WDO Based Security Constrained Unit Commitment with Flexible Set for Variable Wind Power

M.Sumathy, A.Gnana Saravanan, S.Murugan and A.Amala Manuela

***Abstract*-Power system operation has witnessed great challenges due to the large-scale integration of wind power. In this project, a two-stage robust security constrained unit commitment (SCUC) model is proposed for managing the wind power uncertainty in the hourly power system scheduling. Different from most existing works on robust SCUC, the flexible uncertainty set for wind power is taken into account, rather than the predefined deterministic one. The proposed method does not only pay attention to the feasible and economic operations within the flexible sets but also consider the risk in wind spillage or load curtailment out of them. It makes a better trade-off between wind power absorption and the economic grid operation, as well as obtaining feasible dispatch schedules. The proposed model and the corresponding solution method have been verified by several case studies in the modified IEEE systems. The results demonstrate the merits of the proposed solution method for managing large variations in the available wind power and lowering the overall cost of power system operations in an uncertain environment. The influence factors are also discussed such as the flexible resource and transmission capacity.**

***Index Terms*—Fuzzy Energy, Renewable Energy, ANFIS function, tow stage robust model.**

I. INTRODUCTION

Wind power, a renewable and virtually inexhaustible power source, is a promising means of green energy production. Currently, wind power is not in wide use and accounts for the production of only 1% of energy used world-wide. The wind power industry has experienced continued growth in the past year. Wind power is basically converted solar power. As the sun heats the earth, land masses and oceans, are heated in varying degrees as they absorb and reflect heat at different rates. This causes portions of the atmosphere to warm differently and as hot air rises, atmospheric pressure causes cooler air to replace it. The resulting movement in the air is wind. The kinetic energy of wind is converted by turbine bladeswhich drive a generator to produce electrical energy. Wind power can be harnessed using wind turbines grouped together on wind farms, located either on land or offshore, for large-scale production. Wind power generation varies in size from small generators which produce sufficient electrical power for a small farm to wind farms which can generate power for thousands of households.

The combination of the (already, many) traditional forms of UC problems with the several (old and) new forms of uncertainty gives rise to the even larger family of Uncertain Unit Commitment (UUC) problems, which are currently at the frontier of applied and methodological research.

Unit commitment (UC) is an optimization problem used to determine the operation schedule of the generating units at every hour interval with varying loads under different constraints and environments. Many algorithms have been invented in the past five decades for optimization of the UC problem, but still researchers are working in this field to find new hybrid algorithms to make the problem more realistic. The importance of UC is increasing with the constantly varying demands. Therefore, there is an urgent need in the power sector to keep track of the latest methodologies to further optimize the working criterions of the generating units. This paper focuses on providing a clear review of the latest techniques employed in optimizing UC problems for both stochastic and deterministic loads, which has been acquired from many peer reviewed published papers. It has been divided into many sections which include various constraints based on profit, security, emission and time.

Some additional efforts are made in earlier works on devising variable uncertainty sets. The work in considers a series of uncertainty sets and decision-makers choose one of the uncertainty sets for determining the power system operation plan. Such variable sets are not sufficiently flexible for the set candidates are rather limited and discrete. The same problem also exists for the multi-band uncertainty set adopted in, where the original sets are divided into several sub-parts indexed by discrete variables.

II. RELATED WORK

In M. Lubin, and S. Backhaus et al.,[1] proposed an Optimal Power Flow (OPF) dispatches controllable generation at minimum cost subject to operational constraints on generation and transmission assets. The uncertainty and variability of intermittent renewable generation was challenging current deterministic OPF approaches. The RCC OPF was solved using a cutting-plane algorithm that scales to large power systems. Deterministic, chance constrained (CC), and RCC OPF formulations were compared using several metrics including cost of generation, area control error, ramping of controllable generators, and occurrence of transmission line overloads as well as the respective computational performance.

Wang, F. et al., [2] presenteda risk-based admissibility assessment approach was proposed to quantitatively evaluate how much wind generation can be accommodated by the bulk power system under a given unit commitment (UC) strategy. First, the operational risk brought by the variation and uncertainty of wind generation was developed as an admissibility measure of wind generation. Then its linear approximation is derived for practical implementation. Furthermore, a risk-minimization model is established to mathematically characterize the admissible region of wind generation.

Zhang, et al., [3]develop a unified framework for studying constrained robust optimal control problems with adjustable uncertainty sets. In contrast to standard constrained robust optimal control problems with known uncertainty sets, the authors treat the uncertainty sets in our problems as additional decision variables. In particular, given a finite prediction horizon and a metric for adjusting the uncertainty sets, we address the question of determining the optimal size and shape of the uncertainty sets, while simultaneously ensuring the existence of a control policy that will keep the system within its constraints for all possible disturbance realizations inside the adjusted uncertainty set.

Hu and L. Wu, et al., [4] discusses a multi-band robust security- constrained unit commitment (SCUC) model for addressing spatial/temporal relationship of nodal load uncertainties. Case studies show that the proposed multi-band model derives less conservative robust solutions while maintaining the same solution robustness as compared to the single-band model in literature.

Y.An and B. Zeng et al., [5] to explore and extend the modeling capacity of two-stage robust optimization and present two new robust unit commitment variants: the expanded robust unit commitment and the risk constrained robust unit commitment model.

