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Adaptive Grid Controller - Cost Reduction and Dispatch with Emphasis on Renewable Energy Sources

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Abstract: ***The combination of energy storage systems (ESS) and renewable energy source (RES) in hybrid grid provide benefits towards the system operation and as well as for end users. The main problem with RES is irregularity and ESS should be cost effective in order to provide economically operation of hybrid grid system. In this paper, we proposed the adaptive grid controller based upon the Super capacitor (SC) and battery at ESS in order to optimize the operation of grid system. An adaptive controller module includes hybrid ESS and consist of two modules, the Corse grain controller module is used to schedule the power dispatch in order to decrease the operational cost, while fine grain controller module is used to overcome the power fluctuation by RESs and to predict the uncertainties during real time power demand. The major aim is to minimize the energy loss through minimizing the average long period cost of hybrid ESS. The two-controller module optimizes the energy resources and power sources in a fixed interval of time, so the grid performs economically with several operational limits.***

Keywords* : *Super Capacitor (SC); Energy Storage System (ESS); Renewable Energy Sources (RES); Depth of Discharge (DOD)

I. INTRODUCTION

In according to the international energy agency there is large increment in CO2 emissions and will be seventy percent more increment in oil consumption by the 2050, which will cause global average temperature increment [1]. These types of problem can be minimalized by using RES, where wind, hydraulics and solar energies are the best for generation of electric power. The RESs has been a better solution in order to fulfill the required demand of electric energy that tends to decrease the greenhouse gas with a growing trend. The clean energy sources has influenced the generation of power unfavorably, also it is a challenge to provide regular and uninterrupted power supply to the consumer, therefore the grids operation is considered in terms of technical and operational aspects. A grid as the distributed operation and cluster of loads is considered in order to maximize the RES benefits, where it can be operated at grid-connection modes.

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In grid utility system, an ESS could help to add the RESs to provide power quality improvement, RESs fluctuations minimization, and several ancillary services [2].Presently, several researchers have been performed on grid power management, to manage with the help of RES uncertainty. In paper [3] [4], different type of stochastic optimization models have been proposed to reduce the estimated operation of grid cost. In [5], represented a CVaR based energy management method to decide the optimal balance among the grid resilience and operation cost for commercial building using grid, in that the CVaR technique was explained by the help of using different scenario. In paper [6], FCCUC model was developed where the RES uncertainty was defined as well as the several parameters. In [7], the author developed a method known as SRES (scenario-based robust energy scheduling) to improve total exchange cost while simultaneously gaining the smallest social advantages cost. In paper [8], an economical optimization model has been proposed, which is based on the interval linear programming for DAS (Day-ahead scheduling) of the grid operation. Generally, above studies implemented more than one optimizing methods such as interval programming [8], fuzzy programming [6], stochastic programming [3] [5], and robust programming [7] to manage the uncertainty and hence it minimizes the operation risks of the utility grid. However, utilization of the RES data with larger precision in the management of grid system is need to considered because it affects the power control management. The multi-timescale scheduling will facilitate the grid system to provide solution for RES uncertainly, and also give more particular power plan which can simply apply in real-time operation. Therefore, the hierarchical energy management is observed to be the alternative approach for the solution of RES uncertainly.In [9], presented the ESS-integrated grid on the model of EMS (energy management system) to enhance the operation reliability and energy efficiency of utility-grids. In paper [10], the problem of unit commitment in the energy management of grid has been discussed to tackle the frequency and voltage regulation, also to address the problem of optimal power flow to give the support towards reactive power. In [11], the heuristic method is integrated with the help of local EMSs and centralized EMS in order to define the operation of real-time ESS in various load, resources and environment conditions [12], and presumed fixed prices as well as operational cost [13]. Various generation resources such as short-term dispatch for the ESS has important impact on the existence in long-term, the battery life would be significantly depreciated by the help of frequent discharging and charging.

