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Energy buffering for large wind farms

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ABSTRACT

Storage technologies are essential if the renewables penetration level, into electricity generation, is to increase. This project aims to define an appropriate form of electricity storage, for regulating the output of a large wind farm, and carries out a cost analysis of the chosen storage. An intensive literature review, on storage for power systems, found that flow batteries, such as all vanadium redox energy storage system (VRB-ESS), are the most suitable technologies. They allow high input/output power for longer periods than other advanced batteries and, contrary to hydro pumped and compressed air energy storage, VRB-ESS batteries do not need any specific site requirements.

This project assessed different battery storage operating strategies in relation to the operation of the British electricity market. Data, from the Braes of Doune wind farm, was used to test three scenarios that were developed to incorporate the batteries into a wind farm. The first scenario was to smooth the output of the wind farm so as to give a constant power output every thirty minutes. The second scenario involved smoothing the wind farm output to give a constant power output every four hours. The final scenario investigated delivering power mainly during peak-time periods. In order to assess the functioning of the batteries, these scenarios were simulated with two different control systems: the first one runs simultaneously with the wind farm output and regulates it; the second one delivers a constant power based only on the energy available in the storage device. For each one of these configurations, the necessary size of the battery was set up. Considering the additional revenue given for providing constant power, a cost analysis was carried out to define which configurations were cost-beneficial by the end of the project lifetime.

Taking into account the shortest period of time and using the simultaneous control system gave the best results. It was shown that the storage system has a break-even point after 30 years and considering that a wind farms' lifetime is 25 years, this configuration is not viable yet. Therefore the initial cost of the battery has to be reduced or the additional revenue increased in order to expand the use of VRB-ESS flow batteries for buffering wind farms' output.

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A. INTRODUCTION :

Renewables, and especially wind power, have achieved a significant level of penetration in the British power generation market in recent years and are supposed to reach the target of 20% by 2020. It can be anticipated that they will make increasing contributions to electricity generation in the near future. However, renewable energy production is intermittent and matching the supply and the demand is often a problem. This is a barrier to their extensive use.

Most renewables are tied to strong grids where the base load power plants (generated by hydro-electric, coal or nuclear) minimise quality concerns and make it less important for wind generation to be matched to consumption. According to experts, renewables' generation up to 20-30% of overall electricity generation should not destabilise the grid. In isolated electrical grids such as islands which are not linked to strong grids, renewables' generation can be very destabilising for the grid, with dramatic consequences for the quality of the power delivered. Indeed, for both of these cases, reducing greenhouse gas emissions for a sustainable and clean future is achieved at the expense of grid planning and predictability. The main solution to this problem is storage. Indeed, it can provide output stability, ramping control, but can also guarantee power generation when there is no natural resource (sun, wind, wave…) [1]; a storage component will allow renewables to achieve a high penetration into the grid.

Unfortunately, direct storage of electricity is not possible. Research and development of economical and efficient storage systems is currently being carried out [2]. Of all the new energy storage technologies, the redox (reduction/oxidation reaction) flow battery appears to offer great promise as a low cost and high-efficiency large scale energy storage system. This storage system is able to deliver several MW over a period of several hours. Based on these attractive features, the main objective of this project is to find out if this technology is suitable for regulating the output of wind farms. This project aims to assess different operating strategies in relation to the operation of the British electricity market.

Redox flow batteries are currently used in a few wind farms to smooth out their output. For example, Tomamae Wind Villa, the biggest wind farm in Japan has been using it for a few years in order to smooth out the power delivered to the grid and to give a constant value every twenty minutes. In Australia, the King Island wind farm has also been using it to give their system support in order to enable them to run a higher wind penetration knowing that the battery would give short term support in case of a rapid load increase [3]. This project is different from the ones above because it aims at tackling a different objective: studying the feasibility of considering redox flow batteries to smooth out the output power of a wind farm for longer periods and check if this solution is economically viable. This will be done by using a time step simulation to assess the size of the battery necessary for a large wind farm and then its performance.

In order to run accurate simulations, this project will be based on real data: the output power of a wind farm (Braes of Doune) located in Scotland near Dunblane, and generates up to 98 megawatts from 49 turbines. The main manufacturer of redox flow batteries: VRB-ESS based in Canada provided the technical characteristics of the equipment. From this data, different scenarios (using simulation) were studied in order to define the most suitable one for the wind farm considered, following this an economical feasibility study was carried out.

B. BACKGROUND OF THE PROJECT

Energy storage is unavoidable if we want to increase the penetration level of intermittent power sources such as renewables [4] or generally to match the demand with the supply. Indeed, the demand for electricity from consumers (domestic and industrial) is constantly changing within the following time scales:

- Minutes and hours: due to individuals' and industries' actions;
- Daily: due to the peak time consumption period;
- Weekly: due to the fact that industries are closed on weekends;
- Seasonal: winter require more lighting and heating.

To cope with this changing demand, additional power plants can be brought online such as combustion gas turbines, spinning reserves can be connected; or stored energy can be released. Since direct storage of electricity is not possible, energy must be stored by indirect ways instead [4]:

- electro-chemically (batteries, fuel cells),
- mechanically (flywheels),
- electrostatically (capacitors),
- magnetically (magnetic superconductors),
- hydraulically (pumped storage),
- pneumatically (compressed air),
- producing hydrogen.

Ideally, the perfect storage would require little space (high energy density) and would be able to deliver the energy stored under full control (rapidly or slowly). It should be safe, affordable and require little maintenance. It should operate on a reversible charge/discharge cycle with a long cycle life, and be capable of deep discharge without reducing its lifetime.

Currently, there is no equipment that can meet all these requirements and this reduces the potential of renewables to challenge the use of fossil fuels. As mentioned before, variability is the main barrier to the development of renewables. In the following paragraph, the needs for storage will be explained in more detail in order to understand the importance of storage technologies.

1. A real need for storage:

1.1. Intermittency: unavoidable drawback of renewables

Since renewables use fluctuating sources of energy (wind, solar, wave…) their output power cannot be constant. This is due to the nature itself of these sources of energy. For example, wind turbine output variations are due to several causes on different time scales. The following table gives a summary:

Causes of variation	Time scale of variation
Wind gusts (turbulence)	Short term seconds
Normal wind speed variations	Minutes
Inversion layers	Hourly
Diurnal cycle	Daily
Changing (long term) wind patterns	Days
Seasonal cycle	Monthly
Annual variation	Yearly

Table 1 - Causes and Time scale of wind variation [5].

The following chart represents the magnitude of wind power changes. It can be seen that it can reach until 1000% annually, and 100% monthly.

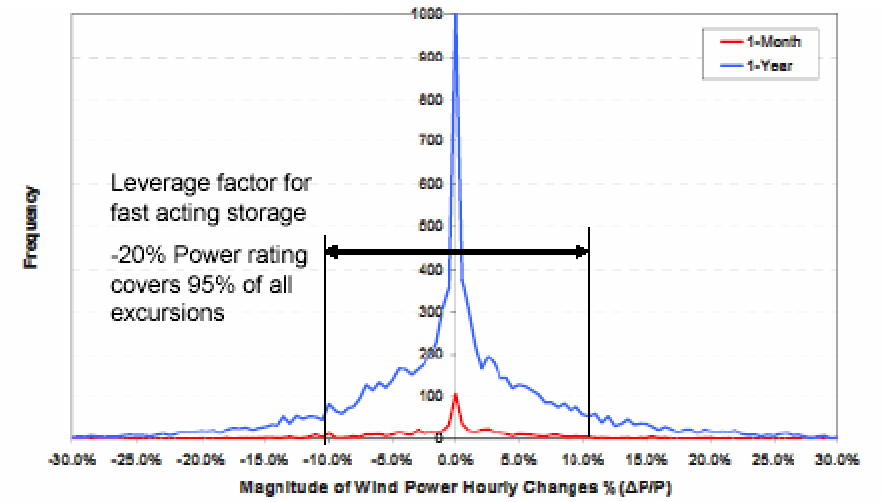


Figure 1 - Magnitude of wind power hourly changes [1]

In order to save all the energy recoverable and to sell it when needed (peak time period daily or during winter annually) or constantly (by minimising the fluctuations), a good storage system has to be considered to improve a wind farms output. Indeed, many benefits can be brought by storage applications considering several time scales. Table 2 shows the advantages that can be brought by storing energy within different periods.

Period of storage	Task – improvements
0.02 – 0.2s	Improvement of stability
0.12 – 0.2s	Countermeasure against supply disruption

Few seconds	Output smoothing
0.5 – 120s	Voltage stabilisation, frequency regulation
30 – 300s	Spinning reserve
180 – 10000s	Peak shaving
Daily 4 – 12h Weekly 40 – 60h Seasonal 3 months	Load levelling

Table 2 - Time characteristics required for storage applications [1].

1.2. Costs of intermittency.

We can say that energy storage is economical when the marginal cost of electricity is higher than the costs of storing and retrieving the energy plus the price of the energy lost in the process. Indeed, all these costs have to be considered in order to accept the installation of a storage system [6].

Concerning renewables, renewable electricity is sold cheaper than controllable power from conventional sources due to the varying nature of the output. As renewable supplies become increasingly popular, this difference in price creates an increasingly large economic opportunity for grid energy storage.

An in-depth analysis has to be carried out to estimate the marginal cost of electricity in this case for different scenarios as the price of electricity varies with its quality and length of constant period delivered. More details about the British electricity market will be given later.

In order to validate the choice of flow batteries, their characteristics and those of other storage technologies are described and then compared.

2. Storage methods:

2.1. Lead acid batteries:

Lead-acid batteries are very common in many applications. They are the oldest chemical storage device. Because they are used so widely, the manufacturing cost is very low (£150-300/kWh) [7].They are used in cars but also as a back-up power supply for electricity needs. Figure 2 represents the operation of a lead-acid battery.

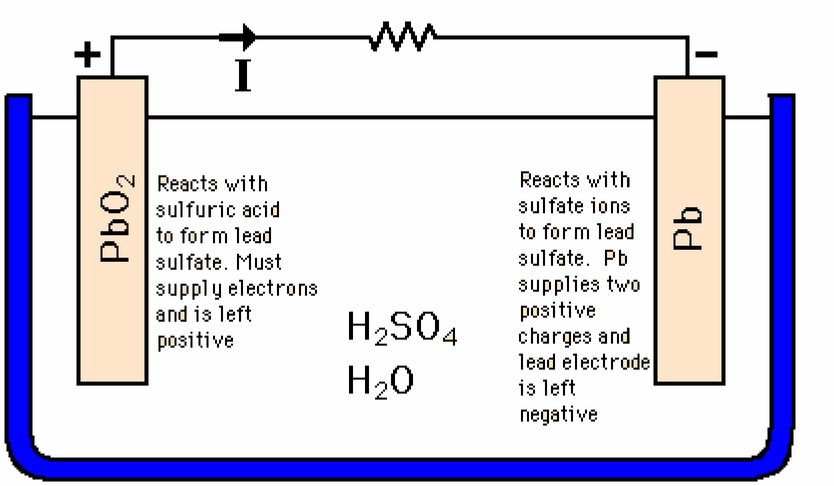


Figure 2 - Lead acid battery description [7]

The battery consists of pairs of plate, one lead ad the other lead coated with lead dioxide. Both are immersed in a dilute solution of sulphuric acid which is the electrolyte. During the discharge mode the cathode is positive and the anode negative; both electrodes are converted into lead sulphate. Charging restores the positive electrode to lead dioxide and the negative one to metallic lead [8].

Lead-acid batteries are sized in Ampere-hours. To increase the amp-hour rating, it is necessary to add more batteries – the current rating is tied to the amp-hour rating. This way of storing energy is very convenient for short duration applications (less than one hour). Its characteristics are summarised here:

- Battery lifetime:

The battery lifetime is defined for 5, 10 or 20 years [9]. If fully discharged, there is a life degradation curve because of the irreversible physical changes in the electrodes, so the battery will have a reduced life. Basically, using a 5 year lifetime battery regularly, leads to only 3 years of use. Usually, the ultimate failure occurs between several hundred and 2000 cycles [8].

- Depth of discharge (DoD):

Maximum DoD of 30% without damaging the battery and shortening the life of the battery [9]. It is impossible to measure State of charge (SoC) accurately without taking it off line [7].

- Recharging rate:

The battery may be recharged at any rate that does not produce excessive gassing, overcharge or high temperature. A discharged battery may be recharged at a high current initially. However, as the battery approaches its full charge the current must be decreased to reduce gassing and excessive overcharging. It takes 5 times as long to recharge a lead acid battery to the same charge capacity as it does to discharge it. For a 4 hours discharge the full capacity is only available after 20 hours, so in any given 24 hours period, you can only get one complete discharge [9].

- Sizing the battery:

Usable energy density for storage applications is only about 12Wh/litre [9].

- Costs and maintenance:

The disposal cost is estimated between 500 and 1500$/kWh. Maintenance costs around $0.02/kWh [9].

2.2. Advanced batteries:

The main advantage of advanced batteries is that they offer higher energy densities than lead-acid batteries. At the moment, they are not used so widely and therefore, are much more expensive. They are used for the same applications: power quality and back-up at manufacturing plants, electronic devices and cars. They also offer a longer life time and specific characteristics as detailed below:

- Nickel-cadmium :

Ni-Cad batteries, while more expensive initially, have a lifetime over double than of lead-acid batteries (up to 3500 cycles at 85% depth of discharge [7]). In stationary applications where reliability is important, these are used in standby applications. Because they require no attention, stand high temperatures and are environmentally tolerant, they can be installed in remote locations and virtually forgotten due to their very low maintenance requirements. Their main disadvantages, apart from cost ($0.80/Wh) [7], include the high cost of post-life toxic disposal and a limited global reserve of cadmium.

- Lithium ion :

As they have a nigh energy density (200Wh/kg of lithium) [7], Lithium-ion batteries are light and provide a high voltage (about 4V per cell) [7]. They almost have a 100% efficiency and a long lifecycle - about 3000 cycles at 80% depth of discharge. With lithium being the lightest solid element ($0.534\ g\cdot cm^{-3}$) [7], Lithium ion batteries based on it can be much lighter than conventional types and therefore, very handy for portable application. However, moving up to large scale creates difficulties regarding safety aspects, in particular the high cost of containing the reactivity of lithium and electrode assembly.

- Sodium-sulphur or high temperature battery:

These batteries are attractive for large storage system. Contrary to most electro-chemical systems, in a sodium-sulphur cell the electrodes are liquid (molten sodium for the cathode and molten sulphur for the anode) and the electrolyte solid, made of alumina ceramic. The assembly has to be kept at 300-350℃ to remain active materials liquid [10]. A reversible reaction (sodium + sulphur = sodium sulphide) yields electrons in an external circuit which generate a potential difference of 2V per cell [7]. However, even if this technology is very promising, its cost is still too high to implement it into large scale applications.

- Metal-air :

Potentially the cheapest batteries are metal-air types. Anodes of commonly available metals (zinc, aluminium, lead and even iron) placed in a liquid or polymer impregnated electrolyte of potassium or other conducting hydroxide, release electrons during the ensuing oxidation reaction. These, attracted towards the carbon plus catalyst cathode when flowing in an external circuit, create a potential drop at the battery terminals. Metal-air batteries are inherently safe and environmentally benign. They have a high energy density (until 13kWh/kg) [7]. But while high energy, controllable discharge and low cost could suit them to many primary battery applications, the only known big rechargeable unit available so far (a zinc-air system) has a very short lifecycle and a charge/discharge efficiency of about 50% only [4].

2.3. Electrostatic storage: capacitors:

Capacitors are another option for storage, especially super and ultracapacitors. Energy is stored in the form of an electrostatic field. This technology offers extremely fast charge and discharge capability, even if they have a lower energy density than batteries, they can be cycled tens of thousands of times. Supercapacitors store energy in an electric double layer formed between each of two electrodes and the ions existing in the electrolyte. The distance over which the charge separation occurs is just a few angstroms. Capacitance and energy density are thousands of times greater than for conventional electrolytic capacitors. By now, power ratings of around 100kW are feasible, with energy being delivered in anything from one second to a minute [4].

Electrolytes can be either aqueous or organic. The higher energy density available with organic electrolytes can be boosted further by using metal for one of the electrodes, rather than the porous carbon commonly used. Response times down to milliseconds are possible.

2.4. Mechanic storage: flywheels:

Energy is stored in the rotating mass of a flywheel. The energy stored is released when the cylinder reduces its speed which can be controlled in order to be used as back-up systems for low power or short term applications. The rotating mass stores the short energy input so that rotation can In order to minimize aerodynamic losses flywheels are placed in a vacuum enclosure and the use of superconducting electromagnetic bearings can virtually eliminate energy losses caused by friction. The efficiency of the system is estimated at 90%. With the ability of flywheels to store high amounts of energy and respond rapidly, they could smooth out these short and medium-term variations. However, they cannot compensate for long period power intermittencies of wind farms for example.

Cost, in the present stage of evolution is an issue, as 250kW units cost around £50,000. A compensating factor is the high lifecycle. Indeed, the predicted life is over 10 million cycles (some 15-20 years in high frequency renewables use) minimal attention is needed. Future flywheels (under development) of up to 1.5MW spinning at 60,000rev/min or more are envisaged, with discharge times of up to 15 minutes [4].

2.5. Hydraulic storage: pumped storage:

Pumped hydro energy storage consists in storing water in a vessel in a high elevation, and then releasing it into a lower vessel through a turbine when power is needed (peak time). When there is no demand (off-peak time), the water is pumped back to the upper vessel. This way electricity can be stored indefinitely and in large quantities with a good efficiency (80%) [8]. It is the only large power system technique widely used to create seasonal storage. This system as it allows big energy storage can be used to smooth out the demand for base load power plants (can be switched on within few minutes). However, this is extremely site specific, has a considerable environmental impact, and is normally used at large scale because of the big investment that it represents. By now, over 90GW of pumped storage (associated with dams) is available worldwide [4].

2.6. Pneumatic storage: compressed air:

During the off-peak periods, air is compressed by an electrically powered turbo-compressor in big underground storage reservoirs such as a cavern or an abandoned mine. Later, when energy is needed, expansion is achieved with a natural-gas powered heater which drives a combustion turbine and then produces electricity back. This system is usually used on a daily cycle, charging at night (off-peak time) and discharging during the day. Small-scale installations used as energy stores for wind farms could add value by enabling the power to be sold at peak demand times; they are still under development [4].

2.7. Magnetic storage: magnetic superconductors:

Superconducting magnetic energy storage (SMES) stores energy in the magnetic field created by the flow of direct current through a coil that has been super-cooled by a refrigerator (possibly cryogenic systems). SMES loses the least amount of electricity in the energy storage process compared to other methods of storing energy. Indeed, once the superconducting coil is charged, the current will not decay and the magnetic energy can be stored indefinitely. They are highly efficient; the round-trip efficiency is greater than 95%, however, even if they can provide power almost instantaneously, they can only deliver a high power during a brief period. The loss of efficiency is due to the energy consumed by the cooling system [8]. If SMES were to be used for utilities it would be a diurnal storage device, charged from base load power at night and meeting peak loads during the day. By now, several 1MW units are used for power quality control in installations around the world, especially to provide power quality at manufacturing plants requiring ultra-clean power. Using them to smooth out the power output of a wind farm should be then considered. Considering their short time power issues, they cannot be used as back-up power supply. Equipments with a 20MWh capacity are still under development [4].

2.8. Hydrogen:

Hydrogen storage can respond to the fluctuations in energy production from renewables on a short term (hourly) or longer term (seasonally). The power generated from renewables (wind or solar power) can be used to produce hydrogen by water electrolysis [11]. This process has a good efficiency (>70%), but it is also expensive (large-scale production cost is £2.5-4.0/GJ). The hydrogen produced can be stored as a solid, a liquid or a gas.

	Gaseous H_2 Storage	Liquid H_2 Storage	Solid H_2 Storage
Current status	Available technology	Available technology	Developing technology
Technology used	C-fibre composite vessels (6-10 wt% H_2 at 350-700 bar).	Cryogenic insulated tank (ca. 20 wt% H_2 at 1 bar and -253℃).	Metal hydrides (potential for > 8 wt.% H_2 and > 90 kg/m3 H_2-storage capacities at 10-60 bar).

Table 3: Characteristics of Hydrogen storage [11]

When energy is needed, hydrogen is then transformed back into electricity. Therefore, it is much better to use this way of storing energy when hydrogen itself is needed as a source of energy (e.g. fuel for transportation). The whole process including the water electrolysis and turning the hydrogen into electricity is far too expensive for the moment.

3. The VRB-ESS technology:

3.1. The Technology:

Redox flow batteries like VRB-ESS are more and more used to store energy for renewables. The electrolyte (liquid vanadium for VRB-ESS) is stored externally and is pumped to the cell stack as the energy is needed. The main advantage of VRB-ESS system is that the storage capacity can be increased by raising the electrolyte volume and the power output by increasing the number of cell stacks. The main drawback is that the energy density of the electrolyte used is low compared to other batteries, therefore, big storage capacities have to be used. The characteristics of VRB-ESS flow batteries are detailed below [9]:

- Principle of VRB

As shown in figure 3, the VRB has two electrolyte loops both containing vanadium in sulphuric acid medium, but in different valence states which may be oxidized/reduced at the electrodes. The vanadium redox pairs are V_{2+}/V_{3+} and V_{4+}/V_{5+} for negative and positive halves of the cell, respectively. The electrical balance is achieved by the transport of hydrogen ions in the electrolytes across the membrane during operation of the cell.

