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A Diversified Portfolio of Tokenised Revenue Streams Can Provide Hedging Opportunities for Renewable Electricity Generators

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Abstract: The revenue streams of renewable energy generators are subject to both price and volumetric risks, owing to the variable nature of weather patterns. This negatively impacts viability of the generation projects. Blockchain-based decentralised finance methods may present new means for generators to hedge against such volatility. This paper proposes tokenised revenue streams *(RevToks)* as a novel tool for electrical generators. By holding a RevTok, a participant can directly claim a portion of that generator's revenue. To articulate how such exotic financial arrangements may benefit renewable generators, a case study market simulation is performed. Generators can trade RevToks to diversify their cash flows, decreasing their variance and thus overall risk exposure. The simulation uses Multiportfolio Theory — an extension of Modern Portfolio Theory — to optimise the RevTok holdings of all generators simultaneously. Examining the results show that RevTok trades occur between generators of varying technology and remuneration schema. By trading RevToks amongst themselves, all generators achieve far less volatile revenue streams, while maintaining constant expected revenues. Thus, the RevTok paradigm potentially offers improved revenue hedging when compared to established methods for energy firms. Results show that implementing such a blockchain-based arrangement for existing central pool operators unlocks downstream opportunities for renewable generators.

1 Introduction

An increased presence of Renewable Energy Systems (RES) in power systems has necessitated changes in market operations [1]. Existing designs of deregulated markets see generators selling directly to electricity suppliers through a central pool market operator, which sets the spot price at which units of energy are purchased at any one time [2]. However, non-dispatchable RES generation methods present challenges when paired with such existing market structures [3]. The lower marginal cost of wind or solar production compared to fossil fuel-based methods has been observed to drive price downward, as electricity from RES is often purchased in advance by commercial suppliers. This is known as the *merit-order effect* [4], and serves as a major impetus for the transformation of electricity markets. If such markets are unable to adapt, a situation may occur where RES investment is indirectly disincentivised [4]. Markets therefore need to be adapted to address this inherent stochasticity.

Such RES generation methods offer environmental and sustainability benefits [5]. However, their production is notably volatile, owing to dependence on fluctuating weather patterns [5, 6]. This results in high levels of variance in generator revenue. Variance is a common measure of risk within the fields of finance and economics [7, 8]. As such, RES generators often seek to decrease their variance (and thus risk) by hedging their revenue streams.

Renewable electrical generators are exposed to both *price* and *volumetric risk* [9]. Price risk is associated with the volatility of fluctuating spot prices, affecting the generators' remuneration for produced electricity. Volumetric risk, on the other hand, refers to uncertainty in the supply of a commodity. Organisations typically use hedging tools to reduce price risk for stakeholders [10]. This is accomplished through traded securities such as options and futures contracts or derivatives, as in [11, 12]. However the effectiveness of these tools has been debated. For instance, Hain *et. al* claim that *"existing vanilla derivatives are poor hedges"* [6] owing to an evolving energy market and the variable nature of increasingly-popular RES generation. That is, a higher penetration of intermittent RES indirectly results in unpredictable fluctuations of supply, which correlates to a more erratic spot price at any time [13]. Ultimately, as an emerging field, conclusive evidence of over-the-counter derivative-based hedging for RES has yet to be provided [6].

Furthermore, volumetric risk is difficult to hedge against for RES firms [14], owing to the stochasticity of weather conditions that dictate RES production [15]. Weather derivatives have been proposed in a manner similar to the agriculture industry [16], but these have been found to be unsuitable in their consideration of short-scale climactic conditions. Furthermore, such derivatives are hard to price, and have had difficulty in establishing a market [17].

In response to this rapidly-changing environment, Decentralised Finance (DEFI) based solutions have been suggested as an alternative means of hedging against these risks, such as examples in [18, 19]. DEFI is an application of blockchain principles that leverages the technology for granular financial operations, such as loans, derivatives, exchanges, insurance, and financial escrow. This allows for the autonomously chaining together of constituent financial operations as a means to distribute and claim funds. Much like the underlying blockchain technology [20], DEFI has been the subject of much research attention in the world of energy [21], and is proposed as an alternative means of implementing exotic payment methods and market structures [21–23]. This paper attempts to chart and articulate what a potential use-case could look like.

Despite this, blockchain and its associated technologies remain somewhat controversial and unproven [24]. These aspects stem mostly from the technology's unregulated status, with governments and financial institutions unwilling to commit to its acceptance [25]. The technology is perceived as creating a risky environment, with a comparative abundance of fraudulent activities within blockchain ecosystems [26]. The *proof of work* "mining" method that underlies many common blockchains (including Bitcoin) has also been found to be highly energy inefficient when compared to established electronic payment methods. Furthermore, the method has exhibited problems with scaling to accommodate an increased userbase [26]. Proponents, on the other hand, highlight blockchain's transparent

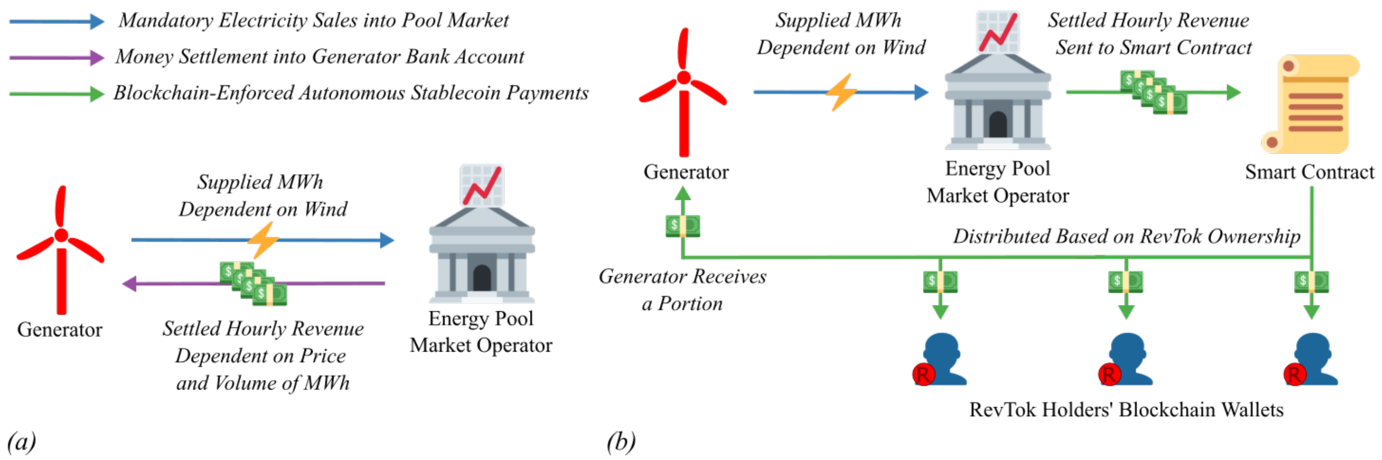

Fig. 1: Regular periodic revenue distribution schemes for electrical generators visual demonstration. The arrangement in *(a)* shows the existing method [32, 33]. The arrangement in *(b)* shows the smart contract-based arrangement proposed in this paper.

and decentralised nature, touted as a means of democratising transactions in a trust-free way [27]. The technology also allows access to previously unattainable finance mechanisms for the general public.

The present paper will investigate the potential for DeFi-type approaches to facilitate such arrangements as tokenised revenue sharing. Examining existing implementations within the blockchain world, *Coinsilium* [28] describe the idea of a *coded income model*, that *"build(s) a bridge...between the crypto economy and the real world economy"*. This is accomplished by allowing project owners to sell a share of a project's revenue that is then automatically distributed by smart contract to investors blockchain wallets. They cite DeFi cryptocurrency loans as the inspiration. The blockchain research group *Smith and Crown* discuss a similar concept in the form of *revenue-sharing tokens*, which they describe as *"on-chain dividends"* and *"exotic investment instruments"* [29]. They go on to describe these tokens as analogous to company equity. Similar still is the idea of *revenue participation tokens* by blockchain developers *Coreledger*. They offer these as a product for businesses that allow *"investments only into a company's...revenue, instead of selling parts of the company itself"*. *Coreledger* describes the tool as useful to business cases where revenue is generated over time [30]. Finally, work by Malinova *et. al* suggest a token contract to formalise a project's revenue sharing agreement. They propose this as a solution to perceived problems with initial coin offerings [31].

Drawing on the ideas discussed above, this paper develops a concept in which a tradable non-fungible token (NFT) embodies a claim to a portion of a specific generator's regular energy market revenue, which is paid out at a predictable time interval by a trusted and transparent central entity. The inherent nature of electricity market revenues make them an ideal example of a tokenisable revenue stream, and thereby serve as a clear topic that can begin to articulate the potential value of DeFi for renewable generators. Tokens can be traded frictionlessly on a dedicated exchange. Once these Revenue-bearing Tokens *(RevToks)* change hands, the token holder is entitled to a pro rata portion of that revenue stream, and can claim revenues through centralised pool market operators on a predetermined periodic basis. Having a centralised authority in charge of distribution makes this possible, and the arrangement can be implemented on a blockchain or on dedicated centralised servers. Such an arrangement is demonstrated visually in Fig. 1 and compared to the traditional method of generator remuneration.

This paper investigates the potential usefulness of implementing such a system for grid scale RES generators. In this paradigm, generators are able to tokenise a portion of their revenue stream and sell it through an exchange. This revenue originates from a centralised operator of the energy pool market in a manner similar to existing arrangements [32, 33]. However, the market operator publicly and transparently sends this money to the disbursal smart contract in the form of stablecoins. This smart contract is able to observe token ownership, and proportionally distributes funds based on these tokens. Token buyers can thus legally and securely claim a portion of an electrical generator's regular proceeds. This system represents only a minor change in the current widespread model of operation for central pool market operators. However, the incorporation of blockchain-based smart contract technology presents new downstream opportunities for RES generators that significantly improves their business environment. The proposed arrangement is somewhat similar to existing cryptocurrency and stablecoin payment methods, but adds *an additional layer* that allows for the fractionalisation of regular sources of revenue. In a DeFi context, fractionalisation has been proposed as a a means of allowing investment on a smaller scale. This in turn allows individuals to avail of investing opportunities that may have previously been out of their financial reach [34]. Further more, the regular and recurrent nature of a RevToks-based arrangement adds fluidity and transparency to the operation of an electricity pool market operator. In other words, the mechanism leverages some of the advantages of existing crypto payment methods through the use of unique smart contract arrangements.

The authors examine the value unlocked by implementing such a tokenised revenue stream arrangement, and provide a comprehensive worked example. This attempts to answer the question: are tokenised revenue streams a potentially useful tool for grid-scale electrical generators? Is an arrangement that makes use of tokenised revenue streams desirable within an energy systems context?

