A DYNAMIC SIMULATION MODEL FOR LONG-TERM ANALYSIS OF THE POWER MARKET

Audun Botterud*, Magnus Korpås, Klaus-Ole Vogstad, Ivar Wangensteen
Dept. of Electrical Power Engineering, NTNU, N-7491 Trondheim, Norway
E-mail: audun.botterud@energy.sintef.no
*Visiting MIT Laboratory for Energy and the Environment, Sept. 2001 to Dec. 2002

Abstract – This paper presents a new model concept for long-term analysis of deregulated power markets. In the model we try to capture the main factors influencing long-term development of the power system. In the deregulated power markets, investment decisions are no longer part of centralised planning and optimisation. Investors' lack of perfect foresight, together with permissions and construction delays, could possibly result in periods of overcapacity or capacity deficits in the system. By using a dynamic description of investments we are able to include these effects into our model. The average spot price in the power market is calculated from year to year, using a linear optimisation algorithm. The electricity price in turn influences investments in different technologies for generation and end-use of electricity. A modelling technique based on system dynamics is used to model these investment decisions. Public authorities and energy companies are potential users of the model, for learning and decision support in policy design and scenario planning. Results from a case study of the deregulated power market in Norway are included to illustrate potential use of the model.

Keywords: power market, simulation, system dynamics, policy design, scenario planning

1 INTRODUCTION

The ongoing deregulation of power markets around the world presents the electric power industry with several new challenges. Long-term investment planning under the new and more uncertain conditions is one of them. The importance of making the right investment decisions has increased in the new environment, where the utilities have less influence on what price they can charge from their customers in the future. A fundamental understanding of how the power market is likely to work in the long run is therefore of major importance to improve decisions on technology choice, size and timing of system expansions. Consequently, new planning approaches and models are needed to better understand the conditions in the deregulated electricity markets, as pointed out in [1].

The new organization of the industry also creates challenges for the authorities in a region or country. Even though deregulation has left regulating institutions with less direct influence on the power market, the authorities still want to make sure that the power system develops in a desirable direction. A balanced development of supply and demand, accompanied by non-fluctuating prices is usually looked upon as one indication of a well-functioning market[1]. Most authorities are also aiming at lowering the environmental impact of the power supply. A well-functioning power market in the long run can be achieved by creating the right incentives for investments on both supply and demand side. To create such incentives the authorities also need comprehensive knowledge about how different factors influence the long-term development of the power system.

This paper presents a new model concept for long-term analysis of the power market. The model is a possible tool for increasing the understanding of the prevailing conditions in deregulated power markets. It is specifically suitable for scenario planning, and both energy companies and public authorities could make use of the model in their long term strategic planning. In the model we calculate the annual average electricity price using a linear optimisation algorithm, while the description of investment decisions is based on system dynamics. In the first part of the paper we discuss investment dynamics in the power market, and how this is incorporated into traditional and new power market models. The main part of the paper is devoted to a detailed presentation of our new model concept. At the end we also briefly present results from a case study of the Norwegian power market, to illustrate potential use of the model.

2 INVESTMENT DYNAMICS IN THE POWER MARKET

2.1 Decentralised and imperfect decision making

One of the characteristics of the deregulated power market is that many of the decisions that used to be centralised are now made at more decentralised levels in the power system. This is also the case for decisions regarding investments in new power generation. The introduction of competition in the market has shifted the investment focus from meeting demand to maximising profits. Under these circumstances it is no longer certain that installed generation capacity is always ahead of the load development. Power plants have a long lifetime and a substantial fraction of the total costs are paid up front. At the same time there is high uncertainty

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[1] This is not necessarily the situation in recently deregulated power markets, as clearly illustrated by the problems in California.

regarding the future electricity prices. Consequently, investors might be reluctant to invest in new generation capacity in time to meet increasing demand. Delays caused by the time it takes to get construction permits and to construct new plants, also contribute to the likelihood for an imbalance between load and generation capacity.

