Electricity Production Scheduling under Uncertainty: Max Social Welfare vs. Min Emission vs. Max Renewable Production

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Abstract

Some areas in China are facing pressing air pollution problems. Measures from the power sector can be taken to cope with air pollution issues, including reducing emission levels of thermal units and integrating wind and solar power. Social welfare, emission, and renewable integration are three major concerns in modern power system operations. This paper describes three stochastic scheduling models aiming at maximizing social welfare (SW), minimizing emission (EM) and maximizing renewable production (RE). A multi-objective scheduling model (MT) is also proposed that properly balances the above objectives. Wind power uncertainty and dispatchable loads are considered in the model. The outcomes of the three models are compared through an illustrative example and a 57-node case study. Results show that model EM results in 36% of the social welfare of model SW, 27% of its emissions, and 43% of its wind spillage, while model RE results in 55% of the social welfare of model SW, 56% of its emissions and 28% of its wind spillage. Additionally, we analyze how the optimal generation scheduling is affected by the weights in model MT. This work provides insight to policy makers on how to balance social welfare, emissions and renewable production.

Keywords: Generation schedule, emission, renewable integration, social welfare, multi-objective

1. Introduction

1.1. Motivation and Aim

Some areas in China face significant air pollution problems. The power sector contributed 35% of SO₂ emissions and 38% of NO_x emissions in 2014 [1]. Measures are being implemented in the power sector to alleviate this air pollution problem. On one hand, the overall emission characteristics of thermal units have been greatly improved. On the other hand, the capacity of renewable energy, such as wind and solar power, has grown rapidly in the last decade.

Wind power has low marginal cost compared with thermal units, and involves neither air pollution emissions nor CO₂ emissions. Wind power capacity is growing rapidly. However, the stochastic charac-

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10 teristics of wind power increase the possibility of energy curtailment. Wind spillage reached 15% of wind production in China in 2015 [2].

Besides deployment of up/down reserves by thermal units, dispatchable loads provide an appropriate mechanism to deal with uncertainty. Dispatchable loads can be scheduled and re-dispatched like generators to achieve the scheduling objective. Dispatchable loads increase the flexibility of the system, which is helpful
15 in system with high renewable production.

To minimize the operating cost is the main objective for most Independent System Operators (ISO), but nowadays other objectives appear. For some highly-polluted areas, the ISO may seek to minimize emissions to ensure air quality. For areas with high renewable integration, the ISO may seek to maximize renewable production to make electricity production as “green” as possible. These distinct objectives result
20 in different generation scheduling outcomes.

Considering the pressing problems of air pollution and wind curtailment in China, this paper focuses on the comparison of three stochastic scheduling models taking into account wind power uncertainty and dispatchable loads. The objectives are to maximize social welfare, to minimize emissions, and to maximize renewable integration, respectively. A multi-objective scheduling model that properly combines the above
25 objectives is proposed as well. A similar methodology has not been reported in the technical literature. An illustrative example and a 57-node case study are considered to illustrate the proposed models.

1.2. Literature Review

Relevant works pertaining to electricity generation scheduling models with different objectives are reviewed below. Minimizing cost (or maximizing social welfare) is the most common goal [3, 4] in unit
30 commitment problems. Soares et al. [3] formulates a day-ahead generation scheduling model to minimize the cost considering system reserves, and proposes a two-stage optimization method to solve the model. Wang et al. [4] proposes a security-constrained unit commitment model that minimizes cost considering the volatility of wind power generation. Jiang et al. [5] compares maximizing social welfare and minimizing cost in a day-ahead wholesale electricity market considering demand side management. Gent and Lamont
35 [6] propose a dispatch model to minimize NO_x emissions. An optimal power flow model to minimize wind spillage is proposed in [7].

To deal with multiple targets in power system scheduling, multi-objective optimization models are used. Many works co-optimize cost and emission in deterministic or stochastic unit commitment problems [8, 9, 10, 11, 12]. Glotic and Zamuda [8] compare minimizing fuel cost and minimizing emissions in a
40 hydro thermal power system, and formulate a decomposition model to co-optimize these two objectives together. In [9] and [10], similar power generation scheduling models with thermal and hydro units are formulated, and the cost vs. emission curve are provided using Pareto optimality. Sadeghian et al. [11] builds a generation scheduling model with the objective of maximizing profit and minimizing emissions considering heat and electricity supply. A stochastic model with the goal of cost and emission minimization

that considers the uncertainty of wind power and photovoltaic units and market price is proposed in [12]. References [13] and [14] minimize cost and emissions in generation scheduling problems considering wind power uncertainty and demand response. Prebeg et al. [15] focus on the long-term energy planning of the Croatian power system with renewable energy and electric vehicles, and considers the objectives of minimizing the net present value, minimizing the net present value divided by the energy produced, and maximizing the renewable energy production.