In the present paper the generators themselves also act as counterparties, buying RevToks from and selling RevToks to each other. Generators can exchange RevToks so as to benefit from holding a diverse array of revenue streams, resulting in a lower total cash flow variance, thus reducing risk without affecting return. This serves to address the risk-related problems previously discussed. This novel arrangement is proposed as an alternative means of hedging against price and volumetric risk that may be cheaper than traditional methods.

To establish optimally diversified generator RevToks portfolios, Modern Portfolio Theory (MPT) will be employed. First proposed by economist Harry Markowitz [7, 8] as a means of asset portfolio diversification, MPT strives to optimally allocate a party's investment capital in a way that minimises their variance without sacrificing expected returns. Since its introduction the process has seen extensive use in energy finance, as summarised in [35]. The authors will take a novel approach to employing MPT in an electrical energy context by incorporating concepts from the blockchain and DeFi space as a means of minimising participant risk.

2 Assumptions

This section describes the assumptions embodied in the schema described in this paper, and concludes with a summarised list of these.

At the time of writing there is minimal regulation within the DeFi space [26]. Notwithstanding this, the present treatment assumes that the necessary legal regulation by traditional institutions has been put in place to legitimise the trading and holding of RevToks.

In the scenario presented here, a regulated energy pool market operator exists that settles electricity market out-turns, similar to widespread arrangements [32, 33]. Downstream of this is a dedicated smart contract that enforces revenue claims. This smart contract is sent generators' proceeds from electricity pool marker outturns. In principal, a generator may opt (publicly) to receive their pool market revenues by stablecoin transfer to a nominated blockchain wallet address. If this address is controlled by a smart contract the onward flow of revenue can be immutably controlled via ownership rights embodied in non-fungible tokens. The energy pool market operator transparently and credibly commits to this arrangement. The smart contract then offers RevTok owners an inalienable right to claim revenues. RevToks can be transacted without friction on a dedicated exchange. This arrangement potentially presents a low risk profile, as the smart contract code can be audited to verify a user's right to withdraw revenue. DeFi projects often adopt this *"code as law"* philosophy in lieu of formal regulation [25]. This arrangement is summarised in the visual explanation in Fig. 1 *.

The list below summarises the main assumptions made in this paper.

- There exists a central mandatory pool market operator that buys electrical revenues from generators and settles revenues based on energy markets outturns [32, 33].
- Inalienable, self-enforcing claims on these revenue streams can be subdivided and tokenised into *RevToks*, which can be transferred, traded, and stored [28, 29, 31].
- The pool market operator sends funds in the form of stablecoins to a dedicated smart contract that autonomously and transparently oversees monetary distribution to RevTok holders.
- There exists this platform that allows for the trade of RevToks, and integrates with participants' blockchain wallets for the transfer of currency.
- While in principle any stakeholder may wish to buy and hold RevToks, in this paper only simple first-party transaction between comparable generators in a closed marketplace are considered.
- Participating generators have the necessary hardware and software installed to tokenise, store, and transfer RevToks.
- RevTok transaction costs are negligible. This is a reasonable assumption when considering the magnitudes of energy and RevTok costs.
- Generators desire to hedge their revenues by diversifying their revenue streams. They combine their own revenue stream with tokenised portions of other generators', using RevToks to accomplish this.
- Generators are afforded one single opportunity to trade and transfer RevToks between themselves. An actual marketplace would see continuous RevTok transactions.
- In the isolated single case study, only a single generator is examined at a time i.e it treats the system as a deep liquid market, similar to MPT's classic usage. This presents the best possible case for each generator.
- In the simultaneous multiportfolio case study, the portfolios of all generators are optimised at the same time. This acts as to represent one mutually-beneficial equilibrium that the market might achieve.

3 Methodology

This section describes the methodology used in this paper, with MPT as its basis. The first case study uses MPT in its classic form to calculate how a single generator might diversify their portfolio when examined in isolation i.e. treating the rest of the system as a deep liquid market. In the second case, *Multiportfolio theory*, an expansion on standard MPT, is used in a modified form to perform simultaneous generator portfolio optimisations. This acts as a full market simulation, considering all generators at once. Finally, coefficients of variation are examined and their role in this paper described.

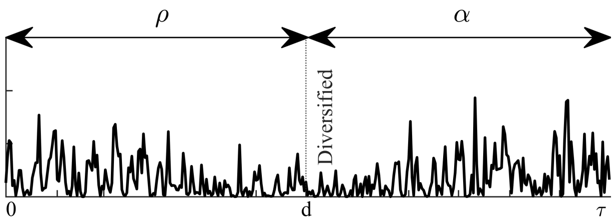

Fig. 2: Revenue profile before and after diversification notation

Markowitz' standard MPT problem has two common forms. The first attempts to maximise revenue under a certain acceptable risk level, while the second attempts to minimise risk for an acceptable level of return [7, 8]. The methodology employed here will utilise a version of the latter. This is chosen as investors will pursue the best possible risk/return profile, but will not accept a reduction in revenue for an improvement in revenue variance. The MPT methodology is expanded and imitates that of *multiportfolio optimisation*, as developed in [36, 37]. This methodology, however, differs in that it is applied to a closed system of participants, rather than a deep liquid market as in the examples above.

With n generators, a time series of revenues $\boldsymbol{\mathscr{R}_i}$ with τ datapoints is defined for generator i as in (1) and calculated as in (2). The term $\mathscr{r}_{it}$ represents generator i's revenue at time point t. This time series encompasses the entire examined period. The time series vector $\boldsymbol{g_i}$ is the generator i's electrical energy output in MWh. The time series vector $\boldsymbol{c_i}$ is generator i's energy price in € per megawatt-hour corresponding to the market they participate in. The value of $\boldsymbol{c}$ could be a constant, as in the case of generators on Power Purchase Agreement (PPA) tariffs *, or varying, as in the case of generators participating in the spot market. $\boldsymbol{\mathscr{R}}$ is the sum of element-wise multiplications of vectors $\boldsymbol{g}$ and $\boldsymbol{c}$.

$$\boldsymbol{\mathscr{R}_i} = \left\{\mathscr{R}_{it}\right\}_{t=1}^{\tau} = \left\{\mathscr{r}_{i1} \quad \mathscr{r}_{i2} \quad \cdots \quad \mathscr{r}_{i\tau}\right\} \tag{1}$$

$$\boldsymbol{\mathscr{R}_i} = \mathbf{g_i} \circ \mathbf{c_i} = \left\{g_{i1}c_{i1} \quad g_{i2}c_{i2} \quad \cdots \quad g_{i\tau}c_{i\tau}\right\} \tag{2}$$

With $\boldsymbol{\mathscr{R}_i}$ as the complete time series of revenues for a generator, the profile is split into two sections. These two sections bookend the moment of diversification $t = d$ i.e. the point in time when generators coordinate and exchange RevToks to decrease their individual variances. Thus, the total examined time series revenue profile is split into the revenue profile *before* diversification, ρ, and revenue profile *after* diversification, α. This is defined in terms of revenues in equation (3), with $\boldsymbol{\mathscr{R}^{\rho}}$ as the time series of revenues during the ρ time period and $\boldsymbol{\mathscr{R}^{\alpha}}$ the time series of revenues during the α time period. Equation (3) thus shows $\boldsymbol{\mathscr{R}}$ as the concatenation of $\boldsymbol{\mathscr{R}^{\rho}}$ and $\boldsymbol{\mathscr{R}^{\alpha}}$. Fig. 2 demonstrates these time periods visually.

$$\boldsymbol{\mathscr{R}} = \boldsymbol{\mathscr{R}^{\rho}} {}^\frown \boldsymbol{\mathscr{R}^{\alpha}} \tag{3}$$

Hence forth the term $\boldsymbol{\mathscr{R}_i^{\rho}}$ will refer to the total sum of revenue over the ρ time period for generator i, as in equation (4). Furthermore, $\boldsymbol{\mathscr{R}_i^{\alpha}}$ will refer to the total sum of revenue over the α time period for generator i, also shown in equation (4).

$$\mathscr{R}_i^{\rho} = \sum_{t=1}^{d} \boldsymbol{\mathscr{R}_{ti}^{\rho}} \qquad \mathscr{R}_i^{\alpha} = \sum_{t=d}^{\tau} \boldsymbol{\mathscr{R}_{ti}^{\alpha}} \tag{4}$$

While this paper considers a blockchain/smart contract based system, a centralised implementation is also possible.

The term PPA as used here refers to the fixed price that generators are assumed to have settled on with the market operator.

3.1 Formulation of single case quadratic programming problem

A portfolio is defined as in equation 5, referring to a generator's portfolio of RevToks. The values for p make up the percentages of the portfolio, as in equation (6). The values of this matrix can be understood as the percentage of the examined generator's total revenue invested into each generator's available RevToks.

$$\mathbf{p} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix} \tag{5}$$

$$\sum_{i=1}^{n} p_i = 1 \tag{6}$$

Related to the above, an optimisation variable $\boldsymbol{r}$ is defined, representing the revenue gathered from each generator's RevToks, as in equation 7. The sum of elements in $\boldsymbol{r}$ is equal to $\mathscr{R}^\rho$ i.e. the sum of expected revenues in the examined period. That is, a generator does not expect to increase the revenue gained after portfolio diversification. This is shown in equation 8.

$$\mathbf{r} = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_n \end{bmatrix} \tag{7}$$

$$\sum_{i=1}^{n} r_i = \mathscr{R}_i^\rho \tag{8}$$

Next, an optimisation variable $\boldsymbol{\mathcal{O}}$ is defined as in equation 9. This represents the percentage of each participating generator owned by the examined generator. The $\boldsymbol{\mathcal{O}}$ row vector can be understood as the counterpart of the $\boldsymbol{p}$ vector in equation 5.

$$\boldsymbol{\mathcal{O}} = \left[o_1, o_2, \cdots, o_n \right] \tag{9}$$

The $\boldsymbol{\mathcal{O}}$ and $\boldsymbol{p}$ vectors are related by the ratio of the sum of $\mathscr{R}\rho$ vectors between generators, as in equations 10 and 11. The resulting $\boldsymbol{E}$ is a matrix of *"exchange rates"* between generators used to compare ownership portions while taking magnitude differences into account. For example, a larger generator may allocate 10% of its investment portfolio and end up owning 30% of a smaller generator.

