Application of a Relevance Matrix to Thermal Unit Commitment in the Presence of Renewable Energy Sources

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Abstract. The short-term unit commitment problem is considered hard to optimally solve given the combinatorial explosion of the operation decisions regarding the generating units involved in the daily operation planning. The problem's complexity further increases when introducing renewable energy sources, e.g., solar and wind, to the planning. This paper applies a recently proposed search space reduction method to thermal unit commitment systems penetrated by solar and wind power generation.

Keywords: unit commitment, thermoelectric power, optimization, renewable energy sources.

1 Introduction

The short-term unit commitment can be described as an engineering and computational problem that seeks to minimize the operational costs of the generating units over up to 24 hours [1]. The thermal unit commitment (TUC) comprises two basic stages: the decisions of units to operate, often referred to as unit commitment (UC); and the economic dispatch (ED). The problem's significant complexity comes from the combinatorial explosion of the binary variables representing the ON/OFF operation decisions concerning the thermoelectric units. Furthermore, the temporal coupling of the decision variables among different periods of the planning horizon also complicates the problem. There are many techniques to plan the operation in a way to meet the operational constraints whilst minimizing costs. Among these methods, the following are some that stand out when it comes to solving UC: decomposition methods [3], priority lists [4], and evolutionary algorithms [5]. In recent previous work, the authors of this paper proposed a method to effectively reduce the search space of TUC problems [7,8]. This paper proposes the application of the method from [7,8] to systems penetrated by wind and solar power.

2 Formulation

The TUC problem is usually formulated as a minimization problem regarding the operational cost and subjected to a set of constraints [9]. The following subsections present the objective function and the constraints considered in this paper, which are based on [10].

2.1 Operational cost

The total cost (TC) of operations can be written as the power production cost plus startup and shutdown costs concerning each generating unit i at each period h of the planning horizon, as in Eq. (1).

$$minimize\ TC = \sum_{h=1}^{H}\sum_{i=1}^{NG} a_i u_{i_h} + b_i P_{i_h} + c_i P_{i_h}^2 + s_{i_h}^{cold} \cdot s_{i_{cost}}^{cold} + s_{i_h}^{hot} \cdot s_{i_{cost}}^{hot} \tag{1}$$

Where: H is the total number of periods in the planning horizon; NG is the total number of thermal units; a_i, b_i and c_i are the fuel cost coefficients of unit i; u_{i_h} is the binary variable related to the operation decision of unit i at period h ($u_{i_h} = 1 \rightarrow ON, u_{i_h} = 0 \rightarrow OFF$); P_{i_h} is the power generated by thermal unit i at period h; $s_{i_h}^{cold}$ is the binary decision representing a cold startup; $s_{i_{cost}}^{cold}$ is the cost of a cold startup; $s_{i_h}^{hot}$ is the binary decision representing a hot startup; $s_{i_{cost}}^{hot}$ is the cost of a hot startup.

2.2 Cold or hot startup

Whether a startup will be cold or hot depends on how much time has passed since the unit has been shut down, as modeled by Eqs. (2) and (3).

$$s_{i_h}^{cold} + s_{i_h}^{hot} = x_{i_h}, \forall h \in H, \forall i \in NG \tag{2}$$

$$u_{i_h} - \sum_{w=h-t_{csu_i}-MDT_i-1}^{h-1} u_{i_w} = s_{i_h}^{cold}, \forall h \in H, \forall i \in NG \tag{3}$$

Where: x_{i_h} is an auxiliary binary variable that is only equal to 1 when the unit is turned from OFF to ON at period h; w is an auxiliary index required for calculations; MDT_i is the minimum down time of unit i; t_{csu_i} is the number of periods, after MDT_i, that should pass for the startup to be cold.

2.3 Minimum up and down times

Once a unit is activated/deactivated, it must remain ON/OFF for a specific number of periods before it can be turned OFF/ON. Equations (4) and (5) represent this behavior.

$$\sum_{w=h-MUT_i+1}^{h} x_{i_w} \leq u_{i_h}, \forall h \in H, \forall i \in NG \tag{4}$$

$$\sum_{w=h-MDT_i+1}^{h} y_{i_w} \leq 1 - u_{i_h}, \forall h \in H, \forall i \in NG \tag{5}$$

Where: y_{i_h} is an auxiliary binary variable that is only equal to 1 when the unit is turned from ON to OFF at period h; MUT_i is the minimum up time of unit i.

