixed-integer linear program (S-MILP).[1] The objective function of the program is:

$$\min_{c_{g,i},e_{n,t}^{grid},e_{n,t}^{fi}} ANF \sum_{g} \sum_{i} cost_i \cdot c_{g,i} + \sum_{n} \pi_n \sum_{t} p^{grid} \cdot e_{n,t}^{grid} - p^{fi} \cdot e_{n,t}^{fi}, \tag{1}$$

where the capital cost of investment $i$ of building group $g$ is converted into equivalent series of uniform amounts per period at the first stage. Thereby, the annuity factor $ANF$ takes into account the lifetime of the investment and an alternative investment at a certain interest rate of the fixed capital. At the second stage, the sum of energy obtained from the external grid $e_{n,t}^{grid}$ at price $p^{grid}$ minus the energy fed into the grid $e_{n,t}^{fi}$ at tariff $p^{fi}$ over all time steps $t = \{1, ..., T\}$ results in energy cost of each scenario $n = \{1, ..., N\}$ that occurs with probability $\pi_n$.

In the case study, storage units for space heating and for domestic hot water are optimised assuming a technical lifetime of 20 years related to an interest rate of 10%. The period $t = \{1, ..., 35040\}$ includes one year with a temporal resolution of 15 minutes. Essential constraints are that the electrical supply and demand as well as the thermal supply and demand are balanced at any time. Furthermore, the storage possibility and the heat supply are limited. Uncertain parameters are the supply of the PV system and heat pumps as well as the electrical and thermal demand of the households. These uncertainties are represented by different scenarios generated on the basis of a Markov process which have proven suitable to this kind of problem. The whole program and further information are presented in [9].

## 3 Distributed optimisation process on HPC systems

In order to keep the program feasible, it is decoupled and distributively optimised on HPC systems. In principle, every stochastic program can be decoupled by losing intra- and inter-scenario connections. In the case study, a scenario is internally connected by the storage capacities and the storage levels over the time steps. The storage capacities connect the scenarios among each other. The intra- and inter-scenario-connected variables are fixed and optimised by an outer derivative-free optimisation (DFO): a steepest-ascent hill-climbing approach [11].[2] As a consequence, the program can be decoupled in $M$x$N$ sub-programs which are optimised by *CPLEX*, a commercial MILP solver, on C computing nodes. As soon as all sub-programs are optimised, they are coupled to compute the minimal cost of the fixed variables which is needed for the DFO. Fig. 1 shows the distributed optimisation process of the stochastic program.

[1] Further information about two-stage stochastic programming can be found, for instance, in [10].

[2] Note that the used hill-climbing approach is a local search approach that can only guarantee local optimality. It can be replaced by any other DFO algorithm, even by a global search approach, if enough computing resources are available.

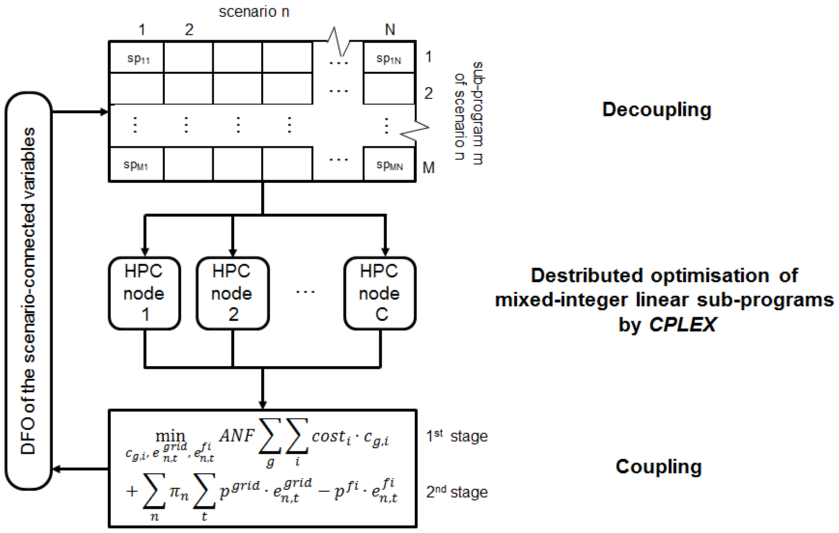


Figure 1: Distributed optimisation process of the stochastic program.

