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Operational Planning of a Hybrid Power Plant for Off-Grid Mining site: A Risk-contrained Optimization Approach

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***Abstract*—One of the difficulties of mining worldwide is that it must be carried out in remote places without grid connection. Therefore it is important to choose the most profitable and reliable combination of energy sources for electrification. In this paper, different technologies to meet the demand of a mine located in Western Australia are studied. Using HOMER Pro, several viable systems, for the resources considered are obtained. Using analytic hierarchy process (AHP), the most suitable case is selected for further study. Using Monte-Carlo simulations several scenarios are developed for the study of uncertainties, and a risk-constrained optimization algorithm is implemented to obtain the optimal scheduling, the expected cost and conditional value at risk (CVaR). Numerical results demonstrate that the variations of operation cost and CVaR with the increase in risk aversion factor are not of high magnitude, due to rather low variable operation costs of renewable energy sources. It is shown that the proposed hybrid electrification plan based on WT, PVs and battery could not only provide a reliable power generation, but also very low daily operating cost.**

***Index Terms*—AHP, CVaR, HOMER Pro, off-grid mining, stochastic optimization, operational planning.**

NOMENCLATURE

Indices

s Scenario
t Hour

Parameters

$F_{min,d}$ Minimal fuel consumption of diesel $[l]$
I_b Number of installed batteries [number of batteries]
I_{pv} Installed power of PVs $[kW]$
I_{wt} Installed power of wind turbines $[kW]$
$OM_{b,e}$ Operation and maintenance cost of the batteries, dependent on the throughput energy $[\$/kWh]$
$OM_{b,y}$ Yearly operation and maintenance cost of the battery [\$/number of batteries]
OM_d Operation and maintenance cost of the diesel generator $[\$/h]$
$OM_{pv,y}$ Yearly operation and maintenance cost of the PVs, dependent on the amount of PVs $[\$/kW]$
$OM_{wt,e}$ Operation and maintenance cost of the wind turbines, dependent on the amount of generated energy $[\$/kWh]$
$OM_{wt,y}$ Yearly operation and maintenance cost of the wind turbines, dependent on the amount of WTs $[\$/kW]$
$P_{max,bc}$ Maximum charging power of the battery $[kW]$
$P_{max,bd}$ Maximum discharging power of the battery $[kW]$
$P_{max,d}$ Maximum output power of the diesel generator $[kW]$
$P_{min,d}$ Minimum output power of the diesel generator $[kW]$
SoC_{max} Maximum SoC of the battery $[\%]$
SoC_{min} Minimum SoC of the battery $[\%]$
SU_d Start-up cost of the diesel generator $[\$/start]$
T Considered optimization period expressed in hours $[h]$

Variables

$B_{c,t,s}$ Charging power of the battery $[kW]$
$b_{c,t,s}$ Charging indicator of the battery
$B_{d,t,s}$ Discharging power of the battery $[kW]$
$D_{t,s}$ Demand to satisfy $[kW]$
DT_d Minimum down time of the diesel generator $[h]$
eff Round trip efficiency of charging and discharging of the battery $[\%]$
$l_{pv,t,s}$ Loading of the PVs
$l_{wt,t,s}$ Loading of the WTs
$P_{d,t,s}$ Power output of the diesel generator $[kW]$
$P_{pv,t,s}$ PV power output $[kW]$
$P_{wt,t,s}$ Power output of all installed WTs $[kW]$
S_{max} Maximum possible storage content $[\%]$
SoC_{init} Initial SoC of the battery $[\%]$
$SoC_{t,s}$ State of charge of the battery $[\%]$
$u_{d,t,s}$ Commitment status of the diesel generator
UT_d Minimum up time of the diesel generator $[h]$
$y_{d,t,s}$ Start-up indicator of the diesel generator
$z_{d,t,s}$ Shutdown indicator of diesel generator

I. INTRODUCTION

Australia has a huge potential for the mining industry. However, the resources are in areas where there is no point of connection to the grid, and where building a line to the grid would be too expensive. Therefore it is necessary to explore other solutions, which would enable the mine to operate as an islanded system.