$$o_i = p_i E_i \tag{10}$$

$$\mathbf{E} = \begin{bmatrix} E_1 = \frac{\mathscr{R}^\rho}{\mathscr{R}_1^\rho} \\ E_2 = \frac{\mathscr{R}^\rho}{\mathscr{R}_2^\rho} \\ \vdots \\ E_n = \frac{\mathscr{R}^\rho}{\mathscr{R}_n^\rho} \end{bmatrix} \tag{11}$$

Additionally, a generator may choose not tokenise and sell access to their entire revenue stream. The variable ϕ_i is defined as the portion of revenue that generator i maintains, defined as in equation 12.

$$o_{ii} \geq \phi_i \tag{12}$$

While this case study considers each generator in isolation, it is necessary to check that other generators' ϕ values (i.e. other generators' available RevToks) are never being exceeded. This is shown for generator i in equation 13.

$$o_{ij} \leq \phi_{ij} \quad \forall j \in 1, 2, ..., n \quad i \neq j \tag{13}$$

For generators, variance is minimised and expected revenue kept to a constant level R_{lim}. This value is set to the total sum of hypothetical expected return for the examined generator after diversification i.e. the sum of R_i^ρ. This is shown in Equation 14.

$$\boldsymbol{\mathscr{R}_\rho} \circ \mathbf{p_i} = \mathscr{R}_{lim,i} = \mathscr{R}_i^\rho \tag{14}$$

The Index of Dispersion (IoD) is a normalised measure of a variable's dispersion, defined as in equation (15) [38]. The value of the IoD of a generator's revenue is its variance divided by its mean revenue. This is used in the formulation of the optimisation's objective function below.

$$\text{IoD} \quad = \frac{\sigma^2}{\mu} \tag{15}$$

The covariance matrix $\boldsymbol{S}$ is an important part of the quadratic optimisation problem as it considers the variance relationships between generator pairs. The matrix is also used in the calculation of an individual generator's variance, as in the objective function formulated below. The covariance σ_{ij} between generators i and j is calculated as in equation (16), with μ_i as the mean of generator i's expected revenue $\boldsymbol{\mathscr{R}_i^\rho}$. With this in place, the covariance matrix is then formulated as in equation (17).

$$\sigma_{ij} = \frac{\sum(\mathscr{R}_i^\rho - \mu_i^\rho)(\mathscr{R}_j^\rho - \mu_j^\rho)}{n} \tag{16}$$

$$\mathbf{S} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{bmatrix} \tag{17}$$

The objective function minimises the portfolio risk, as in equation 18. This value is the variance of the generator under examination's revenue stream divided by the mean of their revenue over the examined period ρ. Thus, the objective function is the IoD of the generator *. The matrix $\boldsymbol{S}$ is the $n \times n$ covariance matrix between all n participants, as in (17). By minimising this value the generator's variance, and thus risk, will be reduced.

$$\min \quad \frac{\boldsymbol{\mathcal{O}_i S \mathcal{O}_i^T}}{\mu} = \quad \min \quad \frac{\sigma^2}{\mu} \tag{18}$$

3.2 Formulation of simultaneous case quadratic programming problem

This section formulates the optimisation problem when examining all generators simultaneously. This acts as a notional market equilibrium case.

The optimal portfolio quadratic programming problem is now formulated through equations (19) to (30). Three optimisation matrices are defined, each n by n elements in size. These are $\boldsymbol{o}, \boldsymbol{p}$, and $\boldsymbol{r}$.

The matrix $\boldsymbol{o}$, as in equation (19) represents the percentage of each generator's revenue owned by each participating generator. Each row vector sums to one, representing all the available revenue from each generator, as in the equality constraint equation (20), with $\boldsymbol{\mathcal{O}_j}$ representing the ownership row vector for generator j. The matrix thus indicates where all available revenue from a generator ends up.

$$\mathbf{o} = \begin{bmatrix} o_{11} & o_{12} & \cdots & o_{1n} \\ o_{21} & o_{22} & \cdots & o_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ o_{n1} & o_{n2} & \cdots & o_{nn} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\mathcal{O}_1} \\ \boldsymbol{\mathcal{O}_2} \\ \vdots \\ \boldsymbol{\mathcal{O}_n} \end{bmatrix} \tag{19}$$

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[*] *Including the mean adds a constant term to the optimisation that will not affect results in the single isolated optimsation case. However, this term is added to stay consistent with the simultaneous optimisation case in section 3.2, where it will be explained further.*

$$\sum \mathscr{O}_j = \sum_{i=1}^{n} o_{ij} = 1 \quad \forall j \in 1, 2, ..., n \tag{20}$$

Matrix $\boldsymbol{p}$ is then defined as the counterpart of the $\boldsymbol{o}$ matrix in equation (19). Each column vector represents the portfolio of a single generator, as in equation (21) and sums to 100%. This can be understood as what portion of its total available investment funds a generator invests in each of the n generators being examined.

$$\mathbf{p} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{21}$$

The sum of each column must be one, representing 100% of each participant's portfolio, as in the equality constraint in equation (22). A generator may choose to keep a portion of their own revenue (ϕ_i) for themselves, as in the inequality constraint equation (23).

$$\sum_{j=1}^{n} p_{ij} = 1 \quad \forall i \in 1, 2, ..., n \tag{22}$$

$$o_{ii} \geq \phi_i \tag{23}$$

Matrices $\boldsymbol{o}$ and $\boldsymbol{p}$ are related to each other as in equation (24), added to the optimisation problem as an equality constraint. The value of $\mathscr{R}_i^\rho$ is the summed total expected revenue of generator i and $\mathscr{R}_j^\rho$ is the summed total expected revenue of generator j. $\boldsymbol{E}$ is defined as in (25), and accounts for the difference in volumes of production between generators. This is similar to (11). Equation (24) is added as an optimisation constraint to ensure the above conditions.

$$o_{ij} = p_{ij} E_{ij} \tag{24}$$

$$\mathbf{E} = \begin{bmatrix} E_{11} = \frac{\mathscr{R}_1^\rho}{\mathscr{R}_1^\rho} & E_{12} = \frac{\mathscr{R}_2^\rho}{\mathscr{R}_1^\rho} & \cdots & E_{1n} = \frac{\mathscr{R}_n^\rho}{\mathscr{R}_1^\rho} \\ E_{21} = \frac{\mathscr{R}_1^\rho}{\mathscr{R}_2^\rho} & E_{22} = \frac{\mathscr{R}_2^\rho}{\mathscr{R}_2^\rho} & \cdots & E_{2n} = \frac{\mathscr{R}_n^\rho}{\mathscr{R}_2^\rho} \\ \vdots & \vdots & \ddots & \vdots \\ E_{n1} = \frac{\mathscr{R}_1^\rho}{\mathscr{R}_n^\rho} & E_{n2} = \frac{\mathscr{R}_2^\rho}{\mathscr{R}_n^\rho} & \cdots & E_{nn} = \frac{\mathscr{R}_n^\rho}{\mathscr{R}_n^\rho} \end{bmatrix} \tag{25}$$

Matrix $\boldsymbol{r}$ is made up of the actual revenue values in Euro for each generator from each of their token holdings, as in equation (26).

$$\mathbf{r} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix} \tag{26}$$

Each column of equation (26) sums to the total expected revenue $\mathscr{R}^\rho$ for the respective generator. That is, each generator's total expected revenue $\mathscr{R}^\rho$ before diversification is equal to their hypothetical revenue after diversification with portfolio holdings applied $\mathscr{R}^\rho$. Equation (27) is an optimisation constraint that ensures the above conditions, with ρ_i as the total expected revenue for generator i in the examined period.

$$\sum_{i=1}^{n} r_{ij} = \mathscr{R}_i^\rho \quad \forall i \in 1, 2, ..., n \tag{27}$$

The $\boldsymbol{o}$ and $\boldsymbol{r}$ matrices are related to each other as in the equality constraint equation (28). That is, r_{ij} is simply the percentage value o_{ij} multiplied by the total actual revenue of the respective generator i.e. their $\mathscr{R}^\rho$.

$$r_{ij} = o_{ij} \mathscr{R}_i^\rho \tag{28}$$

With the covariance matrix S calculated as in (17), each generator's variance of revenues can be calculated. The $\mathscr{O}$ vector for generator i is used as in equation (29)

$$\boldsymbol{\mathscr{O}_i S \mathscr{O}_i^T} = \sigma_i^2 \tag{29}$$

The objective function is defined as in equation (30), formulated by calculating the IoD for every generator and taking the sum. This is the *collusive* solution, similar to that used in [36], where the total variance is minimised by considering the sum of all individuals' IoDs. Each unique generator's variance is divided by μ_i, the mean of their revenue $\boldsymbol{\mathscr{R}_i^\rho}$ in the examined period. This term is added so as to prevent the optimisation process from favouring larger generators when decreasing the summed magnitudes of total variance, thus ensuring fair conditions in the optimisation. The final objective function is the sum of IoDs of each generator, calculated as in equation (15) [38]. Minimising this summed value theoretically results in reduced risk for all participating generators.

$$\min \quad \sum_{i=1}^{n} \frac{(\boldsymbol{\mathscr{O}_i S \mathscr{O}_i^T})}{\mu_i} = \quad \min \quad \sum_{i=1}^{n} \frac{\sigma_i^2}{\mu_i} \tag{30}$$

The IoD shown above in equation (15) is related to the Coefficient of Variation *(CoV)*, as calculated in equation (31) [39]. This value is simply the standard deviation of a generator divided by their mean expected revenue. The CoV is not used in the objective function in equation (30) as it would require taking the square root of the numerator, resulting in a nonlinear optimisation problems. However, it is used in section 5 to quantify diversification results with clearer comparability between different generators. CoV considers the scale of the dataset, making it an ideal measure of variability to quantify improvements in diversification.

$$\text{CoV} \quad = \frac{\sigma}{\mu} \tag{31}$$

4 Test platform

This section describes the test platform and data used for the case study in this paper. The case study considers a group of wind and solar PV generators. These generators are free to tokenise and sell a portion of their revenue at the moment of diversification between the ρ and α time periods. The market simulation is performed using the YALMIP optimisation package for MATLAB [40].

The test dataset is made up of the time series production for eight grid-scale wind and eight grid-scale solar PV generators. This data is taken from the EMHIRES dataset with an hourly resolution between 1 January 2011 and 31 December 2015 [41]. This dataset presents hypothetical generation data constructed from actual meteorological readings measured in the respective regions. For comparability, the case study generators are all located in Germany. The case study assumes that no new generators are added or major grid expansions are made within the examined time frame.