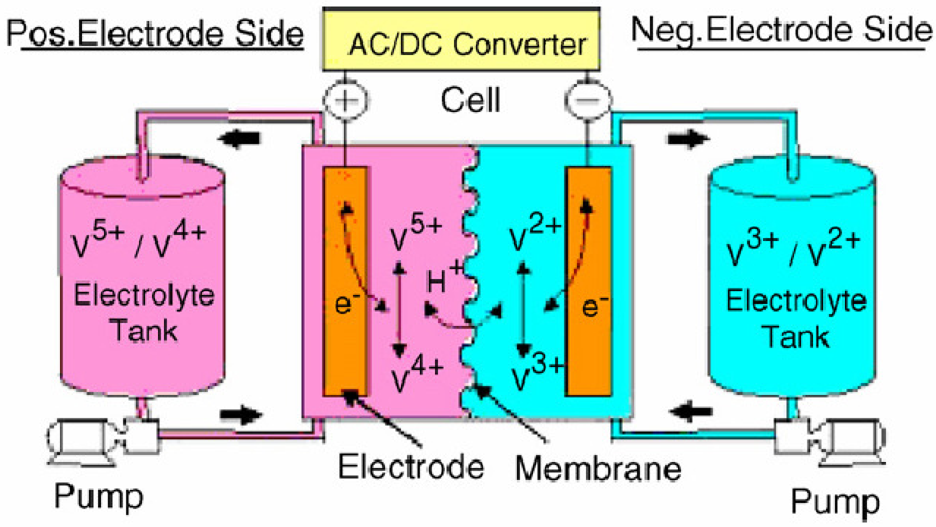


Figure 3: Schematic of the VRB-ESS battery [2]

- Battery lifetime:

The lifetime of this battery is measured in cycles (until 10,000 cycles) that should exceed 10 years. At the end of the lifetime, only the membrane of the cell stacks has to be changed. The lifetime of the electrolyte is indefinite. This lifetime is independent of the rate of discharge, depth of discharge and can be slightly influenced by the temperature. The following chart shows the charge-discharge cyclic curves:

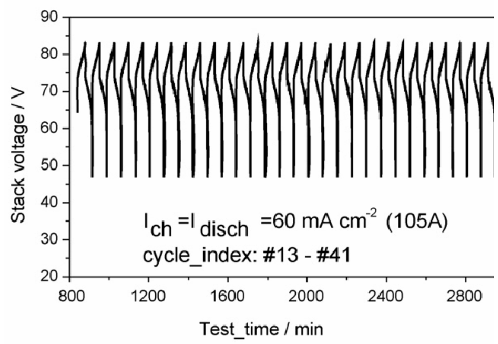


Figure 4 - charge-discharge curve of a VRB battery [2]

- Depth of discharge (DoD):

From 80% to 20% state of charge (During each cycle, it can be discharged to 20% and recharged to 80% indefinitely) thus 60% usable range.

- Discharge rate:

Can be discharged at any rate even at 5 times it nominal rating for up to a minute without any impact on its performance or reduction in its life.

- State of charge (SoC):

Very low to zero self discharge. Besides, on the cell-stack an indicator gives an accurate level of charge.

- Recharging rate:

VRB-ESS charges theoretically over a one-to-one time duration, but practically over a 1.8:1 time duration.

- Sizing:

The system can be easily upgraded, indeed additional storage capacity can be added by increasing the volume of electrolyte (1kWh=70litres) and output power can be increased by adding cell stacks.

- Operations and Maintenance:

Low operating temperatures and low sensitivity to ambient temperature variations allow easier and cheaper maintenance - Very low maintenance costs ($0.003/kWh).

PCS is used for the control of the whole system. Once the signals of charge and discharge, ramp rates and response times are given to the controller it manages the system. For MW size batteries, the PCS costs $150/kW until 2MW.

- Environmental aspect:

Using flow batteries contributes between 7% and 25% of emissions reductions of major polluting gases (CO_2, SO_2, CO, CH_4, NO_x) during their lifecycle when compared to lead-acid batteries.

3.2. VRB-ESS compared to other storage technologies:

From the previous descriptions, the following table summarises the main advantages and disadvantages of various storage technologies:

Storage technology	Main advantages	Main disadvantages	Applications
Lead acid batteries	Low capital cost.	Limited lifecycle when deeply discharged, Low efficiency.	Short term storage.
Advanced batteries	High power and energy densities, High efficiency, Low maintenance.	High production cost, High cost of post life toxic disposal,	Short and medium term storage in remote locations.
Metal – air batteries	Very high energy density.	Very short lifecycle, Low efficiency.	Long term storage only, which can be in remote locations.
Capacitors	Long lifecycle life, High efficiency.	Low energy density.	Very short term storage.
Flywheels	High power, Very durable, Low maintenance.	Low energy density.	Low-power applications or short term power quality support.
Pumped storage & Compressed air energy storage (CAES)	High capacity, Low cost.	Special site requirements. Serious ecological impact.	Emergency power injection to the grid, Smoothing out the demand for base load generation.
Superconducting magnetic energy storage (SMES)	High power.	High production cost	Power quality improvement, Short term back-up power supply.
Hydrogen storage	High energy density, low maintenance, high storage efficiency.	Low efficiency of the overall cycle: electricity – hydrogen – electricity High capital cost	Long term storage, stand-alone power systems, transport.
Flow batteries	High capacity, Independent power and energy ratings.	Low energy density	Short and long term storage.

Table 4: Applications of the different storage technologies

According their characteristics, storage technologies can also be visualised on the following graph which represents the most suitable storage for each configuration: rating power and the discharge time at rated power.

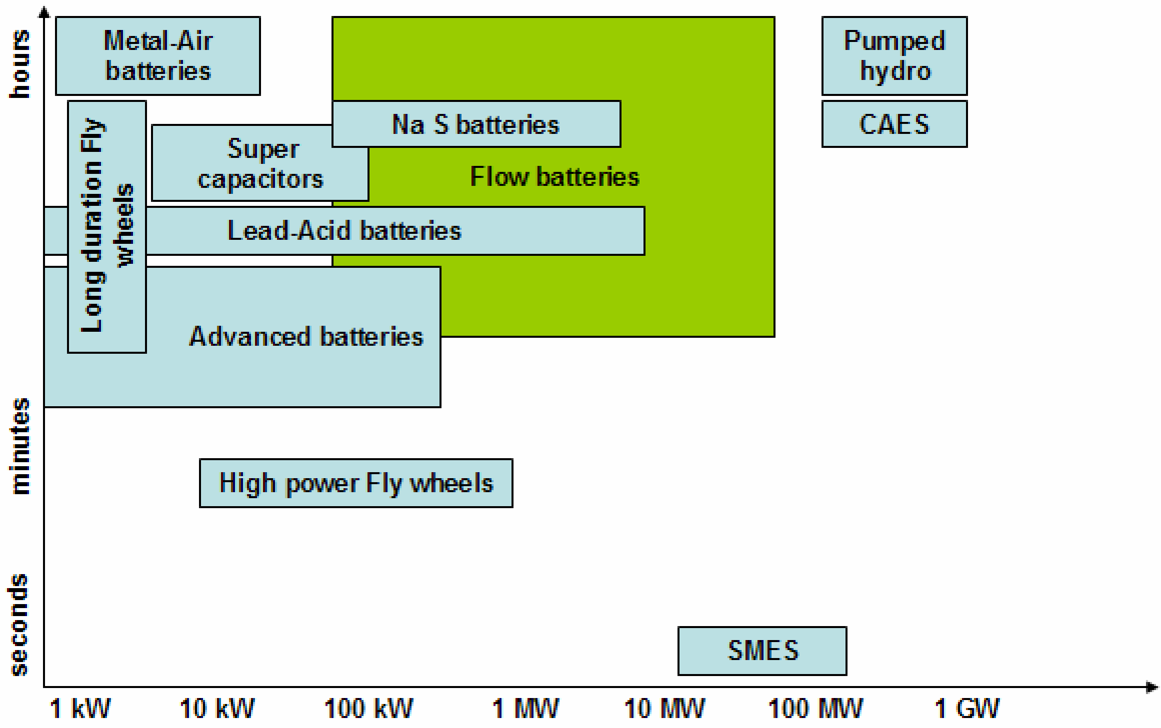


Figure 5: Discharge time at rated power VS system power rating [13]

Taking into account that wind farms considered in this project have an average power rating between 5 and 30MW, and that there is a need to store energy for different range of time going from minutes until hours, the flow batteries are definitely the technology to consider for this project. Their input power can be up to 100MW, which is the maximum size of the cell stacks, and it is possible to increase their energy capacity just by adding some electrolyte. Only pumped hydro and compressed air technologies could provide the same rated power, but they need special site requirement and cannot provide storage for short term applications. They are used only to deliver power for a long period, indeed, regarding the CAES, turning on combustion turbines cannot be considered for a few minutes. The aim of this project is to come up with a storage that could be used for most of renewables, therefore not only those located in special sites.

In order to adjust this project to the British market, the following section provides more details about how it works and how it has to be considered for this project in order to have greater benefits from the battery.

4. Brief presentation of the British electricity market :

The BETTA (British Electricity Trading and Transmission Arrangements) are based on the principle that electricity is traded between suppliers and consumers at prices which they have both agreed on. They include the arrangements needed to provide a mechanism for clearing and settling the imbalances that may occur between the prediction of supply or demand and the actual position. This part of the process is called imbalance settlement; it ensures that the overall system stays in balance in real time. The following diagram shows all the arrangements made by the BETTA:

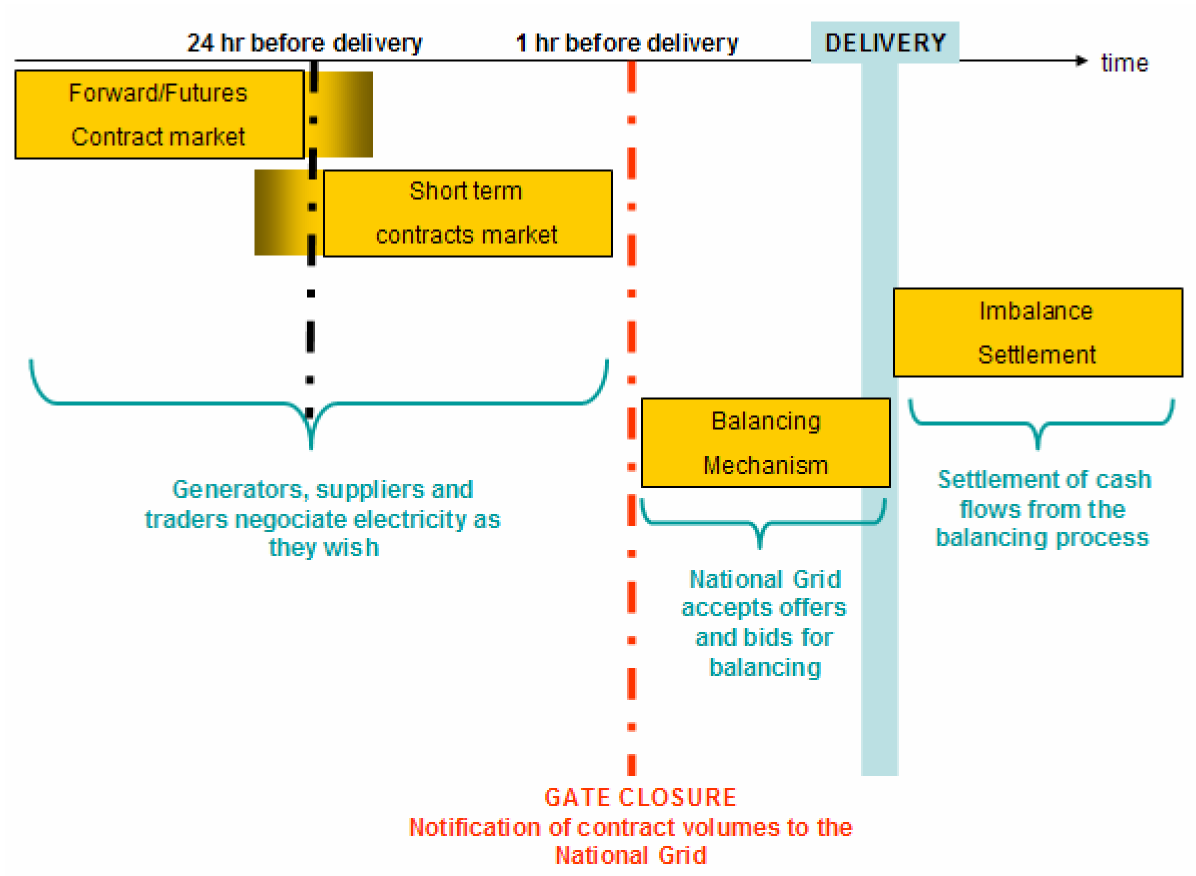


Figure 6: Overview of BETTA [14]

The gate closure is the moment when market participants (generators, suppliers, traders and consumers) notify the system operator of their intended final position and is set at one hour ahead of delivery. Afterwards, no further contract notification can be made. By contracting on ETSA (Electricity Trading Service Arrangements), the generators take the imbalancing risk. This means that if they do not supply the amount of energy predicted they have to pay penalties. On the other hand, if the production is higher than the prediction, the excess will only be bought at SSP (System Sell Price). This price is determined by the grid every thirty minutes. Obviously, as the supplier takes the risk of imbalance in order to assure a quantity of electricity, this amount of energy will be sold more expensively. For the generators, this is the main advantage of contracting on ETSA. The same process occurs for customers with large electricity requirements who contract on ETSA. Electricity consumed without any contract will be bought at SBP (System Buy Price) which also changes every thirty minutes.

4.1. The balancing mechanism:

Participation in the balancing mechanism involves submitting offers (proposed trades to increase the generation or decrease the demand) and/or bids (proposed trades to decrease the generation or increase the demand). This mechanism operates on a ‘pay as bid’ basis. As mentioned before, the price of electricity is mentioned within the bid and is then immediately paid.

National Grid purchases offers, bids and other balancing services to match supply and demand, resolve transmission constraints and thereby balance the system. As the market moves towards the delivery time, National Grid needs to be able to assess the physical position of all the market participants to ensure the security of supply. Before the gate closure each one of them has to supply a final physical notification.

4.2. Imbalances and settlements:

The magnitude of any imbalance between participants’ contractual positions (as notified at gate closure) including accepted offers and bids, and the actual physical flow between suppliers and demanders is determined. The resulting energy imbalance is then settled at the cash out price calculated by the settlement administrator which can be a company such as Elexon in the UK.

As mentioned before, the system sell price (SSP) is paid to parties with a surplus and without a contract. Parties with a deficit will be charged at the system buy price (SBP). These prices are designed to reflect the cost of operating the balancing mechanism or purchasing short term energy ahead of gate closure in the forward and spot markets. In the case of an unpredicted output power, such as the one from renewables, this is how electricity is bought.

These incremental costs are derived by taking the average cost of the marginal 100MWh [14] of actions that the National Grid has taken to resolve the energy imbalance.

4.3. Sell price profile:

The System Sell Price is a good indicator of the evolution electricity prices. Indeed, as supply contracted on ETSA is bought more expensively than SSP, it has to follow its evolution.

Therefore, from the data provided by Elexon (a settlement administrator), the following graphs were plotted:

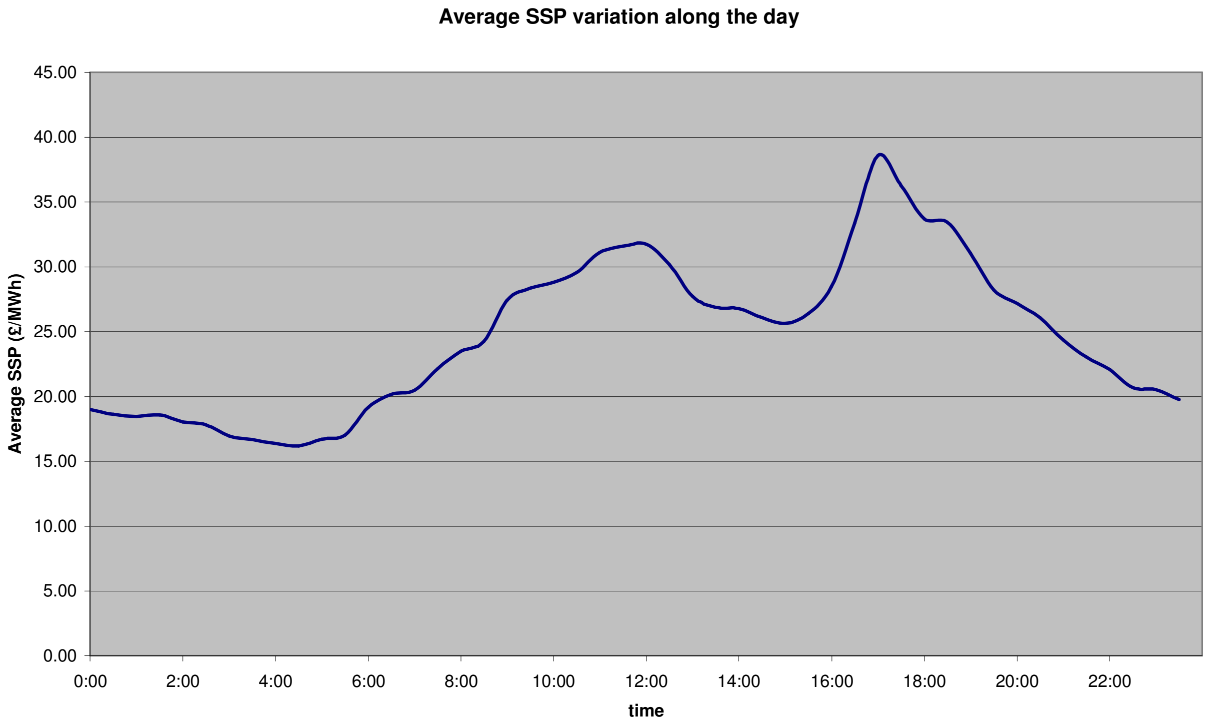


Figure 7: Variation of the SSP along the day [15]

These prices (SSP) fluctuate every thirty minutes. Each value represents the average price per year at the considered time. These fluctuations explain why traders divide days in trading blocks. Indeed, each block represents 4 hours. These blocks represent the main variations of the SSP. The following table illustrates it:

	Average SSP (£/MWh)
block 1	18.03
block 2	18.54
block 3	28.07
block 4	27.68
block 5	32.89
block 6	22.97

Table 5: Variation of the SSP block per block

The previous values show that the best period to sell electricity is during the block 5, also called the “peak time” period. Indeed, during this period, electricity is sold 30.3% more expensive than the daily average SSP. For this reason, it can be really interesting for a storing technology to save energy all day long and deliver it during these hours. On the other hand, there is no point of selling electricity during block 1 and block 2 as the electricity is then sold 24% less expensive than the daily average SSP.

