Energy Strategy Reviews 17 (2017) 1–5

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.ees.elsevier.com/esr

Fundamental indexation: An application to the Nordic wholesale electricity market

Tarjei Kristiansen, PhD

Asegardsvegen 65, 6017 Alesund, Norway

ARTICLE INFO

Article history:
Received 28 January 2016
Received in revised form
26 May 2017
Accepted 30 May 2017

Keywords:
Efficient portfolio theory
Nordic power market
Fundamental indexation
Renewable energy

ABSTRACT

In commodities futures trading, models are often applied to determine an optimal trading strategy. Traditional trading strategies employed include short (sell) and long (buy) positions, time, and locational spreads. Shorter-term power contracts, however, have relatively low correlations with financial markets because of fundamental supply-demand factors including a high correlation with weather effects. Based on the concept of fundamental indexation pioneered by Arnott et al. we investigate the application of a fundamental portfolio weighting indexation to power markets. We propose three fundamental indices, inverse inflow, inverse production and consumption, related to supply and demand, and which historically exhibit strong correlations with power prices. We benchmark the three indices to an equally weighted portfolio of the Nordic market's weekly futures prices (one to six weeks to delivery) from 1996 to 2006. The results show that the inverse inflow index obtains the highest returns. We conclude that the use of the indices combined with portfolio theory would benefit renewable energy plant operators and energy traders.

1. Introduction

The objective of this paper is to develop electricity futures portfolios with improved risk-return characteristics by using fundamental factors as a guide. In energy trading, portfolio-based techniques can be used to develop well-diversified trading or hedging portfolios. Depending on their time to maturity, futures contracts have different return and variability characteristics including market liquidity. Generally, an energy trader assembles a portfolio of contracts, which requires analyzing the portfolio's complete return, not the individual contracts. Using a volatility-adjusted, position-sizing analysis potentially smooths out the portfolio's returns and improves its risk characteristics. In this trading scenario, the higher volatility in an asset implies a smaller position size.

The objective of this paper is to construct an electricity futures portfolio with improved risk-return characteristics by using fundamental factors as a guide. Basically, fundamental indexing [1] weights a portfolio's components by fundamental factors rather than by market capitalization or equal weighting. In wholesale electricity markets characterized by a high share of renewables, there may be an inverse relationship between renewables output with low (or zero) marginal cost and price. Higher production (more supply) could lead to lower prices and thus a negative correlation. Hydropower production can be estimated proportionally to the inflows in the current period minus the changes in reservoir levels from the previous period (holds true from the reservoir balance equation). High reservoir levels and/or inflow levels (indicating excess supply) contribute to lower prices and vice versa. Likewise, there is a relationship between the consumption level (i.e. high in cold weather) and price. Everything else being equal, higher consumption leads to higher prices. To utilize these relationships in a trading strategy we need to create weights that express these relationships over time. The weights should reflect the relationship between reservoir levels, inflows, and consumption in order to capture the trading portfolio's future expected performance. Portfolio rebalancing is necessary if recalculating the weights indicates that they have changed materially. A low weight (high hydropower output or low consumption) indicates rebalancing sales, and a high weight (low hydropower output or high consumption) indicates rebalancing purchases. To apply the fundamental indexation concept to energy trading, we need a forecast of expected hydropower output as calculated by the inflow/reservoir levels and a forecast of consumption so that we can adjust the portfolio's weights in advance.

E-mail address: tarjeikr@yahoo.com.

http://dx.doi.org/10.1016/j.esr.2017.05.001
2211-467X/

In this paper, we propose three fundamental indices related to supply and consumption: inverse production, inverse inflow, and consumption. Historically, the three indices exhibit a strong correlation with power prices. We benchmark them to a portfolio with equal weights of the weekly futures prices (one to six weeks to delivery) in the Nordic wholesale electricity market from 1996 to 2006. A few earlier studies have applied the Markowitz portfolio approach [2] to power plant investments [3,4], but to our knowledge we are the first to apply the concept of fundamental indexation to power trading portfolios.