Note that generally these objectives conflict with each other and cannot be optimized simultaneously. A variety of methodologies such as the weighted sum method [11], goal programming [16, 17], and ϵ -constrained method [9, 18] can be used to solve multi-objective optimization problems. In the weighted sum method, the decision maker states the relative importance of each objective function with weight factors and then add the weighted objective functions together. In goal programming, the targets are set for all the objectives, and the idea is to minimize the deviation from the goals. In the ϵ -constrained method, one objective is selected, and the other objectives are converted into constraints. Recently, Charitopoulos and Dua [18] propose a unified framework for multi-objective energy optimization considering uncertain parameters, and develop an algorithm based on the ϵ -constrained method to solve it. Trivedi et al. [19] formulates a multi-objective day-ahead thermal generation scheduling model that considers operation cost, emission cost, loss of load probability and expected unserved energy, as objective functions or constraints.

In some works, specific optimal results are not obtained directly, but a Pareto-optimal frontier (or Pareto-optimal set) is obtained [10, 13, 20] instead. Li and Qiu [20] consider a system with hydro power and photovoltaic power and seek to minimize the variance of power output and/or maximizing total energy generated by this renewable energy production system. The Pareto-optimal set is obtained using a modified version of a non-dominated sorting genetic algorithm [21]. Fuzzy decision-making is a methodology used to find the final optimal solution considering the decision maker's preferences about the objectives after a Pareto optimal solution set is obtained [13, 22]. Hozouri et al. [22] uses a fuzzy decision-making method to balance minimum wind energy curtailment, minimum social cost, and maximum energy storage revenue.

Finally, we note that since wind power is stochastic, stochastic unit commitment is generally used in systems with important wind power uncertainty [23, 24, 25, 26, 27].

1.3. Contributions

Contributions of this paper are threefold:

1. To propose a versatile two-stage stochastic scheduling model considering wind power uncertainty and dispatchable loads pursuing three objectives: maximum social welfare, minimum emissions, and maximum renewable energy integration.
2. To formulate a comprehensive multi-objective scheduling model that combines these three objectives.
3. To analyze the generation scheduling results under different government policies.

Note that the novelty of the proposed analysis regarding the interactions of cost vs. emissions vs. renewable-integration in systems with demand flexibility and important renewable penetration. Moreover, we use a rigorous two-stage stochastic programming modeling framework.

1.4. Paper Organization

This paper is organized as follows. Section 2 formulates the stochastic scheduling problems with the three different objectives and a parameterized combination of these objectives. Case studies are provided in section 3. Conclusions are given in section 4.

2. Model Formulation

In this section, the three single-objective models and the multi-objective model are presented. They follow the model structure proposed in [28, 29, 30].

2.1. Notation

Indexes:

i Index of thermal units

j Index of demands

n Index of nodes

p Index of air pollutants, such as SO₂ and NO_x

s Index of scenarios

t Index of time periods

w Index of wind units

Sets:

T Set of time periods

Ω^N Set of nodes

Ω_n^N Set of nodes adjacent to node n

Ω^I Set of thermal units

Ω_n^I Set of thermal units at node n

Ω^J Set of demands

Ω_n^J Set of demands at node n

Ω^L Set of transmission lines

Ω^P Set of air pollutants

Ω^S Set of scenarios

Ω^W Set of wind units

110 Ω_n^W Set of wind units at node n

Variables:

z_{it} On/off status of unit i at time t : 1 if on, 0 if off

y_{it}^{SD} Shut-down indicator of unit i at time t : 1 if shut-down at the beginning of period t , 0 otherwise

y_{it}^{SU} Start-up indicator of unit i at time t : 1 if started-up at the beginning of period t , 0 otherwise

115 D_{jt} Scheduled load of demand j at time t

D_{jts} Load of demand j at time t in scenario s

D_{jts}^{SHED} Load shedding of demand j at time t in scenario s

d_{jts}^D Load decrease of dispatchable demand j during period t and scenario s

d_{jts}^U Load increase of dispatchable demand j during period t and scenario s

120 P_{it} Scheduled power output of unit i at time t

P_{its} Power output of unit i at time t in scenario s

r_{its}^D Down-reserve deployment of unit i at time t in scenario s to comply with wind uncertainty realization

r_{its}^U Up-reserve deployment of unit i at time t in scenario s to comply with wind uncertainty realization

125 W_{wt} Scheduled power output of wind unit w at time t

W_{wts}^{SP} Power spillage of wind unit w at time t in scenario s

θ_{nt} Voltage angle of node n at time t at the scheduling stage

θ_{nts} Voltage angle of node n at time t in scenario s

Parameters:

130 C_i Marginal cost for unit i , \$/MWh

C_w Cost for wind unit w , \$/MWh

C_w^{WSP} “Cost” for wind spillage for unit w , \$/MWh

C_p^{E} Emission fee of pollutant p , \$/kg

D_{jt}^{max} Maximum load of demand j at time t , MW

135 D_{jt}^{min} Minimum load of demand j at time t , MW

E_j^{min} Minimum energy supplied of demand j during the scheduling period, MWh

F_{nr}^{max} Transmission capacity of line $n - r$, MW

$K_j^{\text{D,max}}$ Ramp down limit for demand j , MW

$K_j^{\text{U,max}}$ Ramp up limit for demand j , MW

140 $L_i^{\text{D,max}}$ Ramp down limit for unit i , MW

$L_i^{\text{U,max}}$ Ramp up limit for unit i , MW

P_i^{max} Capacity of unit i , MW

P_i^{min} Minimum power output of unit i , MW

$R_i^{\text{D,max}}$ Maximum down reserve for unit i , MW

145 $R_i^{\text{U,max}}$ Maximum up reserve for unit i , MW

U_{jt} Marginal utility of demand j , \$/MWh

V_j^{LOL} Value of loss of load for demand j , \$/MWh

W_{wts} Wind power forecast of wind w at time t in scenario s , MW

w_f Weight of the conflicting objectives

150 x_{nr} Per-unit reactance of line $n - r$

π_i^{SU} Start-up cost of unit i , \$

ρ_s Probability of scenario s

σ_i^p Emission factor of pollutant p for unit i , kg/MWh

$\sigma_i^{\text{SU},p}$ Start-up emission of pollutant p for unit i , kg

The proposed model is based on the following assumptions:

1. Wind power production is stochastic and represented by a set of possible scenarios.
2. Load is dispatchable within a given range. The range is deterministic.
3. For each demand, there is a minimum energy consumption per day that should be guaranteed.
- 160 4. The marginal utility of every demand, which changes with time, is data.
5. The cost of up/down reserve deployment for thermal units is the same as the cost of energy production.
6. The transmission network is represented using a dc model.

2.3. Formulation

To deal with the stochastic nature of wind power production, the scheduling problem is formulated as
 165 a two-stage stochastic programming model. At the scheduling stage, the on/off status and the scheduling power output of units, and the scheduling load, are decided. At the operation stage, the power output of units and the loads are adjusted according to wind power realization in each scenario. Detailed formulation is provided below.

2.3.1. Objectives

170 We consider three possible objectives:

1. Minimum minus social welfare (maximum social welfare)

$$\min_{\Xi} f_1 = \sum_{t \in T} \sum_{i \in \Omega^I} \pi_i^{\text{SU}} y_{it}^{\text{SU}} + \sum_{t \in T} \sum_{s \in \Omega^S} \rho_s \left[\sum_{i \in \Omega^I} C_i P_{its} \right. \\ \left. + \sum_{w \in \Omega^W} C_w (W_{wts} - W_{wts}^{\text{SP}}) - \sum_{j \in \Omega^J} U_{jt} D_{jts} + \sum_{j \in \Omega^J} V_j^{\text{LOL}} D_{jts}^{\text{SHED}} \right] \quad (1)$$

2. Minimum emissions

$$\min_{\Xi} f_2 = \sum_{t \in T} \sum_{p \in \Omega^P} \sum_{i \in \Omega^I} C_p^E \sigma_i^{\text{SU},p} y_{it}^{\text{SU}} + \sum_{s \in \Omega^S} \rho_s \sum_{t \in T} \left[\sum_{p \in \Omega^P} \sum_{i \in \Omega^I} C_p^E \sigma_i^p P_{its} + \sum_{j \in \Omega^J} V_j^{\text{LOL}} D_{jts}^{\text{SHED}} \right] \quad (2)$$

3. Minimum wind spillage (maximum renewable integration)

$$\min_{\Xi} f_3 = \sum_{s \in \Omega^S} \rho_s \sum_{t \in T} \left[\sum_{w \in \Omega^W} C_w^{\text{WSP}} W_{wts}^{\text{SP}} + \sum_{j \in \Omega^J} V_j^{\text{LOL}} D_{jts}^{\text{SHED}} \right] \quad (3)$$

Cost for generator start-up and operation and the utility of demand are considered in objective (1). The social welfare is defined as the total utility of loads minus the total cost of generation and the cost of load shedding [5, 31, 32]. f_1 in Equation (1) is the minus social welfare to be minimized. Cost for generator

start-up and operation emissions is considered in objective (2). Cost for wind spillage is considered in
 175 objective (3). Load shedding cost is considered in every objective. Since each objective to be minimized is
 in dollars, the objective function of the multi-objective model is represented by the convex combination of
 the three single-objectives.

$$\min_{\Xi} \quad w_1 f_1 + w_2 f_2 + w_3 f_3 \quad (4)$$

where $w_1 + w_2 + w_3 = 1, w_f \geq 0, f = 1, 2, 3$.