On the other side, the security and economy conflict generally complicate the optimal power management in utility-grid. Maximizing the ESS size capacity will give higher operating reserves and minimizes the probability of loss load but expenses the additional capital investment [14]. The two-fold supplies implementation for the operational cost of ESS is considered to be precisely which is related to long-term of degradation process in the real-time operation, so the degradation cost of ESS was either modeled or neglected on the basis of general term presented in [15].The ESS hybridization generally urges to various decision of dispatch that to considered by ESS characteristics and several operational targets, also the ESSs with huge amount of energy like as the batteries considered to exchange the energy with some other resource devices under a utility grid. Whereas, SC with the high-power rating is used store the power and provide the power when it requires. Therefore, in hybrid ESSs, the various type of time resolution is needed in order to design a comprehensive controller; the short period horizon provides the security at system and the long period horizon provides economically operations. In this paper, an adaptive grid controller is proposed, where the two-controller module is considered to tackle the above described issues. A two-controller module for grid is considered that include hybrid ESS, the Corse grain controller module is used to schedule the power dispatch in order to decrease the operational cost, while fine grain controller module is used to overcome the power fluctuation by RESs and to predict the uncertainties during real time power demand. Here, we developed a function of degradation cost of SC and battery to perform explicit process of degradation, which associating the short period operational cost and the long period capital cost during real-time commercial dispatch. The adaptive controller module is applied in a utility grid system via considering different pricing protocols of electricity. The effectiveness of our proposed model is shown in simulation studies using the ESS at controller module in order to achieve the considered objectives, here we have considered several scenarios with the pricing schemes to validate the performance of our system module.

II. LITERATURE SURVEY

There has been several methodologies that are used in ESS for the electrical energy storage [16] [17]. In paper [18], the author presented a model known as two-stage scheduling is to minimize the RES uncertainty that can efficiently guide all schedule to develop towards economic and stable one. In [19], real time dispatching model and DAS model were developed for electricity and cooling which coordinated the utility grid. In paper [20], the framework of hierarchical scheduling was developed for multi-product and multi-sources grid that incorporated the transient features of dynamics power converters and natural gas flow.

In [21], the framework of hierarchical energy management has been proposed for grid along the storage system of hybrid energy that couldn't achieve the secure operation and economic operation, but also prolong the battery lifetime. Obtained from the local level, DR (demand response) is also observed as promising and effective method to simplifying the management of energy, through utilizing the flexibility of demand side [22]. In paper [23], a model is presented namely stochastic SCUC (security-constrained unit commitment) for DAS in which the DR was deliberated as way to moderate the transmission violations. In paper [24], the model of two-stage stochastic was improved to enhance the DAS which considering the DR and BES (Battery energy storage). Here in [25], stochastic risk-constrained scenario based model has been developed to decide the optimal hourly bids in which the grid aggregator is submitted to day-ahead market. In paper [26], the author introduced the agent based architecture for handling the power in more than one micro-grid with the help of DR and BES. This paper [27], proposed an OGS (optimal generation scheduling) for grid-connected with the help of DR, where improbability of the upstream grid price was categorized by utilizing the IGDT (information gap decision theory). In [28], to optimize the operation of multi-micro grid a MHES framework was established in which the DR program was used to change the peak-load demand. In [29], the author proposed an algorithm in the market operator of trans-active energy structure is to minimize the electricity price, to maximize the profit generators, and also minimize the customer's cost. In [30], a MSS (Multi-stage stochastic) programming is based on the algorithm of ABC (Artificial Bee Colony) was applied to choose the multiple home micro-grid of coalition formation with the help of responsive load demand in the trans-active power of framework. Furthermore, the game theoretical methods were implemented to investigate the interactions among the individual customers and utility company in the DR [31]. However, such type of researchers are only absorbed on the utilization of DR in time-scale, without taking into the consideration their fitted coupling features are available on the time frames. This may demoralize the DR resources to simplify the RES integration and system balance on the various time-scales. In paper [32], author introduced a scheduling framework of MTS (multi-timescale) and CEE (Cost-effective energy) for utility grid in the isolated mode. However, the components of dispatching plan are decided by the help of RPM (Rule-based-Power-Management) algorithm without utilizing optimization techniques. Similarly, security constraints, containing the nodal voltage and branch flow constraints weren't evaluated. In [33], the model of optimization rolling is established whose focus was on the resources of DR reserve in various time-scales. Therefore, BES was eliminated from the model that reducing its applicability and the security constraints weren't taken into the account. Here in [34], the author has introduced the framework of optimal MTS DR scheduling for the industrial consumers but the communication between DR and BES, and the constraints voltage weren't accounted. Therefore, the security constraints are considered as the MTS features of DR and BER in the management of utility grid energy, so it is essential to integrate such type of factors in power management method to maximize the performance of grid operation.