III. SYSTEM IMPLEMENTATION

Based on above robust optimization theories, this project establishes a Robust Optimization with Security-Constrained Unit Commitment (SCUC) model for variable wind power based on Wind Driven Optimization Algorithm (WDO) that is coordinating reliability and economy. The concept of uncertainty budget is introduced for making up for the deficiency of conventional robust optimization of conservation. The uncertain domain can be enlarged or condensed by adjusting uncertainty set so as to control robust optimization solution flexibly.First, it is an extension the conventional robust SCUC (not the distributionally robust one) and highly compatible with the original one. It has taken into account the flexible uncertainty sets and corresponding risks. But if the grid is with abundantly cheap flexible resource, the solution of the proposed model will naturally be that of the original one. Secondly, the risks of wind spillage/load curtailment are evaluated by the corresponding energy cost rather than normalized in terms of the membership functions in fuzzy optimization. It would be convenient to balance them with the generation cost and adjust the balance by properly modifying the penalty price.

Moreover, this work derives an uncertainty decision making method based on the built optimization dispatch model to avoid blindness of uncertainty decision. Because the established WDO optimization dispatch model includes variables with high dimensions and is nonlinear while has the characteristic of uncertainty, it is difficult to solve and demands more in optimization algorithm. Classical optimization algorithms, e.g., Particle Swam Optimization, Genetic Algorithm, and comprehensive learning particle swarm optimization (CLPSO). It has been found to be an effective technique in improving the performance of some established algorithms such as Invasive Weed Optimization (IWO), with simple procedures and explicit results, are not suited for the above mentioned highly complex robust optimization dispatch problem anymore because their derivations are based on local information and their results would inevitably converge to local extreme value.

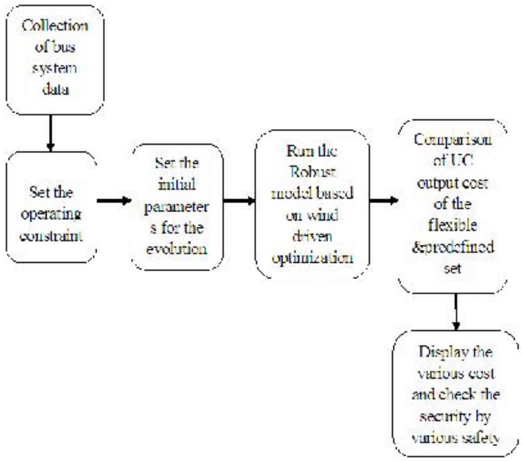

Figure 3.1: Block Diagram of the Proposed System

In the first block the bus system data are collected. In the second block operating constraints are assigned. In here the operating constraints are Fuel start-up costs, Fuel shut-down costs, Minimum on/off time, Generation capacity constraints, Ramping capacity constraints, Power balance constraints, Transmission capacity. From the operating constraints set the initial parameter for evolutionary algorithm. Here the initial parameters are Max no of iterations, Population size, Gravitational constant, Coriolis constant, Maximum allowed speed and RT constant. Then run the WDO. The cost comparison of flexible and predefined sets are obtained in this block. At the final block display the various cost and the SCUC is obtained by various safety factors.

1. OBJECTIVE FUNCTION

The objective function minimizing the base-case operation cost is considered here, to provide an economic base-case operation plan, as shown in (3.1). It consists of the fuel, start-up and shut-down costs. The fuel cost function is usually in the linear form or can be linearized for computation purpose.

$\min \sum_{t} \sum_{gi} [c_{gi}\, p^{b}_{gi,t} + su_{gi}\, z_{gi,t} + sd_{gi} y_{gi,t}]$ (3.1)

(i) FIRST-STAGE CONSTRAINTS

The following constraints are placed onto the base-case operation, including the minimum on/off time (3.2)-(3.5), the generation capacity (3.6), the ramping capacity (3.7)-(3.8), the power balance (3.9) and the transmission capacity (3.10). The wind power is usually assumed to be their expectations at the first stage.

$-u_{gi,t-1}+u_{gi,t}-z_{gi,t}\le 0$ ----------(3.2)

$u_{gi,t-1}-u_{gi,t}-y_{gi,t}\le 0$ ----------(3.3)

$\sum_{\tau-m(0,t-M_{gi}+1)}^{t} z_{gi,\tau} \le u_{gi,t}$-------(3.4)

$\sum_{\tau-m(0,t-M_{gi}+1)}^{t} y_{gi,\tau} \le u_{gi,t}$-----(3.5)

$p_{gi,min}u_{gi,t}\le p^{b}_{gi,t}\le p_{gi,max}u_{gi,t}$ ----------(3.6)

$p^{b}_{gi,t}-p^{b}_{gi,t-1}\le UR_{gi}u_{gi,t-1}\Delta t+p_{gi,min}z_{gi,t}$ ----------(3.7)

$p^{b}_{gi,t-1}-p^{b}_{gi,t}\le DR_{gi}u_{gi,t}\Delta t+p_{gi,min}y_{gi,t-1}$ ----------(3.8)

$\sum_{gi} p_{gi,t} + \sum_{wi} ew_{wi,t} - \sum_{i} L_{i,t}=0$ ----------(3.9)

$-F_{l,max}\le \sum_{gi} л_{l,gi}\, p^{b}_{gi,t}+\sum_{wi} л_{l,wi}e_{wi,t} - \sum_{i} л_{l,i}L_{i,t}\le F_{l,max}$ 3.10)

(ii) SECOND-STAGE CONSTRAINTS

At the second stage, the wind power uncertainty is considered at the second stage. The operation plan should be secure for any wind power realization in the predefined uncertainty set wwhich is interpreted as follows. A feasible responsive re-dispatch plan {*pgi,t*} can be found for any given wind power in w.