2.3.2. Constraints at Scheduling Stage

$$z_{i,t-1} + y_{it}^{\text{SU}} - y_{it}^{\text{SD}} - z_{it} = 0, \quad \forall i \in \Omega^{\text{I}}, \forall t \in T \quad (5a)$$

$$y_{it}^{\text{SU}} + y_{it}^{\text{SD}} \leq 1, \quad \forall i \in \Omega^{\text{I}}, \forall t \in T \quad (5b)$$

$$\sum_{i \in \Omega_n^{\text{I}}} P_{it} + \sum_{w \in \Omega_n^{\text{W}}} W_{wt} - \sum_{j \in \Omega_n^{\text{J}}} D_{jt} + \sum_{r \in \Omega_n^{\text{N}}} \frac{1}{x_{nr}} (\theta_{rt} - \theta_{nt}) = 0, \quad \forall n \in \Omega^{\text{N}}, \forall t \in T \quad (5c)$$

$$z_{it} P_i^{\min} \leq P_{it} \leq z_{it} P_i^{\max}, \quad \forall i \in \Omega^{\text{I}}, \forall t \in T \quad (5d)$$

$$\sum_{t \in T} D_{jt} \geq E_j^{\min}, \quad \forall j \in \Omega^{\text{J}} \quad (5e)$$

$$\theta_{\text{ref},t} = 0, \quad \forall t \in T \quad (5f)$$

$$z_{it}, y_{it}^{\text{SU}}, y_{it}^{\text{SD}} \in \{0, 1\}, \quad \forall i \in \Omega^{\text{I}}, \forall t \in T \quad (5g)$$

180 Constraints (5a) and (5b) model on/off status changes. Constraint (5c) enforces the power balance at
 each node. Constraint (5d) enforces the power output range of production units. Constraint (5e) regulates
 the energy consumption level. Constraint (5f) defines the reference angle. Constraint (5g) specifies binary
 variables.

2.3.3. Constraints at Operation Stage

$$\begin{aligned} & \sum_{i \in \Omega_n^{\text{I}}} (r_{its}^{\text{U}} - r_{its}^{\text{D}}) + \sum_{w \in \Omega_n^{\text{W}}} (W_{wts} - W_{wt} - W_{wts}^{\text{SP}}) - \sum_{j \in \Omega_n^{\text{J}}} (d_{jts}^{\text{U}} - d_{jts}^{\text{D}} - D_{jts}^{\text{SHED}}) \\ & + \sum_{r \in \Omega_n^{\text{N}}} \frac{1}{x_{nr}} [(\theta_{rts} - \theta_{nts}) - (\theta_{rt} - \theta_{nt})] = 0, \quad \forall n \in \Omega^{\text{N}}, \forall t \in T, \forall s \in \Omega^{\text{S}} \end{aligned} \quad (6a)$$

$$z_{it} P_i^{\min} \leq P_{its} \leq z_{it} P_i^{\max}, \quad \forall i \in \Omega^{\text{I}}, \forall t \in T, \forall s \in \Omega^{\text{S}} \quad (6b)$$

$$-L_i^{\text{D},\max} \leq P_{its} - P_{i,t-1,s} \leq L_i^{\text{U},\max}, \quad \forall i \in \Omega^{\text{I}}, \forall t \in T, \forall s \in \Omega^{\text{S}} \quad (6c)$$

$$-K_j^{\text{D},\max} \leq D_{jts} - D_{j,t-1,s} \leq K_j^{\text{U},\max}, \quad \forall j \in \Omega^{\text{J}}, \forall t \in T, \forall s \in \Omega^{\text{S}} \quad (6d)$$

$$\sum_{t \in T} D_{jts} \geq E_j^{\min}, \quad \forall j \in \Omega^{\text{J}}, \forall s \in \Omega^{\text{S}} \quad (6e)$$

$$-F_{nr}^{\max} \leq \frac{1}{x_{nr}}(\theta_{nts} - \theta_{rts}) \leq F_{nr}^{\max}, \quad \forall (n, r) \in \Omega^L, \forall t \in T, \forall s \in \Omega^S \quad (6f)$$

$$\theta_{\text{ref},ts} = 0, \quad \forall t \in T, \forall s \in \Omega^S \quad (6g)$$

$$D_{jt}^{\min} \leq D_{jts} \leq D_{jt}^{\max}, \quad \forall j \in \Omega^J, \forall t \in T, \forall s \in \Omega^S \quad (6h)$$

$$0 \leq D_{jts}^{\text{SHED}} \leq D_{jt}, \quad \forall j \in \Omega^J, \forall t \in T, \forall s \in \Omega^S \quad (6i)$$

$$0 \leq W_{wts}^{\text{SP}} \leq W_{wts}, \quad \forall w \in \Omega^W, \forall t \in T, \forall s \in \Omega^S \quad (6j)$$

$$0 \leq r_{its}^{\text{U}} \leq R_i^{\text{U},\max}, \quad \forall i \in \Omega^I, \forall t \in T, \forall s \in \Omega^S \quad (6k)$$

$$0 \leq r_{its}^{\text{D}} \leq R_i^{\text{D},\max}, \quad \forall i \in \Omega^I, \forall t \in T, \forall s \in \Omega^S \quad (6l)$$