Let us now have a look at the variation of the SSP over several years. This is plotted on the following graph:

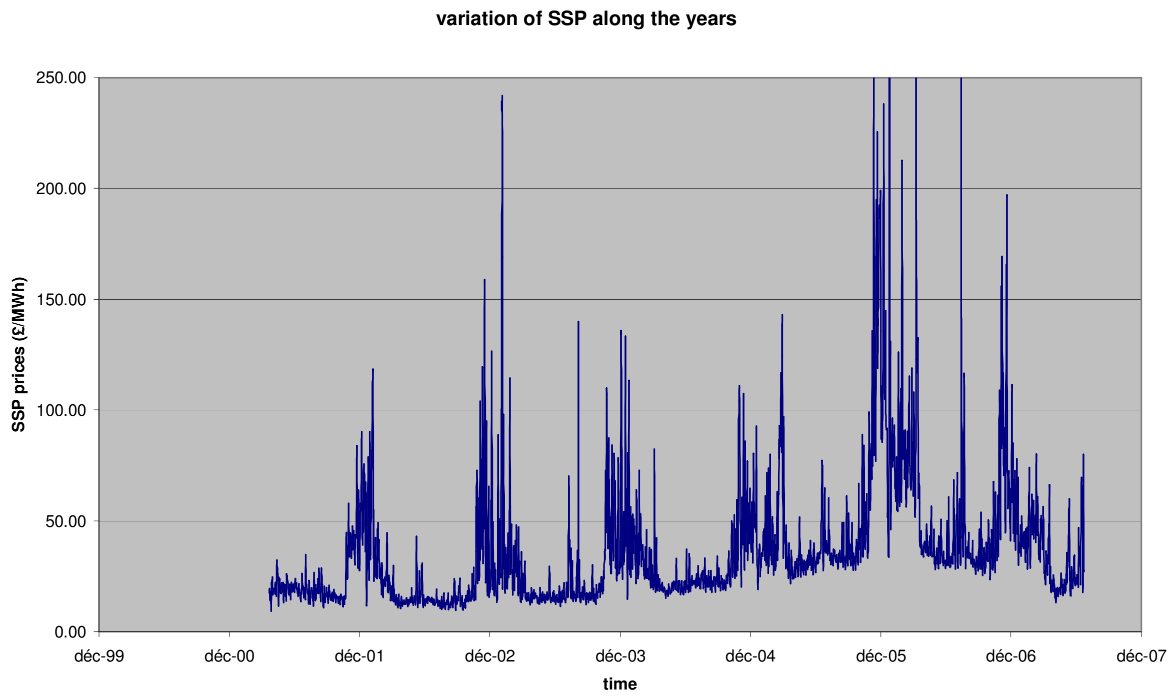


Figure 8: Variation of SSP along the previous years [15]

It can be seen on the graph that the SSP slightly increased since 2000. However, the most important thing to notice is that the SSP always goes up during winter. It is even easier to notice this by plotting the price over one year:

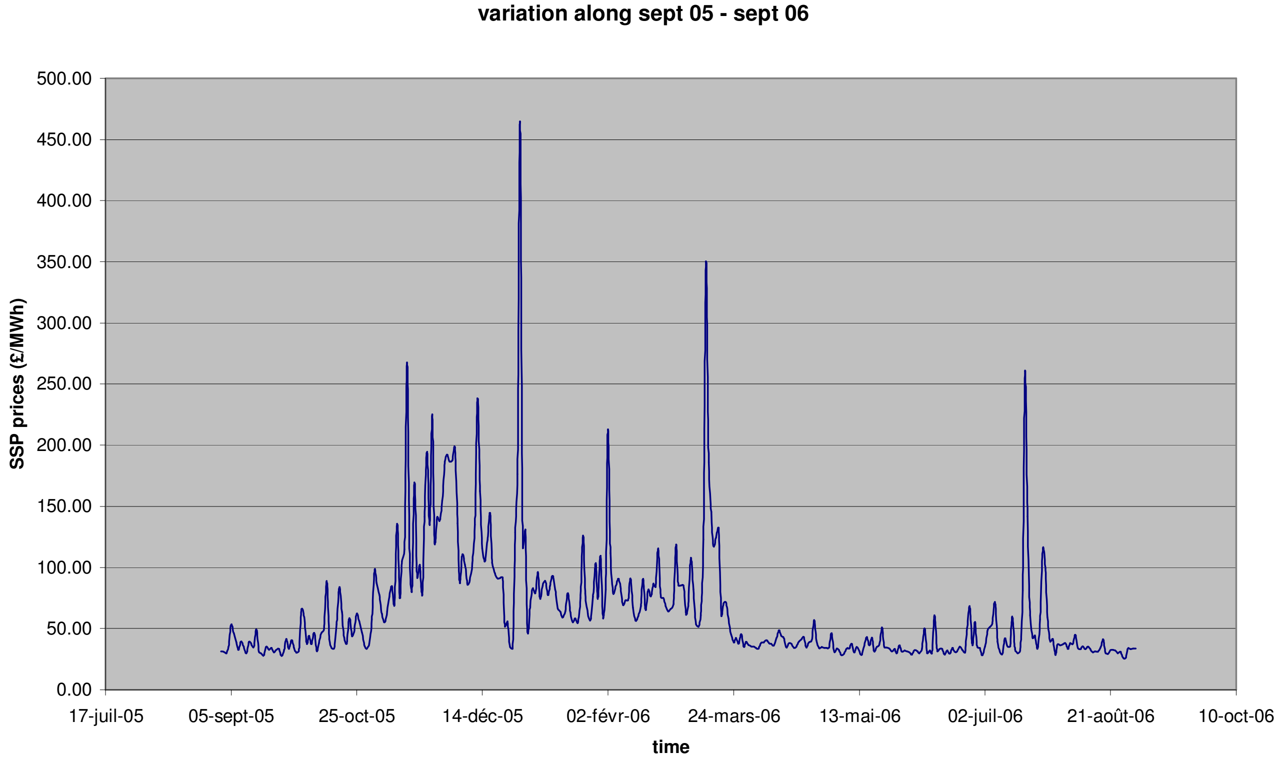


Figure 9: Variation of the SSP along last year [15]

These prices are the average peak time system sell prices for every day. It can be seen that they only reach and go over £50/MWh between October and March. For this reason, storage can be considered in summer in order to deliver energy in the winter. However, this would imply enormous reserves that cannot be reached with current storage technologies. For this reason, in this project, such variations will not be considered.

5. Detailed description of the project :

From the previous literature review, the main objectives of the project were defined, that is to say to assess if flow batteries can be used to smooth a wind farm output and this for several periods of time. Indeed, this storage technology seems to be the most suitable one for smoothing out electricity produced by renewables. Flow batteries can accept a big power input thanks to the size of their cell stacks, and the storage capacity (expressed in kWh) is only limited by the volume of electrolyte which can be increased easily. As the storage has to consider long term applications and without any special requirement, flow batteries appear to be worth looking into.

According to the British electricity market, there is a real need for good and long term predictions in order to make valuable bids which will allow selling electricity at a higher price than the SSP.

Therefore, this project has assessed the different possible ways of using a flow battery for a wind farm example. Once all the configurations (scenarios and control systems) had been set up, they were simulated and then a cost analysis was carried out for each one of them. The simulation was made considering an initial size of the battery, and from that, calculated the SOC and the output of the battery.

Afterwards, some recommendations are given in order to define what kind of application is the most suitable for now.

In this chapter, the simulation processes are detailed. They aim at simulating the behaviour of a considered battery over a period of ten months. The objective is to calculate the SOC and the output power of the flow battery after each step time. Regarding this, the benefit from using the battery can be estimated and, therefore, the net present cost after the lifetime of the project. The optimisation process used afterwards aims to minimise the net present cost by changing the size of the battery and from this the optimum size of battery for each configuration was defined.

In order to work on realistic scenarios, the configurations of this project have been chosen to match the requirements of the British electricity market. From the literature review, three main cases have appeared:

- ✓ Delivering energy mainly during peak-time periods;
- ✓ Delivering a constant power for each trading block (4 hours);
- ✓ Delivering a constant power time periods of half an hour.

All the simulations of this project are based on the output power of the Braes of Doune wind farm, between the 1st of September 2006 and the 1st of May 2007, and include the main characteristics of the considered flow batteries.

Figure 10: Map of Scotland – location of the wind farm

Considering a step time of ten minutes, the SOC (state of charge) of the battery and the energy coming in and going out of the battery has to be determined.

There are 34,848 time steps, of 10 minutes, over the period of ten months. Therefore, there is a real need to create an algorithm. Algorithms used represent only linear calculations so the software Microsoft Excel was chosen to run all the simulations, as there was no need for Matlab or Fortran to calculate the SOC of the battery for each time step. All the calculations, graphs and the optimisations were performed by Excel spreadsheets.

1. <u>Choice of the scenarios:</u>

1.1. <u>Delivering energy mainly during peak-time periods:</u>

The variation of the demand of electricity shows that the biggest consumption of electricity takes place during the "peak-time hours". During this period, electricity is at its most expensive, and can represent a good opportunity to pay back the flow batteries involved. In this case, the income should be much higher than in the following scenarios, since most of the electricity produced will be sold at the highest SSP. However, storing energy twenty hours a day requires a battery with a very big capacity. For this reason, another scenario will be set up: delivering a high constant power during peak-time hours and a low constant power the rest of the time. This should reduce the size of the battery and therefore its costs. With this second scenario, contracts to sell the electricity can be made 24 hours ahead in order to take advantage of the power prediction and then get higher bids when selling the electricity.

1.2. <u>Delivering a constant power in blocks of 4 hours:</u>

The electricity market is basically organised into trading blocks of 4 hours, as explained previously, and the prices of electricity mainly vary according to these blocks. This configuration of the market inspired this scenario, where the battery delivers a constant output power, matching that of the grid, for a period of four hours. The value of this power may be estimated from the prediction of the wind farm power output, from the changing rate of the wind farm power output, or from the energy stored inside the battery. This scenario will consequently reduce the size of the battery as it will store energy for a shorter period of time. However, this period is suitable for short-term contracts. Indeed, one hour after the closing gate time, the output power of the battery can be predicted and therefore electricity is still going to be sold more expensively because of the prediction and the risk of imbalancing taken on.

1.3. Delivering a constant power for a period of half an hour:

SSP and SBP prices change every 30 minutes. Therefore, it would be very interesting to consider a scenario delivering a constant power during this period of time. This will smooth the output of the wind farm and increase the quality of the power delivered. Currently, the period considered is too short to make a short-term contract. However, this situation may change in the future; therefore, additional revenue for the quality of the electricity was still considered.

For each of the above scenarios, simulations will be run in order to optimise the size of the battery to maximise its benefits. The details of this optimisation process and the feasibility of the scenarios will be given in the financial analysis of the project.

The following graph shows how each of the above configurations should affect the output of the battery in comparison to the output of the wind farm:

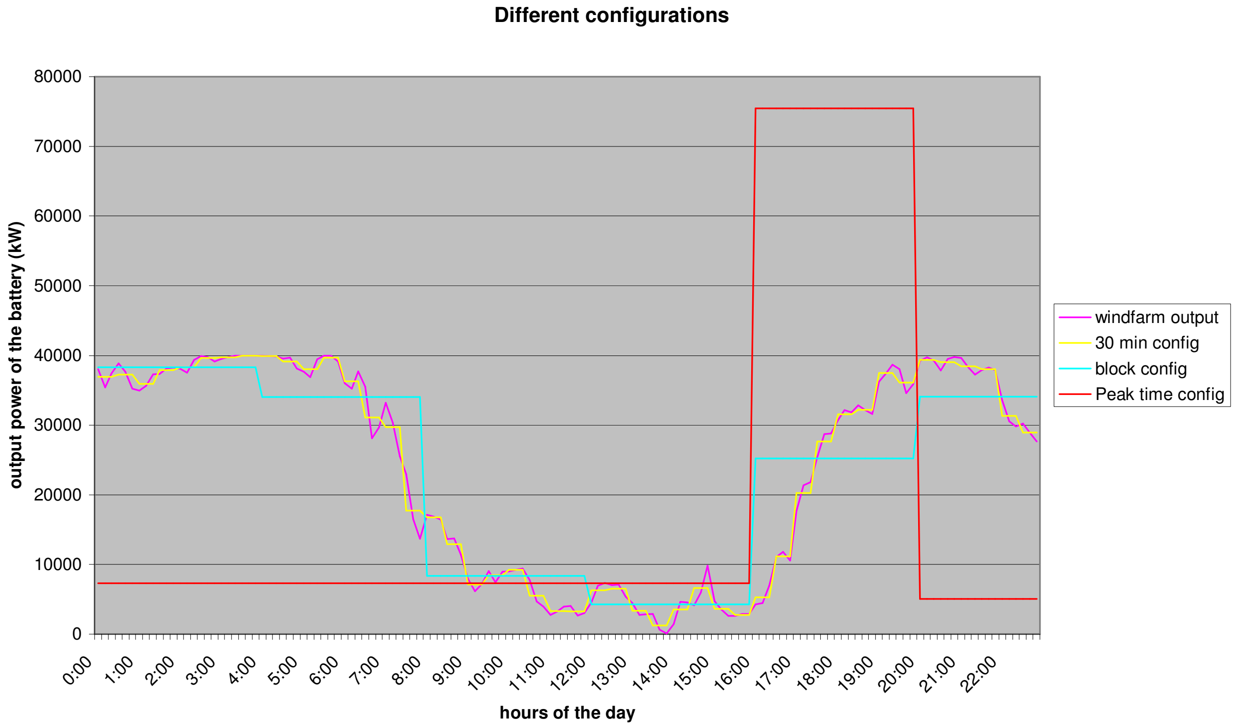


Figure 11: Configurations of power delivered

Now, the control systems are considered as they are the principal tools which regulate the power coming in, and going out of the battery. As mentioned in the characteristics of the VRB-ESS flow batteries, these controls are realised by the PCS controller. However, parameters of the control have to be set up in order to maximise the benefits of the battery. To assess the most suitable control system, two different configurations were tested.

2. Configurations of control systems:

2.1. Simultaneous control:

In this configuration, the battery is only necessary to maintain a constant power over a user defined period of time. Indeed, once the value of the constant power is established for a period, the battery only has to regulate the output power of the wind farm. This implies that when the output power of the wind farm is higher than the constant power which is supposed to be delivered, the excess energy is stored in the battery. If the power provided by the wind farm is not sufficient, the absence of energy will be substituted by the battery. The following chart summarises this:

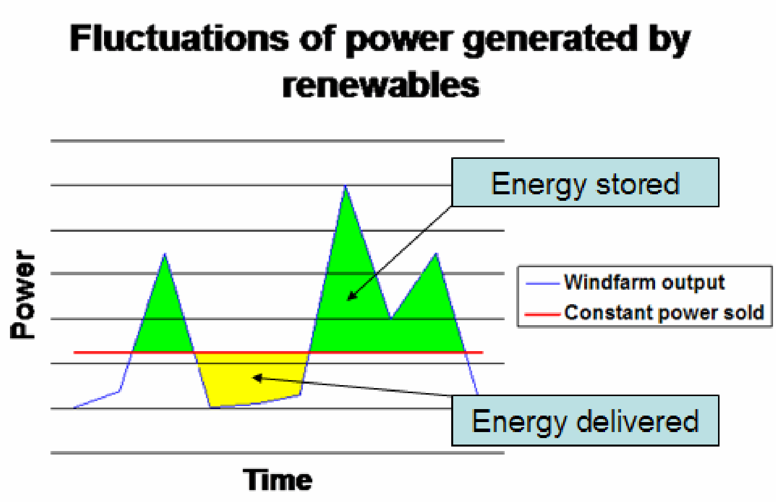


Figure 12: Illustration of the simultaneous control

The above chart explains the behaviour of the battery when it is fully available, that is, when the battery is neither full nor empty. This is because there are some constraints that appear when the battery is either full or empty. According to the specifications of VRB-ESS, the battery's manufacturer, the SOC (state of charge) has to stay between 20% and 80% in order to avoid damaging the battery. Because of these limitations, when the battery is empty, electricity has to be bought from the grid to avoid penalties (due to a default in the electricity sold). This electricity is bought at the SBP which is higher than the SSP, thus, the battery has to minimise the quantity of energy bought. On the other hand, if the battery is full (SOC > 80%), the excess electricity produced by the wind farm is then sold as overspill. This means that it is electricity sold without any guarantee unlike the constant power delivered by the battery. Therefore, this overspill will be sold at the SSP without the possibility of making any bid.

2.2. Two associated controls:

This second control is completely different from the simultaneous control. It is composed of two stages of control. The first one (CTRL 1) manages to fill in the battery and when it is full (SOC > 80%), it delivers the excess as overspill. As mentioned previously, the overspill will be sold at SSP prices as the quality and the quantity of the electricity sold cannot be guaranteed.

The second stage of control (CTRL 2) manages to deliver a constant power to the grid over a user defined period of time. This value can be estimated from the actual amount of energy contained inside the battery. If the flow battery runs out of energy (SOC < 20%), electricity has to be bought from the grid (at SBP) in order to avoid penalties. Like the previous control system, only firm power can provide the possibility of a bid into the market. This means that the power delivered to the grid as overspill will not get any benefits from the battery. The following graph represents these two configurations of control:

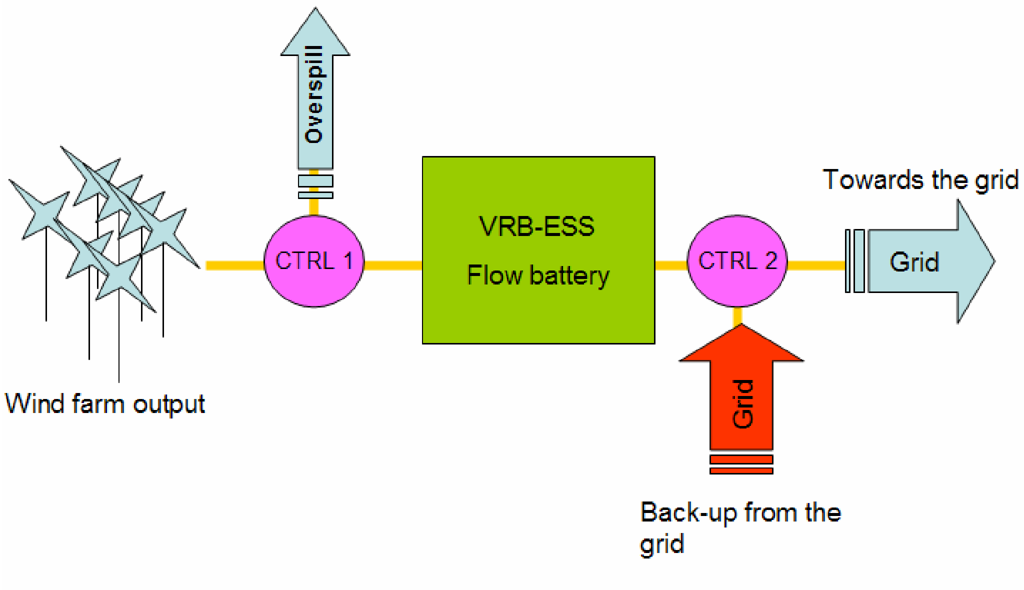


Figure 13: Illustration of the separated control systems

Considering that the second stage of control only takes into account the energy stored inside the battery to deliver a constant power, there is no need for a back-up from the grid. However, this can still be considered if there is a need to increase the generation of electricity. The two controls limit the need for back-up, so there will be no penalties and no power bought from the grid. On the other hand, if the wind farm output increases suddenly, it will be lost in overspill. Comparing the two system controls will then demonstrate which one of them is suitable for the scenarios.

3. Algorithms of both control systems:

The algorithms for the previous controllers are given below. However, the estimation of the constant power for the simultaneous control is not detailed here, as it will be described in detail in the next chapter.

3.1. Simultaneous control:

3.1.1. Presentation of all the variables used for this algorithm:

Capacity of the battery (kWh)	cp	Input data
Minimum SOC (%)	misoc	
Maximum SOC (%)	masoc	
Time step (minutes)	t	
Constant power duration (hours)	dt	
Wind farm output (kW)	wf	
Number of time steps	N	
SSP data (£/MWh)	ssp	
SBP data (£/MWh)	sbp	
Iteration number	i	Calculation details
Energy storable (kWh)	es	
Energy deliverable (kWh)	ed	
SOC (%)	soc	
Power Predicted (kW)	pp	
Power delivered (kW)	pd	
Performance indicator	u	
SSP income (£)	sspi	
SBP cost (£)	sbpi	
Necessary cell stack size (kW)	csi	
Overspill income (£)	ovi	
Overall performance (%)	U	Output data
Total energy delivered constantly (kWh)	E	
Cell stack size (kW)	cs	
Revenue (£)	R	

The input data represent all the variables needed to make the calculations for this first kind of control system. All the values used are accurate.

All the variables used to make the calculation are calculated for each time step.

The output data will be used to make the analysis of the results afterwards.

- Input data:

The capacity, the minimum and the maximum SOC (state of charge) are main characteristics of the battery. An initial value of the capacity is supposed to start the calculation. Later on, this will be optimised. The minimum and the maximum SOC of the battery are respectively 20% and 80% in order to avoid damage.

The time step represents the period of time separating two consecutive time steps. The Data provided (wind farm output) already had a step time of ten minutes. Therefore, this period of time was used for all the calculations. A longer time step could have been considered, but it would have reduced the accuracy of the solution. The number of time steps, N, only represents the number of values provided.

The constant power duration depends on the scenario. For the block configuration, 4 hours were used for this value. For the output smoothing, only thirty minutes are considered. This value is used to calculate the power predicted (consists of the prediction of the power delivered by the wind farm) and when it has to be changed. However, this is detailed in the following chapter.

SSP and SBP values are the actual prices of electricity (sold and bought by the grid) during the same period of time in the United Kingdom. As mentioned before, they change every thirty minutes. For each step time, one value gives the SSP price, and another one gives the SBP price.

- Calculation details:

The energies storable and deliverable respectively represent the amount of energy that can be stored or delivered by the battery. They are the differences between the output power of the wind farm and the targeted power which is supposed to be delivered constantly.

The SOC of the battery is calculated for each time step to check if the battery can work properly (misoc < SOC < masoc) and flatten out the power delivered by the wind farm.

The power predicted is assessed by different methods and then compared in the following chapter. It represents the prediction of the wind farm output in the next period of time considered.

The power delivered is the actual output of the system (the battery and the wind farm). It should match with the power predicted. However, when the battery is fully charged, overspill may increase this value.

For each time step, the performance indicator shows if the battery has been able to supply the power predicted without buying electricity from the grid. It evaluates the performance of the system.

The necessary cell stack size gives for each time step what would be the minimum size required for this characteristic of the battery. It is the amplitude of the power coming in the battery which represents the absolute difference between the wind farm output and the power delivered.

SSP income, SBP cost and overspill income represent the money earned or spent when selling or buying electricity during the time step.

- <u>Output data:</u>

The overall performance coefficient indicates how effective the battery was in this configuration. Indeed it gives the percentage of time steps where electricity was not bought to reach the power predicted.

The total energy delivered constantly will provide data for the financial analysis as this energy should be sold more expensively as it is constant and with a guarantee on the quality and the quantity of power delivered.

The cell stack size gives us this unavoidable characteristic of the battery. It is actually the maximum of the necessary cell stack sizes calculated for each time step.

The revenue is the net income of the wind farm and the battery for the ten month considered.