Nowadays, to calculate the optimal combination sources to energize the mining site, different approaches are used, depending on the set of goals made at the beginning of the project. One way to calculate the optimal combination of electrical sources to energize a system is to use HOMER Pro. It is a software extensively used in the microgrid industry. In [1] HOMER Pro was used to calculate the effectiveness of adding a PV and/or adding a battery energy storage system (BESS). In [2], HOMER Pro was used to plan the strategy for islands in South Korea. An autonomous hybrid power system was modelled in [3] using HOMER Pro for a town in Kenya. The idea of this project is to use a number of feasible solutions from HOMER, which satisfy the demand and then select the most competitive solution that would fulfill the goals set at the beginning of the project throughout Analytic Hierarchy Process (AHP). Similar approach was presented in [4].

After defining the best electrification plan, it is necessary to draw the optimal operation of the system, which would result in the lowest cost of operation. A risk-constraint optimization is used to minimize the cost under uncertainties in renewable resources and load profile of the examined system. These will be accounted for using conditional value-at-risk (CVaR) method [5].

II. Planning Phase

A. HOMER Pro

The first step is to indicate the possible configurations of the power plant. Based on the technical detail of electricity producing units, load data, solar irradiance, wind speed and temperature measurements, the HOMER Pro model was created. The units considered in the model are:

- Photovoltaic modules
- Wind turbines
- Batteries
- Diesel generator

The size of the aforementioned units is optimized by HOMER Pro in order to satisfy the demand at every instance while minimizing the net present cost (NPC). Ten plans have been selected combining the different generation resources considered.

The capacities of technologies installed in each of the selected plans are presented in Table I. The economical and technical details are presented in Table II. These results are used accordingly for the decision making process.

B. AHP

To compare the different cases obtained by HOMER Pro and to make decision regarding the best cases, a multi-criteria decision-making (MCDM) algorithm is used. The tool used for MCDM is analytic hierarchy process (AHP). This process consist of subjective comparison of all the plans of the system by arranging them in a matrix to determine relative priorities [6].

In Table III, the criteria followed in this project for the decision making are shown. Four main attributes are selected namely, economical, robustness, environmental and technical. Under each of the main attributes, different criteria are selected.

TABLE I: Installed capacities of each of the considered technologies in the selected plans

Plan nr	**PV [MW]**	**WT [MW]**	**Diesel Generator [MW]**	**Battery [MWh]**
1	0.0	0.0	60.0	0.0
2	97.0	101.5	55.0	64.4
3	90.0	94.5	55.0	67.8
4	106.0	122.5	55.0	0.0
5	0	122.5	55.0	100.8
6	120.0	0	55.0	40.5
7	60.0	63.0	50.0	38.6
8	60.0	63.0	55.0	0.0
9	30.0	31.5	50.0	11.9
10	0.0	94.5	55.0	90

TABLE II: Economical and technical details of the selected plans

Plan nr	**NPC [M$]**	**COE [$]**	**Operating cost [M$/yr]**	**Initial capital [M$]**	**Ren Frac [%]**	**Excess Elec [%]**
1	1881.8	0.315	131.86	24.30	0.00	0.00
2	444.0	0.074	14.93	233.66	91.95	38.72
3	447.3	0.075	15.96	222.55	91.25	34.67
4	468.6	0.078	16.44	236.94	90.51	48.21
5	605.4	0.101	26.65	229.93	83.83	35.27
6	1273.2	0.213	83.28	100.13	37.08	11.28
7	572.3	0.096	29.92	150.77	79.55	14.21
8	643.4	0.108	36.07	135.27	78.78	15.13
9	1157.3	0.194	76.32	82.15	46.49	1.77
10	647.8	0.108	32.64	188.03	79.1	21.62

This criteria is later used for the comparison of each plan and to finally choose the most relevant based on higher priority for the economical and the robustness respectively, followed by the technical and environmental aspects.