The remainder of this paper is organized as follows. Section 2 describes portfolio theory and fundamental indexing and briefly reviews the relevant literature. Section 3 describes the Nordic power market and its physical and financial markets including the important price drivers. Section 4 introduces the proposed fundamental indices and describes the possible approaches for creating their portfolio weights. Section 4 also discusses their application to the weekly futures prices in the Nordic market from 1996 to 2006. Section 5 highlights some of the issues involved in determining the index weights. Section 6 concludes.

2. Portfolio theory and fundamental indexing

Portfolio analysis guides investors in creating efficient portfolios that exhibit low variability to various outcomes. Portfolio returns are calculated by maximizing the expected return for any given level of risk (i.e. minimizing risk for every given level of expected return). Markowitz portfolio theory [1], which has been applied to financial markets and for asset allocation, does not prescribe a single optimal portfolio combination, but rather a range of efficient choices so that investors can select a risk-return combination based on their own preferences and risk attitude. Although standard deviation is the most commonly used risk measure, this measure is not robust; thus many investors instead use sortino ratio and conditional value at risk (CVar). Portfolio optimization frequently occurs in two stages: determining the optimal weights of portfolio assets and optimizing the weights of assets within the same asset class.

Application of Markowitz portfolio theory to energy markets has been demonstrated by Refs. [3] and [4]. The authors in Ref. [3] introduce mean-variance portfolio theory and evaluate its potential application to the development of efficient EU-15 generating portfolios that enhance energy security and diversification objectives as well as demonstrating the portfolio effects of various generating mixes. The authors in Ref. [4] apply portfolio theory to technology choices in electricity markets, study the effect on long term contracts, and demonstrate that power generation technologies have different risk and returns characteristics because of different exposures to market risks (electricity price, fuel price, and CO_2 price) and different degrees of capital intensity (ratio of investment to operating costs). The research in Ref. [5] examines the market efficiency of oil spot and futures prices by using both mean-variance (MV) and stochastic dominance (SD) approaches. Using crude oil data for the period 1989–2008, they find no evidence of any MV and SD relationships between oil spot and futures indices (i.e. there are no arbitrage opportunities between these two markets). The spot and futures oil markets are efficient and rational because neither can dominate the other.

Arnott el al [1]. introduced the concept of fundamental indexation. In equity markets most indices are market-capitalization weighted (i.e. number of outstanding shares times price per share). The more value a share gains, the more shares are purchased by an index manager. Conversely, the more value a share loses, the more shares are sold by the index manager. While these actions may result in the overvaluation or undervaluation of some companies, market-capitalization weighted indices do provide benefits such as a passive strategy that requires little trading, a convenient way to participate in the equity market, high correlation with liquidity, and high correlation with investment capacity. Arnott et al. [1] suggest using fundamental equity indices when stocks are portfolio-weighted by fundamental factors such as gross revenue, equity book value, gross sales, gross dividends, cash flows, and total employment. They demonstrate that fundamentals-weighted, non-capitalization-based indices provide higher returns and lower risk than traditional capitalization-weighted indices. For example, during a 43-year test period, the fundamental index outperformed the S&P 500 by an average 1.97 pps annually. They rebalance the fundamental index on the last trading day of the year. Possible explanations for the outperformance include superior market portfolio construction, price inefficiency, additional risk exposure to distress risk, or a mix of the three. Arnott el al [1]. conclude that the fundamental indices are materially more mean-variance efficient than standard capitalization-weighted indices. An index consists of several components and thus it is a portfolio. Moreover, by definition an index is less volatile than its individual components.