III. CONSIDERED PRELIMINARIES

The ESS deployment is very necessary to get the economical utility grid operation, in this we majorly concentrated on the super-capacitor and battery. The cost property is the major factor to design the accurate model for grid energy management, also the hybrid ESS (HESS) deployment cost is considered in this section.

There are two major factors that affect the battery lifetime such as; the capacity tends to reflect the amount of usable energy and the cycle life aging that effects the total possible cycle count of the battery. The condition of cycling such as the charging and discharging frequent rate, maintenance period at charging and discharging, have an important factor on lifetime of battery. Acceleration degradation at cycling may cause the reason of failure in battery unit, apart from this conditions, the state parameters have the major influences on lifetime of battery. Extreme low or high SOC may cause extremely depreciate the performance of battery charging and discharging, whereas the temperature also provide the negative impact at battery life. In general, the battery management system includes the temperature controller, so it can be assumed that the degradation of battery through the ambient reasons can be ignored. The direct impact of charging rate on the battery lifetime is very minimal in comparison to the other various parameters [35], when the battery is working under a definite level of rated current. Therefore, the main determinants on lifetime of battery are the DOD and genuine full capacity. Whereas, the DOD has two main definitions, the first is energy discharged from 100% SOC, and the second definition refers that a full complete cycle containing of a period of charging and discharging [36]. In this study, DOD is refer as the amount of energy in one event of charging or discharging with considering the full capacity and SOC is refer towards the remaining energy that associated to full capacity.The degradation cost of battery is considered by a direct denunciation on its associated lifetime and capacity, here a starting time of discharging event is given by p and for Δp time interval the $A_s(p)$ denotes the average power. Therefore, the DOD at this time period can be given as;

$$b_S(\Delta p) = \frac{A_S(p)\Delta p}{D_{AS}(p)} \tag{1}$$

Where, $D_{AS}(p)$ refers the real capacity at p time interval. Though the lifetime of super-capacitor at maximal operational temperature under the actual range of voltage is given through the manufacturer, which also can be considered that the super-capacitor (SC) is expected to long last as per the estimated life-cycle under a normal working conditions. So the degradation cost of SC can be taken as the time linear function of DOD at charging and discharging event. The estimated lifetime of SC is denoted by E_C and F_C denotes the replacement cost, so on the degradation cost of SC at time interval Δp is given as;

$$F_{DCC}(p) = \frac{F_C \Delta p}{E_C} \tag{2}$$

The above (2) shows the degradation cost of battery, the degradation cost of SC is considered to be constant regardless of cyclic circumstances. Therefore, the degradation cost of SC is considered to be time linear till it utilized in grid, this allows frequent operation of charging and discharging in order to provide immediate power inequity.

IV. PROPOSED CONTROLLER MODULE

Here, we have proposed the adaptive grid controller based upon the SC and battery in order to optimize the operation of grid system. The major aim is to minimize the energy loss through minimizing the average long period cost of HESS. The two controller module optimizes the energy resources and power sources in a fixed interval of time, so the grid performs economically performance with several operational limits at some RES uncertainties. A discrete time optimization process is considered to formulate the problem in predictive controller framework. Here, P_{cg} and P_{fg} shows for the estimated horizon length in Corse grain and fine grain controller module. The Corse grain controller module have a non-linear receding predictive controller at time horizon of $p_{fg} \in \{1, \ldots\ldots, P_{fg}\}$, whereas the fine grain controller module have a quadratic predictive controller at time horizon of $p_{cg} \in \{1, \ldots\ldots, P_{cg}\}$. The time intervals in Corse grain and fine grain module is denoted by Δp_{cg} and Δp_{fg}, whereas at each time interval the control actions are acquired through resolving its individual objective function in a module that the results of individual module influence each other. In present scenario, the scheduling process is formulated as P_{cg} in Corse grain that depends upon the estimation of electrical cost, renewable outputs and load profile. The fine grain module provides its own optimization process with the SC implementation in order to minimize the fluctuation of power after the forecast errors realization in individual ΔP_{fg} under a Corse grain P_{fg} time horizon. Afterwards, at Δp_{fg} time the fine grain module sends the efficient state variable to Corse grain module, so on for the next Δp_{fg} scheduling task. While considering both module, the constraints of power balance must be provided all times and power of load $A_K(p)$ can be given as;