The most suitable plan for this case is plan number 2 (PV + Wind turbine + Diesel + Battery). This plan has the lowest NPC of $444M\$$, an initial investment of $233.66M\$$, and an operating (O$M) cost of $14.9M\$/yr$. This plan has a renewable fraction of 91.95% and an excess electricity of 38.72%.

The consistency of the result can be verified by calculating the consistency ratio. The performed calculations proved that all the values satisfy the condition to be below 10% and therefore the calculations are considered to be reliable. [7]

TABLE III: Selection Criteria

Attribute	Subattribute
Economical	NPC[$]
	Initial Capital[$]
	Operating cost[$/yr]
	System/Excess Electricity [%]
Robustness	Diesel
	PV
	Wind Turbine
	Battery
Environmental	CO2 Emissions
	SO2 Emissions
	NOx
	PM
Technical	Ren Frac [%]

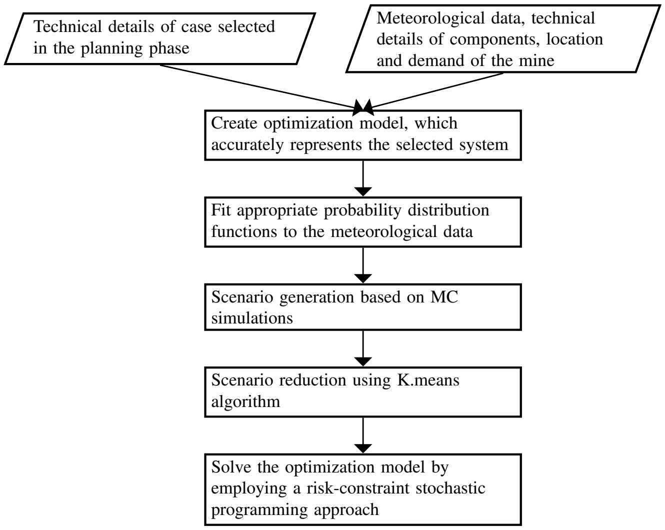


Fig. 1: Flowchart of operation optimization

III. Optimization of Operation

Optimal daily scheduling aims to operate the system in a way so that the operation and maintenance cost is minimized over a 24 hour period. A risk-constraint optimization is used to minimize the cost under uncertainties in renewable resources and load profile of the system. These will be accounted for using conditional value-at-risk(CVaR) method. The process of the optimization of operations can be observed in Fig. 1.

A. Evaluation of Uncertainties

Data measured in 2019 is used for the planing and operating phase, since the renewable energy resources are volatile, certain uncertainties have been added to the optimization formulation to account for these.

Three stochastic variables have been used for the evaluation of uncertainties, PV power, wind and load profile of the mine. 10000 different cases for each stochastic variables have been generated using Monte-Carlo simulations. To improve computational complexity of the examined problem the whole number of generated scenarios are then reduced into 25 using K-means algorithm [8].

The data from the industrial partner is divided into 24 hours. For each hour, the empirical cumulative distribution function (CDF) is calculated for each uncertain parameter.

After obtainig the CDFs the root mean square error (RMSE) is calculated for each of them and the lowest error distribution is chosen as the best fit as observed in 1.

$$RMSE = \sqrt{\frac{1}{Nh}\sum_{h=1}^{Nh} \cdot (CDF_{emp}^{h} - CDF_{sel}^{h})^2} \qquad (1)$$

Where:

- Nh - number of hours
- CDF_{emp}^{h} - empirical CDF
- CDF_{sel}^{h} - selected CDF

In Figs. 2(a), 2(b) and 3 the 25 cases and the mean of the three stochastic parameters are displayed.

It should be noted that the downward spikes in the load profile of Fig. 3 epresent possible daily maintenance of mining equipment.

B. Risk management

Popular risk managing functions are value-at-risk (VaR) and conditional value-at-risk (CVaR). VaR is a measure which is widely used in industry regulations. However, it does not provide information on the extend of losses in the tail of the loss distribution [9]. CVaR, on the other hand, accounts for the losses exceeding VaR. Hence, it provides adequate picture of risk reflected in extreme tails. A great advantage is that CVaR can be optimized and constrained with linear programming methods, whereas VaR is relatively difficult to optimize [10].