$p_{gi,min}u_{gi,t}\le p_{gi,t}\le p_{gi,max}u_{gi,t}$, ----------(3.11)

$\sum_{gi} p_{gi,t}+\sum_{wi} w_{wi,t}-\sum_{i}$ ----------(3.12)

$-F_{l,max}\le \sum_{gi} л_{l,gi}\, p^{b}_{gi,t}+\sum_{wi} л_{l,wi}w_{wi,t} - \sum_{i} л_{l,i}L_{i,t}\le F_{l,max}$ 3.13)

In addition, thethermal generation re-dispatch is restricted by the corrective dispatch in the neighbourhood of the base case, as shown in (3.14), where *ta* stands for the allowed adjustment time duration.

$-DR_{gi}u_{gi,t}t_a\le p_{gi,t}-p_{gi,t}\le UR_{gi}u_{gi,t}t_a$ ----------(3.14)

(iii) MODEL FORMULATION

To take the flexible uncertainty set into account, it is necessary to make some modifications on the conventional robust model. In that way, the objective function in (3.1) can be minimized as possible while the robustness of the solution is lost. In essence, the variation of wind power is not included in the model.

If the actual power of wind farm *wi* is larger than$e_{w,t} + dw^{+}_{w,t}$, an easy and direct way to recovering a feasibleoperation is to spill the excessive wind power. Thus there will be wind spillage and the cost expectation can be calculated by

$$f^{+}_{wi,t} \quad c_w \int_{ew_{wi,t}+d^{+}_{wi,t}}^{w_{wi,t,max}} (w_{wi,t} - ew_{wi,t} - d^{+}_{wi,t})\, pdf(w_{wi,t})\, dw_{wi,t} \quad (3.15)$$

Here the curtailed wind power can be over-estimated, because the spillage can be avoided by proper re-dispatch if the wind power at other nodes is not in extreme scenarios. But this estimation is very easy and practical. The complex grid constraints are excluded as well as the complicated coordination among different power resources. Moreover, in the operation practice, the dispatch signals for individual wind farms should also be separate to which they can response quickly so that the real-time security can be guaranteed.

Correspondingly, if the wind actual power is low, the expectation of the load curtailment cost is

$$f^{-}_{wi,t} - c_l \int_{w_{wi,t,min}}^{ew_{wi,t}-d^{-}_{wi,t}} (w_{wi,t} - ew_{wi,t} - d^{-}_{wi,t})\, pdf(w_{wi,t})\, dw_{wi,t} \text{ -- } (3.16)$$

Assuming the probability distribution of forecasted wind power, we can obtain the above costs as a measurement of the risks. Here they are added to the objective function and a modified one in (3.17) can be obtained. They can also be taken as constraints added to the model. The base-case operation cost minimization tends to shrink the flexible set while the consideration of the risk requires a solution working for larger sets. A balance can be obtained between them by considering the certain penalty coefficients c_w and c_l.

$$\min \sum_{t} \sum_{gi} (c_{gi} p^{b}_{gi,t} + su_{gi} z_{gi,t} - sd_{gi} y_{gi,t}) + \sum_{t} \sum_{wi} (f^{+}_{wi,t} + f^{-}_{wi,t}) \text{ --- } (3.17)$$

2. WIND DRIVEN OPTIMIZATION

The Wind Driven Optimization (WDO) algorithm is a new type of nature-inspired global optimization methodology based on atmospheric motion. The Wind Driven Optimization (WDO) technique is a population based iterative heuristic global optimization algorithm for multi-dimensional and multi-modal problems with the ability to implement constraints on the search domain. At its core, a population of infinitesimally small air parcels navigates over an N-dimensional search space assigned random velocities such that the positions of air parcels are updated at each iteration based on the physical equations that govern large-scale atmospheric motion following Newton's second law of motion, which is also used to describe the motion of air parcels within the earth's atmosphere. Compared to similar particle based algorithms, WDO employs additional terms in the velocity update equation (e.g. gravitation and Coriolis forces), providing robustness and extra degrees of freedom to fine tune the optimization.