The expected electricity price is clearly the main feedback signal for investments on the supply side of the market. The demand side, on the other hand, consists of a large number of consumers, and the link between price and investment in end-use technology is less clear. Small consumers, for example single households, do not base their investment decisions on purely economic arguments. Their behaviour is more likely to be described as bounded rationality. It is still reasonable to assume that there is price feedback also to demand, especially to large industry consumers. Moreover, shorter construction delays are also present on the demand side. Certain amounts of investment dynamics are therefore present on both the supply and demand side of the power market. Interventions from regulating authorities, in terms of taxation, subsidies and concession policy, contribute to change these dynamics.

2.2 Traditional modelling approaches

Most traditional long-term planning models for the electricity industry are based on cost optimisation or econometric approaches. These models usually have an underlying assumption of perfect investor foresight, and therefore fail to include the delays and imperfect decision-making that result in the investment dynamics described above. Alternative modelling approaches are therefore needed, but most of the models that are being developed for the new competitive environment seem to focus on shorter-term issues like operation planning, trading and economic risk management. One of the few new power market models that also address the long-term investment effects is documented in [2].

2.3 System dynamics

In our model we use *system dynamics* to model investments in the power system. The theory of system dynamics was developed during the fifties and sixties by Jay W. Forrester as a policy design tool for complex management problems [3]. The theory draws upon control-, organisation-, and decision theory. Mathematically, system dynamics is a set of non-linear differential equations that are solved numerically. The basic building blocks are stocks and flows within a structure of information feedback loops. System dynamics has been used to analyse dynamic patterns in a range of different industry sectors [4]. It has also been used in previous studies to analyse cycles in power plant constructions in England [5] and California [6]. Our model differs from those two approaches by including several generation technologies in the model. We also introduce a limited feedback from price to electricity demand.

3 THE MODEL

3.1 General characteristics

The model simulates the development of the power system within a region for a long period of time (20-50 years). We model the power market with a supply and demand curve, and the electricity price is derived from the intersection of the two curves. The time resolution in the model is one year, using the simplifying assumption that investment decisions are made at the beginning of each year. New investments in generation and demand-side technology result in a change in the supply and demand for electricity. Consequently, we end up with a dynamic description of the supply and demand curve, with price as the main feedback mechanism.

The level of detail in the model is aggregated. Instead of going into details on the different parts of the system, we try to focus on the relationships that we see as most important for the long-term development of the power system. The model is therefore a tool for generating scenarios to analyse what is likely to happen under certain circumstances (e.g. about the development of fuel prices, taxation, technological improvements etc.). To facilitate communication of the model and its results to decision makers we have therefore used Powersim[2] to implement the dynamic description of the supply and demand curves. The price calculation is carried out in Visual Basic with a corresponding Excel spreadsheet interface. The list below shows the main variables and parameters used in the model.

General variables:

$p(t)$	wholesale electricity price [NOK/MWh]
t	time [years]

Supply, generation groups, $i \in [1,m]$:

$g_i(t)$	annual generation [TWh/year]
$ncap_i(t)$	new capacity [MW]
$acap_i(t)$	approved capacity [MW]
$\hat{p}_i(t)$	price forecast [NOK/MWh]
$RC_i(t)$	remaining reserves [TWh/year]
$GC_i(t)$	annual generation capacity [TWh/year]
$EIC_i(t)$	energy investment costs [NOK/MWh]
$VC_i(t)$	variable costs [NOK/MWh]
$MC_i(t)$	marginal costs [NOK/MWh]
$OC_i(t)$	operation and maint. costs [NOK/MWh]
$FC_i(t)$	fuel costs [NOK/MWh]
$II_i(t)$	investment incentives [NOK/kW]
$OI_i(t)$	operating incentives [NOK/MWh]
$CF_i(RC_i)$	capacity factor, full load hours [hours/year]
$PF_i(t)$	profitability factor
ir_i	internal rate of return
rr_i	investors' required rate of return
δ_i	deviation in required rate of return

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[2] Software developed specifically for system dynamics, with emphasis on the visual presentation of simulation models.