Constraint (6a) is the power balance constraint. Constraint (6b) enforces the power output feasible ranges. Constraint (6c) imposes ramping limits for units. Constraint (6d) imposes ramping limits for loads. The minimum daily supplied energy $E_j^{\min}$ is enforced by constraint (6e). Constraint (6f) enforces transmission limits. Constraint (6g) defines the reference angle for each operating condition. Constraints (6i)-(6l) impose bounds on load shedding, wind spillage and reserve deployment.

2.3.4. Linking Constraints

$$P_{its} = P_{it} + r_{its}^{\text{U}} - r_{its}^{\text{D}}, \quad \forall i \in \Omega^I, \forall t \in T, \forall s \in \Omega^S \quad (7a)$$

$$D_{jts} = D_{jt} + d_{jts}^{\text{U}} - d_{jts}^{\text{D}}, \quad \forall j \in \Omega^J, \forall t \in T, \forall s \in \Omega^S \quad (7b)$$

Constraint (7) links generator power outputs and load at operation and scheduling stages.

The set of the decision variables is $\Xi = \{z_{it}, y_{it}^{\text{SU}}, y_{it}^{\text{SD}}, P_{it}, P_{its}, r_{its}^{\text{U}}, r_{its}^{\text{D}}, W_{wt}, W_{wts}^{\text{SP}}, D_{jt}, D_{jts}, D_{jts}^{\text{SHED}}, d_{jts}^{\text{U}}, d_{jts}^{\text{D}}, \theta_{nt}, \theta_{nts}\}$.

2.4. Computational Complexity

Table 1: Size of formulation

	Number
Binary Vars.	$3 \Omega^I T $
Continuous Vars.	$(1 + 3 \Omega^S) \Omega^I T + (1 + \Omega^S)(\Omega^N + \Omega^W) T + (1 + 4 \Omega^S) \Omega^J T $
Scheduling Cons.	$(4 \Omega^I + \Omega^N) T + \Omega^J $
Operation Cons.	$(\Omega^N + 4 \Omega^I + 2 \Omega^J + \Omega^L) T \Omega^S + \Omega^J \Omega^S $
Linking Cons.	$(\Omega^I + \Omega^J) T \Omega^S $

Problem (1)-(7) is a Mixed-integer Linear Programming (MILP) problem. The size of this problem is provided in Table 1, where $|\Omega|$ represents the cardinality of set Ω . This problem can be solved using standard optimization software, such as CPLEX [33].

3. Case Studies

To test the proposed model, an illustrative 2-node example and a 57-node case study are considered in this section.

3.1. Illustrative Example

3.1.1. Data

First we consider the 2-node example shown in Fig. 1. This example includes 3 time periods and 2 scenarios. Only SO₂ emissions are considered. Generation parameters are provided in Table 2. Load ranges and utilities are provided in Table 3. The value of loss of load is \$200/MWh. There are two scenarios with probabilities 0.6 and 0.4, respectively. Scenario *s*₁ has higher wind production than scenario *s*₂, as provided in Table 4. Costs of wind power and wind spillage are \$3/MWh. Emission cost for SO₂ is \$1/kg. The transmission line has a reactance of 0.13 p.u., and a capacity of 50 MW. The three models are referred to as SW (maximum social welfare), EM (minimum emission) and RE (maximum renewable energy). The comprehensive model is referred to as MT.

Figure 1: 2-node system.

Table 2: Unit parameters

Unit	<i>i</i> 1	<i>i</i> 2	<i>i</i> 3
$P_i^{\max}$ (MW)	50	110	100
$P_i^{\min}$ (MW)	10	10	5
C_i (\$/MWh)	10	30	35
$R_i^{U,\max}$ (MW)	10	22	20
$R_i^{D,\max}$ (MW)	10	22	20
π_i^{SU} (\$)	0	0	0
$\sigma_i^{SO_2}$ (\$/kg)	8	12	3
$L_i^{U,\max}$ (MW/h)	10	20	60
$L_i^{D,\max}$ (MW/h)	10	20	60

Table 3: Load parameters (MW)

Load Range(MW)			Marginal Utility(\$/MWh)	
	D_1	D_2	D_1	D_2
$t1$	32-48	80-120	40	15
$t2$	20-30	64-96	25	30
$t3$	36-54	76-114	35	40

Table 4: Wind power forecast (MW)