3.1.2. Algorithm and explanations:

$$T = \frac{t}{60}$$

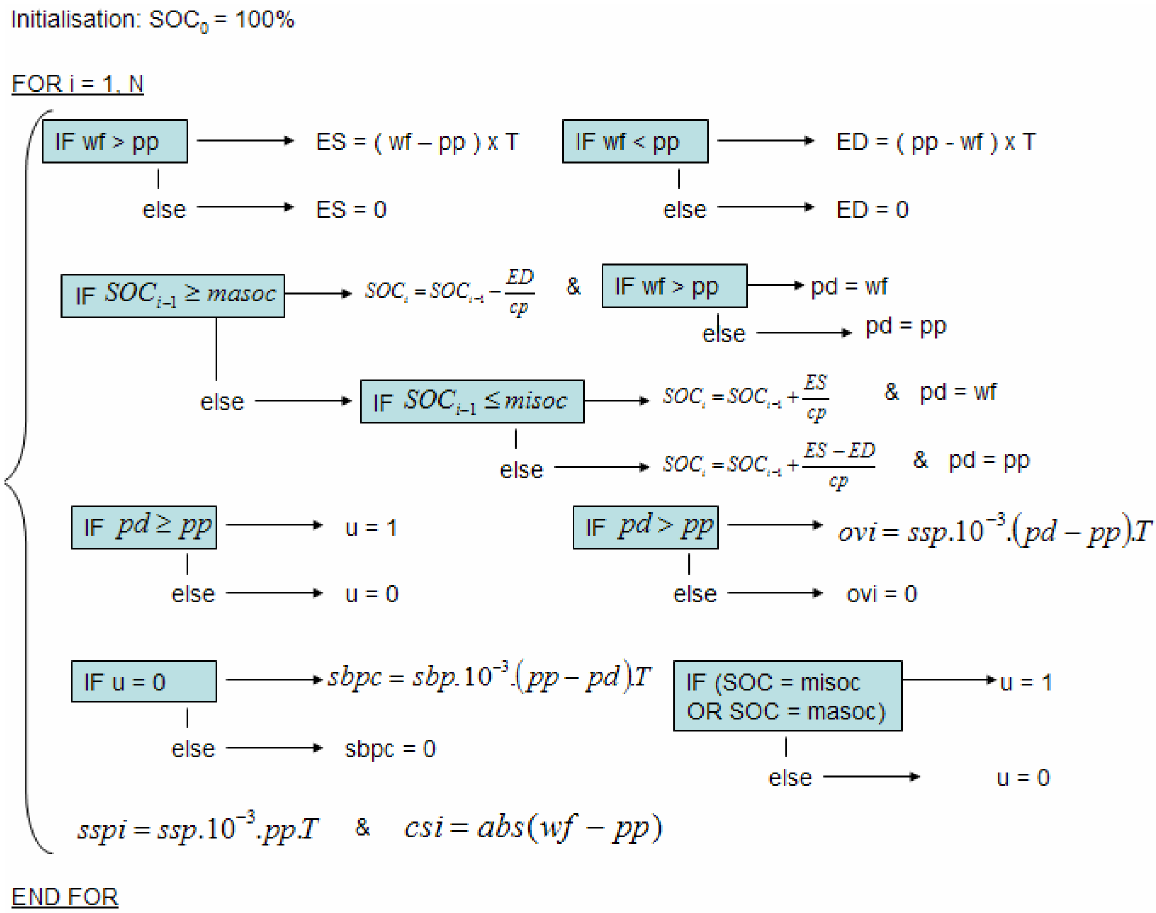


Figure 14: Algorithm of the simultaneous control system

First, the energy which is storable or deliverable by the battery is calculated if the output of the wind farm is different from the power predicted. Then the SOC of the battery is estimated from the previous one. Indeed, if the battery is fully charged (SOC > masoc), it can only deliver power and be discharged. This means that if the wind farm output is greater that the power predicted there will be some overspill, otherwise, the power delivered will be equal to prediction, which is the power predicted for the wind farm output. If the battery is discharged (SOC < misoc), it can only store energy and be charged. This means that the power delivered is equal to the wind farm output. On the other hand, the SOC of the battery is between misoc and masoc, the power delivered will be equal to the prediction.

For each time step, if the power delivered is equal or higher than the prediction, the performance coefficient is equal to one; otherwise it is equal to zero.

According to the suitable case, the money earned or spent by the wind farm and the battery is calculated: the SSP income from the constant power sold, the SBP cost from the energy bought and the overspill income from the excess of energy.

The necessary cell stack size is also estimated by the difference between the wind farm output and the power predicted.

Output data:

$$U = \frac{\sum_{i=1}^{N} u}{N}$$

$$cs = MAX(csi)$$

$$E = \left(\sum_{i=1}^{N} pp \right) T$$

$$R = \sum sspi + \sum ovi - \sum sbpc$$

The overall performance is then the sum of the performance coefficient divided by the number of time steps.

The cell stack size is the maximum value of those calculated for each time step.

The total amount of energy constantly delivered is the sum of the power predicted times the time step.

The revenue is the sum of all the incomes minus the cost of the electricity bought.

3.2. Two associated controls:

The second control system is different from the first one. Indeed, the variables and the calculations used are changed and explained in this part.

3.2.1. Presentation of all the variables used for this algorithm:

Capacity of the battery	cp	Input data
Minimum SOC	misoc	
Maximum SOC	masoc	
Time step (minutes)	t	
Constant power duration (hours)	dt	
Wind farm output (kW)	wf	
Number of time steps	N	
SSP data (£/MWh)	ssp	
SBP data (£/MWh)	sbp	
Iteration number	i	Calculation details
Energy stored (kWh)	es	
Overspill (kW)	ov	
SOC	soc	
Power delivered (kW)	pd	
Energy bought (kWh)	eb	
SSP income (£)	sspi	
SBP cost (£)	sbpi	
Overspill income (£)	ovi	
Total delivered energy constantly (kWh)	E	Output data
Cell stack size (kW)	cs	
Revenue (£)	R	

The input data represent all the variables needed to make the calculations. All the values used are the same as previously.

Once again, all the variables used to make the calculation are calculated for each time step. There is no need for variables such as energy deliverable and predicted power.

The output data will be used to make the comparison with the other control system.

- Input data:

The same input data is used for this control system. For this reason, no details will be provided about them.

- Calculation details:

The energy stored represents the amount of energy that goes inside the battery.

The SOC of the battery is calculated for each time step to check if the battery can work properly (misoc < SOC < masoc) and then CTRL 1 and CTRL 2 decide if there is a need for overspill or buying electricity from the grid.

The power delivered is assessed directly by calculating the amount of energy available inside the battery for the following period of constant power.

Here, there is no need for a performance indicator as the power delivered is based on the energy content of the battery. Therefore, the output power of the battery will always be constant. However, the energy bought is still considered in case of failure of the battery.

SSP income, SBP cost and overspill income represent the same as previously.

- Output data:

All the output values are the same as in the previous control system, except that there is no overall performance indicator

3.2.2. Algorithm and explanations:

$$T = \frac{t}{60}$$

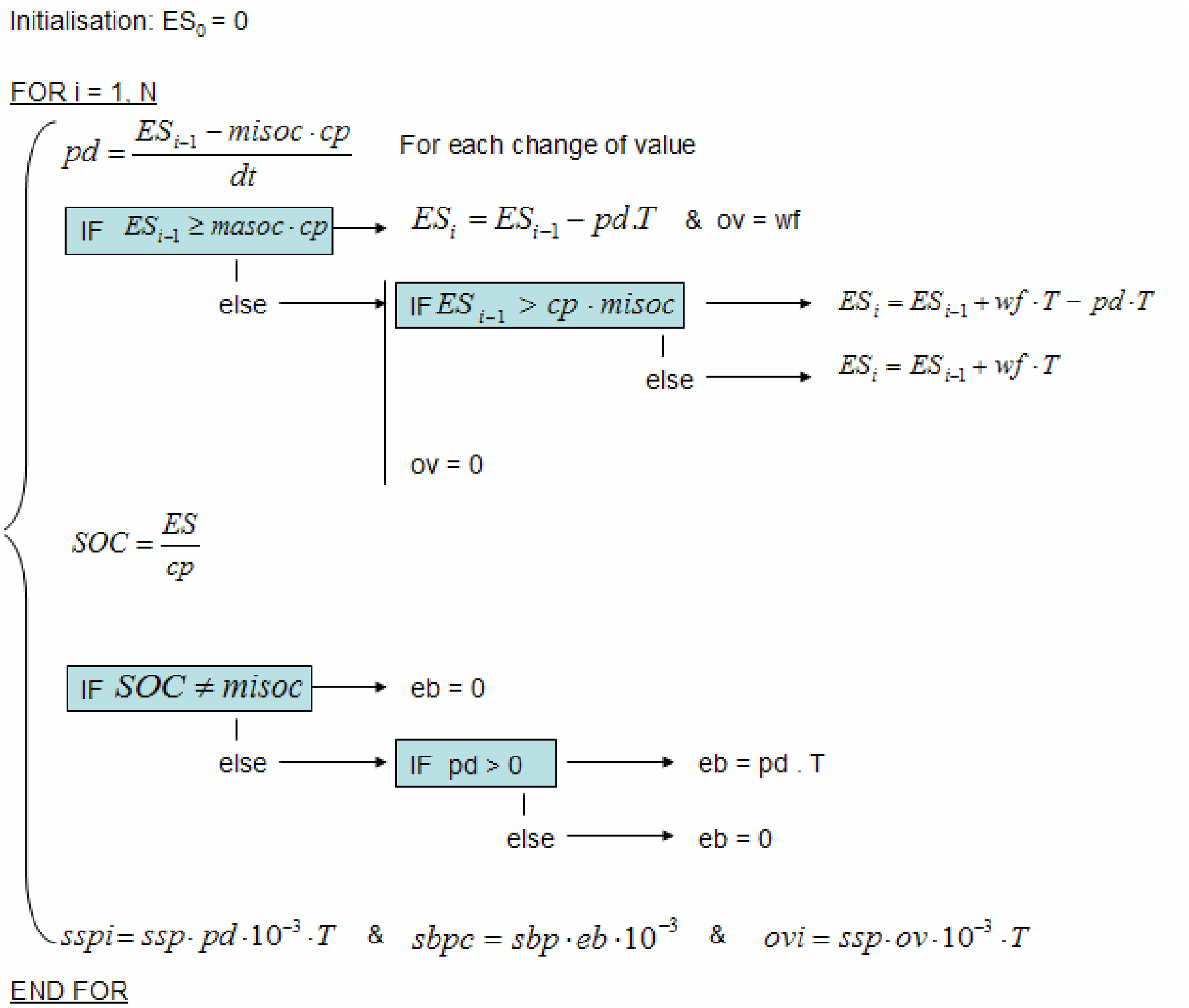


Figure 15: Algorithm of the two associated controllers

First, power which is delivered by the battery is calculated from the energy available inside the battery. When this value changes, it represents the energy contained by the battery minus the minimum energy which has to stay inside the battery to avoid damage. Then this amount of energy is divided by the duration of constant power in order to guarantee that the battery will have enough resources to provide it.

As seen before, if the energy stored is greater than the capacity of the battery, the battery can only be emptied and then there is overspill.

In the case of the battery being empty, some energy can be bought, if needed.

Output data:

$$R = \sum sspi + \sum ovi - \sum sbpc$$

$$cs = MAX(wf)$$

$$E = \left(\sum pd\right) \cdot T$$

The cell stack size is the maximum value of the wind farm output as all the power delivered goes into the battery.

The total amount of energy constantly delivered is the sum of the power delivered times the time step.

The revenue is the sum of all the incomes minus the cost of the electricity bought.

In this chapter, the main parts of the algorithms were explained. In the following one, more details will be provided on some key points of the analysis: the prediction of the output power of the battery, how to size the battery but also how to make the cost analysis considering all these parameters. These have to be detailed separately as they are not direct issues and they have to be estimated with accuracy.

The following chapter will also present how the different configurations will be compared in order to show results and analyse them afterwards.

In this chapter the parameters of the analysis are detailed along with the assumptions made. First, the nature of the wind farm output will be described, and then details will be provided regarding the power predicted and how it can be estimated. A part of this chapter will be dedicated to the flow batteries: their technical characteristics and their cost estimations.

Finally, the financial parameters used will be detailed, and then the optimisation process will be explained.

1. Presentation of the wind farm output data:

1.1. Rough data:

The wind farm output, which is actually the input power of the flow battery, represents the major data used for the simulation. This data comprises of 34,849 values; each one of these values represents the average output power of the wind farm for ten minutes. The fluctuation of the power output can be seen on the following graph which focuses on the data of the 30th of April 2006:

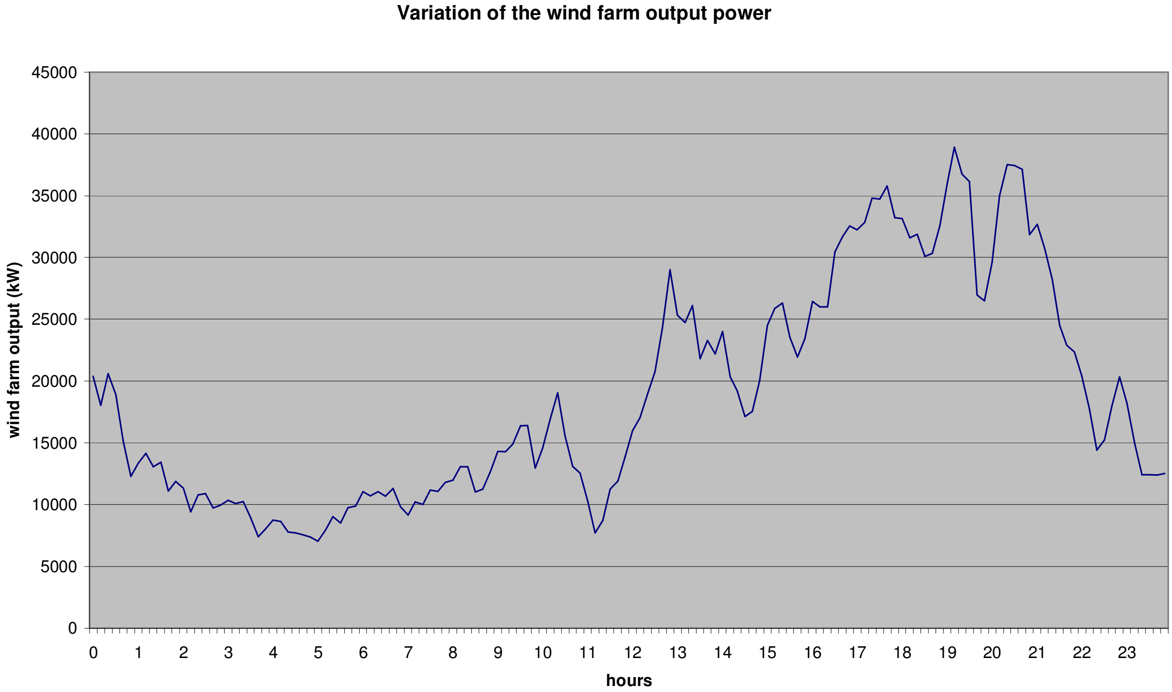


Figure 16: Variation of the wind farm output on the 30th April 2006

1.2. Data characterisation:

The following values characterise the wind farm output data:

MEDIAN	6090.40 kW
AVERAGE	13154.70 kW
ST DEV	16023.24 kW
MINIMUM	0.00 kW
MAXIMUM	71916.20 kW

According to the standard deviation, and the difference between the minimum and the maximum value, when considering a large period of time, a redundancy among the values is not shown. However, we consider that this sample is representative of the power output for longer periods.

Considering a system without any input control for the battery would mean accepting the maximum (72MW) power as going in the battery. This would oversize the cell stack which, according to the financial details, will increase the cost of the battery. The system without rating the input power of the battery will be considered for the second control scenario.

The wind blowing on the site determines the output power of the wind turbines. As this resource changes along the seasons of years, it is worthwhile to make some average values of energy produced month by month.

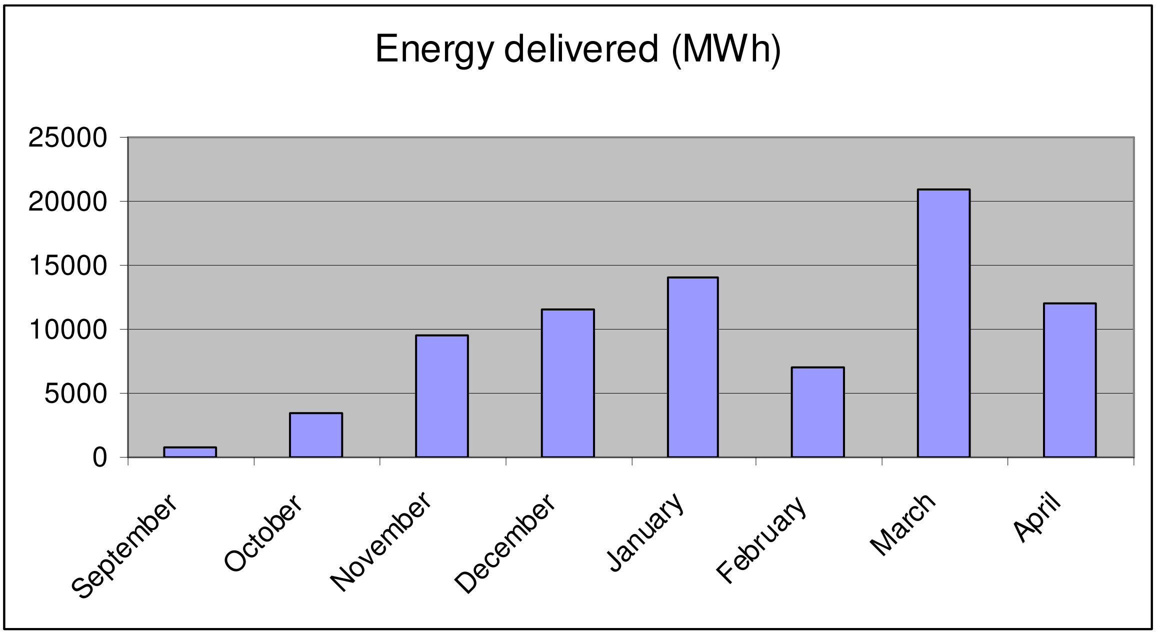


Figure 17: Monthly energy delivered by the wind farm

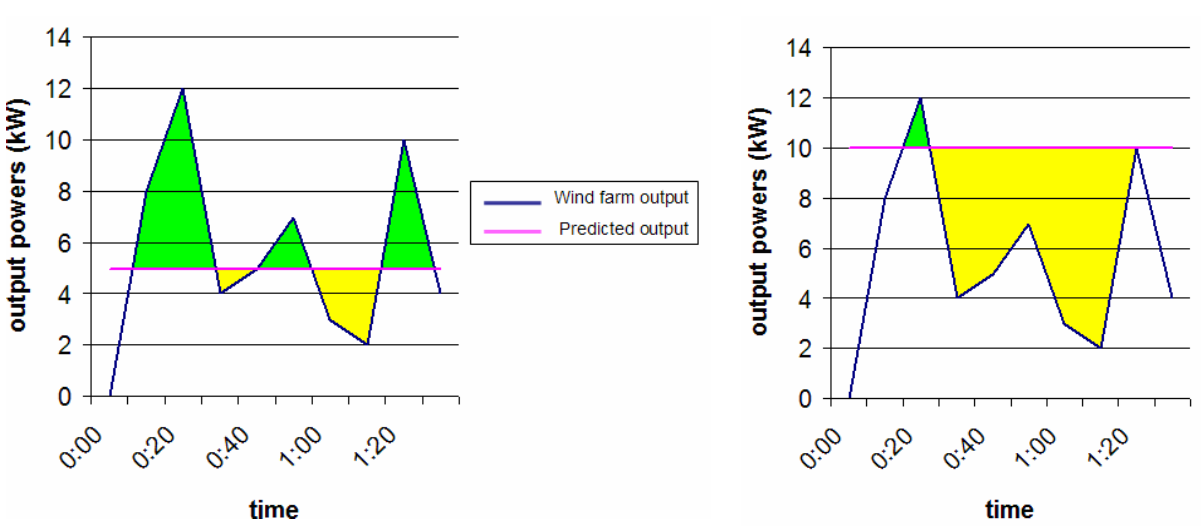
It can be seen in Figure 17 that there is a real correlation between the season and the energy produced by the wind farm. The wind is stronger in the winter and therefore energy production is higher. It would not be accurate to predict the power on a monthly basis since it varies all the time and would oversize the battery, thereby increasing the capital costs.

2. Prediction of the output power of the wind farm:

To mimic the action of a real battery controller it is necessary to estimate the future power output of the wind farm as in reality this will be unknown. This is an important requirement for the simultaneous battery controller. The accuracy of the predicted wind farm power output compared to the actual output is important as it enables a more accurate estimation of the future battery output to the grid, and also minimises the battery size needed. In the second control system, the output power of the flow battery is only based on its energy content. Therefore, for this scenario, there is no need for a prediction of the future wind farm output. In this section, the importance of this estimation is detailed; afterwards different methods will be developed in order to define the most suitable one for the project.

2.1. The prediction: an important parameter.

The more accurate the prediction of the constant power deliverable, the smaller the difference between the estimated and the actual wind farm output. This is important as it reduces the quantity of energy stored or delivered by the battery, and then its size.



a- Good prediction b- Bad prediction

Figure 18: Importance of the predicted power

Figure 18 illustrates the importance of a good wind farm power output prediction as the output of the battery is based on this prediction. If it is close to the actual values (Figure 18a), the need for storage will be smaller than when the prediction is not accurate (Figure 18b). In the case of Figure 18b there is a need for a bigger capacity to compensate for the lack of power. Since we are considering a wind farm output with high fluctuations, this is really important. Currently, research is being carried out on neural networks to predict, with precision, the wind farm resources. However, this is not the main objective of this project. For this reason, estimations will be based on simple methods to make this prediction, later; they will be compared to the results from a perfect model of prediction. These predictions will be used with the simultaneous controller system.