$$A_K(p) = A_G(p) + A_{ESS}(p) + A_{RES}(p) \tag{3}$$

$$\begin{aligned} A_{ESS}(p) &= A_S(p) + A_C(p) \\ A_{RES}(p) &= A_{PV}(p) + A_{WT}(p) \end{aligned} \tag{4}$$

Whereas, the state dynamics should be provided for both SC and battery with respect to charging and discharging power capacity for both module, power of utility grid is denoted by $A_G(p)$. Here, $A_S(p)$ and $A_C(p)$ shows for the battery and SC power, while taking account of charging and discharging effectiveness, the different equations of SC and battery for discrete time capacity can be written as;

$$D_S(p) = D_S(p-1) + H_{SCh} A_S(p)\Delta p \tag{5}$$

$$D_S(P) = D_S(p-1) + \frac{A_S(p)\Delta p}{H_{SDh}} \tag{6}$$

Where, H_{SCh} denotes the charging efficiency of the battery and H_{SDh} denotes the discharging efficiency of the battery. The energy of SC at time p can be given as;

$$D_C(p) = D_C(p-1) + H_{CCh} A_C(p) \Delta p_{fg} \quad (7)$$

$$D_C(p) = D_C(p-1) + \frac{A_C(p)\Delta p_{fg}}{H_{CDh}} \quad (8)$$

Where, H_{CCh} denotes the charging efficiency of the SC and H_{CDh} denotes the discharging efficiency of the SC. Moreover, here we include the inequality constraints to the limits of power capacity for SC, battery and utility grid, this can be represented as follows;

$$A_G^{min}(p) \le A_G(p) \le A_G^{max}(p) \quad (9)$$

$$A_S^{min}(p) \le A_S(p) \le A_S^{max}(p) \quad (10)$$

$$A_C^{min}(p_{fg}) \le A_C(p_{fg}) \le A_C^{max}(p_{fg}) \quad (11)$$

Furthermore, the SOC limit is also considered in order to restrict the battery from being extra discharged and over charged, it can be represented as follows;

$$M_S^{min}(p) < \frac{D_S(p)}{D_{SA}(p)} < M_S^{max}(p) \quad (12)$$

Similarly, SOC limit of SC can be given as;

$$M_C^{min}(p) < \frac{D_C(p)}{D_{CRt}} < M_C^{max}(p) \quad (13)$$

Where, D_{CRt} denotes the rated SC capacity, further the SC scheduling is not included in a Corse grain module because of its lower capacity, therefore, (8) state dynamics and (11) power constraints are only taken in fine grain module. The fine grain boundary of $A_G(p)$ is considered to be negative when the grid is permissible in order to sell the electricity power to utility grid.

4.1 Corse Grain Controller Module

The main aim of Corse grain controller module is to enhance the decision variable $\{A_G(p_{cg}) A_S(p_{cg})\}_{p_{cg}=1}^{P_{cg}}$ which able to minimalize the overall operational cost that include the battery degradation cost and electricity cost of effective grid. The $F_G^{cg}(p_{cg})$ denotes the electricity cost and it can be given as;

$$F_G^{cg}(p_{cg}) = F_{cg}(p_{cg}) A_G^{cg}(p_{cg}) \Delta p_{cg} \quad (14)$$

The $F_S^{cg}(p_{cg})$ represents the degradation cost of battery in a Δp time interval, which can computed after the end of charging/discharging event and it is necessary to consider the battery power flow direction $A_S(p_{cg})$. The $n(p_{cg})$ denotes the auxiliary binary values in order to signify the transition state of charging and discharging event under two different time periods; if $A_S(p_{cg}) A_S(p_{cg}-1) \le 0$ then $n(p_{cg})$ is set to be 1 and otherwise if $A_S(p_{cg}) A_S(p_{cg}-1) > 0$ then $n(p_{cg})$ is set to be 0. Here, $D_{acc}(p_{cg})$ denotes the accumulative energy in terms of kilo watt, so on it can be given as;

$$D_{acc}(p_{cg}) = (1 - n(p_{cg})) D_{acc}(p_{cg}-1) + A_S(p_{cg}) \Delta p_{cg} \quad (15)$$