	$s1$ High	$s2$ Low
$t1$	50	10
$t2$	75	30
$t3$	35	15

Table 5: Total cost, emissions, wind spillage and load shedding using each model

Model		Social Welfare (\$)	Demand Utility (\$)	Cost (\$)	Emissions (kg)	Wind Spillage (MWh)	Demand Supplied (MWh)	Load Shedding (MWh)
exp.	SW	5,261	12,588	7,327	1,806	21	403	0
	EM	2,560	11,465	8,905	988	3	385	0
	RE	2,339	11,969	9,630	1,198	0	395	0
	MT	5,142	12,105	6,963	1,574	20	389	0
$s1$	SW	6,035	12,840	6,805	1,716	35	410	0
	EM	3,685	11,450	7,765	840	5	385	0
	RE	3,825	12,365	8,540	1,064	0	402	0
	MT	5,904	12,105	6,201	1,456	33	389	0
$s2$	SW	4,100	12,210	8,110	1,941	0	392	0
	EM	835	11,450	10,615	1,210	0	385	0
	RE	110	11,375	11,265	1,400	0	385	0
	MT	4,000	12,105	8,105	1,752	0	389	0

3.1.2. Results

The total expected and per scenario social welfare, demand utility, cost, emission, wind spillage, demand supplied, and load shedding are provided in Table 5. Model SW results in the highest social welfare (total demand utility minus total expected cost), but highest emissions and wind spillage among all the models. The higher wind scenario results in lower cost under each model. However, wind integration can be expensive, as we can see from the high cost under model RE. Model MT, with weights (0.2, 0.3, 0.5), provides intermediate results in social welfare, emissions and wind spillage, but the lowest cost.

The power outputs from each model are provided in Table 6. Power flows for the four models are provided in Table 7. The most polluting unit, $i2$, is not committed if model EM is used. Although expensive, unit $i3$ is committed even if model SW is used due to the congestion in the transmission line.

The lowest load and highest wind happen simultaneously at time $t2$, when wind spillage appears as provided by Table 9. Under model RE, unit $i1$ and $i2$ are both shut down at time $t2$ to accommodate wind power at the same node.

Results of load at the scheduling and operation levels from each model are provided in Table 8. Generally, load flexibility helps. Loads are high at nodes where the marginal utility is higher than the marginal cost if model SW is used. If model EM is used, the peak load tends to be curtailed and the valley load tends to increase, to reduce the peak emissions during peak load. If model RE is used, loads increases to their maximum to accommodate increasing amounts of wind power until wind spillage drops to zero.

Table 6: Power outputs from each model(MW)

Time		Schedule			Operation					
		i1	i2	i3	i1		i2		i3	
					s1	s2	s1	s2	s1	s2
SW	t1	48	0	48	48	50	0	0	30	68
	t2	40	0	30	40	50	0	0	34	34
	t3	50	19	64	50	50	19	20	64	65
EM	t1	14	0	84	10	14	0	0	64	100
	t2	10	0	66	10	10	0	0	46	86
	t3	10	0	100	10	20	0	0	90	100
RE	t1	10	20	69	10	10	20	20	49	89
	t2	0	0	71	0	0	0	0	51	91
	t3	0	12	100	0	0	12	20	100	100
MT	t1	48	0	48	48	50	0	0	30	68
	t2	40	0	32.5	38	50	0	0	32.5	32.5
	t3	48	0	65.5	48	50	0	0	65.5	83.5

Table 7: Power flow from $n1$ to $n2$ (MW)

	SW		EM		RE		MT	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$t1$	50	12	28	-8	36	8	50	12
$t2$	50	50	50	10	45	3.5	50	50
$t3$	50	49	-3	-13	11	-16.5	47	29

Table 8: Load from each model(MW)

Time		Schedule		Operation			
		$j1$	$j2$	j^1		j^2	
				$s1$	$s2$	$s1$	$s2$
SW	$t1$	48	80	48	48	80	80
	$t2$	30	84	30	30	84	84
	$t3$	54	114	54	36	114	114
EM	$t1$	32	92	32	32	92	92
	$t2$	30	96	30	30	96	96
	$t3$	48	87	48	48	87	87
RN	$t1$	32	80	44	32	85	97
	$t2$	20	64	30	26.5	96	94.5
	$t3$	36	76	36	51.5	111	83.5
MT	$t1$	48	80	48	48	80	80
	$t2$	30	82.5	30	30	82.5	82.5
	$t3$	36	112.5	36	36	112.5	112.5

Table 9: Wind power schedule and spillage (MW)

Wind Schedule					Wind Spillage							
SW	EM	RN	MT		SW		EM		RN		MT	
					$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$t1$	32	26	13	32	0	0	0	0	0	0	0	0
$t2$	40	50	13	40	35	0	5	0	0	0	33	0
$t3$	35	25	0	35	0	0	0	0	0	0	0	0

3.1.3. Weights of the Comprehensive Model

In multi-objective optimization problems, the weights are set to ensure appropriate policy objectives. Since the proposed three single-objective models can be regarded as particular cases of the MT model, different weight combinations are possible. Weights (0.2, 0.3, 0.5) above provides an example. To find out how weights affect the optimal scheduling results, every possible combination of weights with a step size of 0.04 are tested in this subsection.