2.2. Prediction based on the previous output values of the wind farm:

In this method, the estimation of the power delivered by the wind farm is based only on the previous values of the wind farm output. This predicted power delivery is then used to estimate the future battery power delivery to the grid. A period of time is considered just before the prediction, and the power delivered is estimated to be the average of the wind farm output during the previous period taken into account. For this algorithm, the following variables are used:

Time step (minutes)	t	Input data
Constant power duration (hours)	dt	
Wind farm output (kW)	wf	
Number of time steps	N	
Iteration number	i	Calculation details
Power predicted (kW)	pp	
Number of interval	m	

Considering that $T = \frac{t}{60}$ and $m = \frac{dt}{T}$, the calculations are the following:

Initialisation: pp_0 = 10 000

FOR i = 1, N

IF MOD(i, m) = 0 $\rightarrow$ $pp_i = average\ (wf_{i-1}, wf_{i-2}, \ldots, wf_{i-z});\ z\ \ depends\ \ on\ \ the\ \ period\ \ considered$

else $\rightarrow$ $pp_i = pp_{i-1}$

END FOR

Figure 19: Algorithm for prediction of the wind farm output based on the previous values

Every time a period of constant power is finished, the new predicted power is based on the average of the previous wind farm outputs. For this method, different periods were taken into account in order to estimate the one which is most suitable for the simulations. Considering the same input conditions: size of the battery, wind farm output, and the same output conditions: energy delivered constantly trading block per trading block (4 hours), the performance of the method prediction was assessed using the overall performance indicator, U. The overall performance indicator mentions the proportion of the time steps where there is no need to buy electricity to reach the power predicted. This makes the prediction much better.

For the block configuration, a battery of 33MWh of capacity and a cell stack of 40MW was used and the U was calculated by taking into account the average wind farm output for several periods of time. The following graph shows the influence of the period of time considered to make the prediction accurate.

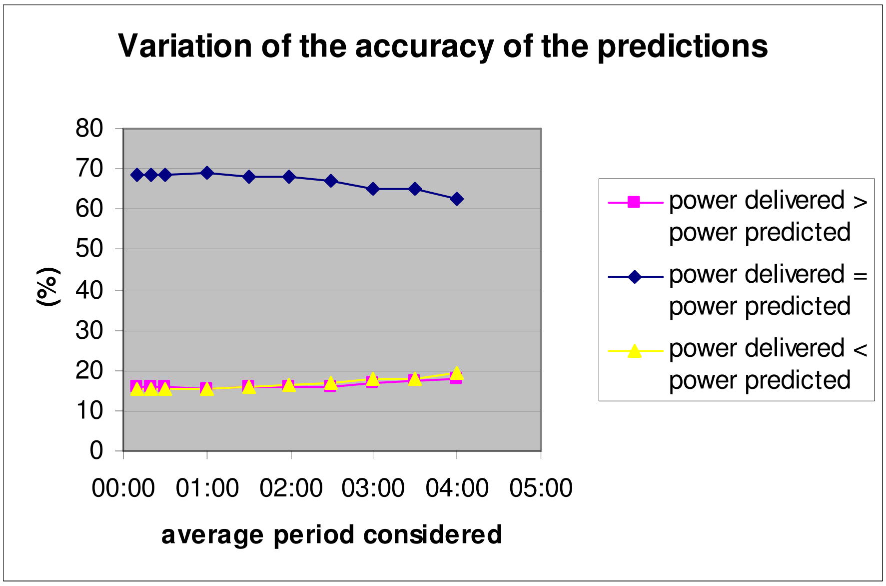


Figure 20: Influence of the period of time for the prediction based on the previous values

In Figure 20 the upper curve represents the percentage of cases when the power delivered by the battery and the wind farm is exactly equal to the power predicted for the wind farm output. The pink curve represents the cases with overspill, which means that the electricity generation is higher than expected. The lower curve (yellow) represents cases when energy has to be bought from the grid.

It can be seen that the longer the period taken into account to make the average, the worse the prediction. This is due to the fluctuating nature of the wind farm output. Since basing all the predictions on one value (equal to ten minutes) is not representative (sometimes the wind farm output suddenly drops), the choice of considering the average of the previous half hour was made. It takes into account three values and still gives a good performance indicator (U=84.55%).

It should be noted that according to the other scenario which consists of delivering a constant power every thirty minutes, there is no need to make these estimations as the longest period that can be considered is thirty minutes. Therefore, a period of thirty minutes will be used to make the calculations.

2.3. <u>Prediction based on the previous values of the wind farm and the energy stored:</u>

In this second method, the estimation of the power delivered is not only based on the previous values of the wind farm output, but also on the energy content left in the battery. As previously, this method has been tested for several periods of time. The same variables as previously were used for this following algorithm:

Initialisation: $pp_0 = 10\ 000$

FOR i = 1, N

$\boxed{\text{IF MOD(i, m) = 0}} \rightarrow pp_i = average\ (wf_{i-1}, wf_{i-2}, \ldots, wf_{i-z}) + (SOC_{i-1} - misoc) \cdot cp \cdot \frac{T}{dt}$

else $\rightarrow pp_i = pp_{i-1}$

END FOR

Figure 21: Algorithm for prediction of the wind farm output based on the previous values and the battery energy content

Every time a period of constant power is over, the new predicted power is based on the average of the previous wind farm outputs plus the energy content inside the battery. The energy available $(SOC_{i-1} - misoc) \cdot cp$ is then multiplied by the factor $T/_{dt}$ in order to deliver this content constantly over the period of time considered (4 hours for the block configuration, or 30 minutes for the other case).

For this method, different periods were taken into account again in order to estimate the most suitable for the simulations. Considering a block configuration, a battery of 33MWh of capacity and a cell stack of 40MW, the overall performance indicator (U) has been calculated taking into account the average wind farm output for several periods of time. Results are shown in the following graph:

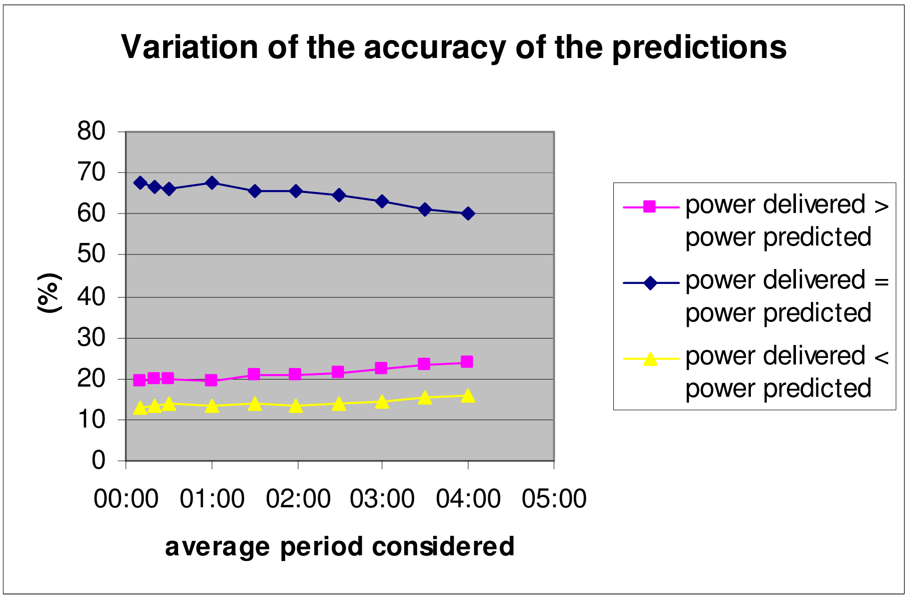


Figure 22: Influence of the period of time for the prediction based on the previous values and the energy content of the battery

The curves in Figure 22 have the same pattern as those in Figure 20. However, the proportion of overspill is higher. This means that using the energy available in the battery decreases the accuracy of the prediction. Therefore, this method increases the value of the prediction, and sometimes the battery cannot provide for this rise of power. This explains why the overall values are smaller. The highest indicator is 80.63%.

This method was not used as its results are lower than the previous one.

2.4. Prediction based on the changing rate of the wind farm output:

In this third method, the estimation of the power delivered by the wind farm is based on the rate-of-change of the previous values of the wind farm output. Here, the assumption made is that the wind farm output is going to keep the same behaviour as in the preceding period. Based on what was done previously, this method has only been tested for thirty minutes as it seems to be the best period to observe the estimated power deliverable. The same variables used previously were used for this following algorithm:

Initialisation: $pp_0 = 10\ 000$

FOR i = 1, N

IF MOD(i, m) = 0 $\rightarrow cr_i = \dfrac{wf_{i-1}}{wf_{i-z}}$, $and \quad pp_i = average\ (wf_{i-1}, wf_{i-2}, \ldots, wf_{i-z}) \cdot cr_i$

else $\rightarrow cr_i = 0, \quad and \quad pp_i = pp_{i-1}$

END FOR

Figure 23: Algorithm for prediction of the wind farm output based on the changing rate

When a period of constant power is over, the changing rate “cr” is calculated, and then, the new predicted power is based on the average of the previous wind farm outputs multiplied by this changing rate. This implies that the curve of the wind farm output is going to keep the same trend.

The same parameters as previously have been used in order to make a comparison. Using a block configuration, a battery of 33MWh of capacity and a cell stack of 40MW, the overall performance indicator (U) has been calculated taking into account this third method.

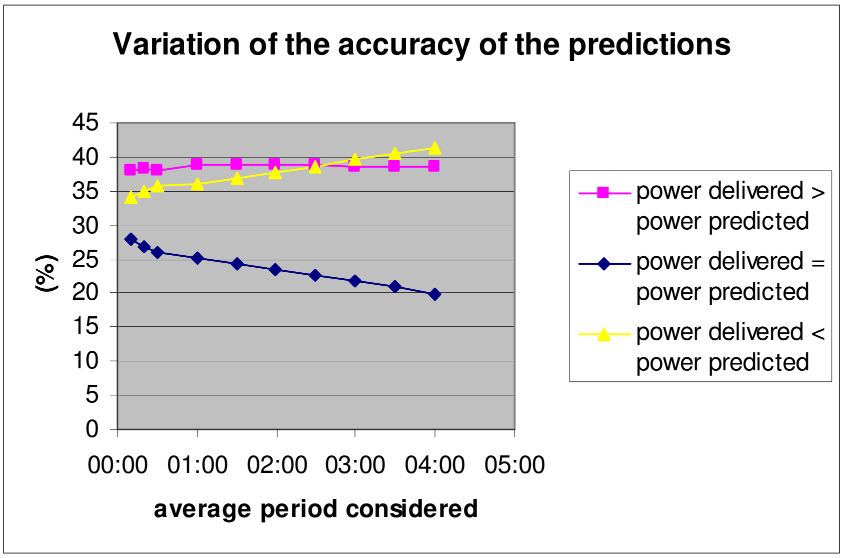


Figure 24: Influence of the period of time for the prediction based on the changing rate

The power delivered by the system equals or surpasses the power predicted only 64.13% of the time steps. This indicates that the rate of change model gives a very poor prediction of the likely wind farm output.

2.5. Comparison between the three previous methods and conclusion:

The following table summarises the previous tests which were done to estimate the best way of predicting the output power of the battery:

Method / **U**	**pd = pp**	**pd > pp**	**pd < pp**
Average of the previous half hour	**68.61**	15.94	15.45
Average of the previous half hour and energy content of the battery	66.29	13.75	19.96
Average of the previous half hour and changing rate	26.09	38.04	35.85

Table 6: Comparison between the wind farm output prediction methods

It can be seen that the first method, which is actually the simplest one, gives the best results. For this reason, it was used in the next calculations and simulations.

2.6. Ideal prediction of the wind farm power output:

As mentioned at the beginning of this chapter, the accuracy of prediction for wind farm output is very important, as it can reduce the size (both storage tank and cell stack components) of the battery. As the simulations are done with a simplistic model, it can be interesting to compare them with a perfect prediction of the wind farm output.

The easiest way to simulate this is to pretend that the power predicted is the average of the future time period wind farm output values. Considering several battery capacities, the following graph shows the evolution of the performance indicator:

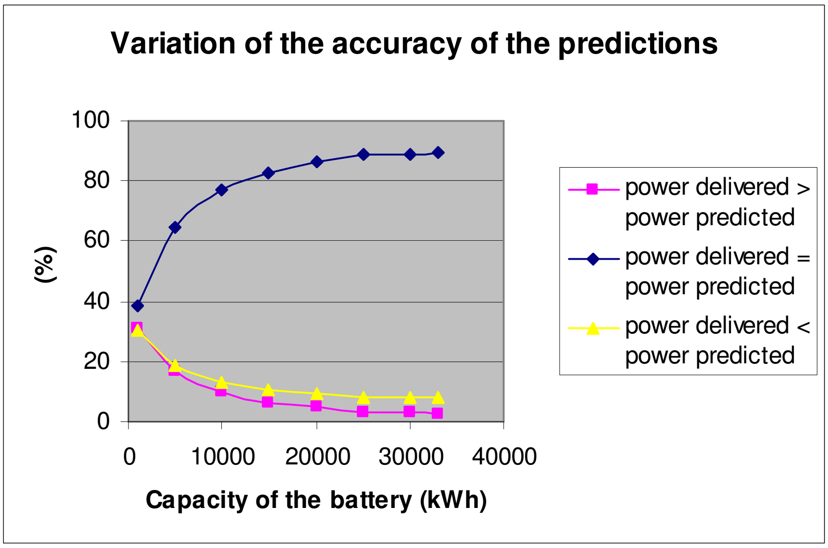


Figure 25: Perfect prediction - performance indicator VS capacity of the battery

For Figure 25, the maximum value considered was 33000 kWh as it was the value used for the previous methods. In the same conditions, the power delivered equals or exceeds the power predicted 92.21% of the time steps. There is no need for such a good prediction as it will over size the battery. Therefore, several simulations were run in order to define the one which would give the same performance. With a capacity of 8000kWh and the perfect prediction scenario, the performance of the system (85%) is better than all the previous methods with 33000kWh. It can be seen that even if we use a “perfect” prediction of the wind farm output, the power delivered by the system (battery + wind farm) is not always equal to the power predicted. This is due to sudden big fluctuations. Indeed, the value taken into account for the prediction is the average of the wind farm output during the period considered. If suddenly there is a big fluctuation, the capacity of the battery may not be enough to contain this. Thus, some overspill or lack of electricity generation may appear. Therefore, sometimes the power delivered by the system does not match the predicted wind farm output. Taking into consideration that the prediction method used for the simultaneous control is too simplistic, the results from the perfect prediction are also considered for the project as complex models are still being developed in order to reach this accuracy.

2.7. Peak-time model of the wind farm power output:

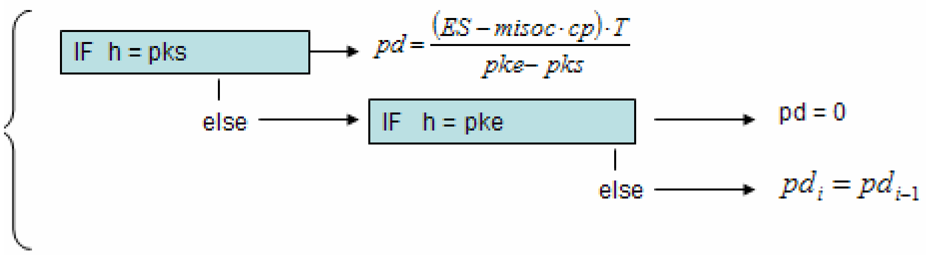
This scenario is supposed to deliver power during the peak time period only. For this configuration, only the second control system, which regulates the input and the output of the battery separately, was used. Once again, the objective was to deliver the maximum constant power during peak time. Therefore, energy is stored all day long within the battery, and then released constantly during these few hours. To simulate this, the following algorithm has been applied:

h = hour of the day

pks = peak time starting time

pke = peak time ending time

FOR i = 1, N



END FOR

Figure 26: Algorithm for prediction of the wind farm output on peak time periods

Out of peak time, the battery does not deliver any power. This will imply immense storage capacities which will be discussed later on in this chapter. Moreover, during peak time periods, wind does not stop blowing, and thus continues to charge the battery.

Thus, another algorithm has been created in order to deliver the quantity of energy stored during peak time. This energy is released constantly during the rest of the time providing a minimum “base load”. This was done in order to reduce the size of the battery. Actually, it would be much better to sell all the power stored during peak time periods. However, this would increase the size of the battery too much. This is why this second algorithm was used instead of the previous one.

The algorithm below was considered next:

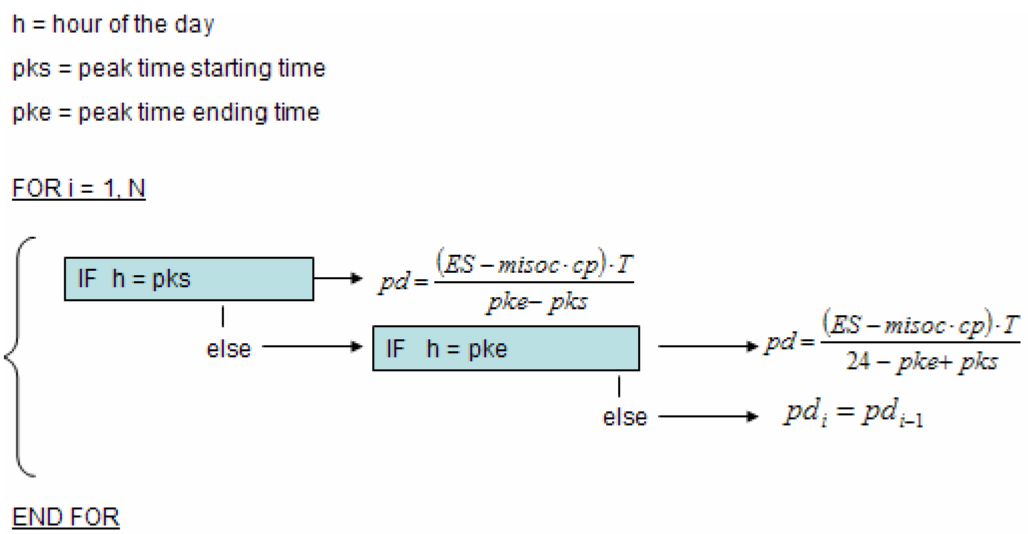


Figure 27: Improved algorithm for prediction of the wind farm output on peak time periods

The battery now delivers a constant power (equal to the energy stored during peak time divided by the 20 following hours) instead of 0kW.

2.8. Matrix of configurations:

The two control systems used and the three scenarios created was simulated. This data set represents a matrix of configurations. The perfect prediction is presented as a new type of control system. Indeed, running the simulations with this control system will highlight the importance of the prediction, but will also give much better results. Therefore, the matrix of configurations can be presented as such:

	Smoothing scenario	Block scenario	Peak Time scenario
Simultaneous control	✓	✓	
Ideal control system	✓	✓	
2 associated controls	✓	✓	✓

Table 7: Matrix of configurations

For the peak time configuration, considering storage of energy for a long period, it is not possible to use the simultaneous control system or the ideal control system which is actually based on the same algorithm. Therefore, only the algorithm using two associated controls will be used for this configuration.

This matrix is used in the following chapter to show the results and compare them after optimisation.

3. <u>Characteristics of the flow batteries:</u>

3.1. <u>Sizing the battery:</u>

Before running the optimisations, the size of the batteries for each configuration was assessed in order to minimise the time steps for the solver.

For each scenario, the size of the battery was assessed by estimating the energy storable during the period of time considered (30 minutes, 4 hours or 20 hours). This storable energy is based on the sum of the energy stored during this period of time. This can be seen in the following algorithm:

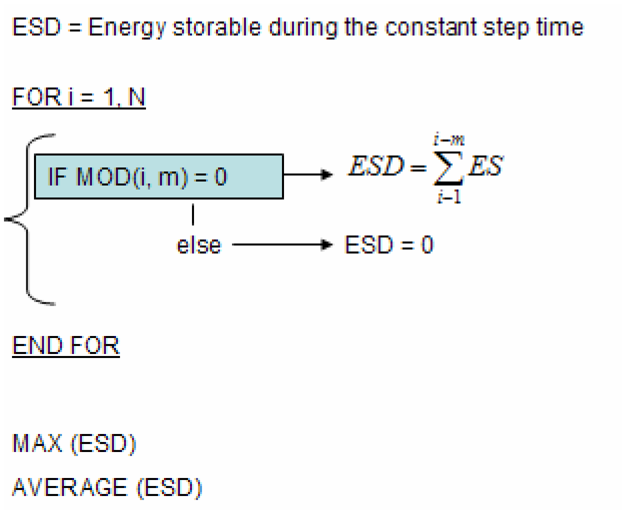


Figure 28: Algorithm to estimate the initial size of the battery

The output data are the maximum value and the average value of this set of storable energies. From these values, storage considered was estimated. This value has to be a realistic in order to reduce the optimisation process. For this reason, the initial storage capacity taken into account was estimated higher than the average amount of energy storage during the period considered, but not more than the maximum one.

