

# Planning Renewable Energy Systems at the District Scale using Mixed-Integer Linear Programming

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## Introduction

Heating is the largest end-use category of energy, accounting for around 50% of global final energy consumption [1]. In the European Union (EU), only 28% of the delivered residential heating was from renewable sources in 2019 [2]. New planning methods and tools capable to cope with high-shares of intermittent renewable energy sources are needed to speed up the transition to resilient, sustainable energy systems at the district level.

## Methodology

Heat, power and cooling demands of the studied district are estimated from Level of Detail 2 (LoD2) Geographical Information System (GIS) data (Figure 1), which is pre-processed with the software FME [3]. Then, an age category is assigned to each building given the age distribution information provided by the Zensus2011 dataset [4]. A TABULA building type [5] is assigned to define building thermal properties. The obtained data is then used to compute heating, electricity and cooling demands with City Energy Analyst (CEA) [6].

A mixed-integer linear programming (MILP) problem is formulated (see model structure in Figure 2) with the given energy demands. The optimization objective is to minimize the system costs (Eq. 1 and 2). The optimization therefore selects optimal investment decision variables ( $C_{inv}$ , first stage) and operates a whole year ( $C_{op}$ , second stage).

$$\min C_{inv} + C_{op} \quad (\text{Eq. 1})$$

$$C_{inv} = \sum_i [CRF_i \cdot (C_i \cdot G_i)] + C_{DHN} \cdot y \quad (\text{Eq. 2})$$

To integrate price uncertainty in the optimization formulation, a two-stage stochastic programming (SP) formulation is used. To solve the generally intractable expectation function, it is approximated through  $S$  scenarios with a user-defined probability  $\pi_s$  (Eq. 3).

$$\min C_{inv} + \mathbb{E}[C_{op,s}] \rightarrow \min C_{inv} + \sum_{s \in S} (\pi_s \cdot C_{op,s}) \quad (\text{Eq. 3})$$