Four wind and four solar generators participate in the country's electricity spot market. The remaining four wind and four solar generators have pre-negotiated PPA prices, and sell at a constant tariff. It is assumed that both arrangements settle every hour. The historical electricity spot price data for Germany in the examined period is taken from *Energi Data Services* [42], shown in Fig. 3. Thus, generators participating in the electricity spot market are exposed to both price and volume volatility, while generators on PPA payment are exposed only to volume volatility. The average daily value of the electricity spot price is 39 €/MWh. The PPA price is chosen to be roughly half of the strike price at €20/MWh, a value selected so as to clearly demonstrate the proposed system's advantage for both types of pricing structure. Generators on the PPA price settle for a lower average selling price in return for decreased risk. Furthermore, the electricity spot price's hourly value becomes negative on rare occasions. During these periods generators on spot price tariffs are assumed to temporarily cease their production.

Geographical locations are selected such that spot- and PPA price earning generators are loosely paired in the geographic North, East, South, and West of the country. The table 1 shows the name, NUTS2 code, geographical alignment, generating technology, and tariff

Table 1
Case Study Generators

Name	Colour	Area	NUTS2 Code	Mean Daily Revenue	Tariff	Tariff Value	Tech.	Size	Capacity	Coefficient of Variation		
										CoV_d	CoV_w	CoV_m
W-S-XL	🟦🟦🟦🟦	North	DE60	€747	Spot		Wind	XL	100 MW	0.98	0.63	0.42
W-S-L	🟦🟦🟦🟦	East	DED2	€394	Spot		Wind	L	70 MW	1.12	0.77	0.55
W-S-M	🟦🟦🟦🟦	South	DE21	€228	Spot		Wind	M	50 MW	1.46	0.94	0.58
W-S-S	🟦🟦🟦🟦	West	DEA2	€124	Spot		Wind	S	20 MW	1.10	0.80	0.60
W-PPA-XL	🟩🟩🟩🟩	West	DEA1	€573	PPA	€20/MWh	Wind	XL	100 MW	0.89	0.64	0.44
W-PPA-L	🟩🟩🟩🟩	South	DE11	€207	PPA	€20/MWh	Wind	L	70 MW	1.17	0.79	0.54
W-PPA-M	🟩🟩🟩🟩	East	DE30	€120	PPA	€20/MWh	Wind	M	50 MW	1.47	1.01	0.62
W-PPA-S	🟩🟩🟩🟩	North	DE50	€82	PPA	€20/MWh	Wind	S	20 MW	1.11	0.82	0.60
PV-S-XL	🟥🟥🟥🟥	South	DE21	€446	Spot		PV	XL	100 MW	0.78	0.57	0.52
PV-S-L	🟥🟥🟥🟥	West	DEA2	€342	Spot		PV	L	70 MW	0.72	0.51	0.45
PV-S-M	🟥🟥🟥🟥	North	DE60	€259	Spot		PV	M	50 MW	0.68	0.47	0.39
PV-S-S	🟥🟥🟥🟥	East	DED2	€96	Spot		PV	S	20 MW	0.70	0.49	0.43
PV-PPA-XL	🟪🟪🟪🟪	East	DE30	€223	PPA	€20/MWh	PV	XL	100 MW	0.70	0.55	0.51
PV-PPA-L	🟪🟪🟪🟪	North	DE50	€167	PPA	€20/MWh	PV	L	70 MW	0.69	0.55	0.50
PV-PPA-M	🟪🟪🟪🟪	West	DEA1	€126	PPA	€20/MWh	PV	M	50 MW	0.64	0.51	0.46
PV-PPA-S	🟪🟪🟪🟪	South	DE11	€47	PPA	€20/MWh	PV	S	20 MW	0.67	0.51	0.46

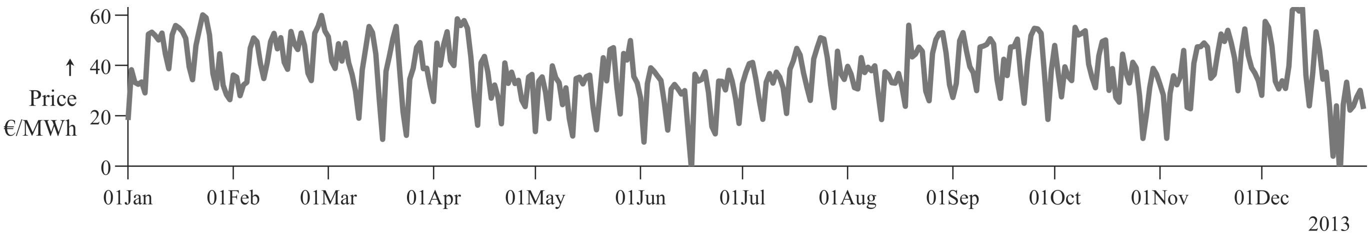


Fig. 3: Daily mean spot price

scheme for each generator. The label *S* and *PPA* indicate spot and PPA tariffs respectively. The labels *XL*, *L*, *M*, and *S* indicate extra large, large, medium, and small generators sizes. As in table 1, these size classifications correspond to 100MW, 70MW, 50MW, and 20MW respectively. These maximum capacity values are applied to the per-unit dataset with an hourly resolution to produced hourly power output values in MWh. Generator legend colours are shown in table 1, and are kept consistent throughout this paper. Colours are generated from [43].

Table 1 also shows the CoV values for all case study generators during the initial α time period. Different CoV values are calculated as in equation (31) on a daily, weekly, and monthly binning granularity. They are labelled CoV_d, CoV_w, and CoV_m respectively, and this notation is used henceforth.

The correlation between generators is examined as in Fig. 4 using a daily resolution. Only the α period is used to formulate this matrix, as this is when generators are afforded the opportunity to diversify their revenue streams. Correlation between wind and solar generators is negative, owing to the generally higher wind levels at night. Furthermore, wind generators see increased generation during the winter season, while solar generator perform better during the longer sunlight hours of summer. These negative correlations point to opportunities for reductions in variance, especially between wind and PV generators. Similarly, the related covariance matrix is shown in Fig. 5, showing similar opportunities for diversification. The optimisation objective functions in equation (30) exploits this covariance matrix directly.

5 Results

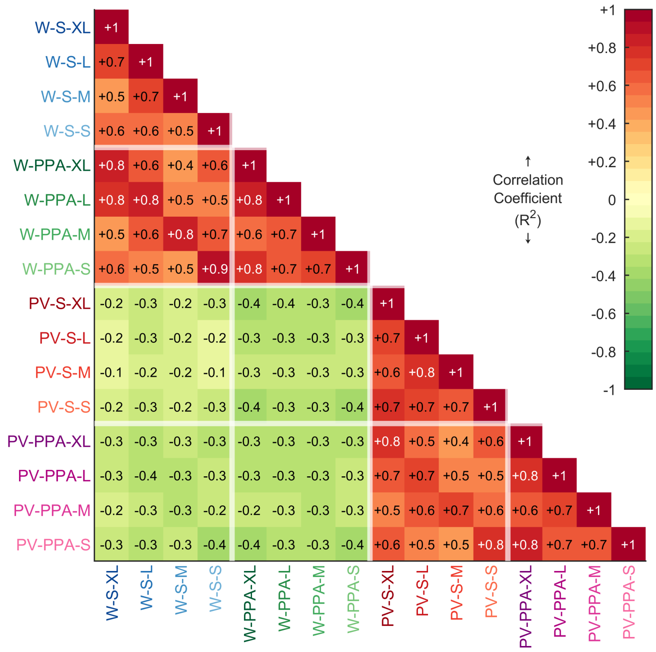
This section discusses results for both the single and simultaneous cases. Time resolution sensitivity analyses are included for the latter case.

At the start of July 2013 generators are afforded the opportunity to trade RevToks and diversify their revenue. It is assumed that no trading costs are present and generators are free to perform as many exchanges as required. Generators make decisions based on expected returns and trends i.e. historical data. They construct their portfolios in such a way as to minimise variance based on this data. In other words, generators make use of a *hypothetical* scenario whereby their portfolios weights are applied to past data. The scenario attempts to keep expected revenue the same as pre-diversification, as per the MPT arrangement in section 3.

5.1 Single Generator Portfolio Diversification Results

This section describes the results of single generator portfolio diversification. All results presented here use daily time resolution. These simulations are conducted in isolation i.e. the actions and effects on other participating generators are not considered. This represents the *ideal case* for each generator. This approximates the steps a real-world energy firm would take to diversify their revenue streams. The optimisation is performed as in 3.1.

Fig. 6 shows the individual optimised portfolios for all 16 generators as a heatmap. This figure is a visualisation of each generator's



	W-S-XL	W-S-L	W-S-M	W-S-S	W-PPA-XL	W-PPA-L	W-PPA-M	W-PPA-S	PV-S-XL	PV-S-L	PV-S-M	PV-S-S	PV-PPA-XL	PV-PPA-L	PV-PPA-M	PV-PPA-S
W-S-XL	+1															
W-S-L	+0.7	+1														
W-S-M	+0.5	+0.7	+1													
W-S-S	+0.6	+0.6	+0.5	+1												
W-PPA-XL	+0.8	+0.6	+0.4	+0.6	+1											
W-PPA-L	+0.8	+0.8	+0.5	+0.5	+0.8	+1										
W-PPA-M	+0.5	+0.6	+0.8	+0.7	+0.6	+0.7	+1									
W-PPA-S	+0.6	+0.5	+0.5	+0.9	+0.8	+0.7	+0.7	+1								
PV-S-XL	-0.2	-0.3	-0.2	-0.3	-0.4	-0.4	-0.3	-0.4	+1							
PV-S-L	-0.2	-0.3	-0.2	-0.2	-0.3	-0.3	-0.3	-0.3	+0.7	+1						
PV-S-M	-0.1	-0.2	-0.2	-0.1	-0.3	-0.3	-0.3	-0.3	+0.6	+0.8	+1					
PV-S-S	-0.2	-0.3	-0.2	-0.3	-0.4	-0.3	-0.3	-0.4	+0.7	+0.7	+0.7	+1				
PV-PPA-XL	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	+0.8	+0.5	+0.4	+0.6	+1			
PV-PPA-L	-0.3	-0.4	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	+0.7	+0.7	+0.5	+0.5	+0.8	+1		
PV-PPA-M	-0.2	-0.3	-0.3	-0.2	-0.2	-0.3	-0.3	-0.3	+0.5	+0.6	+0.7	+0.6	+0.6	+0.7	+1	
PV-PPA-S	-0.3	-0.3	-0.3	-0.4	-0.4	-0.3	-0.3	-0.4	+0.6	+0.5	+0.5	+0.8	+0.8	+0.7	+0.7	+1

Fig. 4: Heatmap of correlation coefficients between daily revenues of generators during α time period