Results are depicted in Fig. 2, where each dot represents an optimal solution under a set of weights. The weights are represented by the distance from the point to the corresponding edge of the equilateral triangle, as illustrated in Fig. 3. The color of the dot provides the relative value of the key performance indicators (KPIs), where blue means the lowest and red means the highest, as shown in Fig. 2(g). See

Figure 2: KPIs under different weights.

Figure 3: Illustration of the weights.

Table 5 for the ranges of actual values.

Optimal results under all the possible weights form the Pareto optimal set of the three objectives. Fig. 4 depicts the relationship among social welfare, cost and emission under different wind spillage levels. Allowing higher wind power spillage generally yields higher social welfare, but higher emissions as well. There is a non-trivial trade-off among wind power spillage, emissions, and social welfare. A medium level of wind power spillage is advisable to balance emissions and social welfare. Since generally there are multiple optimal solutions, especially for the 'zero wind spillage' cases, some points may deviate from the general trend. Using a multi-objective model with small weights on secondary objectives instead of single-objective models mitigates this issue.

(a) Social Welfare vs. Emissions

(b) Cost vs. Emissions

Figure 4: Social welfare, cost, emission and wind spillage.

Since the weights affect the optimization results, they should be carefully selected. From the perspective of goal planning, one may set the weights according to the KPIs of the optimization results and the expected KPIs. For example, if the system operator would like to keep the social welfare above a certain level, then an available area can be specified in Fig. 2(a). Similarly, another appropriate area can be selected in Fig. 2(d). A feasible set of weights can be obtained by overlapping the KPI triangles and taking the intersection of the available areas of each triangle. The corresponding values or weights are then set according to the government policies.

3.2.1. Data

The IEEE 57-node system [34] is used to compare the proposed models. 24-hour load curves based on some areas of PJM on 7/30/2014 [35] are adopted. The peak load is 2,000 MW, and the valley load is 1,197 MW. The average marginal load utility in each hour is depicted in Fig. 5. The generation mix includes 10 coal-fired units, 6 gas-fired units and 1 wind unit. Parameters of the thermal units come from [36] and [37], and are provided in Table 10. The total thermal capacity is 3,229 MW. 10 wind production scenarios are generated using the model in [38].

Figure 5: Average marginal demand utility.

Table 10: Data of thermal units

Unit	Fuel	Node	$P_i^{\max}$ (MW)	$P_i^{\min}$ (MW)	C_i (\$/MWh)	π_i^{SU} (\$)	$\sigma_i^{\text{NO}_x}$ (kg/MWh)	$\sigma_i^{\text{SO}_2}$ (kg/MWh)	$\sigma_i^{\text{SU,NO}_x}$ (kg)	$\sigma_i^{\text{SU,SO}_2}$ (kg)
$i1$	gas	$n1$	49.3	10	47.9	478.7	0.404	0.003	0.404	0.003
$i2$	coal	$n2$	403.7	200	24.3	1,166.9	2.326	4.730	4.652	9.461
$i3$	coal	$n3$	236	140	25.2	1,208.2	1.499	1.181	11.990	2.363
$i4$	coal	$n6$	200	56	26.2	1,259.5	2.459	8.810	4.918	17.621
$i5$	coal	$n8$	299.2	110	21.7	1,041.7	1.997	12.818	3.993	25.637
$i6$	gas	$n9$	170	111	47.0	469.8	0.165	0.003	0.165	0.003
$i7$	gas	$n12$	107	6	55.6	556.0	0.410	0.004	0.410	0.004
$i8$	coal	$n13$	125	50	25.6	1,230.6	0.898	0.365	1.796	0.731
$i9$	coal	$n17$	125	50	25.2	1,210.6	1.036	0.293	2.072	0.586
$i10$	coal	$n19$	725.9	225	25.4	1,221.5	0.775	0.650	1.549	1.301
$i11$	coal	$n23$	81.6	40	25.8	1,236.2	0.975	3.554	1.951	7.108
$i12$	coal	$n29$	163.2	65	23.4	1,122.2	3.396	11.402	6.792	22.803
$i13$	gas	$n31$	121	65	52.7	526.8	0.210	0.004	0.210	0.004
$i14$	gas	$n37$	173.4	95	32.4	323.9	0.036	0.002	0.144	0.002
$i15$	gas	$n43$	173.4	95	31.3	313.5	0.040	0.002	0.161	0.002
$i16$	coal	$n53$	75	25	24.7	1,186.5	0.722	2.385	1.444	4.770

3.2.2. Results

The summary of the simulation results is provided in Table 11. Model SW results in the highest social welfare, the highest demand utility, the lowest cost, the highest demand supplied, and the highest emissions. Model EM has the lowest demand supplied to reduce emission. Compared with model SW, model EM results in 73% reduction in emissions, but a reduction in social welfare of 64%. Wind spillage in model EM is lower than that in model SW. Model RE results in the lowest wind spillage. The social welfare and emissions range from those from model SW and those from model EM. Model MT, with the weights $(w_{SW}, w_{EM}, w_{RE}) = (0.05, 0.4, 0.55)$, provides intermediate results.