For a discrete distribution and at given confidence level α the equation for minimizing CVaR is formulated as follows [5] [11] [12]:

$$CVaR = min(\zeta_t + \frac{1}{1-\alpha}\sum_{s=1}^{N_s} \pi_s \eta_{t,s}) \qquad (2)$$

Subjected to:
$$\eta_{t,s} - cost_{t,s} + \zeta_t \geq 0 \qquad (3)$$
$$\eta_{s,t} \geq 0 \qquad (4)$$

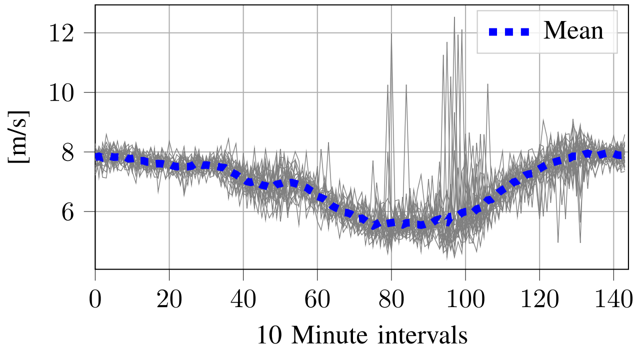
Where:

- α - confidence level
- ζ_t - threshold to recognize $(1-\alpha)\cdot 100$ percent worst scenarios of each stochastic environment at hour t. It equals to VaR, which means that $(1-\alpha)\cdot 100$ costs in hour t are higher or equal to ζ_t
- $cost_{t,s}$ - operational cost of scenario s in hour t
- $\eta_{t,s}$ - an auxiliary non-negative variable, equal to the difference between $cost_{t,s}$ and ζ_t when the $cost_{t,s}$ is higher than ζ_t.
- π_s - probability of scenario s

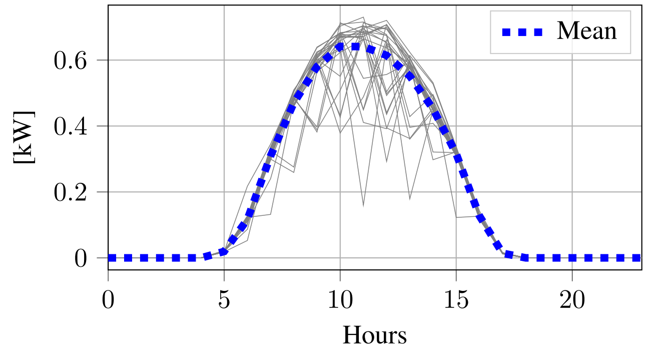
C. Optimal operation management

The variables must be selected to accurately describe operation of each of the elements of the examined system. The variables are defined for every hour of the optimization period (t), as well as for each of the considered scenarios (s) generated. The variables are summarized and described in the Nomenclature.

The constraints can be divided into two main categories: the bounds of variables and the ones that describe the operation of the system. The bounds are defined based on the system specification. The constraints defining the operation of the power plant are defined in 5 - 15. The two main constraints are: the equality of supply and demand in the mine - constraint 5, and stored energy balance - constraint 6. Constraint 7 is introduced to define the state of operation of the diesel generator. The start and stop of the generator is defined by constraint 8 and the simultaneous turning on and off is prohibited by 9. Constraints 10 - 12. define the state of charging and discharging of the



(a) Wind cases



(b) Solar cases

Fig. 2: Wind and Solar irradiance cases

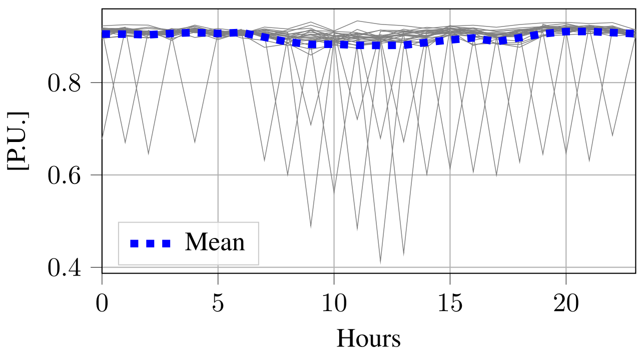


Fig. 3: Load cases

battery and ensure that charging and discharging does not happen at the same time. The minimum up and down times of the diesel generator are defined with constraints 13 and 14 respectively. Finally, constraint 15 defines the initial SoC of the battery.