Perold (2007) [6], who describes the flaws associated with fundamental indexing, argues that capitalization weighting in fact does not underperform, i.e. it does not invest more in overvalued stocks than undervalued stocks but because it invests in the same proportions, the capital and equal weighted indices will have identical returns. Perold (2007) [6] also claims that fundamental indexing has a flavor of value investing by engaging in active security selection. Fundamental indexing, however, may be effective when value stocks are systematically mispriced, but investors should be well-skilled in value investing and active strategies.

In the commodity space, skilled investors can avail themselves of some fundamental indices. The SummerHaven Dynamic Commodity Index (SDCI) developed by SummerHaven Index Management provides an active commodity index benchmark [7]. The underlying concepts are that commodities with low inventories will tend to outperform commodities with high inventories, and that priced-based measures, such as futures basis and price momentum, will be used to guide the assessment of commodity inventories. The SDCI fund holds the commodities that should outperform over the next month according to their price histories. Specifically, the fund only holds 14 of 27 possible commodities based on two criteria:

- It owns the seven commodities with the greatest backwardation, and
- It owns the strongest seven commodities based on 12-month price change.

In other words, the SDCI fund profits by selecting futures contracts with the largest available backwardations accompanied by the strongest uptrends.

The Dow Jones RAFI Commodity Index [8] is a fundamental factor-weighted, broad-market commodity index with a modified roll mechanism. This approach yields an alternative beta (i.e. the general market risk) by generating alpha (i.e. the outperformance relative to a suitable market index). The Dow Jones RAFI Commodity Index utilizes momentum and modified dynamic roll methodology based on liquidity and implied roll yield to overweight or underweight the commodities within the equally weighted sectors of the Dow Jones Commodity Index.[1]

[1] It includes only contracts extending 24 months ahead and requires that each eligible contract must have open interest of at least 5% of the total open interest in the nearby most liquid contracts. The roll occurs over the five first business days with the monthly rebalancing.

Electricity is a unique commodity because it is a non-storable property delivered during time periods rather than a single point in time [9]. Electricity prices are especially subject to supply and demand shocks (e.g., price may increase by a factor of 100 or more, followed by a relatively quick return to normal levels). Arbitrage strategies between spot and forward prices are inconsistent because of the non-storable property. Additionally, electricity markets may present locational price risk where the forward settlement price differs from the local spot price. Analyses of the Nordic power market find that futures prices tend to exceed spot prices [10]. It implies a negative convenience yield with seasonal variations and hydro storage levels. The Nordic supply and demand sectors have different risk preferences and abilities to exploit short-term price volatility, and the relationship between futures and spot prices correlates closely with hydro inflows, reservoir levels, and demand.

3. The Nordic power market

Nord Pool, the common Nordic power exchange, was formed in 1993. Nord Pool spot organizes the spot market and Nasdaq OMX organizes the financial power market. A day-ahead system price is calculated daily by Nord Pool spot based on market players' bids and offers. The system price is used as the settlement price for the financial contracts during the delivery period. Additionally, local spot prices are calculated with respect to transmission congestion. Day ahead and weekly futures as well as monthly, quarterly, and annual forwards are traded on the financial market. However, liquidity is typically poor for day ahead contracts and weekly contracts beyond the closest weeks. In this analysis, we focus on weekly futures contracts, which have been traded on the Nord Pool power exchange since its inception. In our analysis period, 1996–2006, it was possible to trade weekly futures contracts with delivery up to 6 weeks ahead.

Hydro generation is almost 100% in Norway,[2] around 50% in Sweden, and around 20% in Finland. Most of the generation is storage hydro with a potential for storage up to several years in certain cases. Hydro storage and consumption drive short- and long-term prices, and hydropower generation provides fast ramping ability to match any demand/supply shocks. System spot prices and reservoirs exhibit seasonal patterns. Low reservoir levels cause higher prices. Likewise, precipitation expectations influence the power price formation. The inflows to reservoirs from snow melt peak between weeks 18 and 27. Conversely, winter inflows reach their lowest levels between weeks 1 and 17. Hydro reservoirs reach their maximum level around September–November and their minimum level around April–May, and consumption levels reach their maximum peak (highest heating consumption) in December–March. Hydro storage and consumption drive short- and long-term prices, and hydropower generation provides fast ramping ability to match any demand/supply shocks. Generally, prices tend to be smooth although short-term spikes can also occur.