Results for all the configurations considered are given below:

	Smoothing scenario	Block scenario	Peak Time scenario
MAX(ESD)	35,584kWh	269,650kWh	1,291,390kWh
AVERAGE(ESD)	5,397kWh	43,153kWh	258,467kWh
STORAGE CONSIDERED	10,000kWh	60,000kWh	400,000kWh

Table 8: Initial capacities of the battery

These results will be commented after optimisation in the following chapter with the analysis of all the results.

3.2. Establishing the cost of the battery:

To establish the cost of the different batteries (for each configuration), the different components were considered separately. Some of them were based on the power rating, others on the capacity. All these costs have been assessed with data provided by VRB-ESS. In order to respect the confidentiality of the manufacturer the sales margin and the contingency will not be detailed.

3.2.1. The tank and the electrolyte:

As mentioned in the literature review, these components of the battery are only based on its energy capacity. According to the manufacturer, it costs $220/kWh no matter what the quantity ordered is.

3.2.2. The PCS controller and the cell stack:

Both of these equipments were based on the power rating of the battery. Regarding the PCS controller, which controls the input and the output of the battery, the rates used were the following ones:

Size estimations given (kW)	>125	>1 000	>2 000
Effective cost $/kW	320	220	150

The bigger the rating power of the battery, the lower is the effective cost per kW. However, for batteries bigger than 2000kW, the cost of the PCS controller does not decrease and remains at $150/kW.

For the cell stack, the following rates have been used:

Size estimations given (kW)	>50	>2 000
Effective cost $/kW	1 800	1 125

The cell stack price does not decrease anymore after 2000 kW.

3.2.3. The BOP:

For the balance of the plant (BOP), the following rates have been considered:

Size estimations given	<250kW	-	>1000kW
% cost of (Stack+PCS+Electrolyte)	29	linear	18

The prices considered are actually a proportion of the cost of the overall equipments of the battery. Between 250kW and 1000kW, the assumption is made that the percentage taken into account decreases linearly.

3.2.4. Overall costs:

Considering the previous initial sizes of the battery and the block configuration (4 hours of constant power delivered), the following has been plotted in order to show the variations of all the costs according to the variation of the power rating:

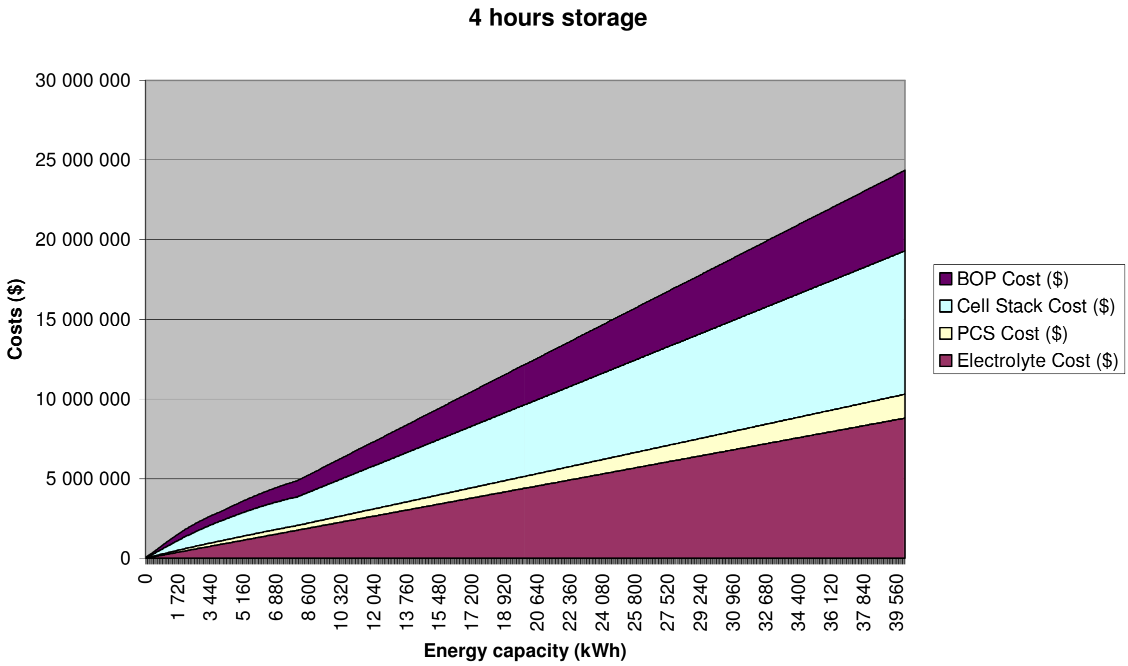


Figure 29: Variation of the costs of the battery for the block configuration

It can be seen that the overall cost almost varies linearly. It reaches $ 24 million for a maximum energy capacity of 40MWh. For the analysis, these costs were used, and if needed, higher costs were assessed by a linear variation.

4. **Financial analysis parameters:**

The financial analysis parameters are based on the calculations made by the software HOMER. In this part of the chapter, the calculations will be detailed and then the optimisation process will be explained.

4.1. Calculation of the Net Present Cost (NPC):

The NPC is the present value of the cost of installing and operating the system over the lifetime of the project (Rproj). Regarding financial aspects, the lower the NPC, the better is the project. Indeed, if the NPC is negative, that means that the project has made a profit by the end of its lifetime. On the other hand, a positive NPC indicates that the project just looses money.

The project lifetime (Rproj) is also used to calculate the annualised replacement cost and annual capital cost of each component of the battery. For the battery, the lifetime considered is 25 years as it is the lifetime usually taken into account for a wind farm.

In this paragraph, all the calculations made to estimate the NPC are detailed.

4.1.1. Initial Capital Cost (Ccap):

The initial capital cost of a component is the total installed cost of that component at the beginning of the project. In the project, it consists of the price of the battery (including all its components), plus the price of the shipping and the engineering costs.

Regarding the shipping costs, for every 125kW unit, two containers are required. Each container costs $4500 to bring to the UK (from Canada). Therefore, shipping costs are $9000/125kW unit.

The engineering costs are also based on the power rating of the battery. Indeed, for small devices (< 500kW) they are supposed to be equal to 10% of the price of the battery. For bigger batteries, only 3% of margin is considered.

4.1.2. Capital recovery factor (CRF):

The capital recovery factor is a ratio used to calculate the present value of an annuity. It is based on the interest rate (i) and the number of years considered (N). The equation used is:

$$\mathrm{CRF}(i, N) = \frac{i(1+i)^N}{(1+i)^N - 1}$$

For the project, the interest rate is assumed to be 6%.

4.1.3. Total Annualised costs (Cann,tot):

The annualised cost of a component is equal to its actual operating cost plus its capital and replacement costs annualised over the project lifetime. The annualised cost of each component is equal to:

Annualised capital cost

\+ Annualised replacement cost

\+ Annual O&M cost

\- Revenues

The annual cost is useful for comparing the costs of different components because it measures their relative contribution to the total net present cost. It allows for a fair cost comparison between components with low capital expenditure and high operating costs and those with high capital and low operating costs such as the flow batteries that we are considering.

✓ Annualized Capital Cost (Cacap):

The initial capital of each component of the battery is annualised over the project lifetime to calculate the annualised capital cost (Cacap). According to the definition of the CRF, the equation used is the following one:

$$C_{acap} = C_{cap} \cdot \mathbf{CRF}(i, R_{proj})$$

✓ Annualised Replacement Cost

The replacement cost (Crep) is the cost of replacing a component at the end of its lifetime. This may be different from the capital cost for different reasons. Regarding the project, not all the components may require replacement at the end of its lifetime. For example, for the batteries, only the cell stack has to be changed every 10 years. For this reason, this criterion has to be taken into account.

The annualised replacement cost (Carep) of a system component is the annualised value of all the replacement costs occurring throughout the lifetime of the project, minus the salvage value at the end of the project lifetime. The following equation is then used:

$$C_{arep} = C_{rep} \cdot f_{rep} \cdot \mathbf{SFF}(i, R_{comp}) - S \cdot \mathbf{SFF}(i, R_{proj})$$

Rcomp is the lifetime of the component considered.

The Sinking Fund Factor (SFF) is a ratio used to calculate the future value of a series of equal annual cash flows. Considering a number of years (N) and an interest rate (i), it is given by the following equation:

$$\mathbf{SFF}(i, N) = \frac{i}{(1+i)^N - 1}$$

frep is a factor arising because the component lifetime can be different from the project lifetime. Its equation is given by:

$$f_{rep} = \begin{cases} \mathbf{CRF}(i, R_{proj}) / \mathbf{CRF}(i, R_{rep}) & , R_{rep} > 0 \\ 0 & , R_{rep} = 0 \end{cases}$$

$$R_{rep} = R_{comp} \cdot \mathrm{INT}\left(\frac{R_{proj}}{R_{comp}}\right)$$

The replacement cost duration (Rrep) is given by:

Where INT() is the integer function, returning the integer part of a real value. It is worth to notice that the integer function does not round up.

Assuming that the salvage value for a component at the end of the project lifetime is proportional to its remaining life, the following equation gives the salvage value (S):

$$S = C_{rep} \cdot \frac{R_{rem}}{R_{comp}}$$

Where Rrem, the remaining life of the component at the end of the project lifetime, is given by: $R_{rem} = R_{comp} - \left(R_{proj} - R_{rep}\right)$

- ✓ O&M cost:

The O&M (Operation and Maintenance) cost of a component is the annual cost of operating and maintaining that component. This cost has been estimated by VRB-ESS, and it is supposed to be £0.0015/kWh of energy going through the battery.

- ✓ Revenues:

The revenues represent the benefit from using the equipment. As mentioned previously, these are defined by short term contracts for the block configurations. They represents a bonus of X £/kWh of energy delivered constantly and predicted in advance. However, additional revenue is not predictable as it depends on too many parameters. Therefore, simulations will be carried out for different values for X.

Regarding the shortest scenario, which only flats the power for 30 minutes, a short term contract cannot be done. For this reason, it is impossible to get a benefit from this scenario. However, the assumption that a subvention can give a few p/kWh is made.

Considering this lack of data, the assumption that initially this bonus can be equal to £0.025/kWh is made. Even if this value is too high, it was used to make preliminary calculations before estimating the minimum additional revenue required to make the investment cost viable.

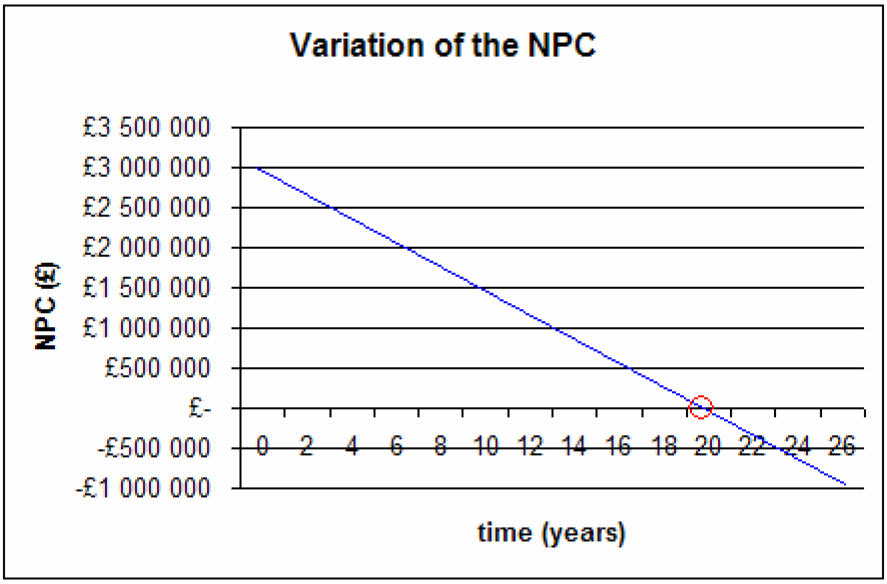
4.1.4. Total Net Present Cost (C_{NPC}):

Once the previous calculations are done, the Total Net Present Cost is calculated according to the following equation:

$$C_{NPC} = \frac{C_{ann,tot}}{\mathrm{CRF}\left(i, R_{proj}\right)}$$

4.2. Calculation of the Break-Even:

The break-even matches with the time when the NPC is equal to zero. Considering the following graph:



Graph 1: Illustration of the break-even

In this example, the NPC is equal to £3,500,000.00 the first year, and after 25 years (the lifetime of the project), it reaches -£500,000.00. As it can be seen on the graph, the break-even is approximately 20 years. That means that after this period of time, the NPC becomes negative, and the project starts to bring money back.

4.3. Optimisation process:

The optimisation process consists then in minimising the NPC after 25 years of the battery. Considering that the battery is expensive and that the bonus is low, this process will considerably decrease the storage system. To avoid that, a constraint was taken into account: the indicator performance (U) has at least to be equal to 80%.

In this chapter, all the results and their analysis will be detailed. First, the initial results are given. Then, after developing their analysis and the need for improvement, the optimised results are specified.

Once the final results are obtained, the influence of the important parameters is shown and then, the final results, analysis and recommendations are given.

1. Initial results:

1.1. Detailed results of the simultaneous control for the block scenario:

Considering the initial energy capacity of the battery (60MWh) and the algorithm described for the simultaneous control, the following results are obtained:

Total energy delivered (kWh):	77,018,053.27
Overall performance indicator (%):	82.88
Total amount of energy bought (kWh):	6,156,165.80
Revenue (£):	1,784,732.87
Cell stack size (kW):	54,684.00
Price of the battery (£):	32,695,227.68

Table 9: Results from the simultaneous control for the block configuration

Before the optimisation, it can be seen that the overall performance indicator is close to 80% (the minimum value required for the optimisation process). With this configuration, 6GWh of electricity had to be bought from the grid in order to provide 77GWh constantly. This represents 7.8% of the energy delivered.

Without considering any financial benefit from the power as constant power, only the system sell price (SSP), the wind farm and the battery have a revenue of £1,784,732.87.

Considering a benefit on top of the SSP of £0.025 per kWh of energy constantly delivered and the 77GWh sold constantly, during these ten months (the period considered) the battery represents a financial bonus of £320,908.58. That matches with 1% of the price of the battery. The NPC after 25 years is £69,995,017.43. That means that the equipment has not provided any cost benefit, but only enormous losses, even bigger than the price of the equipment itself. Indeed, in this configuration, more power was bought at expensive rate than actually sold. Besides, pieces of equipment had to be replaced after ten years of lifetime. The following graphic shows how the battery worked during two consecutive days (from the 1st until the 3rd October).

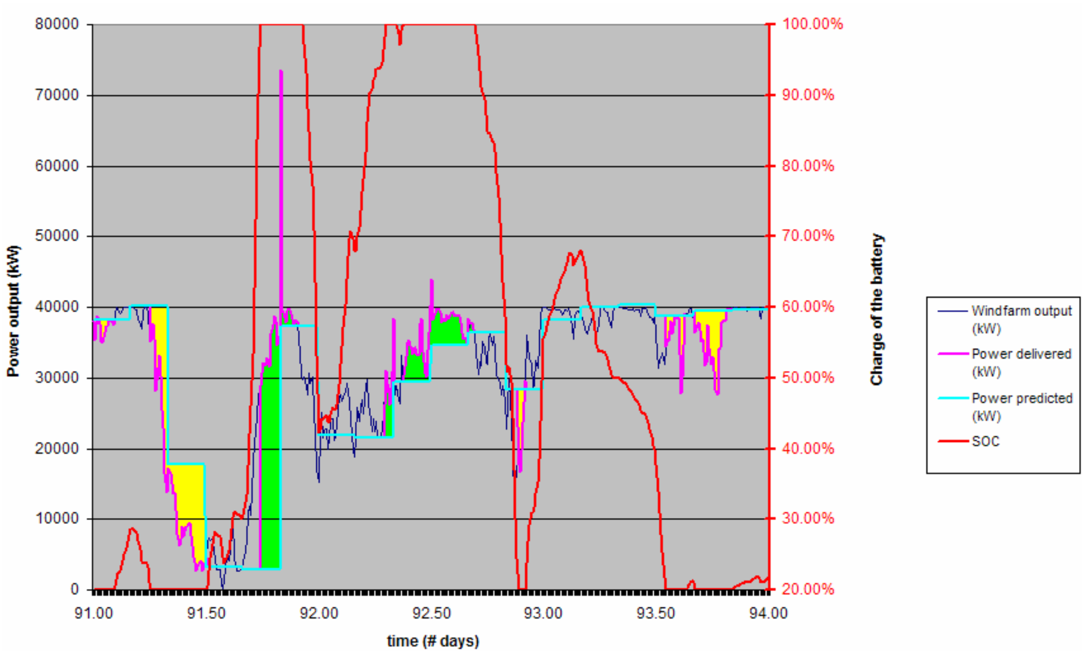


Figure 30: Results of the battery on the wind farm output before optimisation

The previous graph shows that most of the time, the power delivered by the system (battery + wind farm) is the same as the power predicted (for the wind farm output). However, when the SOC reaches at its maximum, there is overspill (in green), and when it is at its minimum, energy has to be bought from the grid (in yellow).

It can be seen that the prediction is close to the actual wind farm output. When there are large fluctuations, the prediction is not accurate anymore, and then the SOC drops or increases a lot and consequently overspill or a deficit of power can be noticed.

1.2. Results and analysis of the configurations with simultaneous control:

Regarding the configurations using the simultaneous control system, the results are the following:

	Smoothing		Block	
	Average prediction	Perfect prediction	Average prediction	Perfect prediction
Energy capacity (kWh)	10 000.00	10 000.00	60 000.00	60 000.00
Performance indicator (%)	90.05	98.68	82.88	92.85
Energy delivered (kWh):	77 550 199.99	76 539 517.40	77 018 053.27	76 207 711.40
Revenue (£)	1 856 782.71	1 824 008.20	1 784 732.87	1 807 129.04
Cell stack size (kW)	35 663.43	26 383.47	54 684.00	38 555.74
Price of the battery (£)	23 959 753.22	18 012 829.21	32 695 227.68	31 311 932.36
NPC after 25 years (£)	**53 626 706.89**	**38 893 705.29**	**69 995 017.43**	**66 202 096.15**

Table 10: Results for simultaneous control before optimisation

All the previous results are based on the initial size of the battery. As its characteristics are oversized, the price of the battery for each configuration is far too high. Consequently, the NPC after 25 years is still positive.

We can tell that the batteries are oversized because the performance indicator is too high. Indeed, there is no need for such large energy capacities, especially as it is not cost effective. Some overspill or lack of electricity generation can be tolerated.

In fact, to check it, different simulations have been plotted in order to observe how the performance indicator changes with increasing the size of the batteries. Considering the smoothing configuration and the average prediction, the following curve shows the results:

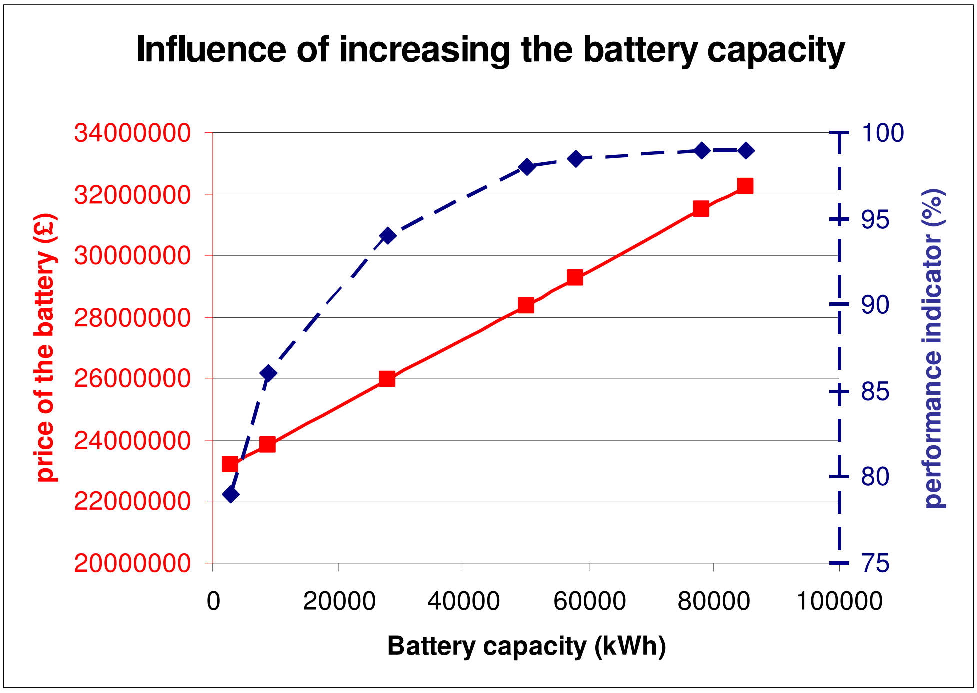


Figure 31: Influence of the size of the battery on the performance and the cost of the system

It can be seen that there is no point on increasing the size of the battery to avoid grid supply for this configuration. Indeed, even if increasing the battery capacity means increasing the performance, the variation of the costs involved is much higher.

Considering the high price of the flow batteries and the low benefit obtained for the constant output power delivered, an optimisation process would decrease the size of the battery in order to minimise the NPC after 25 years. However, the objective of this project is to assess the results from using flow batteries. Therefore, for the optimisation process, a constraint of U = 80% was used. According to the previous graph there is no doubt that this reduced the size of the battery and correspondingly the NPC.