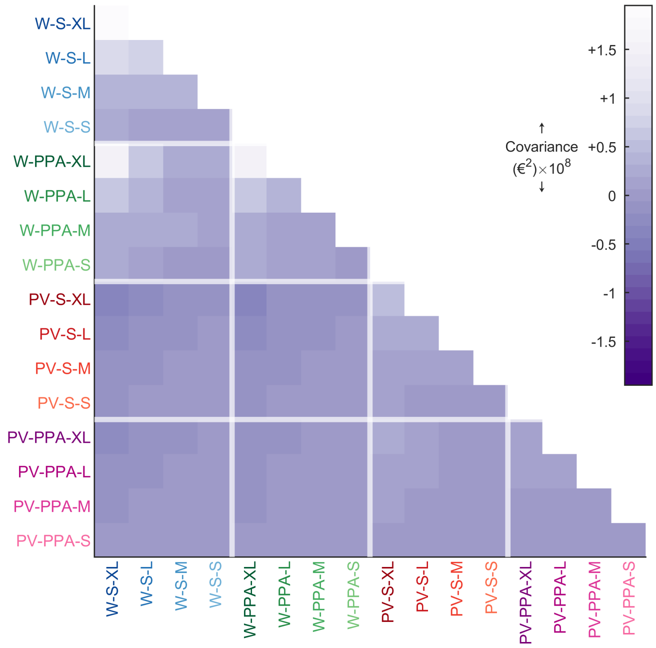
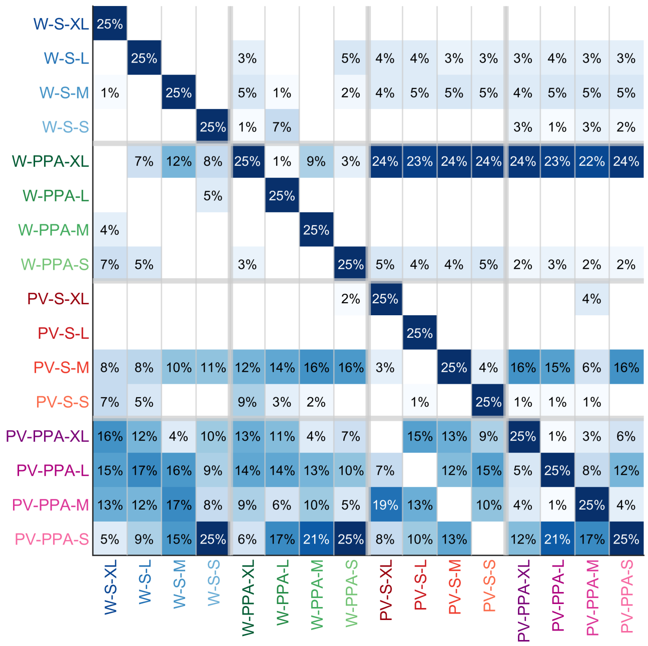
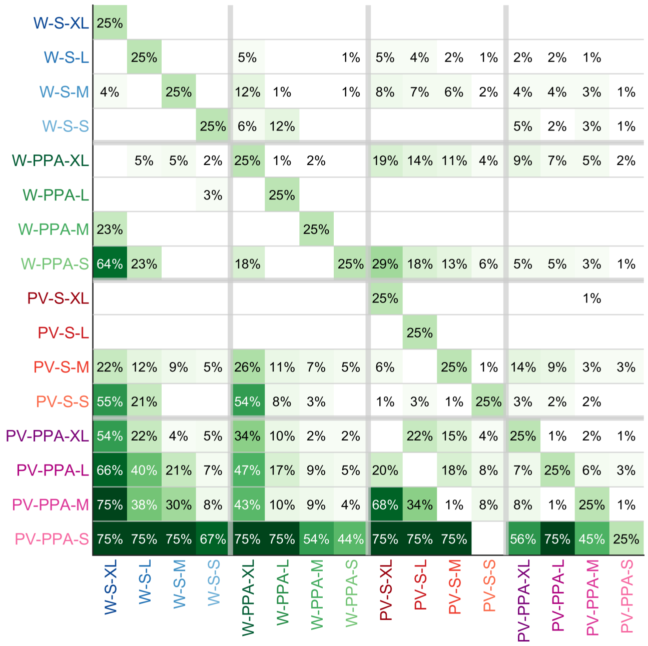


Fig. 5: Covariance (S) between daily revenues of generators during α time period



	W-S-XL	W-S-L	W-S-M	W-S-S	W-PPA-XL	W-PPA-L	W-PPA-M	W-PPA-S	PV-S-XL	PV-S-L	PV-S-M	PV-S-S	PV-PPA-XL	PV-PPA-L	PV-PPA-M	PV-PPA-S
W-S-XL	25%															
W-S-L		25%			3%			5%	4%	4%	3%	3%	3%	4%	3%	3%
W-S-M	1%		25%		5%	1%		2%	4%	5%	5%	5%	4%	5%	5%	5%
W-S-S				25%	1%	7%							3%	1%	3%	2%
W-PPA-XL		7%	12%	8%	25%	1%	9%	3%	24%	23%	24%	24%	24%	23%	22%	24%
W-PPA-L				5%		25%										
W-PPA-M	4%						25%									
W-PPA-S	7%	5%			3%			25%	5%	4%	4%	5%	2%	3%	2%	2%
PV-S-XL								2%	25%						4%	
PV-S-L										25%						
PV-S-M	8%	8%	10%	11%	12%	14%	16%	16%	3%		25%	4%	16%	15%	6%	16%
PV-S-S	7%	5%			9%	3%	2%			1%		25%	1%	1%	1%	
PV-PPA-XL	16%	12%	4%	10%	13%	11%	4%	7%		15%	13%	9%	25%	1%	3%	6%
PV-PPA-L	15%	17%	16%	9%	14%	14%	13%	10%	7%		12%	15%	5%	25%	8%	12%
PV-PPA-M	13%	12%	17%	8%	9%	6%	10%	5%	19%	13%		10%	4%	1%	25%	4%
PV-PPA-S	5%	9%	15%	25%	6%	17%	21%	25%	8%	10%	13%		12%	21%	17%	25%

Fig. 6: Portfolio allocation results for all generators in single isolated case and visualisation of post-optimisation values of $\boldsymbol{p}$ matrix. Columns represent the allocation of generator (horizontal) investments and sum to 100%.



	W-S-XL	W-S-L	W-S-M	W-S-S	W-PPA-XL	W-PPA-L	W-PPA-M	W-PPA-S	PV-S-XL	PV-S-L	PV-S-M	PV-S-S	PV-PPA-XL	PV-PPA-L	PV-PPA-M	PV-PPA-S
W-S-XL	25%															
W-S-L		25%			5%			1%	5%	4%	2%	1%	2%	2%	1%	
W-S-M	4%		25%		12%	1%		1%	8%	7%	6%	2%	4%	4%	3%	1%
W-S-S				25%	6%	12%							5%	2%	3%	1%
W-PPA-XL		5%	5%	2%	25%	1%	2%		19%	14%	11%	4%	9%	7%	5%	2%
W-PPA-L				3%		25%										
W-PPA-M	23%						25%									
W-PPA-S	64%	23%			18%			25%	29%	18%	13%	6%	5%	5%	3%	1%
PV-S-XL									25%						1%	
PV-S-L										25%						
PV-S-M	22%	12%	9%	5%	26%	11%	7%	5%	6%		25%	1%	14%	9%	3%	3%
PV-S-S	55%	21%			54%	8%	3%		1%	3%	1%	25%	3%	2%	2%	
PV-PPA-XL	54%	22%	4%	5%	34%	10%	2%	2%		22%	15%	4%	25%	1%	2%	1%
PV-PPA-L	66%	40%	21%	7%	47%	17%	9%	5%	20%		18%	8%	7%	25%	6%	3%
PV-PPA-M	75%	38%	30%	8%	43%	10%	9%	4%	68%	34%	1%	8%	8%	1%	25%	1%
PV-PPA-S	75%	75%	75%	67%	75%	75%	54%	44%	75%	75%	75%		56%	75%	45%	25%

Fig. 7: Portfolio ownership results for all generators in single isolated case, representing what portion of each generator's RevToks (horizontal) are owned by which generator (vertical). Rows sum to 100%, representing all of a generator's available revenue. This is a visualisation of post-optimisation values of $\boldsymbol{o}$ matrix.

matrix as in equation 5, with columns summing to 100% of a generator's investments. Examining this figure reveals that wind generators prefer to invest in solar PPA generators, owing to the generally stronger negative correlation between them. PV generators also invest in PV PPA generation (although to a lesser extent), as these generators mostly have the lowest variance. However, they also favour investing in wind PPA generators. When compared to the correlation table in Fig. 4, RevTok investments generally follow the stronger negative correlations. For example,W-S-XL and W-PPA-S are both strongly negatively correlated with all PV generators, thus they are a popular choice. It is important to note that these portfolios cannot necessarily exist simultaneously; rather this a demonstration of a *best case scenario* for each generator's portfolio.

Fig. 7 is the counterpart to Fig. 6 and shows ownership of tokens. Generators on the vertical axes represent the source of RevToks, while those on the horizontal represent the purchaser. For example, W-S-XL owns 75% of PV-PPA-S's revenue, 75% of PV-PPA-M's revenue, etc.

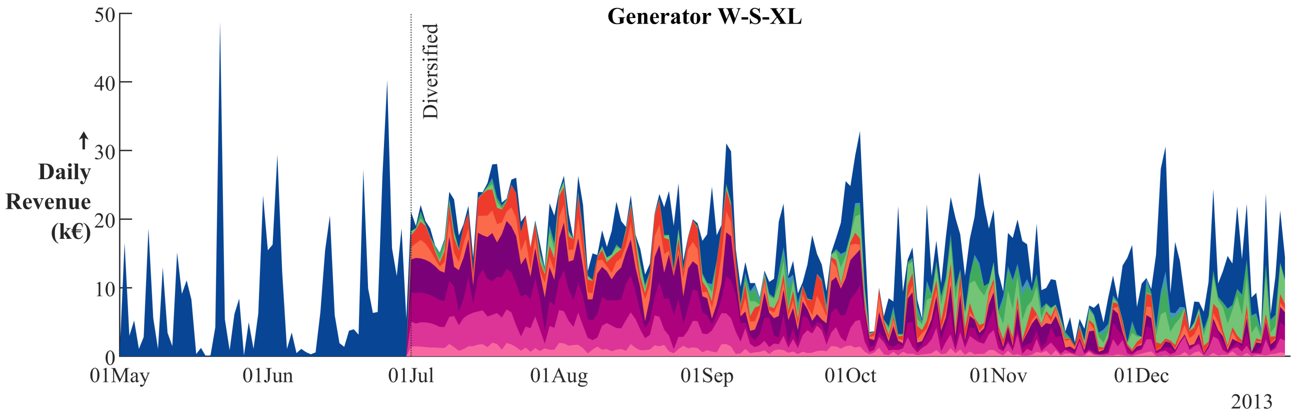


Fig. 8: Generator W-S-XL diversified profile, showing time series contributions from each generator's revenue for single isolated case. Significant increases in contribution from solar PV PPA generators can be observed.