4. Fundamental indexation for Nord Pool

We apply fundamental indexing to Nord Pool futures price data from week 1 in 1996 to week 52 in 2006. In addition to the weekly futures price data, the time series include inflow, reservoir and consumption levels for Norway and Sweden. We use price data[3] and the inflow, reservoir levels, and consumption from Point Carbon (now Thomson Reuters) [11]. Figs. 1 and 2 illustrate the time series of fundamental data. Based on these data we create weights for our proposed portfolio. Our objective is to understand how traders can buy and sell power in anticipation of price advances/declines.

We begin by defining the important concepts used to determine the weights and returns. Conceptually, we formulate the fundamental index weekly return r in week i as:

$$r_i = \frac{1}{\sum_{j=i}^{n+i-1} w_j} \left(\sum_{j=i}^{n+i-1} w_j \cdot f_{j+1,i} \right), \tag{1}$$

Where r_i is the weekly fundamental return for week i, w_j is the fundamental weight (i.e. fundamental value) for week j which spans from i to $n + i$-1 weeks into the future, and $f_{j+1,i}$ is the log return of the futures price for week j as of week i, where j spans from i to n + i-1, $f_{j+1,i} = \ln(P_{j+1,i}) - \ln(P_{j+1,i-1})$.

We calculate the total annualized portfolio returns (AR) over the entire analysis period K weeks as:

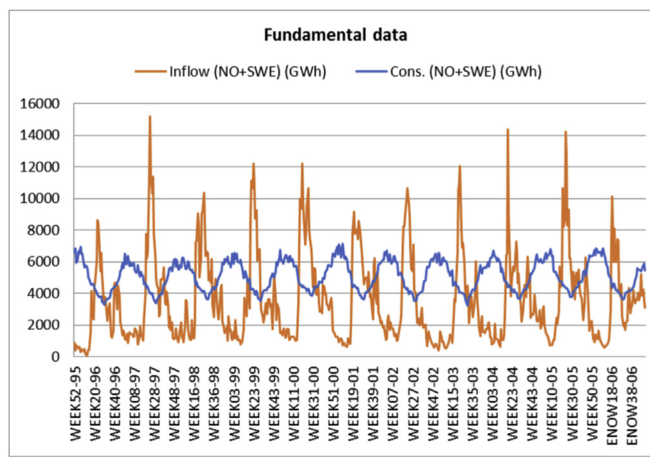

Fig. 1. Inflows and consumption in Norway and Sweden from week 1 in 1996 to week 52 in 2006.

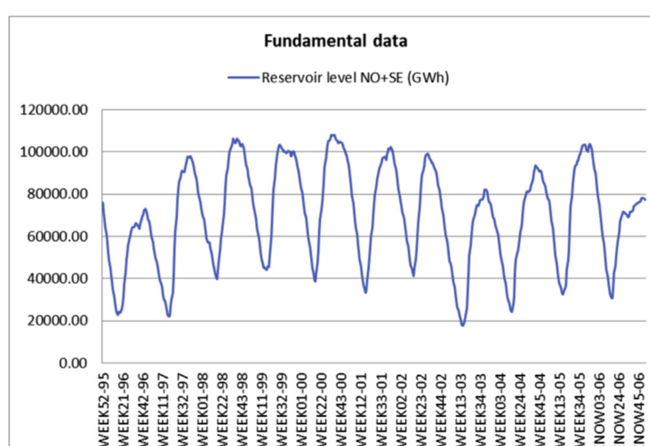

Fig. 2. Reservoir levels in Norway and Sweden from week 1 in 1996 to week 52 in 2006.