(i)THEORETICAL BACKGROUND

In the atmosphere, wind blows in an attempt to equalize imbalances in air pressure. More specifically, it blows in the direction from a region of high pressure to low pressure at a velocity which is proportional to the pressure gradient. Assuming the air is in hydrostatic balance and considering that the horizontal motion is stronger than the vertical motion, the pressure variation, and hence the wind can be treated as a horizontal movement. Albeit, we live in a three-dimensional world, our abstraction of wind motion addresses multi-dimensional problems. Moreover, certain assumptions and simplifications will be made in the derivation of the operators used in the WDO algorithm. The starting point in the development of WDO is with Newton's second law of motion, which is known to provide very accurate results when applied o the analysis of atmospheric motion:

$$\rho\, \vec{a} = \sum \vec{F}_i \quad \text{----------}\ (3.18)$$

Where *a* is the acceleration vector, ρ is the air density for an infinitesimal element of volume, and F_i are the forces acting on the mass. The equation that relates air pressure to its density and temperature is given by the ideal gas law:

$$P = \rho\ R\ T \quad \text{---------}\ (3.19)$$

where P is the pressure, R is the universal gas constant and T is the temperature.In (3.18), there are four major forces that either cause the wind to move in a certain direction ordeflect it from its path. The most observable force causing the air to move is the pressuregradient force (FPG), while the friction force (FF) simply acts to oppose such motion. The exactdescription of the friction force is very complex and hence we use a simplified form asdescribed in (3.23). Even though the gravitational force (FG) acts as a vertical force in our physicalthree-dimensional atmosphere, when it is mapped to N-dimensional space, it becomes anattractive force that pulls towards the origin of the coordinate system. For this reason, thegravitational force is included in our algorithm. The coriolis force (FC) is caused by the rotationof the earth, and deflects the path of the wind from one dimension to another. In WDO, it isimplemented as a motion in one dimension that affects the velocity in another.

The physical equations that govern each of these forces are given below, where δV represents aninfinitesimal air volume. ∇P is the pressure gradient, Ω represents the rotation of the earth, g isthe gravitational acceleration, and u is the velocity vector of the wind.

$\vec{F}_{PG=} - \nabla P \Delta v$ ---------- (3.20)$\vec{F}_G = \rho \delta V \vec{g}$ ---------- (3.21)

$\vec{F}_C = -2\Omega \square \vec{u}$ ---------- (3.22)

$\vec{F}_F = -\rho\alpha\vec{u}$ ---------- (3.23)

All of these forces can be summed together and plugged in the right-hand side of the Newton'ssecond law of motion as given in (3.18). The resulting equation is shown below:

$$\rho\ \vec{u}\ \Delta t = (\rho\ \delta V\ \vec{g}) + (-\nabla P\ \delta V) + (-\rho\alpha\vec{u}) + (-2\Omega\times\vec{u}) \quad \text{---}\ (3.24)$$

If we consider an infinitesimal air parcel that is moving with the wind, we can derive a velocityupdate equation by simplifying (3.24). Using the ideal gas law equation from (3.19), we can write ρin terms of the pressure and we can assume a unity time step, Δt = 1, for simplicity. Afterrearranging the terms in (3.24), we can derive the following velocity update equation:

$$\vec{u}_{new} = \left((1-\alpha)\vec{u}_{old}\right) + g\left(-\vec{x}_{old}\right) + \left(\left|\frac{P_{max}}{P_{old}} - 1\right| RT\left(x_{max} - x_{old}\right)\right) + \left(\frac{-c\ u_{old}^{other\ dim}}{P_{old}}\right) \quad \text{----------}\ (3.25)$$

In (3.25), the updated velocity for the next iteration, unew, depends on the current iteration velocity(u_{old}), the current location of the air parcel in the search space (x_{old}), the distance from thehighest pressure point that has been found (x_{max}), the maximum pressure (P), the pressure atthe current location (P_{old}), the temperature (T), the gravitational acceleration (g), and theconstants R, α, and c. The pressure term in the WDO is analogous to the fitness of achromosome in GA terminology. If WDO is compared against PSO, similar velocity updateequations can be observed.

Yet, WDO depends on a population of infinitesimally small airparcels distributed randomly over the search space iteratively moving towards the highestpressure point, where this motion is driven by the physical equations that govern wind motion inthe atmosphere. The position of the air parcel can be updated by (4.9) after the velocity of the parcel is updated by (3.25):

$$\vec{x}_{new} = \vec{x}_{old} + (\vec{u}_{new} \times \Delta t) \quad \text{----------}\ (3.26)$$

The first term on the right-hand side of equation (3.25) tells us that the air parcel would continue to travel on its previous path with some opposition generated by the friction. The second term is an attractive force that pulls towards the center of the coordinate system. The third term contributes a force towards the location of maximum pressure which, in the algorithm, is assumed to be the global best location for the optimization problem. The last term emulates the coriolis force, which in reality is a deflecting force. Here it is implemented such that movement in one dimension is affected by the movement in another dimension. Similar to PSO, velocity limitation and boundary checks are also implemented in WDO. The following figure represents the flow chart for the WDO.

(ii) ADVANTAGESOF WDO

1) Compared with other particle optimization velocity updation is possible in the WDO.

2) Provides robustness and extra degree of freedom to fine tune the optimization.

3) The convergence speed is high.

4) Precision of Wind Driven optimization are higher.

Figure 4.1 shows the flowchart of the wind driven optimization algorithm which has the main advantage of the low time consumption. The main and the first step of this process were initializing all the necessary values. Then evaluate the pressure for each air parcel. If it was satisfied then update all the initialized values. This process repeated again and again until the optimized values were obtained.

