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# A bi-level programming for multistage co-expansion planning of the integrated gas and electricity system

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## HIGHLIGHTS

- Coordinated expansion planning of the integrated power and gas system is studied.
- A bi-level framework to minimize the investment plus operational cost is built.
- Bi-directional energy conversions between power and gas systems are considered.
- Hybrid approach combining the heuristic and analytical optimization is proposed.
- Case studies on the practical western Danish energy system are conducted.

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## ABSTRACT

This paper focuses on the coordinated expansion planning of the integrated natural gas and electrical power systems with bi-directional energy conversion. Both the Gas-fired Power Generations (GPGs) and Power-to-Gas stations (P2Gs) are considered as the linkages between the natural gas and electric power systems. The system operation is optimized and embedded in the planning horizon. A bi-level multi-stage programming problem is formulated to minimize the investment cost plus the operational cost. The upper-level optimizes the expansion plan and determines the network topology as well as the generation capacities, while the lower-level is formulated as an optimal economic dispatch under the operational constraints given by the upper-level decision. To solve the bi-level multi-stage programming problem, a hybrid algorithm is proposed combining the modified binary particle swarm optimization (BPSO) and the interior point method (IPM). The BPSO is used for the upper-level sub-problem, and the IPM is adopted for the lower-level sub-problem. Numerical case studies have been carried out on the practical gas and electricity transmission network in western Denmark. Simulation results demonstrate the effectiveness of the proposed approach.



## 1. Introduction

The integration of multi-energy systems (MES) presents the opportunity to improve the efficiency and sustainability of the energy utilization as it can optimally interact with each other among different energy systems such as electricity, gas, heating, cooling and transport [1]. Among all the energy systems, the natural gas system and electrical power system are the most common options for bulk energy transmission over thousands of kilometers. Also, the interdependency between the electricity power and natural gas systems are dramatically increasing in recent years [2]. First, natural gas (NG) becomes one of the important energy sources in the world. It accounts for 25% of the world's primary energy production, and it is still expected to grow at a rate of 2.9–3.2% per year until 2030 [3]. Second, Gas-fired power generation (GPG) provides a linkage between natural gas and power systems [4]. As the GPG has the fast response capability, low fuel cost and low environmental emission, it currently plays an important role in ensuring security in power systems with high wind power penetrations [5], which results in an increasingly close coupling between the natural gas and electrical power systems [4,6]. Third, the emerging Power to Gas (P2G) technology enables the reverse energy conversion from the electricity system to the natural gas network, and the converted gas fuel can be used later for electricity production [7]. It might be one of the most promising energy storage technologies in the mid-term [8,9]. The P2G not only helps avoid the curtailment of renewables in the electrical power system

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**Nomenclature**

*Parameter*

| | |
|---|---|
| $A$ | the present value of annuity factor |
| $a, b, c$ | first, second, and third order coefficient of the utility function for the generator |
| $B$ | electrical susceptance |
| $c_k$ | specific heat ratio for the natural gas |
| $C$ | the equivalent annual cost for the expansion planning component |
| $d$ | day |
| $e$ | acceleration coefficient |
| $E$ | compressors parasitic efficiency, 0.99 for centrifugal units |
| $f$ | random numbers in (0,1) interval |
| $g_{id}^k$ | the individual optimum's positions of $i$th-particle in $d$th-dimension and the $k$th-iteration |
| $g_{gd}^k$ | the global optimum's positions in $d$th-dimension and the $k$th-iteration |
| $HR$ | heat rate |
| $K$ | constant of compressor |
| $L$ | length in km |
| $N$ | the total number of a certain facility |
| $r$ | the discount rate in % |
| $t$ | time, h |
| $T$ | suction temperature of compressor, °R |
| $w$ | the inertia weight |
| $y$ | year |
| $Y$ | the planning horizon |
| $Z_a$ | average compressibility factor |
| $Z_{ij}$ | the resistance coefficient of the pipeline, kPa/(MW)$^2$ |
| $\alpha, \beta, \gamma$ | first, second, and third order coefficient of the heat rate curve |
| $\eta$ | efficiency, % |
| $\tau$ | the lifespan of the component |
| $\gamma$ | the equivalent annual cost for the reduced capacity |
| $\phi$ | the equivalent annual cost for the new selected location |
| $\sigma$ | the penalty factor |
| $\varepsilon$ | $CO_2$ emission coefficient |
| $\psi$ | the price in Euro |
| $\xi$ | the compression ratio |