ic_i	initial capacity investment cost [NOK/kW]
k_i	annual technology improvement factor
n_i	expected lifetime [years]
$amax_i$	max permit applications per year [MW]
ad_i	approval delay [years]
cd_i	construction delay [years]
a_i	approval rate, $a_i \in [0,1]$
$w(u)$	factor used to adjust marginal value of regulated hydropower, $w \in [0.5,2.5]$
u	stochastic relative inflow, $u \sim N(1,\sigma_u)$

Demand, demand groups, $j \in [1,n]$:

$d_j(t)$	annual load [TWh/year]
$MD_j(t)$	marginal willingness to pay [NOK/MWh]
$DC_j(t)$	max annual demand [TWh/year]
$DTOT(t)$	max total annual demand [TWh/year]
$fp(t)$	flexible fraction of $DTOT(t)$, $fp(t) \in [0,1]$
$tax(t)$	electricity end use tax [NOK/MWh]
dg_{ref}	annual demand growth reference
ε	long-term price elasticity
dd	demand adjustment delay [years]
p_{curt}	curtailment price [NOK/MWh]

Power exchange, import and export groups, $k \in [1,o]$:

$im_k(t)$	annual import [TWh/year]
$ex_k(t)$	annual export [TWh/year]
$IMP_k(t)$	import price [NOK/MWh]
$EXP_k(t)$	export price [NOK/MWh]
$EXC_k(t)$	power exchange capacity [TWh/year]

3.2 Supply side description

Power generation is divided into a number of generation groups, with each group representing one specific technology. The main relationships included in our modelling of investments in new generation capacity follow the same structure for all the generation groups. The causal loop diagram in Figure 1 illustrates this structure.

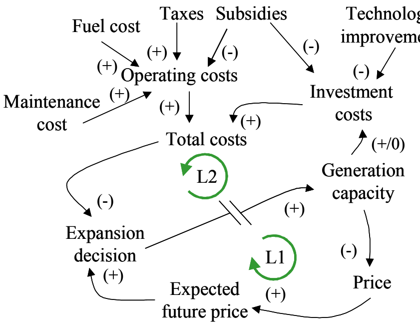

Figure 1: The main factors and relationships influencing on investments in new power supply. The signs on the arrows indicate how the variables are related. L1 and L2 represent feedback loops.

There are two feedback loops in Figure 1. The first feedback loop (L1) states that when generation capacity is increased the price is likely to fall. This lowers expectations of future prices, which in turn reduces the likelihood of future expansion decisions. L1 is therefore a balancing loop that limits the investments in new generation. The second feedback loop (L2) is caused by the connection between current installed capacity and investment costs. The sign and magnitude of this relationship varies for different generation technologies. For renewable technologies like hydropower and wind power we assume that locations with the best energy resources, or the highest expected capacity factor, are utilised first. The investment cost is therefore a function of remaining reserves, which in turn are directly linked to installed capacity. Hence, there is a positive link between installed capacity and investment costs, and L2 becomes a balancing loop for these technologies. On the other hand, fossil-fuelled power plants do not have the same clear link, since there is usually no constraint on the amount of fuel supplied to these plants. The capacity factor is now a function of the dispatch of the power plant, and the change in dispatch due to new installed generation capacity is dependent on the overall power system characteristics. We are treating the capacity factors for thermal technologies as constants in the investment part of the model. As a result, there is currently no link between installed capacity and investment cost for these technologies. However, by including more details in the modelling of the power system operation, we could include this link using simulated capacity factors.

The two bars on the line between expansion decision and generation capacity in Figure 1 represents a delay. An expansion project goes through several stages before it eventually comes on line, as shown in Figure 2. All these stages are represented as aggregation variables in the model. The two main delays are concerned with obtaining a permit to build a new plant and constructing it. These two delays are therefore included in the model to capture the investment dynamics.