[2] Although Norwegian wind power capacity increased from 325 MW in 2006 to about 873 MW in 2015, annual output in 2014 was 2.2 TWh in 2014 compared to annual output of about 130 TWh for hydro in the same year.

[3] Futures prices data are not publicly available.

$$AR = \left(\prod_{i=1}^{K} (r_i + 1) \right)^{\frac{52}{K}} - 1, \tag{2}$$

where r_i is the weekly return and K is the number of weeks in the analysis period.

We calculate the annualized standard deviation σ *is* as:

$$\sigma = \sqrt{\frac{1}{K} \sum_{i=1}^{K} (r_i - \mu)^2} \cdot \sqrt{52}\,, \tag{3}$$

where μ is the mean of the series.

We calculate Sharpe ratio (*SR*) as:

$$SR = \frac{(AR - rf)}{\sigma}, \tag{4}$$

where *rf* is the risk-free interest rate set at 1.0%.

Finally, we calculate the fundamental weight *w* based on the forecast for fundamental factors identified to be a price driver. A higher weight for a week indicates a more favorable outlook for the actual weekly futures contract which infers more purchases of the actual contract. Conversely, a lower weight indicates more sales of the actual weekly futures contract. Thus, we create a portfolio geared toward price advances/declines which is still diversified since it contains six weekly futures contracts. We rebalance the week-ahead futures contract weekly as it expires while other futures contracts are rebalanced if the weights change materially. We use up to six weekly contracts because liquidity is generally poor beyond this number (i.e. pricing inefficiencies could distort our analytical results). A previous study of the hedging and liquidity efficiency of various contracts at Nord Pool in 2000–2010 finds that the weekly futures for up to two weeks ahead have relatively high liquidity and low bid-ask spread [9], but that liquidity and bid-ask spreads decrease with time to delivery and during the summer months, June, and July. Therefore, our study does not consider a trade-off between duration of the futures contracts and price discovery. It also ignores the impacts of the transaction costs.

While other methods can be used to create applicable and useful weights, our weights are not necessarily optimal. To determine the optimal weights, we could run back tests within a Markowitz portfolio approach. Ideally, the weights should reflect the market fundamentals which are strong market drivers to avoid the risk of data mining.

We calculate the fundamental time series weights[4] based on the following:

- **Inverse production:** Production is proportional to the difference in reservoir levels (GWh) in Norway and Sweden in the preceding period and the current period plus the inflows (GWh) in Norway and Sweden in the current period. Production is inverted to calculate the weight.
- **Inverse inflow:** The inverse of the sum of the actual weekly inflow levels (GWh) in Norway and Sweden from 1996 to 2006.
- **Consumption:** Consumption is the sum of the actual weekly consumption in Norway and Sweden from 1996 to 2006.

We illustrate the methodology with the following example. Assume that consumption is 5100 GWh in week 44, 5400 GWh in week 45, 5600 GWh in week 46, 5700 GWh in week 47, 6000 GWh in week 48, and 6300 GWh in week 49 for a total of 34100 GWh. In week 43 purchase the week-ahead contract (week 44) with a weight of 5100/34100 = 0.15, the second week-ahead contract (week 45) with a weight of 5400/34100 = 0.16, and so on up to the weekly contract 49 such that the weights total 1.00. In week 44, repeat the procedure with the new weights based on the new fundamental data, and rebalance the portfolio if it is long the actual contract. Observe that the weights may differ from a pure arithmetic average which equals 1/6 = 0.1666 for a portfolio of six contracts.