Comparing the configurations, the amount of energy delivered remains roughly the same. This quantity of energy only varies according to the amount of electricity bought to maintain a constant supply. It is worth noticing that the results are always better for the perfect prediction scenarios and the smoothing configurations because both of these reduce the size of the battery and thus the initial costs.

1.3. Results and analysis of the configurations with associated controls:

For these configurations, no optimisation can be done. Indeed, the capacity estimated is necessary to store energy during the whole periods considered. It cannot be reduced as it is the purpose of this configuration. Therefore the only results for this part are the following ones:

	Smoothing scenario	Block scenario	Peak time scenario
Energy capacity (kWh)	20,000	60,000	400,000
Energy delivered (kWh):	62,932,407	37,585,400	50,119,474
Cell stack size (kW):	71,000		
Price of the battery (£):	47,710,595	52,133,595	91,360,131
NPC after 25 years (£):	**94,531,405**	**109,494,648**	**107,465,106**

Table 11: Results for associated controls before optimisation

It can be seen on the table that for this configuration the NPC is much higher than previously (1.2). In fact, to accept all the output of the wind farm as the input of the battery the cell stack size has to be equal to 71MW (capacity of the wind farm). As it is the most expensive part of the battery, and as it has to be replaced every ten years, this is not very cost effective.

Revenues from this control system are similar to those of the simultaneous system. Even for the peak time configuration, more electricity is sold during this short term period and this brings a benefit. On the other hand, the quantity of overspill is so high that the benefits made are lost. Indeed, overspill is wind farm output delivered inconstantly to the grid. Therefore it is sold at the SSP.

To sum up, this control system cannot be viable whatever the configuration taken into account. Necessary storage capacity and cell stack size are too high in these conditions.

2. Results after optimisation:

2.1. Optimisation process:

The solver tool of Microsoft Excel has been used to make the optimisation. As mentioned previously, the size of the battery has to be decreased in order to give a better NPC. The objective of this optimisation is then to minimise the NPC by changing the capacity of the battery (kWh) which gives a new rating power (kW). In order to keep a performance indicator of 80%, this is mentioned as a constraint to the optimisation tool.

2.2. Results of all the simultaneous control configurations:

Here are the results for all the simulations using the simultaneous control. The simulations using the associated controls cannot be optimised as mentioned before.

	Smoothing		Block	
	Average prediction	Perfect prediction	Average prediction	Perfect prediction
Energy capacity (kWh)	2 500.00	500.00	33 000.00	4 000.00
Cell stack size (kW)	22 700.00	11 000.00	41 000.00	31 000.00
Energy delivered (kWh)	13 048 489.03	12 994 847.06	12 863 001.52	12 811 731.35
Performance indicator (%)	80.00			
Revenue (£)	1 875 327.92	1 848 259.09	1 781 643.28	1 798 696.49
Price of the battery (£)	14 819 753.92	6 929 340.98	29 698 203.20	20 633 904.62
NPC after 25 years (£)	**31 527 052.80**	**12 147 714.42**	**66 352 433.87**	**47 288 632.24**

Table 12: Results for simultaneous control after optimisation

2.3. Analysis of the results:

2.3.1. Comparison without optimisation:

After optimisation, all the performance indicators dropped to 80%. Improvement has been provided; the main results are compared in this paragraph. The energy capacity and the power rating necessary: the following charts show how the optimisation affects these two characteristics of the flow battery.

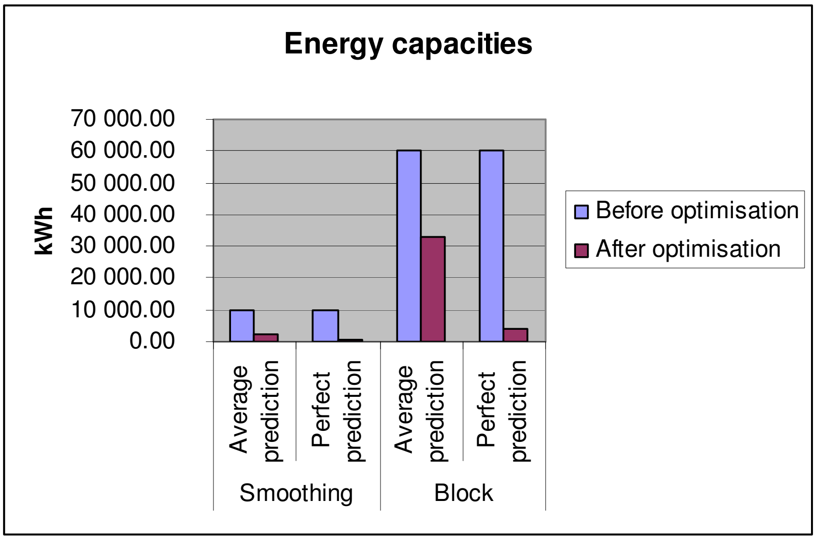


Figure 32: Impact of the optimisation on the energy capacities

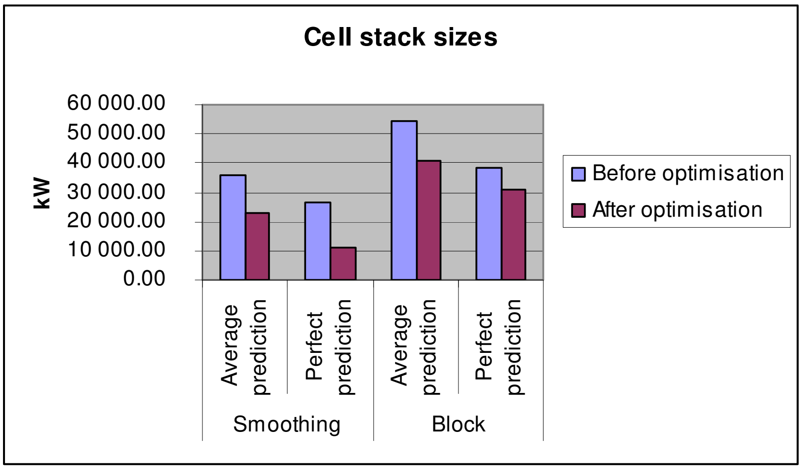


Figure 33: Impact of the optimisation on the cell stack sizes

The previous charts highlighted the improvement brought by the optimisation. Indeed, it reduces the energy capacities and the cell stack sizes, but also makes a difference between the characteristics needed by a system using an average prediction and another one using a perfect prediction. It can be seen that the characteristics for a perfect prediction system are much lower. Thanks to these improvements, the prices of the batteries decreased and so decreased the NPC as it can be noticed on the following bar chart:

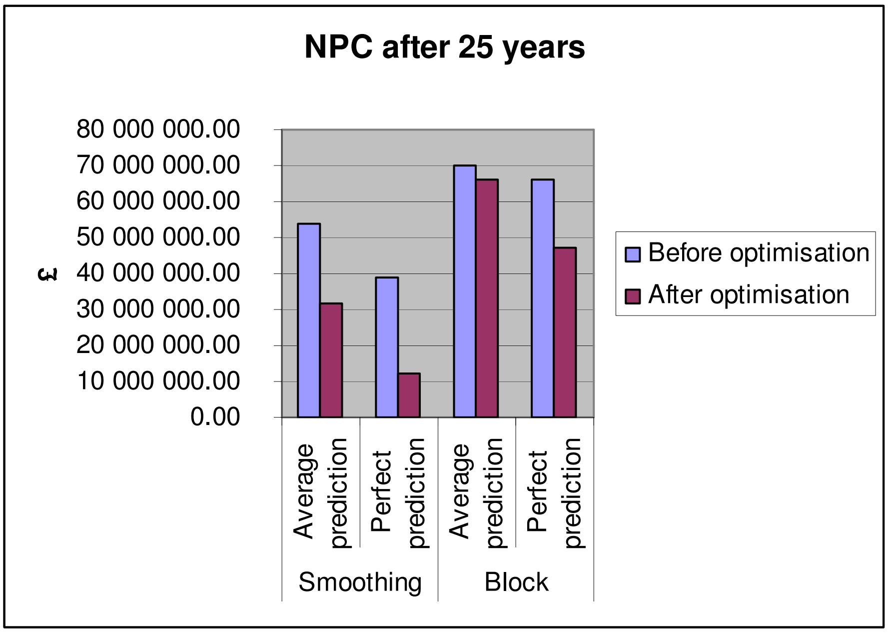


Figure 34: Impact of the optimisation on the NPC

The net present costs have been decreased. However, they remain positive, and that means that none of the configurations are cost effective. It can be seen that the smoothing configuration using the perfect prediction has the lowest NPC.

2.3.2. Solution for reducing the NPC:

Even after optimisation, the NPC is still too high whatever the scenario or the configuration observed. This is due to the price of the battery which is far too high. Considering the figure 20: "*Variation of the costs of the battery for the block configuration*", most of the price of the battery is due to the cost of the cell stack. Moreover, this component is the only one which has to be changed every ten years. For these reasons, by reducing its size, the price of the battery should drop and consequently, the NPC should also be reduced.

Only the power rating limits the size of the cell stack. Therefore, instead of taking into account the maximum value obtained for this characteristic, it was limited at 15,000kWh, a value which is slightly higher than the average wind farm output (13,155kW). That means that sometimes electricity had to be bought to supply the predicted power (when the wind farm output drops for example). This additional cost was added to the amount of electricity already bought to smooth out the power delivered.

3. <u>Limitation of the power rating:</u>

3.1. <u>New results:</u>

By limiting the power rating, more energy had to be bought from the grid to compensate the lack of input and then get the same constant output power. These amounts of electricity have been assessed and shown in the table:

	Smoothing		Block	
	Average prediction	Perfect prediction	Average prediction	Perfect prediction
Energy capacity (kWh)	2450	500	32,896	4000
Old power rating (kW)	22,700	10,727	40,667	31,508
New power rating (kW)	15,000			
Energy bought (kWh)	**470,400**	**380,833**	**2,245,094**	**3,277,278**

Table 13: Excess of energy needed to limit the power rating

The costs of the energy bought have been deducted from the revenues of the battery and the wind farm. Then, the financial analysis was carried out again in order to figure out if there was any improvement.

3.2. Analysis:

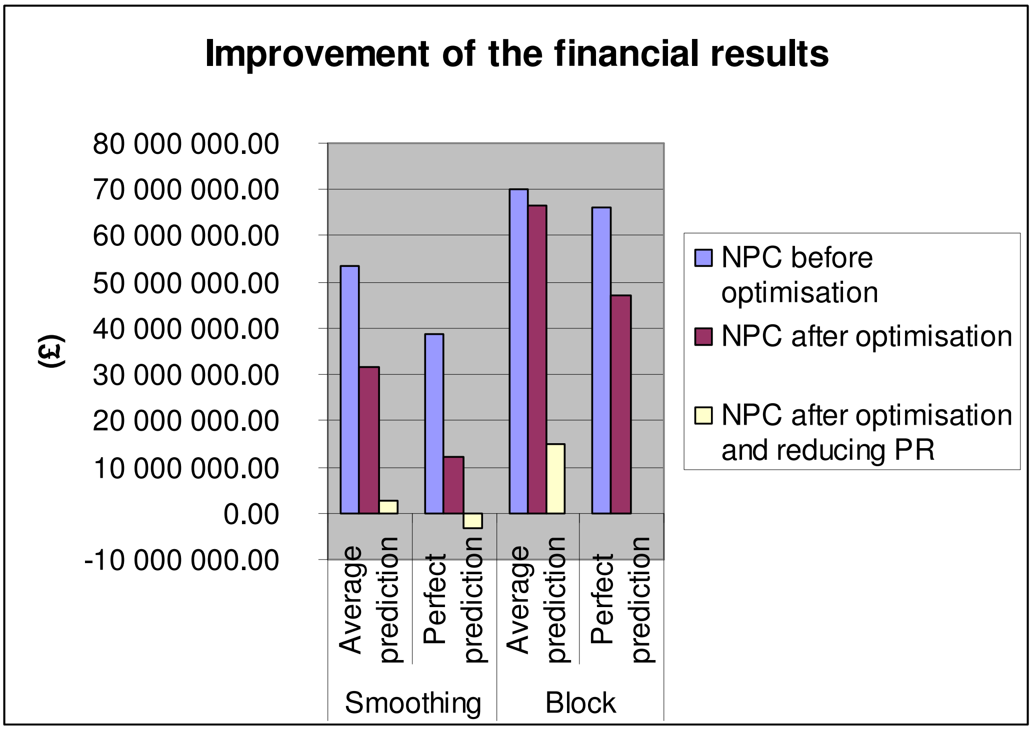


Figure 35: Impact of the limitation of the power rating on the NPC

It can be clearly seen that limiting the power rating has an enormous impact on the cost analysis. Indeed, it drops the net present costs as the price of the battery and the replacement cost (cell stack) are lower. Thanks to this change, the simultaneous control system with perfect predictions gives a profit for both the output smoothing and the block scenarios (respectively £3,432,182.27 and £247,115.54). Once again the shortest application (output smoothing scenario) gives a best result as it uses a smaller battery.

3.3. Limitation of the associated control system configuration:

The main purpose of the associated control system was to accept all the energy produced by the wind farm in the battery. However, according to the results this configuration is not viable.

Therefore, in this part a limitation of the power rating is considered in order to check if this can improve the results.

The same method as previously was used: the same rated power was used as it is roughly higher than the average wind farm output (13,155kW). However, much more energy was lost for the peak time configuration as it was supposed to deliver a maximum output during a short period.

The results after limitation are the following ones:

For the three configurations, as the limitation is the same, 62,293,332.63 kWh are wasted in overspill. This represents a loss of £1,557,333.31 considering the 10 months period analysed and additional revenue of 2.5p/kWh given for a constant output. The new costs of the batteries and the NPC are given below:

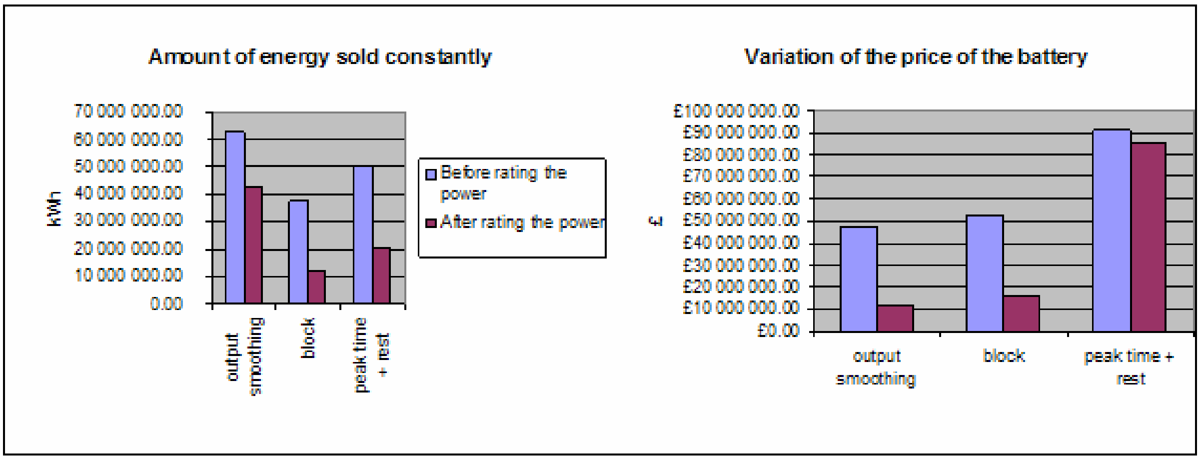


Figure 36: Direct impact of limiting the rate power for the associated control configurations

It can be seen on the previous charts that limiting the size of the cell stack reduces considerably the size of the battery, which means that money is saved. On the other hand, the amount of energy sold constantly is much lower, especially for the long term storage (peak time and block configuration). These parameters lead to the following variations on the NPC:

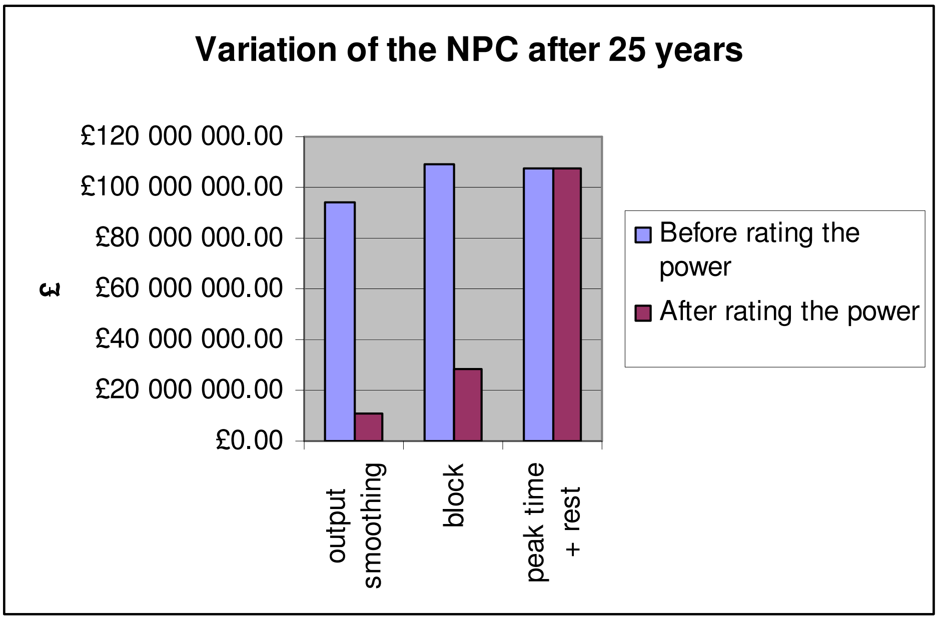


Figure 37: Impact of the rated power on the associated control configurations

Regarding the output smoothing and the block configurations, their NPC have been reduced by 88% and 74% respectively. For the peak time configuration, since the variation of the price is low, and lot of energy is wasted in overspill, the NPC is almost the same (only 0.06% lower).

4. <u>Influence of the main parameter:</u>

4.1. <u>the additional revenue given for delivering the constant power:</u>

The bonus given for delivering a constant power is decided by the grid and changes constantly with the market. However, in this project, it had to be assessed. The previous analyses were based on a benefit of 2.5p/kWh. Taken into account that the average SSP for electricity is 2.6p/kWh; the sell price is doubled. This is not a realistic condition, as typical contracts usually increase the price of constant power electricity sold by 30% [16]. That means that the benefit should be 0.75p/kWh. Using this value considerably increases all of the net present costs. The objective of the following section is to observe the impact of the additional revenue on the NPC after 25 years for all the configurations.

4.2. Results:

The NPC has been calculated for different values for the benefit given per kWh. The results are shown in the table and chart above:

		NPC				
		0.75p/kWh	1.0p/kWh	1.5p/kWh	2.0p/kWh	2.5p/kWh
Output Smoothing	average prediction	£6 372 762.22	£5 872 351.77	£4 871 530.87	£3 870 709.98	£2 869 889.08
	perfect prediction	£56 290.65	-£442 062.62	-£1 438 769.17	-£2 435 475.72	-£3 432 182.27
Block configuration	average prediction	£18 462 870.56	£17 969 573.57	£16 982 979.60	£15 996 385.62	£15 009 791.00
	perfect prediction	£3 192 199.87	£2 700 869.10	£1 718 207.55	£735 546.00	-£247 115.55
Associated controls	block	£31 473 860.97	£31 028 822.40	£30 138 745.27	£29 248 668.14	£28 358 591.02
	smoothing	£22 666 783.72	£21 033 602.32	£17 767 239.52	£14 500 876.72	£11 234 513.91
	peak time	£113 030 962.51	£112 246 276.37	£110 676 904.09	£109 107 531.81	£107 538 159.53

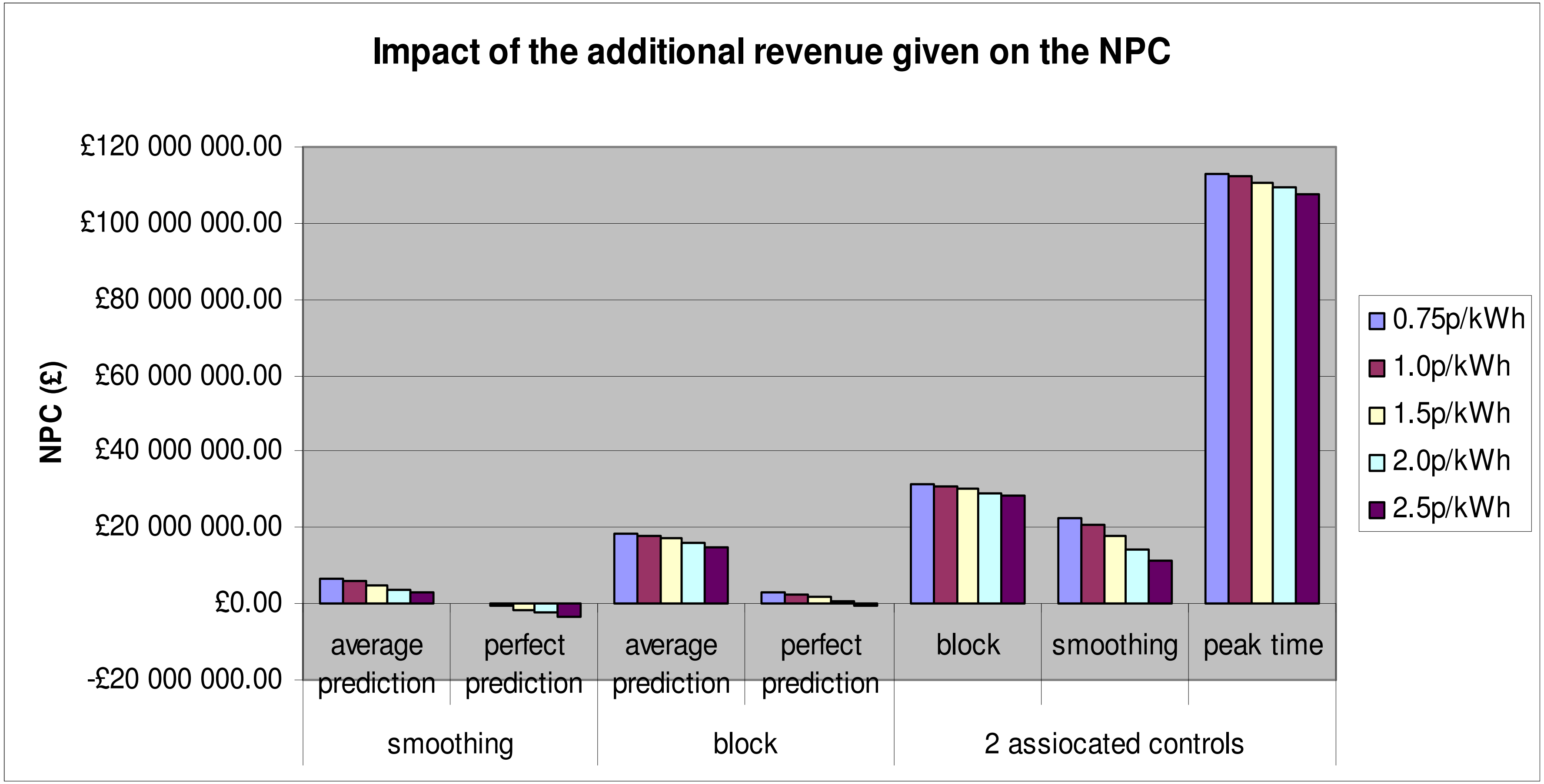


Figure 38: Impact of the additional revenue on the NPC

It can be seen on the previous graphic that the NPC variation is small. Indeed, the bonus sell price is so low that it does not change the NPC which stays high because of the initial investment.