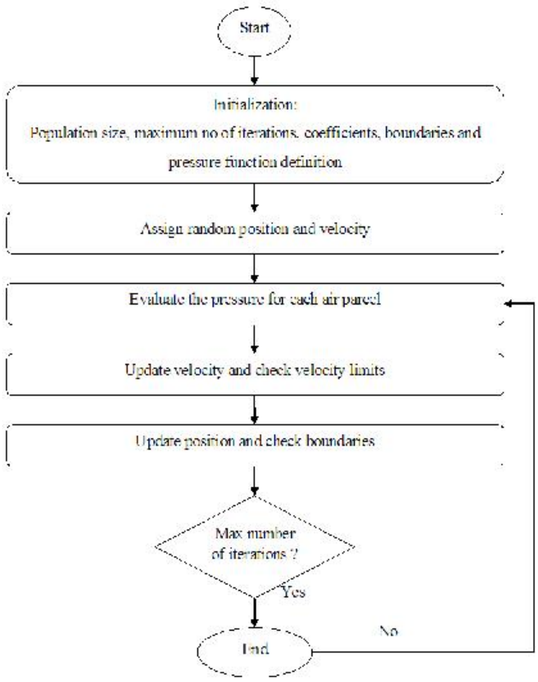

Figure: 3.2: Flowchart of the Wind Driven Optimization

IV. RESULTS AND DISCUSSION

The following figure represents the generated power from wind in Predefined set and Flexible set. And the power generation is scaled for 24 hour time horizon in this work.

The proposed system implements an effective optimization approach for the SCUC. For this, the work wind driven optimization algorithm and its parameters are shown in the following table.

Table 4.1: WDO Parameters

Parameters	Number of item
Max no of iterations	100
Constant, RT	5
Gravitational constant, g	0.2
Friction coefficient, α	0.4
Coriolis constant, c	0.4
Population size	30
No of variable	4
Needed solution	Global minimum
Maximum allowed speed	0.1
Minimum allowed speed	-1

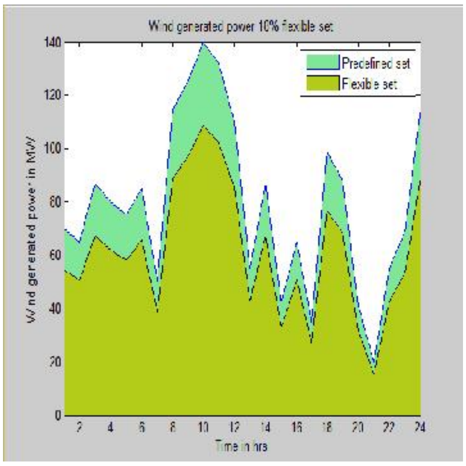

Figure 4.1: Wind power profile with uncertainty

The above figure shows the simulation result of the wind power profile with uncertainty in a day. In here the generated wind power in a day which based on the flexible and predefined deterministic set and the flexible set is considered as a 18% flexible.

Table 4.2: FLEXIBLE WIND POWER GENERATION

TIME	FLEXIBLE WIND POWER GENERATION (MW)	PREDEFINED WIND POWER GENERATION (MW)
2:00	60	10
4:00	70	20
6:00	68	20
8:00	95	20
10:00	118	22
12:00	90	25
14:00	75	15
16:00	55	10
18:00	80	20
20:00	76	18
22:00	42	14
24:00	98	22

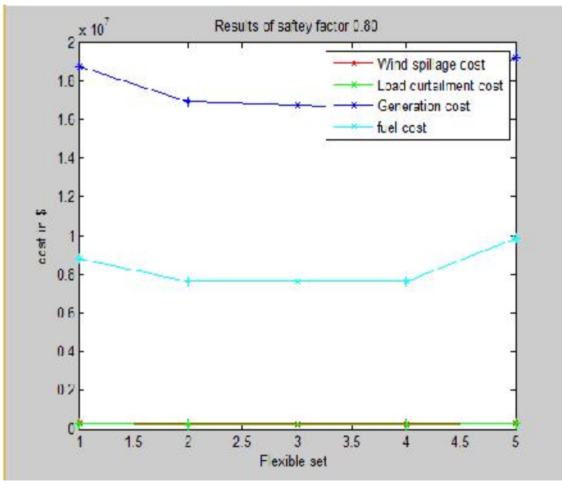

Figure 4.2 Cost value for safety factor 0.8

The above figure shows the simulation result for 0.8 safety factor. From the figure it shows the wind spillage cost, load curtailment cost, generation cost and the fuel cost which are all based on 0.80 safety factor. Here the each cost is represented by different color.

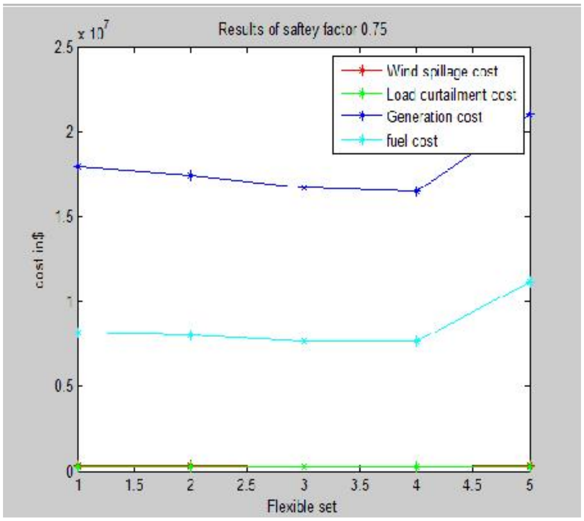

Figure 4.3 Cost value for safety factor 0.75

The figure 4.3 shows the simulation result for 0.75 safety factor. From the figure it shows the various cost like wind spillage cost, load curtailment cost, generation cost and the fuel cost which are all based on 0.75 safety factor.