Table 1 summarizes the results. The weekly returns are calculated with eq. (1), the annual returns are calculated with eq. (2), and the standard deviations are calculated with eq. (3). Two of the proposed strategies outperform the equal weighted futures strategy. The inverse inflow strategy yields 12.88% and the consumption strategy yields 6.87%. The inverse inflow and consumption strategies outperform the equal weighted strategy by 7.3% and 1.2%, respectively. The strategies have a very similar standard deviation: 0.33 for the inverse inflow strategy and 0.32 for the other strategies. The main driver for the outperformance of the inverse inflow strategy is the higher correlation with the weekly futures (0.01–0.1) vs the consumption strategy (−0.02 to 0.11). Recall that hydrology is a stronger driver of the Nordic market than consumption. Therefore, trading strategies should focus on hydrology.

Table 2 shows the annualized returns of the individual weekly contracts which all have negative returns. Conversely, the portfolio of equal weighted weekly contracts has a return of 5.63%. Note that the standard deviation of each weekly futures contract is from 0.74 to 0.51, whereas the standard deviation of the equal weighted portfolio is 0.32. A measure of the risk adjusted return beyond the risk-free interest rate is the Sharpe ratio as defined in eq. (4). The higher the Sharpe ratio the better risk-adjusted return. For a 1% risk-free interest rate, the ratio is 0.36 for the inverse inflow strategy, 0.18 for the consumption strategy, 0.11 for the inverse production, and 0.14 for the equal weighted strategy 4. Table 2 also shows that the individual contracts have negative Sharp ratios with returns in the range −1.30% to −16.71% and standard deviations in the range 0.52–0.74.

5. Determination of fundamental index weights

In a real world setting we must utilize forecasts because we do not have perfect foresight. If we had obtained historic forecasts we would have compared the performance of these strategies with the ones described in this paper. Laukkanen [12], who estimates the inflow forecasting error from 2001 to 2003, finds a mean absolute relative error (MARE) around 10%. Future inflows are stochastic because they depend not only on the existing hydrological conditions but also on the future weather. Lynch [13] notes the lack of success in forecasting seasonal weather for Europe which could be utilized for inflow forecasts. To overcome the problem, Gjelsvik et al. [14] use historical inflow series over a longer period. The Swedish Meteorological and Hydrological Institute's HBV model is widely used in hydrological forecasting in the Nordic region.

Whereas the application of fundamental indexation for equities uses economic and financial data to determine weights, for power markets the determinations should depend on the fundamental factors identified as price drivers.[5] In principle, it is possible to do this with negative weights indicating short positions. In other words, energy traders buy/sell when the fundamentals reflect a

[4] We did test alternative indices such as reservoir level and hydro balance (includes both reservoir and snow balance levels), but we rejected them because the returns were inferior.

[5] In principle there is nothing against short positions but the sum of weights of both long and short positions must still sum up to 1.

Table 1
Annual returns for various fundamental strategies and an equal weighted futures strategy.

	Inverse production	Inverse inflow	Consumption	Equal weighted futures
annual returns	4.42%	12.88%	6.87%	5.63%
annual stdev	0.32	0.33	0.32	0.32
Sharpe ratio	0.11	0.36	0.18	0.14

Table 2
Annual returns for one week-ahead (F-1) up to six weeks ahead (F-6) weekly futures contracts.

	F-1 week	F-2 weeks	F-3 weeks	F-4 weeks	F-5 weeks	F-6 week
annual return	−16.71%	−10.94%	−5.24%	−4.23%	−2.55%	−1.30%
annual stdev	0.74	0.65	0.59	0.57	0.56	0.51
Sharpe ratio	−0.25	−0.18	−0.12	−0.09	−0.08	−0.03

drier (wetter) outlook, lower (higher) reservoir level, and/or higher (lower) consumption (i.e. they buy power in anticipation of price gains and sell in anticipation of price declines).

6. Conclusions

This paper applied fundamental indexation on Nordic power futures to obtain higher returns than an equal weighted futures portfolio and individual weekly futures contracts. Three fundamental indices were developed: inverse inflow, inverse production and consumption levels. Based on the weights in the three indices futures were bought or sold from one week ahead up to six weeks ahead and the portfolio was rebalanced weekly as needed. The results showed that the inverse inflow index yielded superior results, whereas the consumption index yielded marginally better results compared to the equal weighted portfolio. We conclude that these two indices may be of interest for market players holding or desiring to hold a diversified portfolio, or short-term futures contracts.