## Heat Demand Calculation

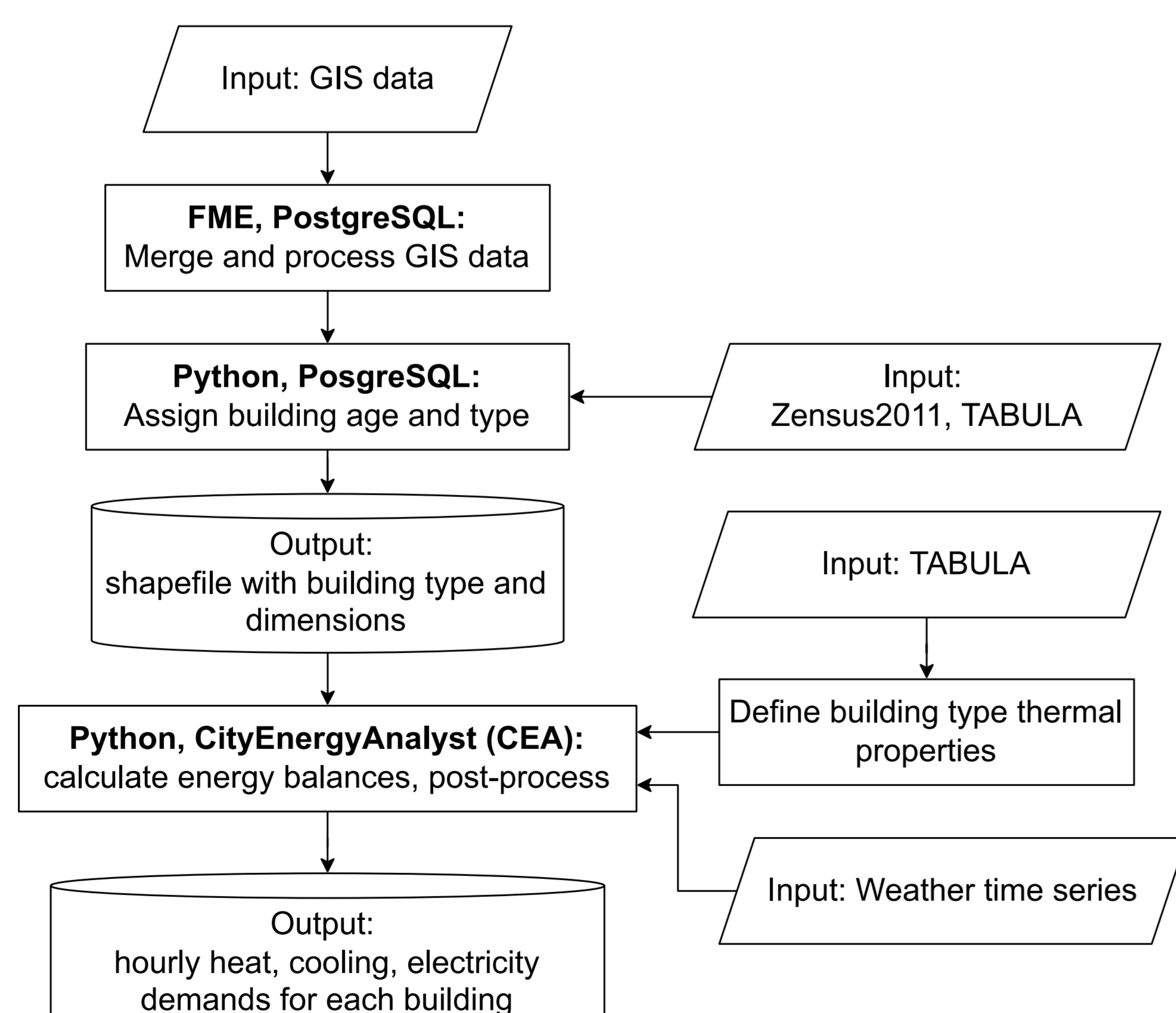


Figure 1. Simplified process to compute heat and electricity demands from GIS data.

## MILP Formulation

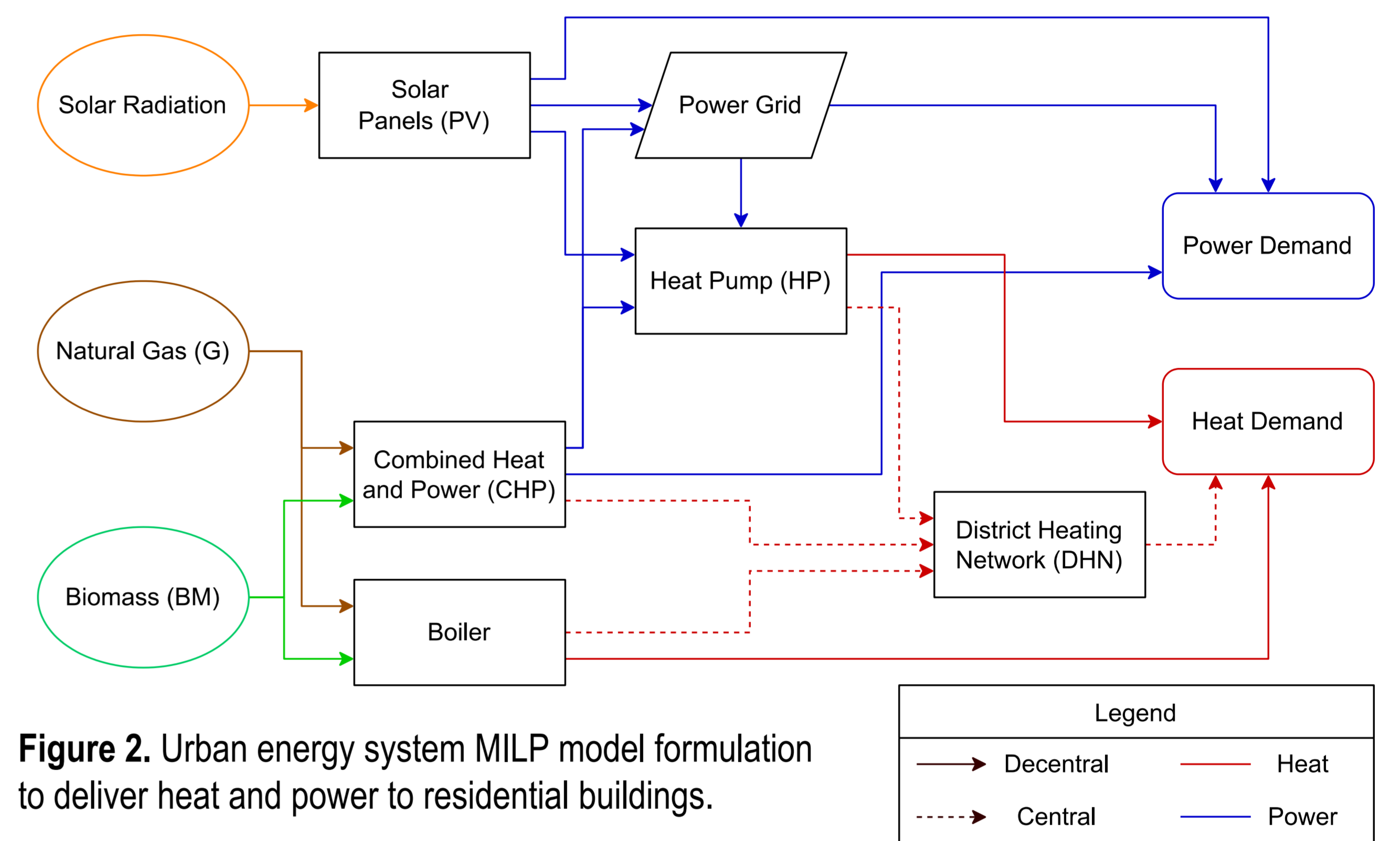


Figure 2. Urban energy system MILP model formulation to deliver heat and power to residential buildings.