The cost of battery degradation in a particular time periods can be given through the signal state transition $n(p_{cg})$ and the $D_{acc}(p_{cg})$ accumulative energy as follows;

$$F_S^{cg}(p_{cg}) = F_{SDC}(p_{cg}, D_{acc}(p_{cg})/D_S(p_{cg})) - (1 - n(p_{cg})) F_{SDC}(p_{cg}, D_{acc}(p_{cg}-1)/D_S(p_{cg}-1)) \quad (16)$$

Integrating the degradation cost of battery F_{SDC} and electricity cost in the main objective function, the Corse grain optimization problem is considered to be non-linear problem due to the degradation cost of battery is highly non-linear. The main function of Corse grain optimization problem Z_{cg} can be written as;

$$Z_{cg}: \min \sum_{p_{cg} \in \{1,\dots,P_{cg}\}} F_G^{cg}(p_{cg}) + \sum_{p_{cg} \in \{1,\dots,P_{cg}\}} F_S^{cg}(p_{cg}) \quad (17)$$

4.2 Fine Grain Controller Module

The main aim of fine grain controller module is to enhance the decision variable $\{A_G(p_{fg}) A_S(p_{fg}) A_C(p_{fg})\}_{p_{fg}=1}^{P_{fg}}$ to minimize the obtained variable outcome from predicted errors with SC implementation. While considering the (2) degradation cost of SC is related with time period, degradation cost of SC $F_C^{fg}(p_{fg})$ can be given as;

$$\sum_{p_{fg} \in P_{fg}} F_C^{fg}(p_{fg}) = {F_C}/{E_C}\, P_{fg} \quad (18)$$

It observed that the degradation cost of SC is fully independent with respect to discharging and charging power, apart from this the penalty costs are signify deviations from the orientations provided through Corse grain module and further integrated into objective task. The $F_S^{fg}(p_{fg})$ and $F_G^{fg}(p_{fg})$ denotes the penalty terms, which shows the variation on the power references of utility grid and battery in order to predict the RES errors in low time period. As per the power references taken by Corse grain module the quadratic formulation of penalty cost is given as;

$$F_S^{fg}(p_{fg}) = \left(A_S^{cg}(p_{cg}) - A_S^{fg}(p_{fg})\right)^2 \quad (19)$$

$$F_G^{fg}(p_{fg}) = \left(A_G^{cg}(p_{cg}) - A_G^{fg}(p_{fg})\right)^2 \quad (20)$$

Where, Moreover, at each prediction stage the SC SOC must need to maintain the optimal value to provide the ramping services in further process. Therefore, the $F_C^{fg}(p_{fg})$ penalty term is considered for the SC capacity in the prediction terminology and given as;

$$F_G^{fg}(p_{fg}) = \left(D_C^{cg}(p_{cg}) - D_{CRt}\right)^2 \tag{21}$$

The above considered factors are integrated in convex constraints and objective function, the main objective function of fine grain module is written in a quadratic form as follows;

$$Z_{fg}\text{:min} \sum_{p_{fg}\in\{1,\dots,P_{fg}\}} F_C^{fg}(P_{fg}) + \sum_{p_{fg}\in\{1,\dots,P_{fg}\}} \left(y_S^{fg}F_S^{fg}(p_{fg}) + y_G^{fg}F_G^{fg}(p_{fg})\right) + y_C^{fg}F_C^{fg}(P_{fg}) \tag{22}$$

Where, y_S^{fg}, y_G^{fg} and y_C^{fg} are the cost weighting coefficient for battery, and SC. Table 4.1 shows for the proposed adaptive grid controller algorithm.