The above figure shows the simulation result for 0.70 safety factor. From the figure the various cost like wind spillage cost, load curtailment cost, generation cost and the fuel cost are obtained and which are all based on 0.70 safety factor. There is some wind spillage at certain hours for the upper boundary of the flexible set is lower than the predefined power range.

The above figure 4.5 shows the simulation result for 0.65 safety factor. From the figure the various cost like wind spillage cost, load curtailment cost, generation cost and the fuel cost are obtained and which are all based on 0.65 safety factor. A more operation plan and a smaller cost can be obtained with the allowable wind spillage and load curtailment.

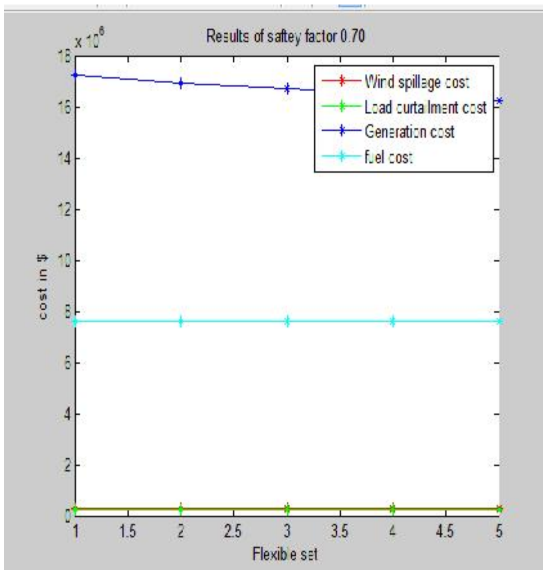

Figure 4.4 Cost value for safety factor 0.70

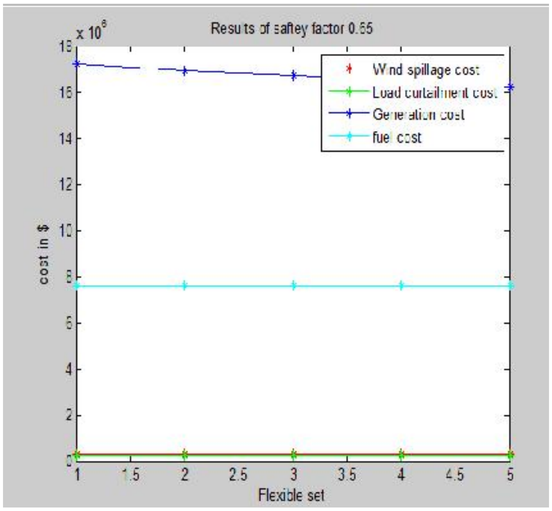

Figure 4.5 Cost value for safety factor 0.65

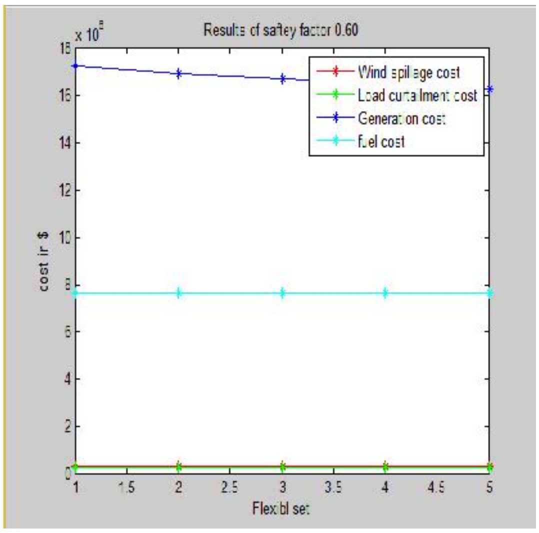

Figure 4.6 Cost value for safety factor 0.60

The above figure shows the simulation result for 0.60 safety factor. From the figure the various cost like wind spillage cost, load curtailment cost, generation cost and the fuel cost are obtained and which are all based on 0.60 safety factor. With small wind power variations, lower operation cost can be obtained by balancing the economics and risks. The safety factor when reduced to 0.60, there will be no feasible solutions due to safety factor deficiency.