## Case Study

The developed method was applied to a town in southern Bavaria, Germany with around 300 residential buildings and the typical meteorological year (TMY) dataset of the closest meteorological station [7]. District heating network costs were obtained from THERMOS [8] and from sources [9-11] for commodity prices and technology life time. An internal rate of return of 8% was assumed. Four scenarios were computed as deterministic MILPs and two scenarios, "SP25" and "SP125", as a two-stage SP (Table 1).

Table 1. Price assumptions for the calculated scenarios using MILP.

Scenario	Description	Natural Gas [€/MWh]	Wood Pellet [€/MWh]	CO <sub>2</sub> cost [€/t CO <sub>2</sub> eq.]
BC	Base Case	16	39	25
S2	High CO <sub>2</sub> tax	16	39	125
S3	2022 prices	140	150	25
CO2	CO <sub>2</sub> minimization	140	150	-
SP25	Two-stage SP	[16, 140, 375]	[39, 150]	25
SP125	Two-stage SP	[16, 140, 375]	[39, 150]	125

## Results

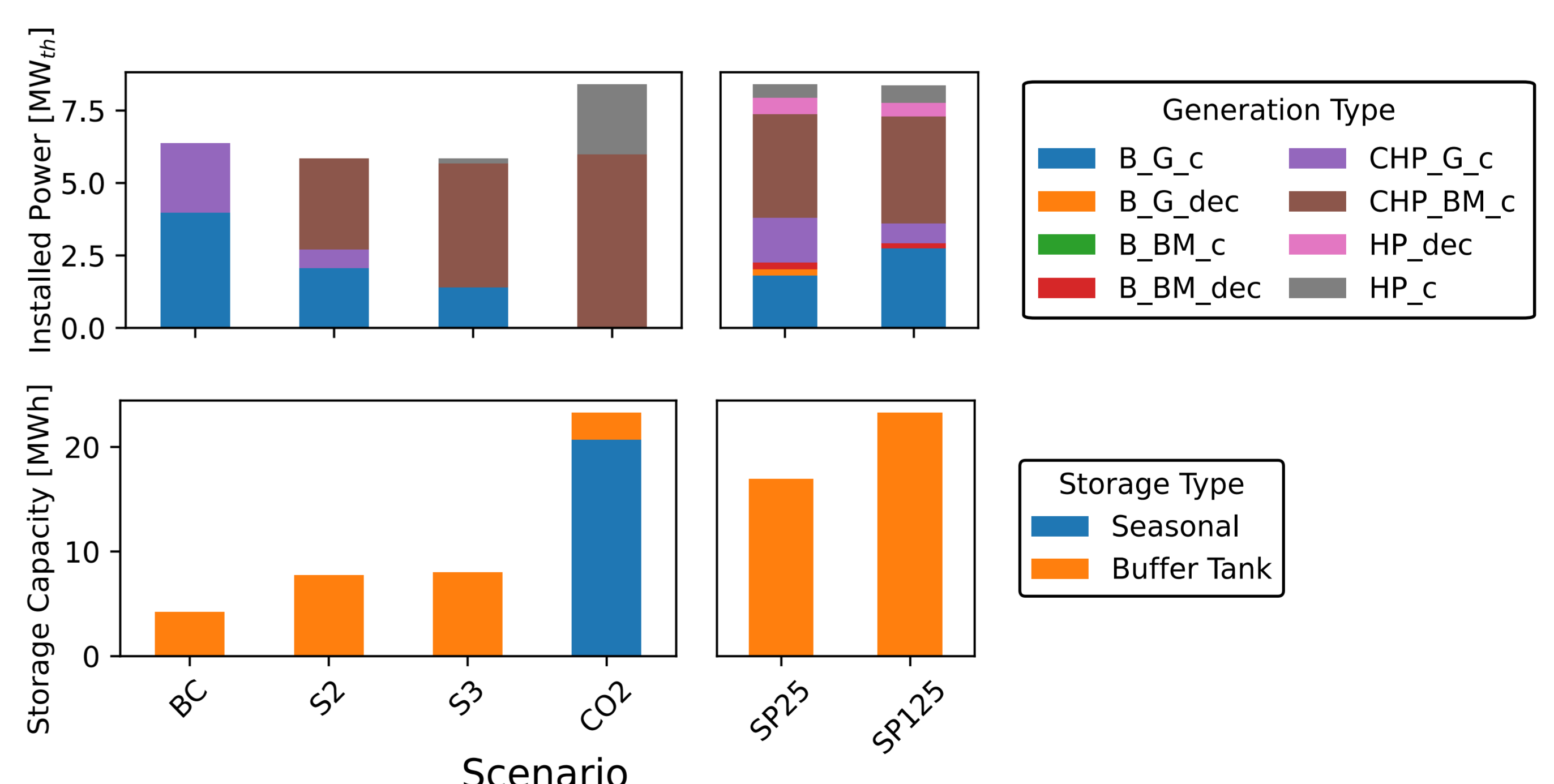


Figure 3. Thermal energy generation and storage results for deterministic MILP ("BC", "S2", "S3", "CO2") and two-stage SP ("SP25" and "SP125") optimization.