*Variables*

| | |
|---|---|
| $EC$ | expanded capacity, MW |
| $LP$ | the amount of linepack storage, MW |
| $p$ | the gas pressure, kPa |
| $P$ | electrical power or gas flow, MW |
| $RC$ | reduced capacity, MW |
| $S$ | gas flow rate in the pipeline, MW |
| $\beta$ | the binary decision variable which represents the state on/off (1/0) of candidate component |
| $\theta$ | voltage phase angle |
| $v_{id}^k$ | the velocity of $i$th-particle in $d$th-dimension and the $k$th-iteration |
| $x_{id}^k$ | the positions of $i$th-particle in $d$th-dimension and the $k$th-iteration |

*Indices and subscripts*

| | |
|---|---|
| con, gen, sup, load | consumption, generation, supply, load |
| CPG, GPG, P2G | coal-fired power generation, Gas-fired power generation, Power to Gas |
| carbon | carbon emission |
| GT, GS, GC | Gas Terminal, Gas storage, Gas compressor |
| $i,j$ | index of nodes, pipes or units |
| $t$ | index of time |
| $^-$, $_-$ | the upper limit, the lower limit |

*Abbreviations*

| | |
|---|---|
| elec, gas | electricity system, gas network |
| UE, WC, W, D | unserved electricity, Wind curtailment, Wind power, Demand |
| with, inject | withdrawal, injection |

but also helps couple the natural gas and power systems with bi-directional energy conversion [4]. Thus, the harmonized integration of natural gas and power system can optimally utilize the flexibility provided by the gas network to improve the sustainability, reliability, and efficiency of energy utilization [10].

Due to these benefits, significant efforts have been devoted to the coordinated operation of the integrated gas and power systems. In the early research, the impact of the interdependency of natural gas and power systems on power security and economic dispatch are investigated in [11–14]: [11] demonstrates that the natural gas supply has a serious impact on the power security and the electricity price [12] also shows that the daily natural gas allocation can impact the security and economics of the power systems. In [11,12], the natural gas network is incorporated in the security-constrained unit commitment (SCUC) by various fuel constraints. However, the network constraints are neglected in these studies. In [13], an integrated model for SCUC is proposed by taking into consideration both the power transmission constraints and the natural gas transmission constraints [14] proposes a mixed-integer linear programming (MILP) security-constrained optimal power and gas flow under $N-1$ contingencies.

In recent years, with the increasing deployment of renewables and energy demands, it is of great importance to consider uncertainties regarding supply, demand and infrastructure for both electricity system and natural gas network. The stochastic programming is generally used to handle uncertainties. In [15], stochastic programming is adopted in the optimization model to deal with wind power uncertainty, in which a large number of wind forecast scenarios are generated and a scenario reduction algorithm is applied [16] applies stochastic optimization to the unit commitment problem with a number of wind power scenarios. And [17] proposed a coordinated stochastic model to consider the impact of the system uncertainties. Stochastic optimization generally requires the probability distribution of renewables or demands, but it is hard to know in reality. The robust optimization is another effective method which is widely used to deal with the problem of uncertainty. A robust optimization approach is proposed in [18] to deal with the scheduling of quick start units considering natural gas transmission constraints [19] proposed a two-stage robust optimization method to make unit commitment decisions under different uncertainty sets. As the robust optimization finds the optimal solution for the worst case scenario which happens at a very low probability, it is always considered too conservative especially in cases where uncertain parameters have a large range of variability [20]. Currently, the interval optimization method is considered as an alternative for addressing the uncertainty problems due to its good computational performance. In [2], an interval optimization framework is introduced to address