Table 11: Key Performance Indicators using each model

Model	Social Welfare (\$)	Demand Utility (\$)	Cost (\$)	Emissions (kg)	Wind Spillage (MWh)	Demand Supplied (MWh)	Solution Time (sec.)	Relative Gap
SW	840,555	1,782,032	941,477	60,449	1,191	40,686	14	0.00055
EM	299,135	1,538,529	1,239,394	16,196	516	39,315	601	0.00003
RE	462,332	1,658,018	1,195,685	34,048	339	39,992	494	0.00086
MT	782,410	1,766,647	984,238	33,376	679	40,263	61	0.00067

Figure 6: Scheduled demand supply: SW vs. EM vs. RE.

The scheduled demand from each model is depicted in Fig. 6, where the dash lines are the maximum and minimum dispatchable loads, and the solid lines are demand supplied at schedule level. Dispatchable loads play an important role to achieve the goal in each optimization model. In model SW, load moves up and down with the marginal utility to maximize social welfare. Since the marginal emission goes up with the load, a *flat* load curve is good for low emissions while complying with the minimum energy consumption constraint. Using model RE, the load adapts to wind production to accommodate more and more renewable energy.

Fig. 7 depict the generation scheduling in the three models by energy type. The cheap coal-fired units produce more energy if model SW is used, while cleaner gas-fired units produce at their maximum if model EM is used. Coal- and gas-fired units as well as the dispatchable loads coordinate to accommodate wind power if model RN is used. Note that the scheduled wind power in (5c) is usually used to get price [39],

Figure 7: Power outputs: SW vs. EM vs. RE.

Figure 8: Average wind power production.

and it is different from the actual wind production (see Fig. 8).

The models are coded in GAMS [40], solved by CPLEX 12.6 and implemented on a laptop with 2.5 GHz CPU and 16 GB of RAM. The models have 61,921 equations, 1,152 binary variables and 89,086 continuous variables. The calculation time and accuracy are listed in Table 11. They may vary among different objectives.

4. Conclusions

This paper compares three stochastic generation scheduling models that seek to maximize social welfare, to minimize emissions, or to minimize wind power spillage. The proposed framework allows analyzing generation scheduling results under different policies, particularly those related to the Chinese government. Conclusions are listed below:

1. Model SW results in the highest social welfare, attained by increasing demand utility and reducing cost. Specifically, the flexible load increases at high utility hours. Model SW may lead to 3.7 times higher emissions and 3.5 times higher wind spillage than the emissions and wind spillage of models EM and RE, respectively.
2. Model EM results in 27% of the emissions of the SW model, 36% of its social welfare, 132% of its cost, 97% of its demand supplied and 43% of its wind spillage.

3. Model RE results in 56% of the emissions of the SW model, 55% of its social welfare, 126% of its cost, 98% of its demand supplied and 28% of its wind spillage. Note that the demand adapts to variations of wind power production in this model.
4. Model MT provides balanced results as compared to any of the single objective models. It results in 93% of the social welfare of the SW model, 55% of its emissions and 57% of its wind spillage.
5. The weights of model MT, set according to system operator's or government's policies, results in an optimal generation scheduling that balances the objectives. A method to set appropriate weights according to KPI targets is proposed.
6. It is sensible to conclude the following: In highly polluted and populated regions, the weight of the emission term should be comparatively high. In power systems with significant wind power, the weight of the wind spillage term should be comparatively high. Generally, weights should be chosen carefully since their marginal impact decreases as emissions or wind spillage decreases, or social welfare increases.

Finally, we point out that this paper proposes a method to analyze scheduling models with different objectives. Specific conclusions generally depend on the characteristics of the power system under study.

Acknowledgments

The authors would like to thank the following funding supports. Z. Geng is partly supported by China Scholarship Council. A. J. Conejo is partly supported by NSF award 1548015. Q. Chen is partly supported by the NSF of China grant 51622705, Fok Ying Tung Education Foundation award 151057 and Beijing New-star Plan of Science and Technology. Q. Xia is partly supported by the NSF of China grant 51537005. C. Kang is partly supported by the NSF of China grant 51325702.

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