$$D_{t,s} = l_{wt,t,s} \cdot P_{wt,t,s} + l_{pv,t,s} \cdot P_{pv,t,s} + P_{d,t,s} + B_{d,t,s} - B_{c,t,s} \tag{5}$$

$$SoC_{t,s} + B_{c,t,s} \cdot \frac{\sqrt{eff}}{S_{max}} - \frac{B_{d,t,s}}{\sqrt{eff} \cdot S_{max}} = SoC_{t+1,s} \tag{6}$$

$$u_{d,t,s} \geq \frac{P_{d,t,s}}{P_{max,d}} \tag{7}$$

$$u_{d,t+1,s} - u_{d,t,s} = y_{d,t+1,s} - z_{d,t+1,s} \tag{8}$$

$$y_{d,t+1,s} + z_{d,t+1,s} \leq 1 \tag{9}$$

$$b_{c,t,s} \geq \frac{B_{c,t,s}}{P_{max,bc}} \tag{10}$$

$$b_{d,t,s} \geq \frac{B_{d,t,s}}{P_{max,bd}} \tag{11}$$

$$b_{d,t,s} + b_{c,t,s} \leq 1 \tag{12}$$

$$UT_d \cdot y_{d,t,s} \leq \sum_{h=t}^{t+UT_d-1} u_{d,h,s} \tag{13}$$

$$\sum_{h=t}^{t+DT_d-2,s} z_{d,h,s} \leq 1 - u_{d,t+DT_d-1,s} \tag{14}$$

$$SoC_{0,s} = SoC_{init,s} \tag{15}$$

The listed constraints can be altered to represent a different configuration of the system. The minimum up and down time of the diesel generator was introduced in order to avoid frequent switching on and off of the unit.

The final step of defining the optimization problem is the formulation of the objective which is defined as the minimization of the cost of operation and maintenance (O&M) of the plant in an uncertain environment. The cost of each scenario is defined as in 16. The first three terms of the equation represent the cost of fuel, the starting cost and O&M cost of diesel generator. The rest of the equation takes into account the O&M of WTs, PVs and battery - both constant yearly values and variable O&M costs associated with the amound of electricity produced.

$$\begin{aligned} cost_s = &\sum_t^T (u_{d,t,s} \cdot F_{min,d} + P_{d,t,s} \cdot 0.244) \cdot DP \\ &+ \sum_t^T (y_{d,t,s} \cdot SU_d) + \sum_t^T (u_{d,t,s} \cdot OM_d \cdot P_{max,d}) \\ &+ (OM_{wt,y} \cdot I_{wt} + OM_{pv,y} \cdot I_{pv} + OM_{b,y} \cdot I_b) \cdot \frac{T}{8760} \\ &+ \sum_t^T (I_{wt,t} \cdot P_{wt,t,s} \cdot OM_{wt,e} + \frac{B_{c,t,s} + B_{d,t,s}}{2} \cdot OM_{b,e}) \end{aligned} \tag{16}$$

Having defined the cost per scenario, the objective function to represent the total expected operating cost can be formulated as in 17, in which the second part incorporates the risk measurement CVaR to the objective function through the risk aversion factor β.

$$Min \sum_{s=1}^{N_s} \pi_s \cdot cost_s + \beta \cdot CVaR \tag{17}$$

IV. Results

This section represents the results of optimization performed for Plan 2, which was selected based on AHP in section II-B.

The optimization problem, formulated in the previous section, was adjusted to accurately represent the selected plan. The optimization was done for 25 different cases of PV power, wind speed and load, generated with use of MCS and with confidence level (α) of 95%. Moreover, 10 different levels of risk aversion factor (β) were considered to observe how the level of risk, incorporated in the optimization, affects the expected profit and CVaR.