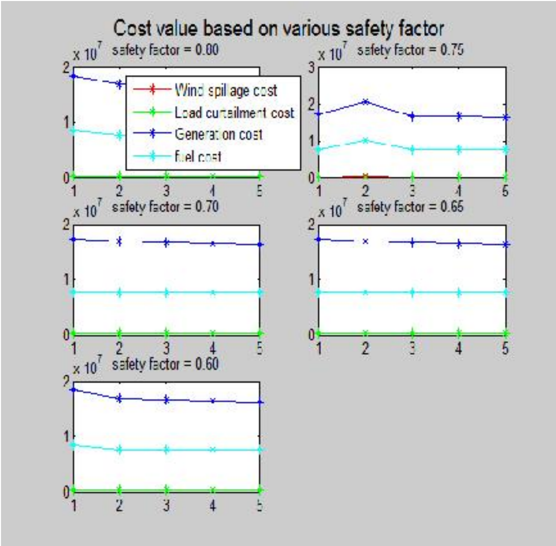

Figure 4.7 Cost values based on various safety factors

The above figure shows the simulation result of comparison of cost values based on various safety factors. Here the safety factor is decreased from 0.80 to 0.60 at a step of 0.05. However, as shown, with the decrease of safety factor, the size of the flexible sets can increase, decrease or even not change. It is because that the base-casegeneration scheme is also adjusted, on which the change of the flexible sets greatly depend. When reduced to 0.60, there will beno feasible solutions due to transmission capacity deficiency.The load allocation among conventionalgenerators is greatly influenced due to the decrease oftransmission resource. The change of flexible sets with respect to the safety factor depends on the wind farmlocations, the power flow directions and the power flow level. Other flexible resources such as batteries, hydro generation and pumped storage can be invested and expanded to manage the wind power uncertainty and promote its penetration.

The above figure shows the simulation result of cost comparison of the total generation of the flexible set system with the predefined deterministic sets. As shown the generation cost of the existing method is larger than those with flexible uncertainty set although a feasible solution is obtained.The average generation cost is about $.25/ MWh.

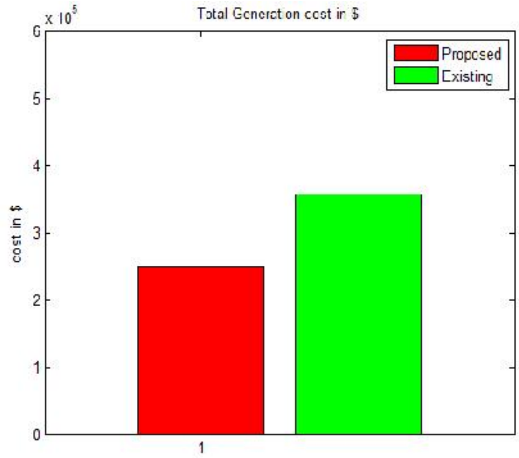

Figure 4.8: Generating cost of flexible system

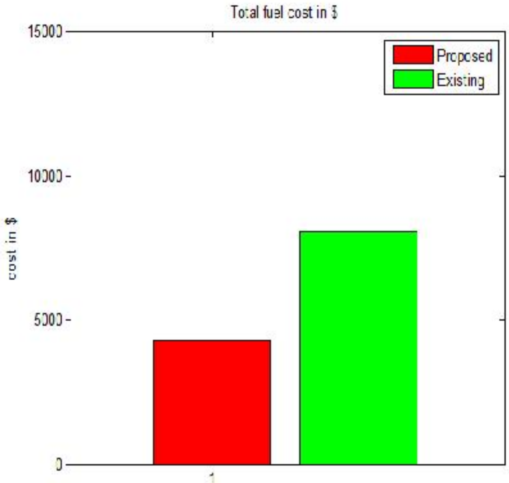

Figure 4.9: Fuel cost of flexible system

The above figure shows the simulation result of the fuel cost comparison of the flexible system with predefined deterministic system.The fuel cost is about $117/kWh.

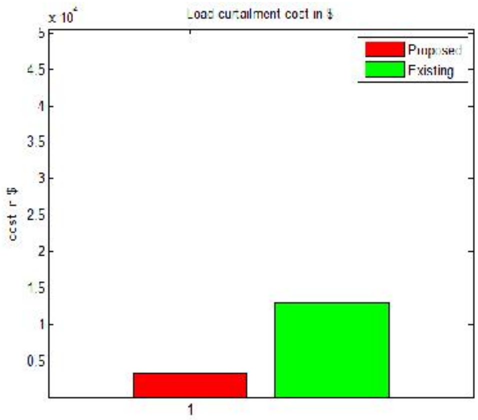

Figure 4.10: Load curtailment cost of flexible system

The above figure shows the simulation result of the cost comparison of load curtailment. The wind spillage and load curtailment will increases with power variations. The penalties on load curtailment is $3/KWh.

Table 4.3:Various Costs of Flexible Wind Power Generation

Various costs	Cost in Rs:	Cost in $
Generation cost	16260554.05	250162.37
wind spillage cost	278758.64	4288.59
load curtailment cost	220779.98	3396.62
Fuel cost	7618427.16	117206.57

V. CONCLUSION

This paper has proposed a robust SCUC model to manage the wind power variations. With the increasing penetration of wind power into the power grid, maintaining system reliability has been a challenging issue, due to the intermittent nature of wind power. The flexible uncertainty set is considered in place of the predefined set, which is different from the existing adaptive robust methods. Thus the feasible operation plan with significant wind variations can be guaranteed. The feasible operation plan can still be obtained even if there is no solution for the existing robust method and the overall cost is reduced further. The proposed method offers the dispatch signals for conventional generators, wind farms and with great potential in operation practice. Numerical results show that the efficiency of the proposed solution approach and the impact of outages of system components and demand uncertainties on system operating costs and allocations of energy allocation, fuel consumption, and emission allowance and long-term utilization of generating units.. The merits of proposed temporal model are featured by the simulation of uncertainties in the solution of stochastic long-term SCUC. The proposed work is handled with the high efficient wind driven optimization algorithm for solving the robust SCUC problems and provides the reduced cost of Wind spillage, Load Curtailment and Generation cost.