The decoupling in combination with the DFO and the distribution of the sub-programs to HPC clusters are implemented by a visual basic application (VBA) on a Windows master machine. In this setup, the Windows master machine communicates to Windows- or Linux-based machines by the tool *PuTTY* or *PsExec*, respectively. Thus, computing nodes of different HPC systems can be used. For the optimisation of the residential quarter, computing nodes of the *bwUniCluster* and the *bwForCluster* (Linux-based) as well as some computing nodes of the Institute of Industrial Production (IIP) (Windows-based) were in use: Nodes with 4-16 GB RAM and 1-16 cores are required for 15-30 minutes to ensure a solution of the sub-programs with a sufficient quality that is needed for the DFO.

## 4 Computational results

For the case study, $M = 100$ scenarios are generated and decoupled. Additionally, the one-year period of each scenario is decoupled into $N = 27$ periods of two weeks leading to $M\text{x}N = 2700$ sub-programs per scenario-connected variable for the outer DFO. About 20 steps of the outer optimisation are needed to find the optimal storage sizes.

The optimisation of one complete scenario for one building group is still feasible within 2 days on one computing node (see Table 1). However, the optimisation of one scenario for the entire residential quarter is not feasible. Therefore, a decoupling of the stochastic program is required. If this decoupled program of one scenario for one building group was sequentially optimised on one computing node, the computing wallclock time would amount to 6 days. Due to the distributed optimisation on HPC systems, the same problem is solved within 5 hours assuming exclusive access to 512 computing nodes for this time period. The full program, i.e. 100 scenarios for the quarter (=4 building groups), takes approximately 7 days.

The computing wallclock time of 7 days of the full program can be further reduced by up to 75% using scenario reduction techniques and automated algorithm configuration of the used

| | Constraints | Decision variables (thereof integer) | Computing wallclock time | | |
|---|---|---|---|---|---|
| | | | 1 node* using *CPLEX* | 1 node** using *CPLEX* + decoupled | 512 nodes** using *CPLEX* + decoupled |
| 1 building group | 946 080 | 490 572 (70 086) | up to 2 days | ~6days | ~5h |
| Quarter (4 building groups) | 3 048 480 | 1 962 285 (280 344) | ∅ | ~90days | ~1day |
| 100 scenarios of 1 building group | 9,E+07 | 5,E+07 (7,E+06) | ∅ | ~1,6years | ~28h |
| 100 scenarios of the quarter | 3,E+08 | 2,E+08 (3,E+07) | ∅ | ~25years | ~7days |

*with up to 1 TB RAM, 32 Cores@2.4-2.6Ghz, max. 72h, rel. Gap=2%

**with up to 16 GB RAM, 16 Cores@2.4-2.6Ghz, max. 0.5h, rel. Gap=0.5%

Table 1: Computing wallclock time of different program variants sequentially or distributively optimised on 1 computing node or 512 computing nodes of a HPC system.

*CPLEX* solver (see [12]). Practically, however, due to time restrictions per job of the HPC queuing systems, the computation still takes almost a week.

A comprehensive analysis of the results with regard to energy economic aspects of the residential quarter is done in [9]. The main findings are:

- Thermal storage units generally prove beneficial.
- Storage units for domestic hot water are more profitable than for space heating due to the more constantly provided demand side flexibility throughout a year.
- The optimal storage capacity for space heating is generally larger when uncertainties are considered in comparison to the deterministic optimisation.

## 5 Conclusions

The centralised German energy structure is changing towards decentralised energy systems that are subjected to manifold uncertainties. Stochastic modelling techniques help to avoid bad investment decisions, but lead to very large-scale programs that require a decoupling to keep it computationally feasible. However, the optimisation of the full program would take about 25 years computing wallclock time on one computing node. The distributed optimisation on HPC systems with, e.g., 512 nodes achieves a solution within 7 days or, if scenario reduction techniques and automated algorithm configuration are employed, within two days.

Nevertheless, the optimisation of decentralised energy systems is still challenging considering the fact that such computer resources are hardly available for those time periods of one day and more. In practice, the computation takes much more time due to resource restrictions of HPC systems. Consequently, model changes and more complex energy system models are still time and cost-intensive. Therefore, the computational effort needs to be reduced by improving the computational interaction between the size and complexity of the employed programs and the used HPC resources. One way would be to optimise the amount of memory required for the inner optimisation of the sub-programs. Reduced memory requirements would allow more runs on a single node or cheaper nodes with less RAM. Another way would be a heuristic solution approach for the sub-programs (e.g. machine learning methods) instead of the resource-intensive optimisation by *CPLEX*. Besides, the outer hill-climbing approach could be replaced by a DFO algorithm that needs fewer steps to find optimal solutions. If enough computing resources are available, it could also be extended by a DFO guaranteeing global optimality.

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