A. *Risk assessment*

The operator of the mine is interested to get a deep insight into the expected cost of operation as well as the one in the worst possible scenario. The latter, considering the possibilities of uncertainties, may have a great influence on the final result. The risk is incorporated to the optimization by the risk aversion factor β. The value of β varies in from 0.1 to 10. The former represents near-zero risk aversion and with increase of beta the risk aversion increases.

The dependency between the expected cost of operation and the CVaR for different levels of risk aversion factor is presented in Fig. 5. With the increase of β, CVaR is reduced and the cost increases. Change of β from 0.1 to 0.4 has significant influence on both variables. However, the change of β from 2 to 10 increases the expected cost without decreasing the CVaR value significantly. The difference between the minimal cost (for β = 0.1) and the maximal cost (for β = 10) is around 0.26%. The difference between extreme values of CVaR is around 0.40%. The CVaR for β= 0.1 is 102.3% of the expected operating cost. When β = 10 is considered, CVaR is 101.7% of the expected cost.

The expected cost was calculated based on the optimization problem presented in the previous section. The arising question is if the optimization reduces the cost when compared to a simple algorithm for operation of the battery and diesel generator. The simple operation assumes that the battery is always charged by RES if the production from RES is higher than the demand and the SoC of the battery is lower than 100%. If the production from RES is lower than the demand the battery is discharged to supply the needed power. In case it is not possible to cover the demand by discharging the battery, the diesel generator is used. This simple algorithm is close to the optimized operation, however, it does not take into account the level of O&M cost of the components. The costs calculated for one of the scenarios, with optimization and simple algorithm, are represented in Table IV. The optimized cost, calculated for β = 0.1, is 1.5% lower than the cost with simple algorithm. Even when the high level of risk is considered in the optimization, the cost is still 1.3% lower than the algorithm.

Finally, the cost of operation of Plan 2 can be compared to the O&M cost if only diesel generator is used to satisfy the demand of the mine. This cost is listed in Table IV and is around 33 times higher, for this typical day, than the cost in Plan 2. That proves that the selected plan could not only provide a reliable power generation, but also very low daily operating cost.

TABLE IV: Cost of operation in one of the scenarios

Approach	Cost of operation
Optimization with β = 0.1	9923 $
Optimization with β = 10	9948 $
Simple algorithm	10073 $
Diesel generator only	339905 $

TABLE V: Average state of charge of the battery for different values of β

β	Average SoC
0.1	32.4%
1	37.5%
10	40.2%

B. *Hourly operation*

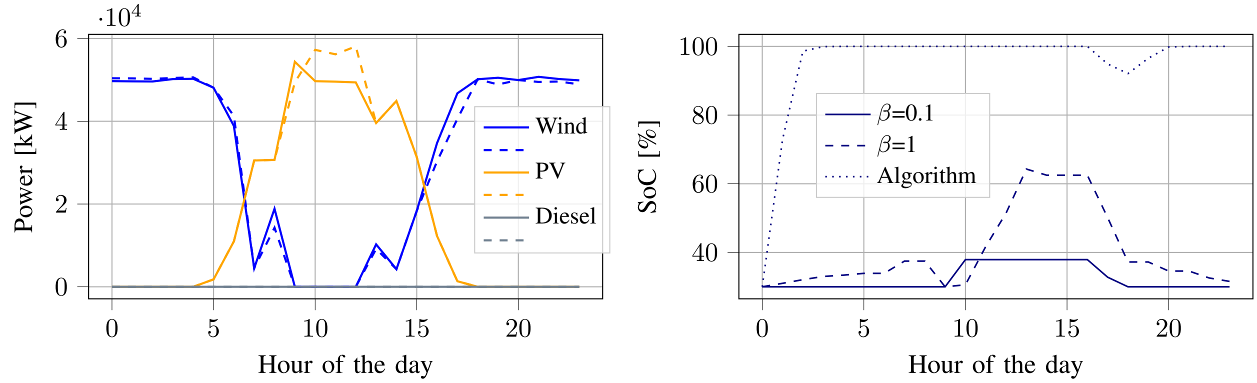
This section represents the hourly dispatch of the units to satisfy the demand of the mine in some typical day in a year. The simulations were performed jointly for all 25 scenarios to account for CVaR in the optimization. An example of hourly dispatch for one of the scenarios is presented in this section. The aim is to compare the optimized operation with low and high levels of risk aversion factor, together with simple operation based on the algorithm discussed in the previous section. The hourly dispatch for the day is plotted for β equal to 0.1 and 10. The SoC of the battery is plotted also for the simple operation with algorithm.