Table IV.1: Adaptive grid controller algorithm

S-1	Parameter initialization
S-2	While $p_{cg} = 1$ till P_{cg}, do
S-3	Importation of renewables and forecast data
	$\{A_K(p_{cg})A_{PV}(p_{cg})A_{WT}(p_{cg})\}_{p_{cg}}^{P_{cg}+p_{cg}}$
S-4	Optimization of Z_{cg} in Corse grain module
S-5	Decision making variables $[A_G(p_{cg})A_S(p_{cg})]_{p_{cg}}^{P_{cg}+p_{cg}}$, under the $\Delta p_{cg} + P_{fg}\Delta p_{fg}$ at fine grain module to set the points
S-6	While $p_{fg} = 1$ till P_{fg}, do
S-7	Importation of renewables and forecast data with the errors $[A_K(p_{fg})A_{PV}(p_{fg})A_{WT}(p_{fg})]_{p_{fg}}^{P_{fg}+p_{fg}}$
S-8	Fine grain module Z_{fg} function optimization
S-9	$[A_G(p_{fg})A_S(p_{fg})A_C(p_{fg})]_{p_{fg}+p_{cg}}$ power dispatch computation
S-10	end while loop
S-11	$[D_S(p_{fg}), D_C(p_{fg})]_{p_{fg}+1}$ state variable send back to Corse grain module
S-12	end while loop

V. RESULTS AND ANALYSIS

In this section, the adaptive grid controller module with the associated degradation cost model is considered for four different scenarios. The mathematical model of our proposed is implemented using Matlab 2016b. Here, considered the datasets which is issued by energy market authority of Singapore [37], which is public dataset offered to get feedback on the implementation of demand response program. Implementation of the demand response is based upon gathering feedback mechanism from the practitioners in order to find out the solution via regularity framework and key features of demand response program. The main objective of our study is to provide the possible impact and feasibility of model implementation and the simulation is take place at virtual environment, which is very similar to the scenario of real world and useful towards the demand response program. In the considered dataset, the end-user participant would succumb the load resources information to the retailer, afterwards the retailer will cumulate all resources of load to define the type of load. Here, the time slot period is considered for one hour, if the energy price from Singapore energy price (SEP) is more than the trigger price, the demand response process is activated for the retailers to bid according of load resources. Afterwards, the market clearing price (MCE) will compute the necessary curtailment of load for the individual retailer and report to all retailers. The point is to be considered that here MCE is not practically integrated in our system model, here the dispatched value is taken same as the submitted bids by the retailers. As we already discussed that the real market data is considered to provide the simulation results, where we have considered that the each of end-users have equal load request and the load curve profile reflects the energy consumption that provided by Singapore energy market company.

- **Scenario-A**

In this scenario, we have considered the zero renewable energy resources to full fill the demand of electricity requirement, which means all the demand of energy is provided by the non-renewable energy resources that is not very cost effective.

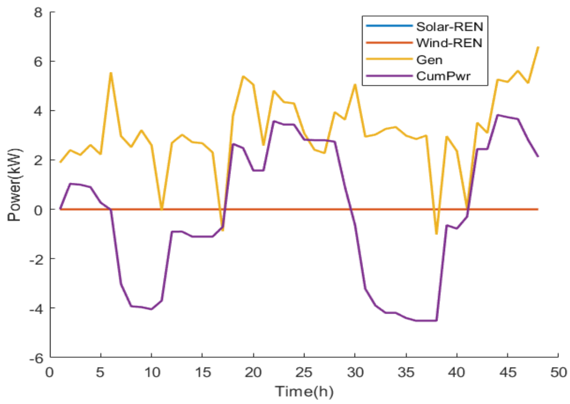

Fig. 5.1. Power generation using non-renewable energy resources

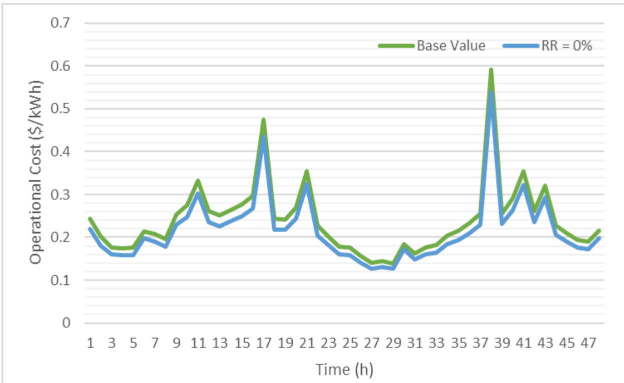

Fig. 5.2. Operational Cost computation at Scenario-A

Figure 5.1 shows the power generation using non-renewable energy resources, where blue and orange lines shows for the solar and wind energy that is null at this scenario. Yellow line shows for power generation by the generators and purple line denotes for the storage power in grid. Figure 5.2 shows the computation of operational cost in terms of $/kWh.