Table 2
RESULTS OF SINGLE ISOLATED INDIVIDUAL PORTFOLIO OPTIMISATIONS

	Coefficient of Variation		
	CoV_d **During** ρ **Period**	CoV_d **During** α **Period Before Diversification**	CoV_d **During** α **Period After Diversification**
W-S-XL	1.00	0.98	0.43
W-S-L	1.15	1.12	0.39
W-S-M	1.39	1.46	0.39
W-S-S	1.09	1.10	0.40
W-PPA-XL	0.86	0.89	0.38
W-PPA-L	1.12	1.17	0.41
W-PPA-M	1.36	1.47	0.47
W-PPA-S	1.05	1.11	0.41
PV-S-XL	0.79	0.78	0.38
PV-S-L	0.75	0.72	0.38
PV-S-M	0.71	0.68	0.37
PV-S-S	0.74	0.70	0.37
PV-PPA-XL	0.72	0.70	0.38
PV-PPA-L	0.68	0.69	0.38
PV-PPA-M	0.63	0.64	0.39
PV-PPA-S	0.69	0.67	0.37

As an example of a diversified revenue profile, that of generator W-S-XL is examined in Fig. 8. Colours remain consistent with the legend in table 1. The purple and pink colours are prominent, showing the wind generator's preference for investments in PV PPA generators. Besides the blue section representing the ϕ portion, a smaller portion of green, representing wind PPA is also visible. The solar generators' revenue dominance is visible in the summer, with wind generator revenue taking over as the majority during winter months. The profile is thus visibly diversified, leading to the reduction in CoV.

Examining table 2 it can be observed that wind generators generally gain the biggest improvements in CoV. Solar generators typically have a lower initial CoV, owing to the the more predictable generation patterns. Furthermore, wind PPA generators are not vulnerable to fluctuations in price volatility, and see a slight advantage in CoV reduction when compared to wind spot generators. However, this phenomenon is less apparent between solar spot and PPA generators. All generators see a significant improvement in CoV. It should be noted that the mean used to calculate this new CoV, as in equation (31), is that of the actual post-diversification α period.

5.2 *Simultaneous Generator Portfolio Diversification Results*

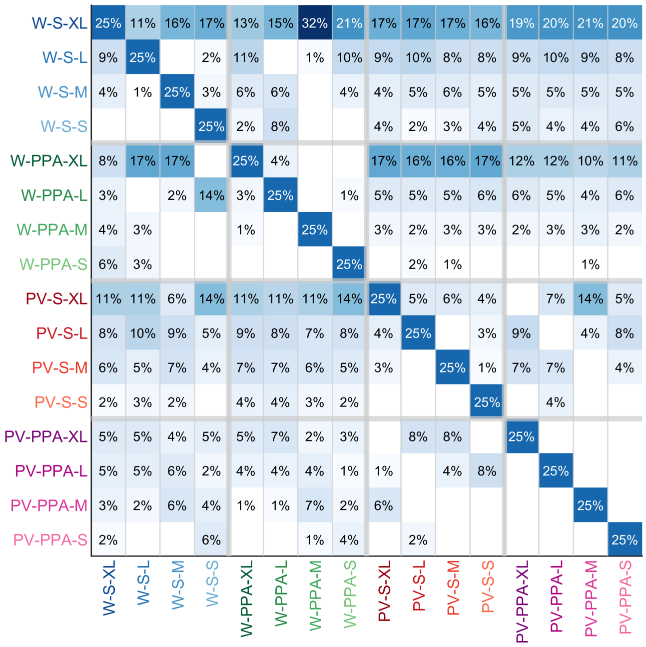
This section considers how all 16 generators can diversify their portfolios simultaneously in a closed system, acting as an approximation of a market equilibrium state. All participants attempt to minimise their variance while maintaining the same revenue, based on expected returns.

An optimisation is performed as in section 3.2. This approximates a market equilibrium state. It is important to note that this is a single possible market outcomes, and is not a sophisticated marketplace or auction simulation. The collusive solution simply sees the total sum of generator IODs after diversification minimised [36]. All generators choose to keep 25% of their own revenue (ϕ) and tokenise and sell the remaining 75% as RevToks. This ϕ value is chosen arbitrarily for the current worked example. Real-world electrical generators would show more variation in what portions of revenue streams they choose to keep or sell.

Table 3 shows the optimisation results. All generators can be observed to have gained a significant improvement in their CoV. The generators that produce more revenue show the best improvements.

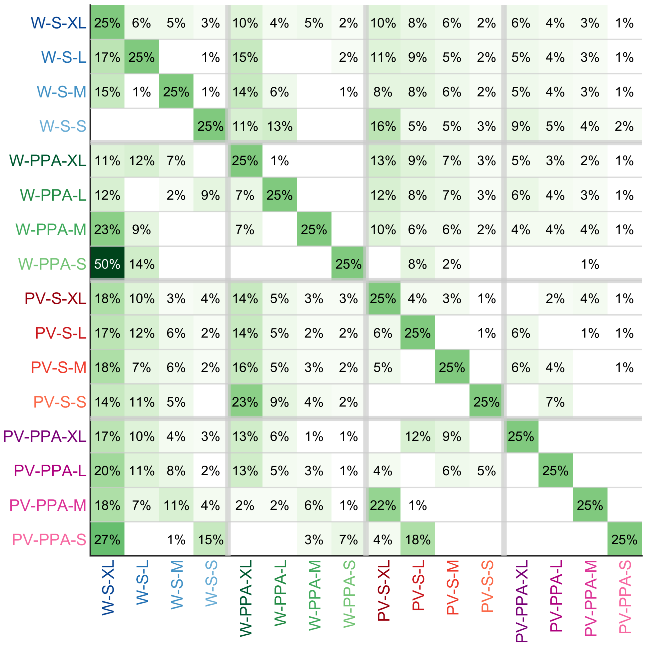
Table 3
RESULTS OF MULTI-PORTFOLIO OPTIMISATION

	Coefficient of Variation		
	CoV_d During ρ Period	**CoV_d During α Period Before Diversification**	**CoV_d During α Period After Diversification**
W-S-XL	1.00	0.98	0.47
W-S-L	1.15	1.12	0.47
W-S-M	1.39	1.46	0.49
W-S-S	1.09	1.10	0.48
W-PPA-XL	0.86	0.89	0.47
W-PPA-L	1.12	1.17	0.50
W-PPA-M	1.36	1.47	0.54
W-PPA-S	1.05	1.11	0.50
PV-S-XL	0.79	0.78	0.48
PV-S-L	0.75	0.72	0.47
PV-S-M	0.71	0.68	0.46
PV-S-S	0.74	0.70	0.47
PV-PPA-XL	0.72	0.70	0.45
PV-PPA-L	0.68	0.69	0.46
PV-PPA-M	0.63	0.64	0.46
PV-PPA-S	0.69	0.67	0.45



	W-S-XL	W-S-L	W-S-M	W-S-S	W-PPA-XL	W-PPA-L	W-PPA-M	W-PPA-S	PV-S-XL	PV-S-L	PV-S-M	PV-S-S	PV-PPA-XL	PV-PPA-L	PV-PPA-M	PV-PPA-S
W-S-XL	25%	11%	16%	17%	13%	15%	32%	21%	17%	17%	17%	16%	19%	20%	21%	20%
W-S-L	9%	25%		2%	11%		1%	10%	9%	10%	8%	8%	9%	10%	9%	8%
W-S-M	4%	1%	25%	3%	6%	6%		4%	4%	5%	6%	5%	5%	5%	5%	5%
W-S-S				25%	2%	8%			4%	2%	3%	4%	5%	4%	4%	6%
W-PPA-XL	8%	17%	17%		25%	4%			17%	16%	16%	17%	12%	12%	10%	11%
W-PPA-L	3%		2%	14%	3%	25%		1%	5%	5%	5%	6%	6%	5%	4%	6%
W-PPA-M	4%	3%			1%		25%		3%	2%	3%	3%	2%	3%	3%	2%
W-PPA-S	6%	3%						25%		2%	1%				1%	
PV-S-XL	11%	11%	6%	14%	11%	11%	11%	14%	25%	5%	6%	4%		7%	14%	5%
PV-S-L	8%	10%	9%	5%	9%	8%	7%	8%	4%	25%		3%	9%		4%	8%
PV-S-M	6%	5%	7%	4%	7%	7%	6%	5%	3%		25%	1%	7%	7%		4%
PV-S-S	2%	3%	2%		4%	4%	3%	2%				25%		4%		
PV-PPA-XL	5%	5%	4%	5%	5%	7%	2%	3%		8%	8%		25%			
PV-PPA-L	5%	5%	6%	2%	4%	4%	4%	1%	1%		4%	8%		25%		
PV-PPA-M	3%	2%	6%	4%	1%	1%	7%	2%	6%						25%	
PV-PPA-S	2%			6%			1%	4%		2%						25%

Fig. 9: Portfolio allocation results for all generators in simultaneous case and visualisation of post-optimisation values of $\boldsymbol{p}$ matrix. Columns represent the allocation of generator (horizontal) investments and sum to 100%.



	W-S-XL	W-S-L	W-S-M	W-S-S	W-PPA-XL	W-PPA-L	W-PPA-M	W-PPA-S	PV-S-XL	PV-S-L	PV-S-M	PV-S-S	PV-PPA-XL	PV-PPA-L	PV-PPA-M	PV-PPA-S
W-S-XL	25%	6%	5%	3%	10%	4%	5%	2%	10%	8%	6%	2%	6%	4%	3%	1%
W-S-L	17%	25%		1%	15%			2%	11%	9%	5%	2%	5%	4%	3%	1%
W-S-M	15%	1%	25%	1%	14%	6%		1%	8%	8%	6%	2%	5%	4%	3%	1%
W-S-S				25%	11%	13%			16%	5%	5%	3%	9%	5%	4%	2%
W-PPA-XL	11%	12%	7%		25%	1%			13%	9%	7%	3%	5%	3%	2%	1%
W-PPA-L	12%		2%	9%	7%	25%			12%	8%	7%	3%	6%	4%	3%	1%
W-PPA-M	23%	9%			7%		25%		10%	6%	6%	2%	4%	4%	4%	1%
W-PPA-S	50%	14%						25%		8%	2%				1%	
PV-S-XL	18%	10%	3%	4%	14%	5%	3%	3%	25%	4%	3%	1%		2%	4%	1%
PV-S-L	17%	12%	6%	2%	14%	5%	2%	2%	6%	25%		1%	6%		1%	1%
PV-S-M	18%	7%	6%	2%	16%	5%	3%	2%	5%		25%		6%	4%		1%
PV-S-S	14%	11%	5%		23%	9%	4%	2%				25%		7%		
PV-PPA-XL	17%	10%	4%	3%	13%	6%	1%	1%		12%	9%		25%			
PV-PPA-L	20%	11%	8%	2%	13%	5%	3%	1%	4%		6%	5%		25%		
PV-PPA-M	18%	7%	11%	4%	2%	2%	6%	1%	22%	1%					25%	
PV-PPA-S	27%		1%	15%			3%	7%	4%	18%						25%

Fig. 10: Portfolio ownership results for all generators in simultaneous case, representing what portion of each generator's RevToks (horizontal) are owned by which generator (vertical). Rows sum to 100%, representing all of a generator's available revenue. This is a visualisation of post-optimisation values of $\boldsymbol{o}$ matrix.