2.4 Startups, shutdowns, and operation decisions

Equations (6) and (7) establish the interactions among the x_{i_h}, y_{i_h}, and u_{i_h} variables.

$$u_{i_h} - u_{i_{h-1}} = x_{i_h} - y_{i_h}, \forall h \in H, \forall i \in NG \tag{6}$$

$$x_{i_h} + y_{i_h} \leq 1, \forall h \in H, \forall i \in NG \tag{7}$$

2.5 Load balance and spinning reserve

For all periods of the planning horizon, the load must be met. In addition, a power reserve must be in place for emergencies, such as the failure of a generator. Equations (8) and (9) represent these constraints, respectively.

$$S_h + W_h + \sum_{i=1}^{NG} P_{i_h} = L_h, \forall h \in H \tag{8}$$

$$S_h + W_h + \sum_{i=1}^{NG} u_{i_h} \bar{P}_i \geq L_h + SR_h, \forall h \in H \tag{9}$$

Where: S_h and W_h represent the solar and wind power generation, respectively, at period h; L_h is the load at period h; SR_h is the spinning reserve required at period h; $\bar{P}_i$ is the maximum power that unit i can generate.

As a remark, it is emphasized that the cases with renewable energy penetration consider the solar and wind power supply as being at nominal values. In addition, no operational cost is considered for these sources [11].

2.6 Maximum and minimum operation limits

Equation (10) models the minimum ($\underline{P}_i$) and maximum power a unit can generate according to its operational state, i.e., ON or OFF.

$$u_{i_h}\underline{P}_i \leq P_{i_h} \leq u_{i_h}\bar{P}_i, \forall h \in H, \forall i \in NG \tag{10}$$

3 Relevance matrix

The methodology utilized in this paper was developed by this paper's authors and applied to purely thermoelectric systems in [7]. The relevance matrix (RM) indicates how important each generating unit is in each period of the planning horizon. The construction of RM bases itself on priority lists algorithms, which aim at activating generating units until the demand constraints are met. The hybrid priority lists (HPLs) forming RM come from hourly permutations regarding a set of pre-constructed priority lists. These lists are generated according to literature-consolidated indices that carry technical information of the generating units. In this paper, the utilized indices are the full load average production cost (FLAC) [12], production marginal cost (PMC) [13], and Lagrange sensitivity (LS) [14]. The indices permutation seeks to enable RM to capture as much information from the generating units as possible, which will impact the searching mechanism of the method. Readers interested in understanding the details of the methodology are encouraged to consult [7].

3.1 Flowchart of the methodology

Figure 1 presents a flowchart of the proposed method considering solar and wind generation. The method begins by defining the maximum number (i_{max}) of decision matrices (DM) that will form RM. It happens that i_{max} is also the number of HPLs created according to permutations of the FLAC, PLC e LS lists. Each DM has a size of H x NG, which represent the number of periods in the planning horizon and the number of generating units, respectively. The process guarantees that a DM will indicate units to be ON or OFF in a way that the demand constraints from Eqs. (3) and (4) are attended. MDT and MUT requirements are met by activating units following the list. This approach avoids compromising constraints that are already satisfied. Upon attending all constraints and reaching i_{max}, RM is given by the sum of all DMs obtained during the iterative procedure.