- **Scenario-B**

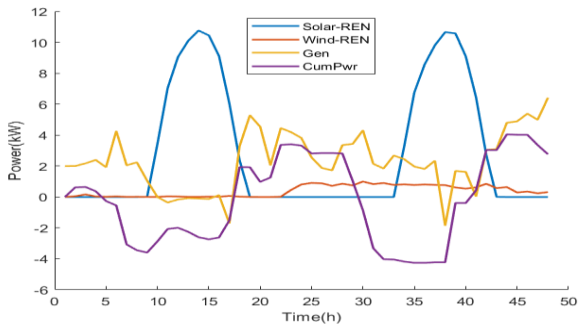

Fig. 5.3. Power generation using non-renewable and renewable energy resources.

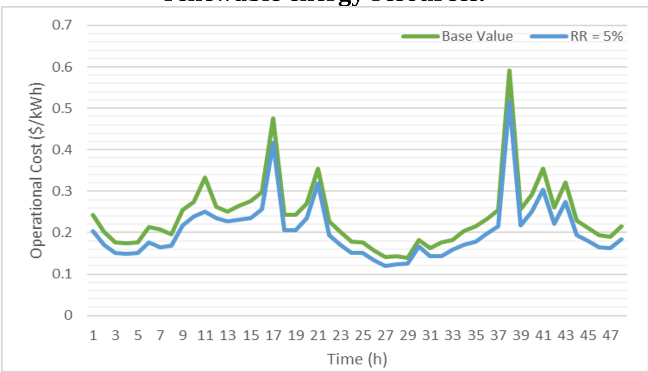

Fig. 5.4.: Operational Cost computation at Scenario-B

In this scenario, we have considered the 5% of renewable energy resources to full fill the demand of electricity requirement.

- **Scenario-C**

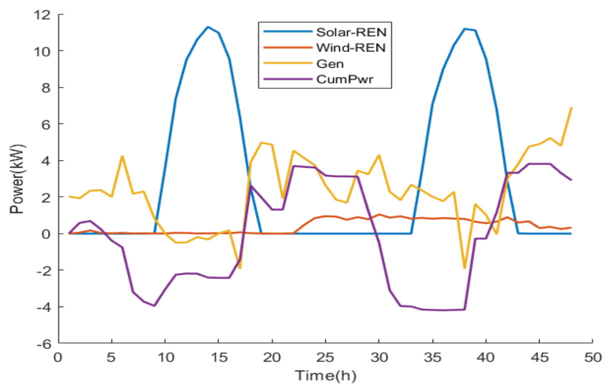

Fig. 5.5. Power generation using non-renewable and renewable energy resources

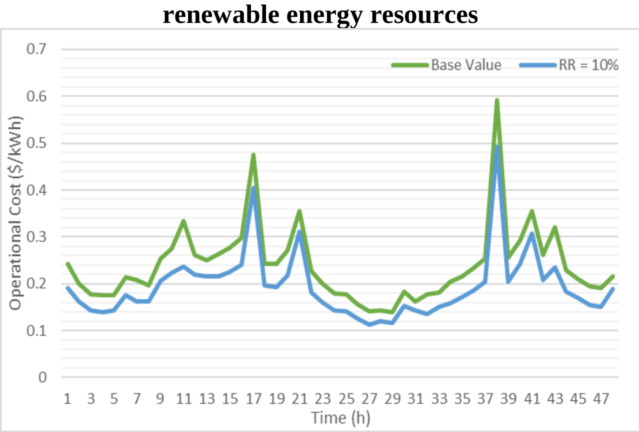

Fig. 5.6. Operational Cost computation at Scenario-C

- **Scenario-D**

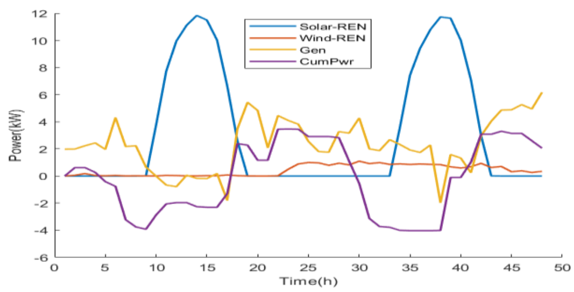

Fig. 5.7. Power generation using non-renewable and renewable energy resources.