Generally these large generators have a higher variance to begin with, and thus have more opportunity for improvement. Generators that produce less revenue, especially the PV PPA examples, show less significant improvement, owing to their lower initial variance. As in the single isolated case, the means used in the calculation of CoV values are those of the post-diversification α period, which differ slightly from pre-diversification values. This is illustrated in Fig. 14.

The columns of Fig. 9 show each generator's optimised portfolio, acting as a visualisation of matrix $\boldsymbol{p}$ shown in equation (21). Results are percentages, representing the portion of each generator's investments in their peers' RevToks. Similarly, Fig. 10 shows which RevToks are owned by which generator, as in matrix $\boldsymbol{o}$ in equation (19). That is, each row shows how a generator's RevToks are distributed. The most popular investments are along the squares on the diagonal corresponding to the stronger negative correlations in Fig. 4 and covariances in 5. Wind and PV generators tend to invest in each

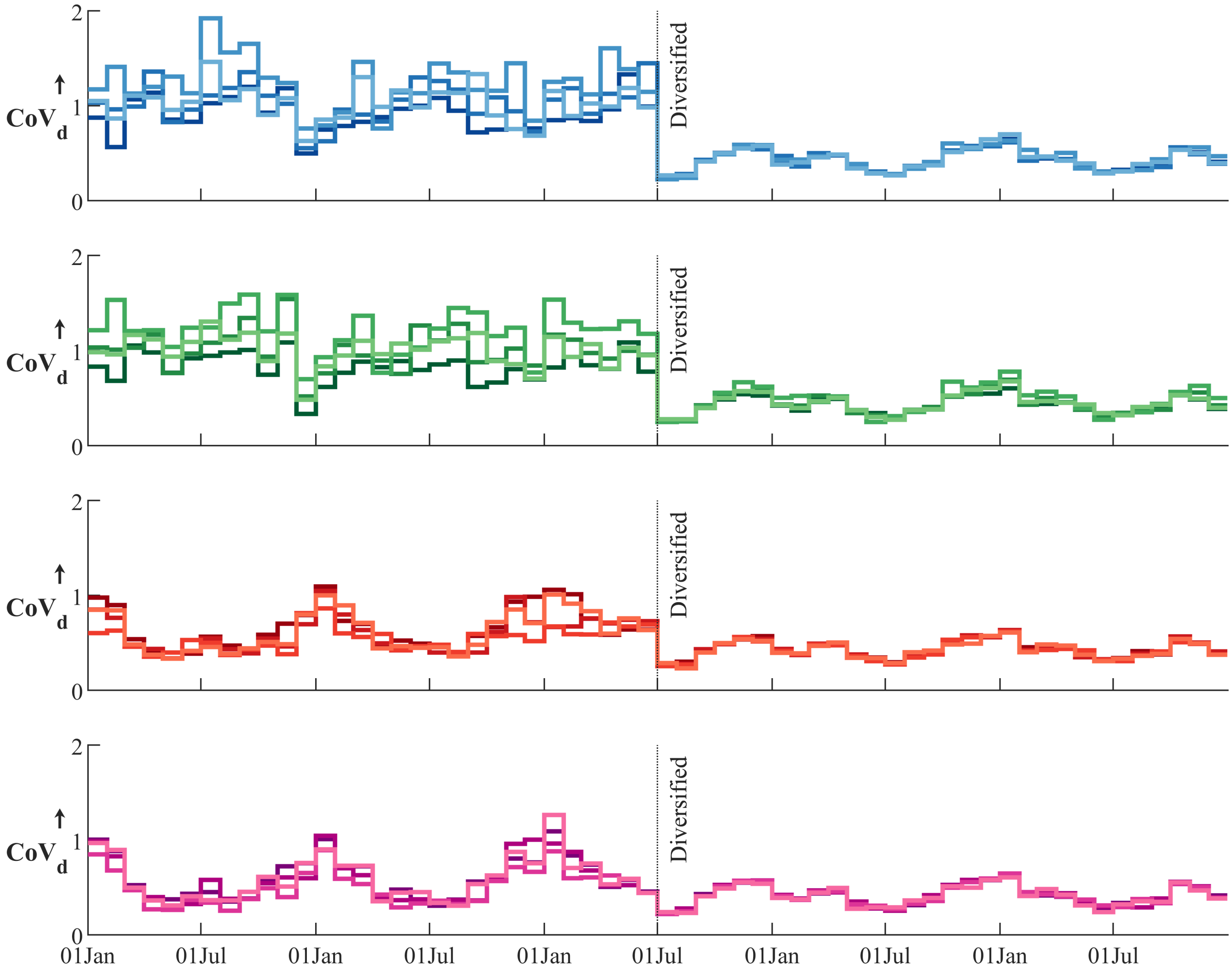


Fig. 11: Daily CoV binned over monthly ranges after simultaneous portfolio diversification for *(a)* Wind Spot, *(b)* Wind PPA, *(c)* Solar Spot, *(d)* Solar PPA generators.

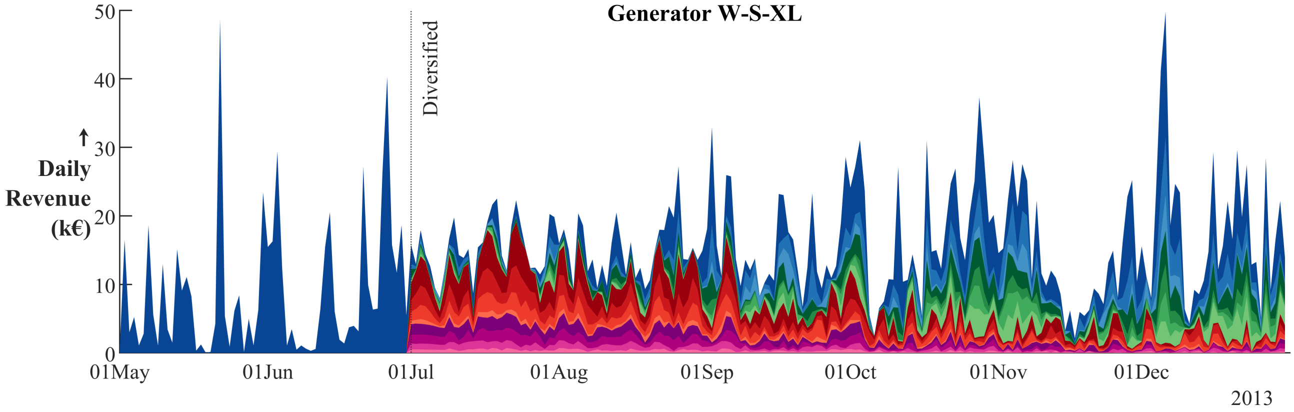


Fig. 12: Generator W-S-XL diversified profile, showing time series contributions from each generator's revenue for multiple case. Significant increases in contribution from PV generators can be observed.

other, and, to a less noticeable extent, spot and PPA generators invest in each other.

Fig. 12 is shown as an example of a diversified profile for generator W-S-XL. This large wind generator gains significant portions of red and pink profiles, indicating its investments in the negatively correlated PV generators as per Fig. 4. These PV generators make up the majority of revenue in the summer months, gradually giving way to the blue and green of wind generators during winter. The dark blue of generator W-S-XL's withheld ϕ portion is visible throughout. The revenue streams from multiple different generators visible in Fig. 12 support the hypothesis that all generators benefit from a very diverse portfolio, spread across both technologies and market structures. However, when compared to the single isolated case in Fig. 8 it can be seen that the generator "compromised" and was unable to purchase the RevToks with the strongest negative correlation, hence the smaller purple portion.

Table 4
GENERATOR REVENUES DURING α PERIOD

Generator	**Revenue Before**	**Revenue After**	**Change**
W-S-XL	€13.1M	€14.3M	+9%
W-S-L	€6.9M	€7.6M	+9%
W-S-M	€3.7M	€4.3M	+15%
W-S-S	€2.3M	€2.4M	+4%
W-PPA-XL	€12.5M	€11.1M	-11%
W-PPA-L	€4.5M	€4.0M	-10%
W-PPA-M	€2.5M	€2.3M	-8%
W-PPA-S	€1.8M	€1.6M	-13%
PV-S-XL	€8.2M	€8.5M	+4%
PV-S-L	€6.2M	€6.6M	+6%
PV-S-M	€4.6M	€5.0M	+7%
PV-S-S	€1.7M	€1.8M	+5%
PV-PPA-XL	€5.0M	€4.4M	-12%
PV-PPA-L	€3.6M	€3.3M	-11%
PV-PPA-M	€2.7M	€2.5M	-10%
PV-PPA-S	€1.0M	€0.9M	-11%

It can be observed that an increase in average revenue occurs post-diversification for generator W-S-XL in Fig. 12. Since actual conditions in the α period differ to those in the previous ρ period, some generators will gain some total revenue, while others will incur a loss. However, the total revenue of all generators remains constant. This is a product of uncertainty, commonplace in stochastic RES sources. Table 4 summarises the changes in total generator revenues in the α period with and without RevTok diversification. Changes can be seen to be relatively insignificant, with no generator straying outside of a 15% profit/loss. Generators participating in the spot market can be observed to make profits, owing to the lower spot prices during the α period

Fig. 11 shows CoV_d values binned over monthly ranges for all participants before and after diversification as a time series. This can be interpreted as the volatility of daily revenues for each calendar month. A sharp drop can be observed in all cases, and reinforces the above points. The greater improvement for wind spot and lesser improvement for PV PPA generators can be clearly seen, as discussed above. In all cases the new profiles appear more similar as new generator revenue profiles are diversified and thus have less variation between them.