Fig. 4(a) represents the optimized hourly operation of the power generating units - PVs, WTs and diesel generator. The difference between $\beta = 0.1$ and $\beta = 10$ is mainly in the operation of PV modules, which are allowed to generate more power in the pick during the middle of the day for $\beta = 10$. The additional power is used to charge the battery. This behaviour is presented in Fig. 4(b). The battery is reaching higher SoC when the risk aversion factor increases. The same observation can be made for the average SoC, presented in Table V. With the increase of β value the average SoC of the battery increases. This is because the uncertainties are incorporated to higher extend into the optimization. Keeping the battery charged throughout the operation assures a better resilience to unexpected changes. The behaviour proves that the CVaR method, presented in this project, works correctly. The SoC calculated with the simple approach differs significantly from the one obtained in the optimization. The battery is kept fully charged throughout the day, even though it is not needed for operation of the mine. Operating the battery with this naive approach increases the O&M cost of the mine.

V. Conclusions

The focus of the study was to find a profitable and reliable combination of energy sources to supply electricity to a mining site in Australia. The selection of the plan was done based on AHP and the configuration with lowest NPC and high renewable fraction was selected.

The assessment of robustness of the system to uncertainties in PV power, wind speed and load profile was done using risk-constrained stochastic framework. The aim was to minimize the expected cost of operation. CVaR was used to model the trade-off between minimizing the cost of operation and risk



(a) Hourly, power output of WTs, PVs and Diesel generator. Solid line for $beta = 0.1$ and dashed line for $beta = 10$

(b) Hourly state of charge of the battery

Fig. 4: Output of the optimization

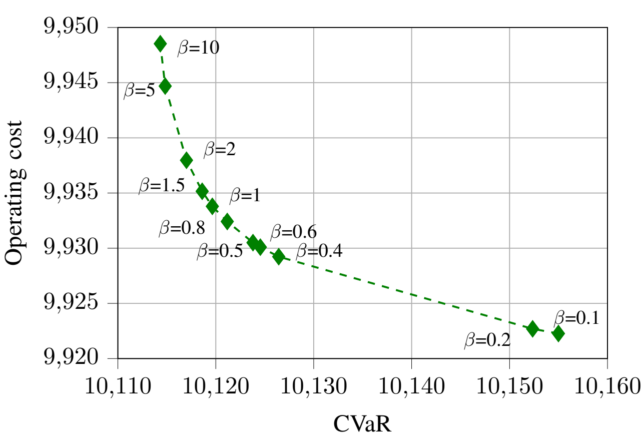


Fig. 5: Expected cost versus CVaR for different values of β

of getting high cost of operation in undesired scenarios. The level of risk incorporated to the optimization problem was controlled by risk aversion factor β. It could be seen that with increase of β the expected cost of operation increased, while the CVaR decreased. The change in the two measures was 0.26% and -0.4% respectively. The operating cost did not increase be increased significantly even considering the worst scenario because the CVaR values were only 2.3% and 1.7% higher than expected cost, for $\beta = 0.1$ and $\beta = 10$ respectively, meaning that the system was robust to the uncertainties. The calculated O&M costs for the selected plan are also significantly lower than costs, which would be obtained if the mine was electrified only with diesel generators. An important observation from the hourly dispatch analysis was that the average SoC of the battery increased with the increase of β. This could be a desired behaviour, because it assures better resilience of the system to unexpected changes.

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