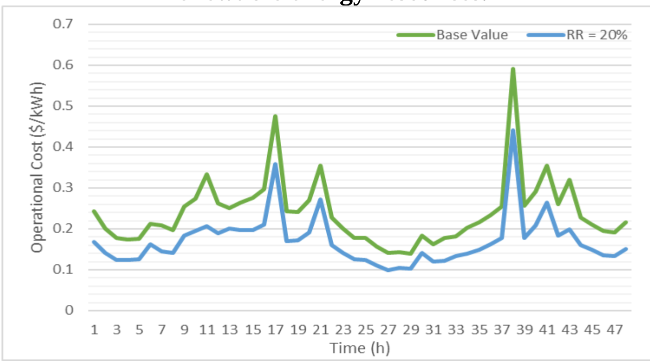

Fig. 5.8. Operational Cost computation at Scenario-D

Figure 5.3 shows the power generation using renewable and non-renewable energy resources, where blue and orange lines shows for the solar and wind energy, it clearly shows that when the solar energy at the peak the power generation through generator is very less. Yellow line shows for power generation by the generators and purple line denotes for the storage power in grid. Figure 5.4 shows the computation of operational cost in terms of $/kWh for scenario-B. In scenario-C, we have considered the 10% of renewable energy resources, where figure 5.5 shows the power generation using renewable and non-renewable energy resources and 5.6 shows the computation of operational cost. Similarly in scenario-D, we have considered the 20% of renewable energy resources, where figure 5.7 shows the power generation using renewable and non-renewable energy resources and 5.8 shows the operational cost computation.

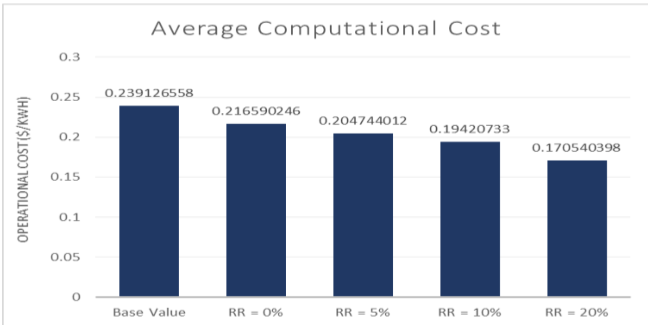

Fig. 5.9. Average operational Cost computation from different considered scenarios

Figure 5.9 shows the average operational cost computation from different considered scenarios, with respect to the base value data our proposed model has achieved 9.4% less computation cost at scenario-A where there is no renewable energy resources is considered.

While at scenario-B, where there is 5% of renewable energy resources is considered, our proposed model causes 14.3% less cost as compared to the base value. Similarly, considering 10% and 20% of renewable energy resources, our proposed model causes 18.7% and 28.6% less average cost as compared to the base value, which means as per increasing in renewable energy resources the cost value is decreasing.

VI. CONCLUSION

Here, we proposed the degradation cost models with help of two module controller with respect to the HESS, where our main motive is to formulate the problem in such a way that the operational cost should be minimization under the power fluctuation occurred at RES. The battery and SC degradation cost models are established to convert the long-period resources cost to the short-period operation problems. The proposed controller modules for grid include hybrid ESS, where it schedule the power dispatch in order to decrease the operational cost and overcome the power fluctuation occurred at RESs, also predict the uncertainties during real time power demand. The adaptive controller module is applied in a utility grid system via considering different pricing protocols of electricity. In addition, the effectiveness of our proposed model is shown in result analysis section, where the proposed method is associated with degradation cost model. We considered four different scenarios for the evaluation, using our proposed model the operational cost value of utility grid is decreasing as per increment of renewable energy resources, which shows the effectiveness of adaptive grid controller algorithm.

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