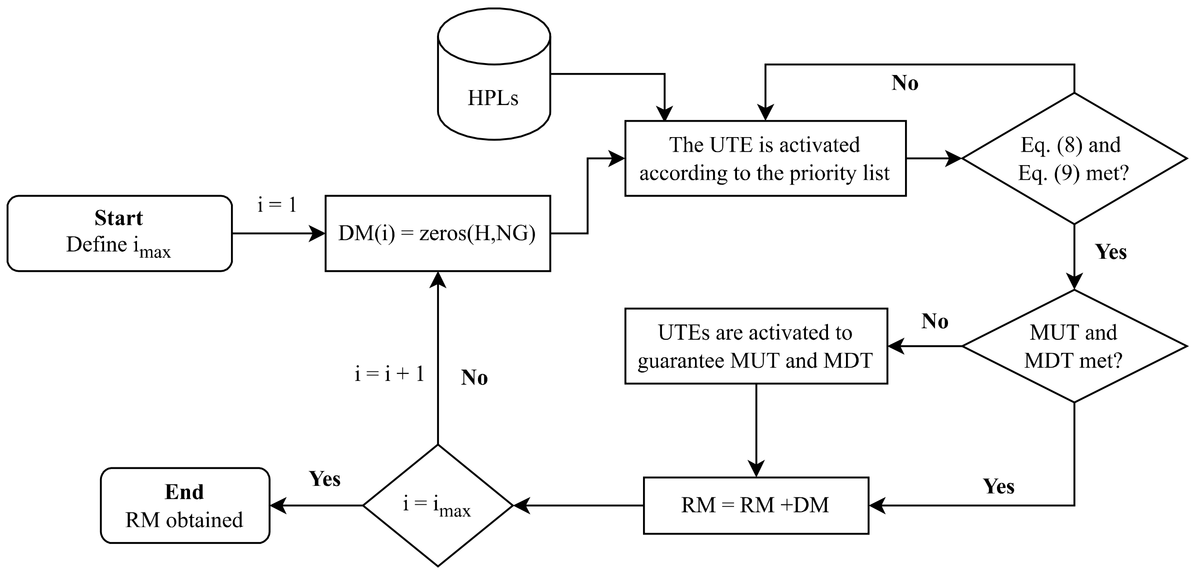

Figure 1. Flowchart of the method

3.2 Relevance matrix indicators

The methodology from Section 3.1 results in a matrix that relates to i_{max} different priority lists. To demonstrate the relevance indicators, a simple theorical case is presented ahead. In this case, i_{max} was taken as equal to 100. The system has 4 generating units to be planned over 4 hours. Figure 2 shows the resulting RM with the relevance indicators.

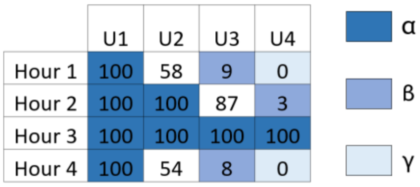

Figure 2. RM example

In Fig. 2, each value corresponds to the number of DMs in which a generating unit was set as ON during a period of the planning horizon. Thus, RM indicates the relevance of each unit at each period according to the HPLs. The relevance levels were classified as α, β and γ. They are described as follows:

- α: indications of high relevance. The unit was ON at the given period for all DMs. This is an indication that such an occurrence is significantly important to attend the constraints.
- β: indications of low relevance. The unit was ON at the given period for 10% or less of the DMs. Such an occurrence has low importance when it comes to attending the constraints. The value of 10% was chosen empirically after many tests.
- γ: indications of no relevance. The unit was OFF at the given period for all DMs. This is an indication that such an occurrence is not important to attend the constraints.

The utilization of the described indicators aims at reducing the number of binary variables in TUC problems, hence also reducing the search space. Such reduction addresses part of the UC subproblem according to Eq. (11).

$$u_{i_h} = \begin{cases} 1, \forall\ \alpha\ units \\ 0, \forall\ \beta\ and\ \gamma\ units \end{cases} \tag{11}$$

By applying Eq. (11), the developed method can decrease the search space of the daily-planned TUC problem, thus attenuating the combinatorial explosion of possible solutions.

4 Case studies

The approach brought in this paper benefits from the reduction scheme previously presented. After the preliminary decision of part of the binary variables based on RM, the remaining binary variables plus the dispatch calculations are solved by a Julia implementation of MOSEK [15]. Three case studies will be presented. The first regards TUC only, i.e., without renewable penetration. The second and third are penetrated by solar and wind generation, respectively, and will be referred to as S-TUC and W-TUC. For all studies, five different applications of the relevance indicators are analyzed: RI-0, no search space reduction; RI-1, only α occurrences are fixed; RI-2, only β occurrences are fixed; RI-3, only γ occurrences are fixed; RI-4, α and γ occurrences are fixed.

The thermal system under analysis is given by the 10 units system from [16]. All required data, such as technical information of the generating units, hourly demands, and power output from renewable sources, are found in [16]. For all studies, i_{max} is equal to 1000. Figure 3 presents the RM for the three cases. Case 1 comprises thermal units only. Cases 2 and 3 add solar and wind systems, respectively.