The treemaps in Fig. 13 and 14 show the *before* and *after* diversification cases for generator portfolios. The size of each labelled rectangle is proportional to the total revenue produced by each generator during the α examined period. Examining Fig. 14, the multicoloured subdivisions within each generator's labelled rectangle represent the makeup of their new portfolio. Subdivisions sizes represent magnitudes of total revenue, and change slightly between the two plots, corresponding to magnitudes in Table 4. Colours remain consistent with those shown in the legend in table 1. The prevalence of "opposed" categories (wind vs PV; spot vs PPA) is somewhat apparent, but each generator's portfolio is visibly diverse, with colours from each category visible in all generator's labelled rectangles. This is in keeping with data presented in Fig. 9 and 10. The case study assumes that RevTok trading costs are negligible, and they are thus not penalised for availing of multiple unique revenue streams as in related studies [36].

Taking a broader view, Fig. 15 shows the correlation matrix from Fig. 4 recalculated with diversified revenue values for the α time period. All generators are now strongly positively correlated, pointing to little opportunity for diversification. This demonstrates that the optimisation approximates a "near-perfect" market equilibrium. Thus, the method presented here offers an improved hedging capability when compared with the traditional methods discussed above, and can, if implemented on a dedicated smart contract, be achieved at a low cost.

Fig. 13: Treemap of generator profiles during α time period before diversification

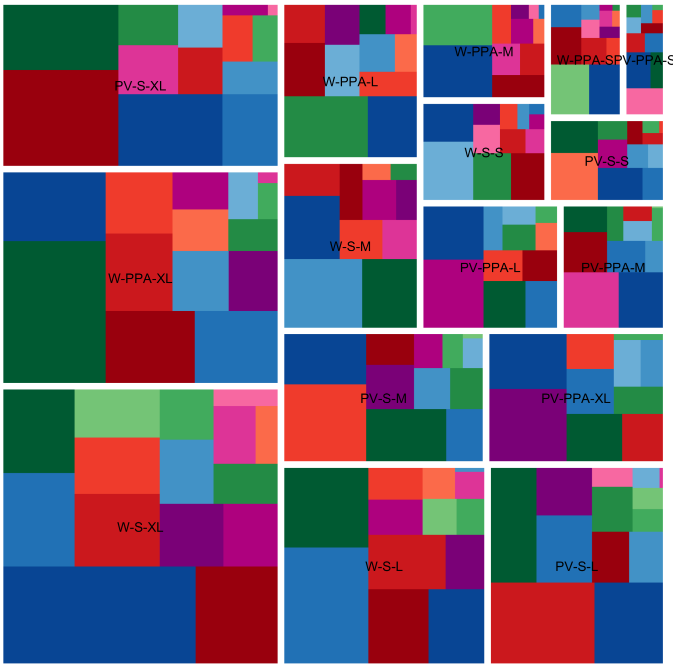


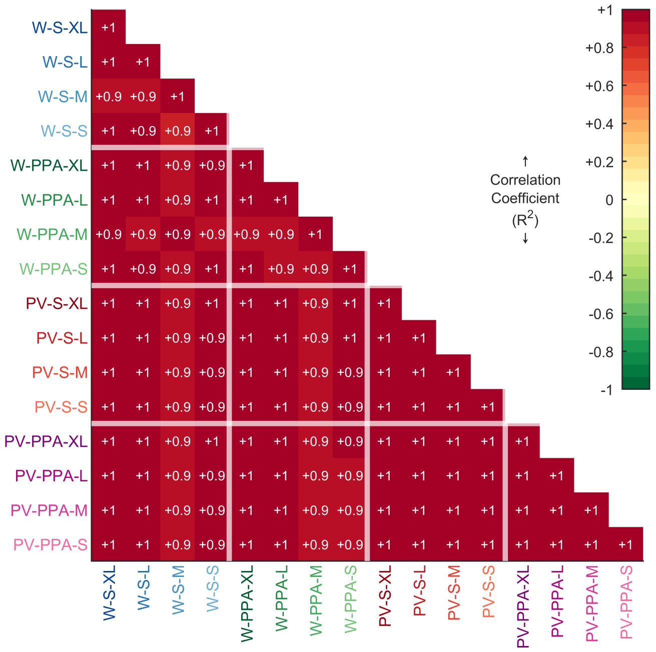
Fig. 14: Treemap of generator profiles during α after diversification. Generator total revenues differ to those in Fig. 13

5.3 *Time resolution sensitivity analysis*

A time sensitivity analysis is performed to establish the longer term effects of the novel RevToks diversification method. Table 5 shows the results of two longer-scale time resolutions. Generally wind and PPA generators show greater improvement than solar generators. Comparing with results in table 3, differences become less significant as

Table 5
Weekly and Monthly CoV Sensitivity Results During α Period.

	Weekly Revenue Volatility		Monthly Revenue Volatility	
Generator	CoV_w **Before**	CoV_w **After**	CoV_m **Before**	CoV_m **After**
W-S-XL	0.63	0.30	0.42	0.17
W-S-L	0.77	0.30	0.55	0.16
W-S-M	0.94	0.31	0.58	0.17
W-S-S	0.80	0.31	0.60	0.18
W-PPA-XL	0.64	0.30	0.44	0.16
W-PPA-L	0.79	0.31	0.54	0.17
W-PPA-M	1.01	0.34	0.62	0.18
W-PPA-S	0.82	0.32	0.60	0.18
PV-S-XL	0.57	0.30	0.52	0.17
PV-S-L	0.51	0.30	0.45	0.17
PV-S-M	0.47	0.30	0.39	0.17
PV-S-S	0.49	0.30	0.43	0.16
PV-PPA-XL	0.55	0.29	0.51	0.15
PV-PPA-L	0.55	0.29	0.50	0.15
PV-PPA-M	0.51	0.30	0.46	0.17
PV-PPA-S	0.51	0.29	0.46	0.16



	W-S-XL	W-S-L	W-S-M	W-S-S	W-PPA-XL	W-PPA-L	W-PPA-M	W-PPA-S	PV-S-XL	PV-S-L	PV-S-M	PV-S-S	PV-PPA-XL	PV-PPA-L	PV-PPA-M	PV-PPA-S
W-S-XL	+1															
W-S-L	+1	+1														
W-S-M	+0.9	+0.9	+1													
W-S-S	+1	+0.9	+0.9	+1												
W-PPA-XL	+1	+1	+0.9	+0.9	+1											
W-PPA-L	+1	+1	+0.9	+1	+1	+1										
W-PPA-M	+0.9	+0.9	+0.9	+0.9	+0.9	+0.9	+1									
W-PPA-S	+1	+0.9	+0.9	+1	+1	+0.9	+0.9	+1								
PV-S-XL	+1	+1	+0.9	+1	+1	+1	+0.9	+1	+1							
PV-S-L	+1	+1	+0.9	+0.9	+1	+1	+0.9	+1	+1	+1						
PV-S-M	+1	+1	+0.9	+0.9	+1	+1	+0.9	+0.9	+1	+1	+1					
PV-S-S	+1	+1	+0.9	+0.9	+1	+1	+0.9	+0.9	+1	+1	+1	+1				
PV-PPA-XL	+1	+1	+0.9	+1	+1	+1	+0.9	+0.9	+1	+1	+1	+1	+1			
PV-PPA-L	+1	+1	+0.9	+0.9	+1	+1	+0.9	+0.9	+1	+1	+1	+1	+1	+1		
PV-PPA-M	+1	+1	+0.9	+0.9	+1	+1	+0.9	+0.9	+1	+1	+1	+1	+1	+1	+1	
PV-PPA-S	+1	+1	+0.9	+0.9	+1	+1	+0.9	+0.9	+1	+1	+1	+1	+1	+1	+1	+1

Fig. 15: Correlation between generators using daily data resolution during α time period after diversification.

time resolution is increased. Variance is naturally lower when considering a higher time resolution, as daily and monthly fluctuations are reduced, presenting less opportunity for improvement. The examined method thus presents a means of reducing risk, even on the longer-term scales.

6 Conclusions

The variable nature of RES sources results in more volatile revenue flow for energy firms. Volatility offers a potential threat to the cashflow of these firms, as it may negatively affect their operational profile, increase the costs of capital, and diminishes the viability of the project. Generators thus strive to reduce their variance, a commonly used indicator of risk. Hedging against volumetric risk is notoriously difficult for energy firms, and traditional hedging methods are often expensive or less effective. Blockchain and decentralised finance technologies present a means of hedging revenue at a lower price.

Concepts developed within the sphere of decentralised finance present a novel means of revenue distribution for firms. This paper examines a hypothetical arrangement where energy firms can tokenise a portion of their revenue stream into RevToks. The electricity produced by these generators is sold to the centralised operator of the energy pool market, as in existing arrangements. This pool market operator will publicly commit to offering remunerations in the form of stablecoins, a minor change in their operating model. These stablecoins are sent to a smart contract that autonomously distributes payments based on RevTok ownership. RevToks owners and the generator themselves will thus receive regular revenue payments. RevToks embody a self-enforcing right to claim a portion of the underlying revenue stream, and can be transferred and traded on a dedicated exchange. This right is ensured by the transparent nature of blockchain and smart contracts, and their associated *"code as law"* qualities. This paper attempted to show that this blockchain-based arrangement opens downstream opportunities that make the business environment for RES generators better, with only minor changes to the existing business practice of pool market operators.

This paper examined the use of a tokenised revenue arrangement as described above as a potential tool for large-scale electrical generators, and examined if such an arrangement is desirable within an electrical energy markets context. As a worked use-case scenario, the present paper attempted to show how novel tokenised revenue streams could allow electrical generators to reduce their risk exposure by diversifying their revenue sources and hedging against both price and volumetric risk. Modern portfolio theory is employed and expanded on using multiportfolio theory to calculate optimal portfolios of diversified revenue sources for generators. A case study is performed utilising a set of generators of varying technologies and market tariff structures, including wind and solar PV, and spot and PPA respectively. The methodology is found to significantly reduce variance and thus risk for all participants, achieving a very effective hedge. This is a significant improvement over the traditional methods available to energy firms, and, if implemented on a dedicated smart contract, can potentially be accomplished for a lower cost. Generator trade generally occur between those that have the lowest mutual correlations. However, generators also benefit from gaining multiple separate revenue sources, resulting in very diverse portfolios of income streams. Time resolution sensitivity analyses showed that, even on a longer temporal scale, generators benefited from decreased variance and thus risk. These results thus present evidence as to tokenised revenue streams' usefulness as a tool for renewable energy firms and builds the case for pool market operators to facilitate this.

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Raw data, figures, and scripts can be viewed at [44].

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