VI. FUTURE IMPLEMENTATION

The future work is planned to implement the same fashion of work with other optimization techniques and comparison of the results. It is chosen to implement multi objective optimization technique for the future work. With the help of this approach, various parameters like load curtailment, wind spillage can be simultaneously optimized.

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REFERENCES

[1] S. Takriti, J. R. Birge, and E. Long, “A stochastic model for the unit commitment problem,” IEEE Trans. Power Syst., vol. 11, pp. 1497–1508, Aug. 1996.

[2] P. Carpentier, G. Cohen, and J. C. Culioli, “Stochastic optimization of unit commitment: a new decomposition framework,” IEEE Trans. Power Syst., vol. 11, no. 2, pp. 1067–1073, 1996.

[3] D. Dentcheva and W. Romisch, “Optimal power generation under uncertainty via stochastic programming,” in Stochastic Programming: Numerical Techniques and Engineering Applications, Lecture Notes in Economics and Mathematical Systems, K. Marti and P. Kall, Eds. Berlin, Germany: Springer-Verlag, 1998, p. 458.

[4] D. Bertsimas and M. Sim, “Robust discrete optimization and network flows,” Mathematical Programming, 2003, vol. 98, no. 1–3, pp. 49–71.

[5] B. Parsons, M. Milligan, B. Zavadil, D. Brooks, B. Kirby, K. Dragoon, and J. Caldwell, “Grid impacts of wind power: A summary of recent studies in the united states,” Wind Energy, vol. 7, no. 2, pp. 87–108, 2004.

[6] Y. Fu, M. Shahidehpour, and Z. Li, “Long-term security constrained unit commitment: Hybrid Dantzig-Wolfe decomposition and subgradient approach,” IEEE Trans. Power Syst., vol. 20, pp. 2093–2106, Nov.2005.

[7] D. Bertsimas and M. Sim, “The price of robustness,” Oper. Res., vol. 52, no.1, pp. 35–53, 2004.

[8] A. Fabbri, T. Gomez, J. Rivier, and V. H. Mendez, “Assesment of the cost associated with wind generation prediction errors in a liberalized electricity market,” IEEE Trans. Power Syst., vol. 20, no. 3, pp. 1440–1446, Aug. 2005.

[9] T. Li and M. Shahidehpour, “Price-based unit commitment: A case of Lagrangian relaxation versus mixed integer programming,” *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 2015–2025, Nov. 2005.

[10] U. A. Ozturk, M. Mazumdar, and B. Norman, “A solution to the stochastic unit commitment problem using chance constrained programming,” IEEE Trans. Power Syst., vol. 19, no. 3, pp. 1589–1598, 2005.

[11] L. Wu, M. Shahidehpour, and T. Li, “Stochastic security-constrained unit commitment,” IEEE Trans. Power Syst., vol. 22, no. 2, pp. 800–811, 2007.

[12] J. Zhao, Z. Dong, Z. Xu, and K. Wong, “A statistical approach for interval forecasting of the electricity price,” *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 267–276, May 2008.

[13] J. Wang, M. Shahidehpour, and Z. Li, “Security-constrained unit commitment with volatile wind power generation,” IEEE Trans. Power Syst., vol. 23, no. 3, pp. 1319–1327, 2008.

[14] F. Aminifar, M. Fotuhi-Firuzabad, and M. Shahidehpour, “Unit commitment with probabilistic spinning reserve and interruptible loadconsiderations,” IEEE Trans. Power Syst., vol. 24, no. 1, pp. 388–397, 2009.

[15] J. F. Restrepo and F. D. Galiana, “Assessing the yearly impact of wind power through a new hybrid deterministic/stochastic unit commitment,” IEEE Trans. Power Syst., vol. 26, no. 1, pp. 401–410, 2011.

[16] L. Wu, M. Shahidehpour, and Z. Li, “Comparison of scenario-based and interval optimization approaches to stochastic SCUC,” IEEE Trans. Power Syst., vol. 27, no. 2, pp. 913–921, 2012.

[17] R. Jiang, J. Wang, and Y. Guan, “Robust unit commitment with wind power and pumped storage hydro,” IEEE Trans. Power Syst., vol. 27, no. 2, pp. 800–810, 2012.

[18] D. Bertsimas, E. Litvinov, X. A. Sun, et al., "Adaptive robust optimization for the security constrained unit commitment problem," IEEE Trans. Power Syst., vol. 28, pp. 52-63, 2013.

[19] C. Zhao, J. Wang, J. P. Watson, and Y. Guan, “Multi-stage robust unit commitment considering wind and demand response uncertainties,” IEEE Trans. Power Syst., vol. 28, no. 3, pp. 2708–2717, 2013.

[20] B. Zeng, “Solving two-stage robust optimization problems using a column-and-constraint generation method,” Oper. Res. Lett., vol. 41, no. 5, pp. 457–461, 2013.

[21] C. Zhao and Y. Guan, “Unified stochastic and robust unit commitment,”IEEE Trans. Power Syst., vol. 28, no. 3, pp. 3353–3361, 2013.

[22] B. Hu, L. Wu, and M. Marwali, “On the robust solution to SCUC with load and wind uncertainty correlations,” IEEE Trans. Power Syst., vol. 29, no. 6, pp. 2952–2964, 2014.