Thermal RM

	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
Hour 1	1000	1000	40	40	0	0	0	0	0	0
Hour 2	1000	1000	75	75	0	0	0	0	0	0
Hour 3	1000	1000	105	524	361	160	0	0	0	0
Hour 4	1000	1000	512	750	725	285	0	0	0	0
Hour 5	1000	1000	765	944	875	453	0	0	0	0
Hour 6	1000	1000	956	995	1000	496	70	0	0	0
Hour 7	1000	1000	990	1000	1000	607	157	0	0	49
Hour 8	1000	1000	999	1000	1000	693	270	0	37	37
Hour 9	1000	1000	1000	1000	1000	1000	973	111	72	35
Hour 10	1000	1000	1000	1000	1000	1000	1000	1000	102	102
Hour 11	1000	1000	1000	1000	1000	1000	1000	1000	1000	103
Hour 12	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Hour 13	1000	1000	1000	1000	1000	1000	1000	1000	116	116
Hour 14	1000	1000	1000	1000	1000	1000	964	126	85	42
Hour 15	1000	1000	999	1000	1000	531	157	0	33	33
Hour 16	1000	1000	999	1000	1000	425	67	0	0	0
Hour 17	1000	1000	999	1000	1000	312	7	0	0	0
Hour 18	1000	1000	999	1000	1000	411	67	0	0	0
Hour 19	1000	1000	999	1000	1000	546	168	0	40	40
Hour 20	1000	1000	1000	1000	1000	1000	974	1000	105	105
Hour 21	1000	1000	991	1000	1000	1000	996	112	74	34
Hour 22	1000	1000	832	966	967	616	838	0	0	0
Hour 23	1000	1000	72	518	376	128	26	0	0	0
Hour 24	1000	1000	32	31	0	0	0	0	0	0

Solar-Thermal RM

	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
Hour 1	1000	1000	34	34	0	0	0	0	0	0
Hour 2	1000	1000	67	67	0	0	0	0	0	0
Hour 3	1000	1000	101	502	382	153	0	0	0	0
Hour 4	1000	1000	544	762	708	280	0	0	0	0
Hour 5	1000	1000	767	958	880	460	0	0	0	0
Hour 6	1000	1000	958	1000	999	523	87	0	0	0
Hour 7	1000	1000	995	1000	1000	584	153	0	0	34
Hour 8	1000	1000	1000	1000	1000	666	245	0	35	35
Hour 9	1000	1000	1000	1000	1000	870	603	74	33	33
Hour 10	1000	1000	1000	1000	1000	1000	986	81	81	55
Hour 11	1000	1000	1000	1000	1000	1000	1000	1000	119	119
Hour 12	1000	1000	1000	1000	1000	1000	1000	1000	1000	105
Hour 13	1000	1000	1000	1000	1000	1000	992	102	80	33
Hour 14	1000	1000	998	1000	1000	817	495	0	44	44
Hour 15	1000	1000	994	1000	1000	481	74	0	0	34
Hour 16	1000	1000	994	1000	1000	367	4	0	0	0
Hour 17	1000	1000	994	1000	1000	296	4	0	0	0
Hour 18	1000	1000	994	1000	1000	417	77	0	0	0
Hour 19	1000	1000	995	1000	1000	535	183	0	35	35
Hour 20	1000	1000	1000	1000	1000	1000	973	1000	116	116
Hour 21	1000	1000	993	1000	1000	1000	994	140	96	47
Hour 22	1000	1000	829	968	967	636	825	0	0	0
Hour 23	1000	1000	83	500	368	154	27	0	0	0
Hour 24	1000	1000	46	41	0	0	0	0	0	0

Wind-Thermal RM

	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
Hour 1	1000	1000	43	43	0	0	0	0	0	0
Hour 2	1000	1000	89	89	0	0	0	0	0	0
Hour 3	1000	1000	115	115	0	0	0	0	0	0
Hour 4	1000	1000	155	155	0	0	0	0	0	0
Hour 5	1000	1000	194	550	384	151	0	0	0	0
Hour 6	1000	1000	606	903	692	332	0	0	0	0
Hour 7	1000	1000	791	985	856	489	0	0	0	0
Hour 8	1000	1000	900	994	996	594	73	0	0	0
Hour 9	1000	1000	983	1000	1000	692	145	0	0	39
Hour 10	1000	1000	1000	1000	1000	878	511	79	45	45
Hour 11	1000	1000	1000	1000	1000	1000	981	99	58	30
Hour 12	1000	1000	1000	1000	1000	1000	998	124	124	88
Hour 13	1000	1000	999	1000	1000	827	781	68	30	30
Hour 14	1000	1000	972	1000	1000	476	219	0	0	41
Hour 15	1000	1000	868	1000	1000	335	85	0	0	0
Hour 16	1000	1000	864	1000	1000	216	0	0	0	0
Hour 17	1000	1000	864	1000	1000	231	0	0	0	0
Hour 18	1000	1000	864	1000	1000	301	0	0	0	0
Hour 19	1000	1000	878	1000	1000	431	67	0	0	0
Hour 20	1000	1000	989	1000	1000	758	485	75	35	35
Hour 21	1000	1000	928	1000	984	625	520	0	0	33
Hour 22	1000	1000	571	522	523	482	453	0	0	0
Hour 23	1000	1000	199	74	0	67	35	0	0	0
Hour 24	1000	1000	157	40	0	28	0	0	0	0