It is worth noticing that for each of the scenarios (output smoothing and block configuration) the NPC is always the lowest for the perfect prediction, and the highest for the two associated controls.

Once again, the system is only cost effective for the perfect prediction in the output smoothing configuration. This is still due to the small size of the battery and then a lower initial investment.

Considering that the additional revenue has a low influence on the NPC results, the following shows the bonus necessary for each configuration to make the configurations cost effective:

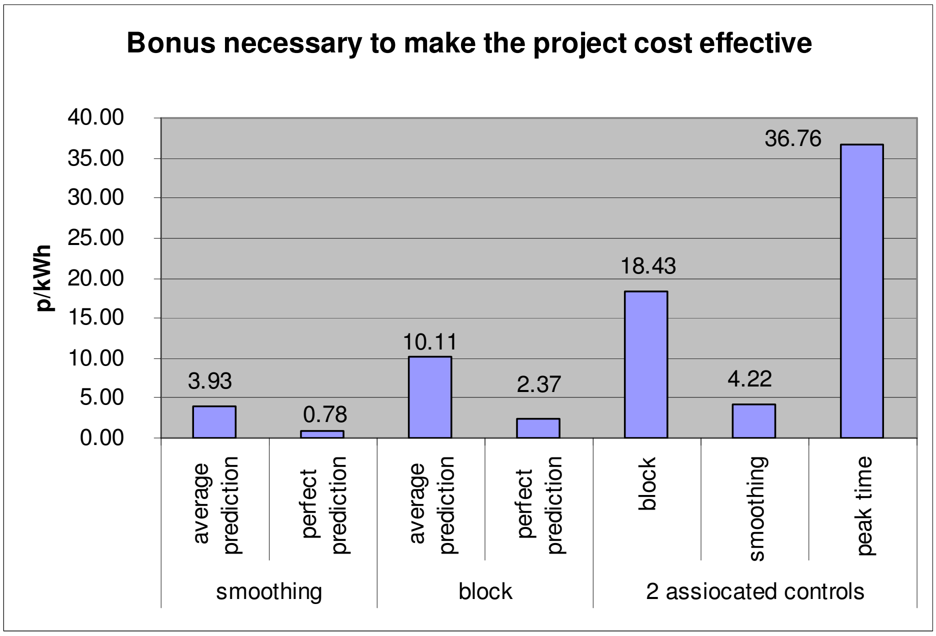


Figure 39: Additional revenue necessary to make the project cost effective

It can be seen that only the short term scenario is viable as the extra price required is realistic compared to the others. Indeed, it is very close to the 30% of the SSP which equals to 0.75p/kWh. The peak time scenario is not considerable as the electricity has to be sold 15 times more expensive than it is.

5. **Final results and recommendations:**

5.1. Costs of the batteries for each configuration:

Taking into account the realistic assumption that the additional revenue provided for the constant power (extra 0.75p/kWh), the following chart shows the actual prices of the batteries and the minimum price required to make the system cost effective after 25 years.

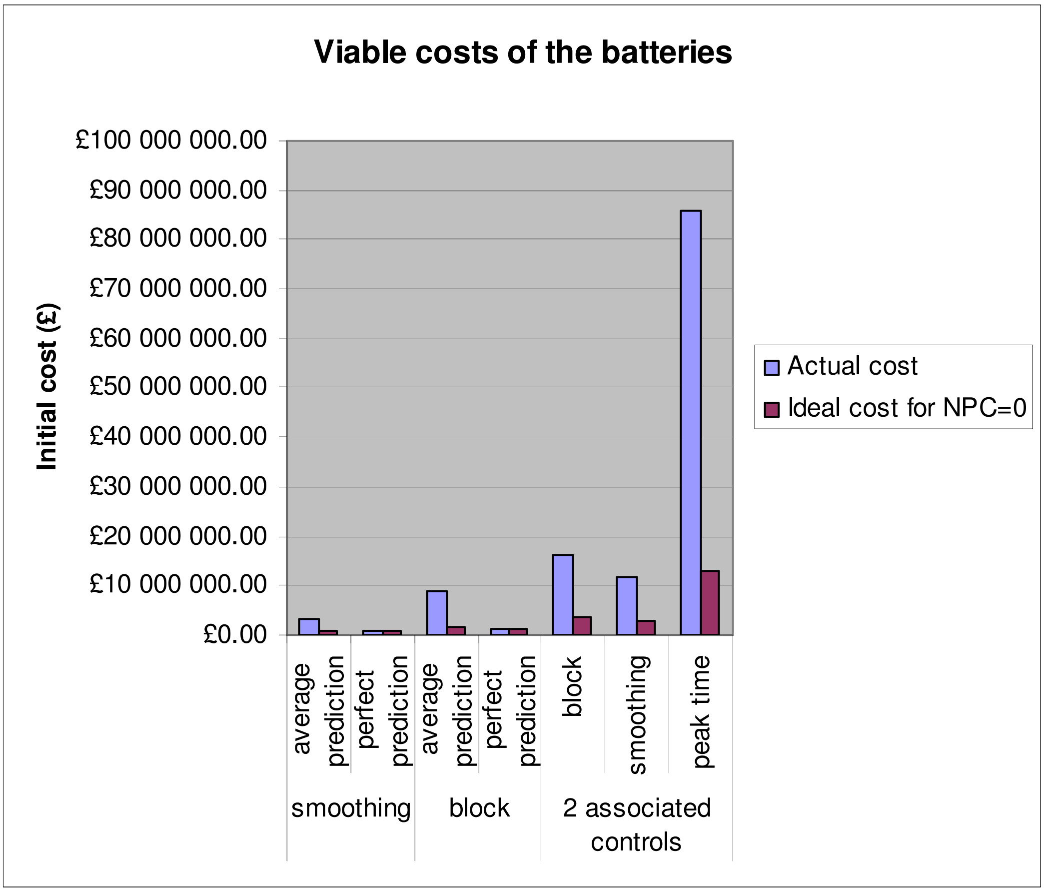


Figure 40: Viable costs of the batteries

The same conclusions as previously can be seen: only the short term configurations using a simultaneous control are viable. However, it is possible to estimate the price of the batteries per kWh delivered during the lifetime of the project (25 years). The following shows them:

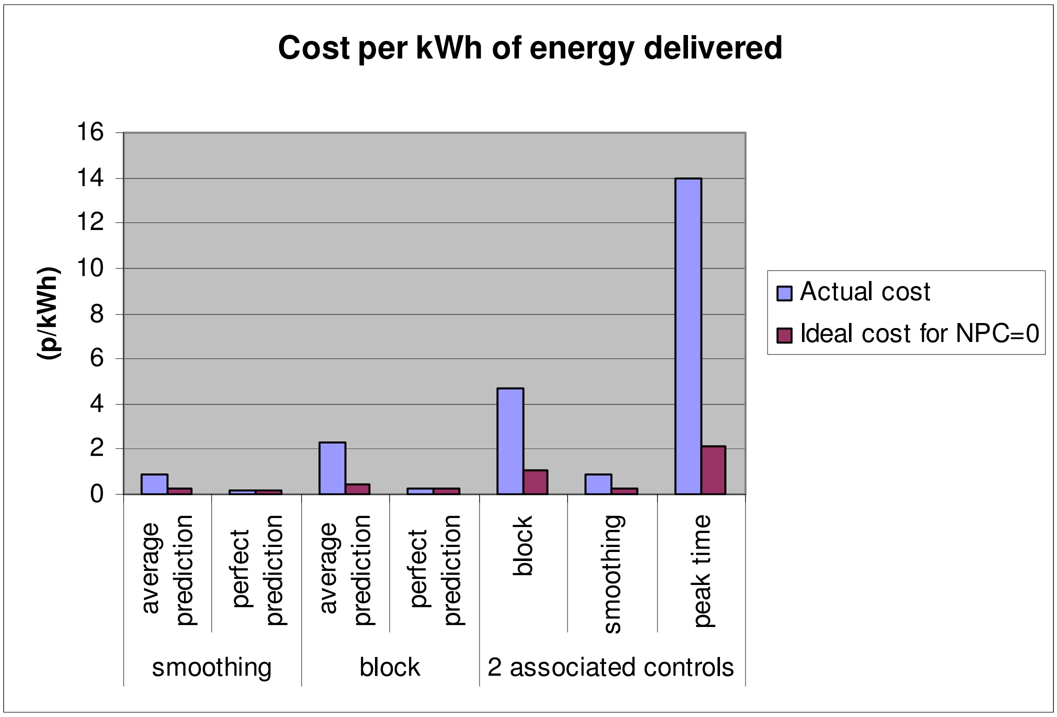


Figure 41: Costs of the batteries per kWh of energy delivered during the project lifetime

The peak time scenario would need a battery seven times cheaper than the actual one. However, the other configurations show that if the price of the flow batteries decreases slightly, considering a perfect prediction of the wind farm output, it would be possible to use them for the block configuration.

It can be seen that higher costs can be tolerated by the associated control system. Indeed, they require less energy bought from the grid. As mentioned previously, the shorter the constant period considered or the better is the wind farm output prediction, the smaller the battery that is required. Therefore, the costs involved are reduced.

By now, only scenarios using simultaneous control system and perfect predictions are viable. Indeed, the actual cost of the battery needed is lower or close to the minimum required to make the equipment cost effective after 25 years.

5.2. Final NPC and break-even for the most suitable configuration:

Regarding only the best scenario (smoothing the wind farm output every thirty minutes, and predicting the power delivered with high accuracy) a deeper financial analysis was carried out. Indeed, it is the only one configuration which reaches a real profit. The following curves represent the evolution of the NPC for different project periods.

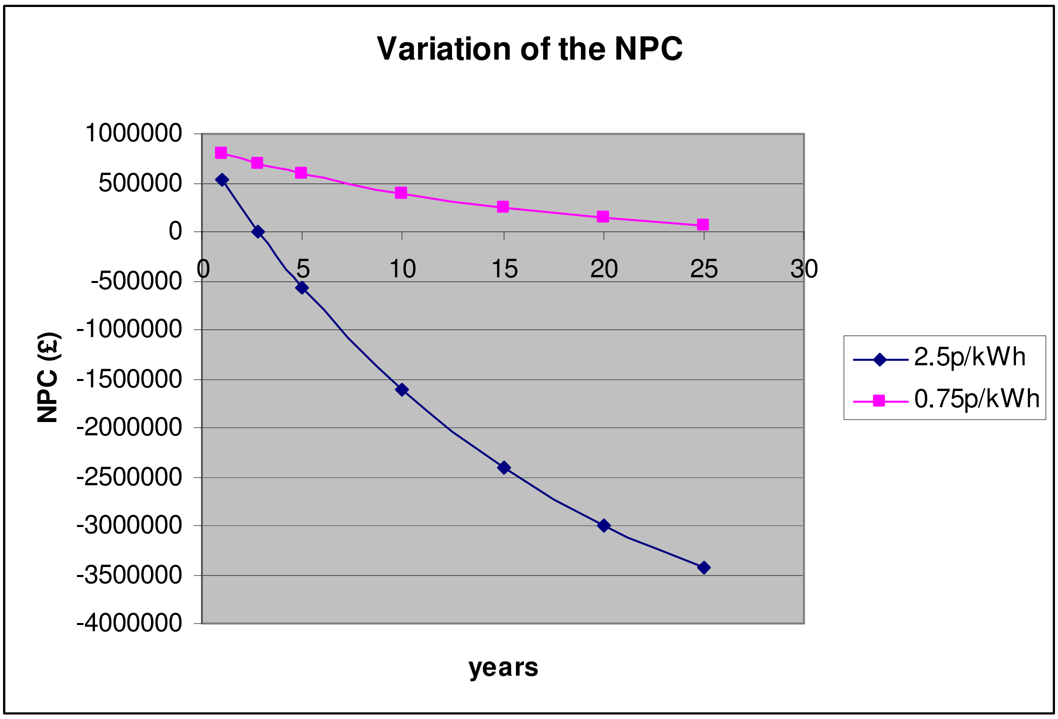


Figure 42: Variation of the NPC for the output smoothing with perfect prediction

As it can be seen in the previous graphic, the break even for this configuration is 2.8 years assuming the initial additional revenue of 2.5p/kWh. That means that after this period the battery and all its components are paid back. Considering a realistic value (0.75p/kWh), the cost analysis shows that the whole battery is almost paid back after 25 years. In fact considering this price, the break-even is 29.5 years. Slightly increasing the project lifetime or the additional revenue would make this configuration cost effective and this with actual data.

Energy storage is unavoidable if we want to increase the penetration level of renewables in the generation market (to reduce greenhouse gas emissions). This individual project intended to size a storage system for a large wind farm, and carry out a cost analysis for the chosen storage system. After taking into account several storage technologies, flow batteries were considered as the most suitable storage system.

Simulations were carried out in order to size these batteries for different working scenarios and to estimate the net present cost of each one of these configurations for a period of 25 years (the project lifetime considered). The first scenario was to smooth the output of the wind farm so as to give a constant power output every thirty minutes. The second scenario involved smoothing the wind farm output to give a constant power output every four hours. The final scenario investigated delivering power mainly during peak-time periods. In order to assess the functioning of the batteries, these scenarios were simulated with two different control systems: the first one runs simultaneously with the wind farm output and regulates it; the second one delivers a constant power based only on the energy available in the storage device.

After assessing the best method for predicting the wind farm output, the most suitable size of the battery was estimated for each one of the previous configurations. An optimisation process was carried out to size the battery that gives the lowest NPC. The results of these calculations (Table 11: "Results for associated controls before optimisation" & Figure 34: "Impact of the optimisation on the NPC") showed that using flow batteries is not viable. Net present costs still remain positive, which means that at the end of the project lifetime using storage only provided losses. The configuration showing the best results (smoothing the output of the wind farm so as to give a constant power output every thirty minutes) has an estimated loss of £12,000,000 (considering additional revenue of 2.5p/kWh of constant power delivered).

To improve these results, the price of the battery, which is the actual initial cost, had to be reduced. Taking into account that it is mostly due to the cost of the cell stack, this component had to be undersized. Rating the input/output power of the battery increased the quantity of overspill and the quantity of energy bought from the grid, but also reduced the initial costs.

Limiting the power rating had an enormous impact on the cost analysis. Thanks to this change, the simultaneous control system, with perfect predictions of the wind farm output, gives a profit for both the output smoothing for thirty minutes and the output smoothing for scenarios of four hours (respectively £3,432,182.27 and £247,115.54). These values were estimated taking into account additional revenue of 2.5p/kWh of constant power delivered. It is worth noting that configurations using simultaneous control system always gave better results and the shorter the output smoothing period, the lower the NPC. Figure 38: "Impact of the additional revenue on the NPC" showed that the NPC mainly varies according to the size of the battery but not the additional revenue given by the grid for providing constant power. Indeed, this revenue is very low; therefore the configurations using the smallest batteries had the best financial results.

In the last part of the results and analysis chapter, the necessary additional revenue to make the use of batteries cost beneficial was assessed. Figure 39: "Additional revenue necessary to make the project cost effective" showed that only the shortest term scenario is viable as the extra price required (0.78p/kWh) is realistic compared to the others. It can be seen that it is very close to the 30% of the SSP provided by the grid which equals to 0.75p/kWh. The peak time scenario is not considerable as the electricity has to be sold at a cost that is 15 times more expensive than the actual SSP. Finally, considering the actual British electricity market, the maximum price of the battery has been assessed on figure 41: "Costs of the batteries per kWh of energy delivered during the project lifetime".

After optimising and rating the input/output power of the batteries, the best result was reached by the thirty minutes output smoothing and a 'perfect' prediction of the wind farm output. Taking into account the actual prices of the electricity market, this configuration would have a break-even point after nearly 30 years (figure 42: Variation of the NPC for the output smoothing with perfect prediction). Actually, this is really similar to the use of the flow batteries in Tomamae wind villa, in Japan. J-power (Japanese electricity generator) takes advantage of flow batteries to smooth the output of the largest wind farm of the country and give a firm power every twenty minutes.

Regarding buffering technologies for large wind farms at the moment, delivering constant power for long durations or peak time periods can only be achieved by using long term storage (pumped hydro or compressed air energy storage). Indeed, even if they require specific sites, they are the only technologies able to deliver a large output power for long periods of time.

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Related to the characteristics of the battery:

- **SOC**: state of charge.
- **Dod**: depth of discharge, refers to the maximum discharge without damage.

Related to the electricity market:

- **SSP**: System sell price.
- **SBP**: System buy price.
- **ETSA**: Electricity trading service arrangements.

U: overall performance indicator. It represents the proportion of the time when the system (battery + wind farm) delivers at least the constant power required.

NPC: Net present cost. It indicates if the configuration taken into account is viable by the end of the project lifetime.

1- **Hennessy T.** (2006*) Flow Battery Storage Application with wind power - a planning option*, VRB ESS presentation, Dallas – IEEE PES Conference 23 May 2006.

2- **Zhao P, Zhang H, Zhou H, Chen J, Gao S** and **Yi B**. (2006) *Characteristics and performance of 10kW class all-vanadium redox-flow battery stack*, Chinese Academy of Sciences.

3- **Koshimizu G.** (Assistant manager for J-Power: Gentarou_Koshimizu@jpower.co.jp), email received the 13th of July 2007

Frankcombe D. (Thermal and Island Generation Manager:

Dennis.Frankcombe@hydro.com.au), email received the 13th of July 2007.

4- **Marsh G.** (2002) *RE Storage the Missing Link*, REFOCUS Magazine (March/April 2002).

5- **Hennessy T.** (2007) *The multiple benefits of integrating the VRB-ESS with Wind Energy – case studies in MWh applications*, the VRB Energy Storage System publication, March 2, 2007.

6- **Gross R, Heptonstall P, Anderson D, Green T, Leach M** and **Skea J.** (2006). *The costs and impacts of intermittency.* UK Energy Research Centre.

7- **Linden D.** (2002) *Handbook of batteries*. 3rd ed. Thomas B. Reddy.

8- **Ter-Gazarian A.** (1994) *Energy storage for power systems*. Peter Peregrinus Ltd (London).

9- **Hennessy T.** (2007) *A comparison with Lead Acid Batteries*, the VRB Energy Storage System publication, March 2, 2007.

10- **Dell R.M.** and **Rand D.A.J.** (2001) *Understanding batteries*. Royal Society of Chemistry.

11- **Strbac G, Price A, Jones A, Kelly N, Ruddell A** and **Harris R** (2003) *Storage of renewable energy*, Seminar proceedings, 27th November 2003.

12- **International Energy Agency** (2006) *Hydrogen production and storage*. IEA publications.

13- Technology comparisons for electricity storage, available at www.electricitystorage.org

14- **KEMA** (2007) *Outline description of studied international markets*.

15- SSP & SBP prices every 30 minutes, data provided by Smartest Energy, electricity trading company and Elexon, a settlement administrator.

16- **Tran T.** (Commercial analyst for SmartestEnergy: tia-tran@smartestenergy.com), email received the 7th of September 2007.