The proposed method may be applicable to other electricity markets with different fuel mixes. First one needs to identify the main price drivers for the relevant market by correlation analysis. For example, in a market with large amounts of fossil fuels, let us assume that there is a correlation between price and baseload plant output. High plant output would therefore imply high prices and vice versa. Hence, we could construct an index based on the historical plant output. On the other hand, given large shares of wind/solar, let us assume an inverse correlation between price and renewable output. Note, however, that solar output usually peaks around noon. Hence, we could construct indices based on the inverse of wind and solar outputs but predicting future wind and solar output relies on forecasts for stochastic weather conditions, e.g., wind speed, cloud coverage. To apply the proposed method to other electricity markets we would use eqs. (1)–(4) with the modification that the weight w will be market- and index-dependent.

The weights determined in this paper may not be the optimal ones, but we leave this topic for future research. The application of fundamental indexation on the power market should be explored further. Likewise, a portfolio of equal weighted futures may yield positive annualized returns even when some of its individual contracts have negative returns. We expect that the outcomes of future research will demonstrate the benefits of portfolio diversification for electricity as well as other types of commodities.

References

[1] R.D. Arnott, J. Hsu, P. Moore, Fundamental indexation, Financial Analysts J. 61 (2) (2005) 83–99.
[2] H.M. Markowitz, Portfolio selection, March, J. Finance 7 (1952) 77–91.
[3] S. Awerbuch, M. Berger, Applying Portfolio Theory to EU Electricity Planning and Policy-making, Report Number EET/2003/03, IEA Research Paper, Paris, 2003.
[4] F.A. Roques, D.M. Newbery, W.J. Nuttall, Fuel mix diversification incentives in liberalized electricity markets: a Mean-Variance Portfolio theory approach, July, Energy Econ. 30 (Issue 4) (2008) 1831–1849.
[5] H.H. Lean, M. McAleer, W.K. Wong, A mean-variance and stochastic dominance approach, September, Energy Econ. 32 (Issue 5) (2010) 979–986.
[6] A. Perold, "Fundamentally flawed indexing" (November/December), Financial Analysts J. 63 (6) (2007) 31–37.
[7] SummerHaven Dynamic Commodity Index℠;("SDCI"), available: SummerHaven Commodity Index Management: Commodities Table, Performance Comparisons, Target Weights, (2016).
[8] Dow Jones RAFI Commodity Index, available: http://us.spindices.com/indices/commodities/dow-jones-rafi-commodity-index, (2016).
[9] D. Frestad, Liquidity and dirty hedging in the Nordic electricity market, Energy Econ. 34 (2012) 1341–1355.
[10] A. Botterud, T. Kristiansen, M. Ilic, The relationship between spot and futures prices in the Nord Pool electricity market, September, Energy Econ. 32 (Issue 5) (2010) 967–978.
[11] Point Carbon now Thomson Reuters, available: http://financial.thomsonreuters.com/en/products/tools-applications/trading-investment-tools/eikon-trading-software/energy-trading.html, (2017).
[12] A. Laukkanen, Short Term Inflow Forecasting in the Nordic Power Market, Master's thesis, Helsinki University of Technology, 2004. March.
[13] P. Lynch, The origins of computer weather prediction and climate modeling, J. Comput. Phys. 227 (4) (2008) 3431–3444.
[14] A. Gjelsvik, T.A. Roetting, J. Joynstrand, Long-term scheduling of hydrothermal power systems, Lillehammer, Norway, 16-18.6, in: E. Broch, D.K. Lysne (Eds.), Hydropower '92: Proceedings of the 2nd International Conference, Balkema, Rotterdam, the Netherlands, 1992, pp. 539–546.