Figure 3. Relevance matrices for TUC (Case study 1), S-TUC (Case study 2) and W-TUC (Case study 3)

Table 1 provides results obtained by MOSEK given the fixed binary decisions. The table presents the total operational cost (TC), number of branches explored by the optimizer, computational time (T) to achieve the solution, and percentage reduction (PR) regarding the total number of binary operation decision variables. It is emphasized that this analysis concerns the u_{i_h} binary variables only. In other words, the other binary variables are not directly affected by the method.

Table 1. Results for each case of relevance indicators

	RI case	TC ($)	Branches	T (s)	PR (%)
TUC Case study 1	RI-0	563937.7	5843	72.45	0%
	RI-1	563937.7	1277	11.8	44.17%
	RI-2	563937.7	944	6.49	22.08%
	RI-3	563937.7	36	0.58	32.5%
	RI-4	563937.7	23	0.58	76.67%
S-TUC Case study 2	RI-0	549138.6	27051	297.13	0%
	RI-1	549138.6	1455	15.95	40.83%
	RI-2	549138.6	2933	22.28	22.92%
	RI-3	549138.6	109	1.19	35.83%
	RI-4	549138.6	27	0.33	76.67%
W-TUC Case study 3	RI-0	481335.6	2529	47.16	0%
	RI-1	481335.6	1354	19.25	32.5%
	RI-2	481335.6	291	3.88	31.25%
	RI-3	482133.7	61	0.72	42.9%
	RI-4	482554.6	145	0.83	75.4%

Case study 1: Neither solar nor wind penetration was considered. The method reduced the computational time from 72.45s to 0.58s. The operational cost remained the same, meaning that the approach reduced the search space in a way that did not compromise the optimal decisions. The method significantly reduced the number of branches explored until convergence, which affects the computational time needed to achieve the final solution.

Case study 2: By comparting the RMs in Fig. 3, one can notice the relevance reduction for some occurrences when solar power contributes to meet the constraints. For instance, unit 10 at hour 12 went from being highly relevant (α) to being a variable to be decided by MOSEK. Such a fact is due to the solar power added to the thermal generation, which decreased the need for thermal power. The method enabled the optimizer to converge in 0.33s, which is a significant decrease compared to the 297.13s required by the non-reduced case.

Case study 3: wind power penetrates the system by means of two wind turbines. It is noteworthy that the total renewable power is greater than the one in the solar case. Thus, some occurrences became even less relevant, as seen in Fig. 3. For instance, unit 10 at hour 12 now has low relevance (β) and will be fixed by RM, depending on the RI case. In this study, the operational cost further decreased, which is also a consequence of the increased renewable penetration. More precisely, TC is 14.65% lower than the cost from case study 1. Table 1 shows that the RI-2 case achieved the same solution from the non-reduced case, though around 12 times faster. TC is even lower for RI-3 and RI-4. However, these reduction cases compromised the solution quality compared to RI-0.

The best solutions for the 3 presented case studies were compared to other papers from the literature. Table 2 provides such results and demonstrates the applicability and effectiveness of the search space reduction technique presented in this paper.

Table 2. Operational costs ($) comparison among the presented method and other works

Method	TUC	S-TUC	W-TUC
IPL [16]	563985.0	549348.6	485401.5
HHO-IGWO [17]	563937.7	559642.1	522814.4
QI-ADP[18]	563977.0	-	511192.0
RM + MOSEK (Proposed)	**563937.7**	**549138.6**	**481335.6**

5 Conclusions

This paper applied a search space reduction technique to TUC problems considering renewable energy penetration. The obtained results demonstrate the operation cost reduction when solar or wind power are considered. The developed method enabled much faster convergence for all case studies while preserving solutions quality, as shown by the comparison to other works from the specialized literature.

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