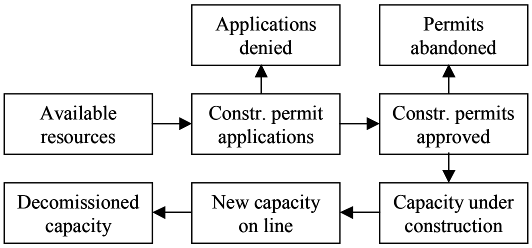

Figure 2: The stages in a power plant's life cycle.

A technology group's total cost is of course one of the main input factors when investments in new generation plants are considered. We therefore need a description of how investment and operating costs are likely to change over time. The investment costs per energy unit (EIC_i) depends on initial investment cost, technology learning, subsidies, expected lifetime and the capacity factor, as shown in equation 1.

$$EIC_i(RC_i,t) = \frac{ic_i \cdot e^{-k_i(t-t_o)} - II_i(t)}{n_i \cdot CF_i(RC_i(t))} \tag{1}$$

The variable costs of a generation group (VC_i) are the sum of fuel, maintenance and operating costs. The authorities could possibly also impose operational incentives such as subsidies for renewable power generation or CO_2 taxation of generation from fossil fuels. All these elements are exogenous inputs to the model, but can still change as a function of time, as shown in equation 2.

$$VC_i(t) = FC_i(t) + OC_i(t) - OI_i(t) \qquad (2)$$

We assume that investments in new power generation are based on purely economic arguments. Power companies invest in plants if the expected profitability is high enough to cover their required rate of return on capital. The expected profitability is dependent on total costs and the expected future price. We employ a first order exponential smoothing process to forecast the price a specific number of years into the future[3]. The time periods used in the backward-looking trend calculation and the forward-looking extrapolation, can be defined individually for each single technology. It is for instance reasonable to assume that investors in wind power have shorter time horizons for their price forecast than hydropower investors, due to shorter lifetime and construction time.

The values for investment costs, variable costs and expected future price can be used to find the expected internal rate of return on new investments in a generation technology. We do this by setting the net present value to zero, as shown in equation 3. The expected price and variable costs are treated as constants within each time period. Hence, we can derive a profitability factor (equation 4) that is used as an indicator for the quantity of new permit applications and constructions. The factor can be expressed either in terms of expected price and cost figures, or as a function of internal rate of return and lifetime. By using figures for lifetime and required rate of return in the last part of equation 4, we can therefore calculate the required profitability factor for investments in different generation groups. Figure 3 shows how approval applications and new constructions are modelled as a function of this profitability factor.

$$-n_i \cdot CF_i \cdot EIC_i(t) + CF_i \sum_{l=1}^{n_i} \frac{\hat{p}_i(t) - VC_i(t)}{(1+ir_i)^l} = 0 \qquad (3)$$

$$PF_i(t) = \frac{\hat{p}_i(t) - VC_i(t)}{EIC_i(t)} = \frac{n_i}{\sum_{l=1}^{n_i} (1+ir_i)^{-l}} \qquad (4)$$

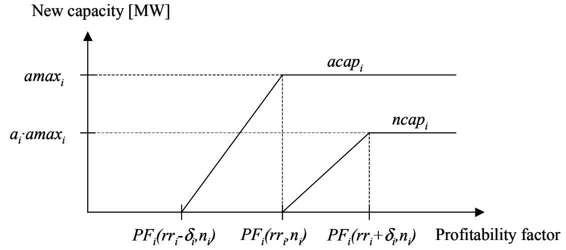

Figure 3: New applications for construction permits ($acap_i$) and new constructions started ($ncap_i$) as function of the profitability factor ($PF_i(t)$).

We assume that a higher profitability factor for a technology *i*, corresponding to a higher expected rate of return, results in an increase in new applications for construction permits for that technology (Figure 3). The capacity of new constructions started is also an increasing linear function of the profitability factor, but with a less steep slope. There is a limit to the capacity of new permit applications that is equal to an exogenous input factor $amax_i$. A corresponding limit to the capacity of new constructions started is lower, and equals the approval rate (a_i) times $amax_i$. Furthermore, we assume that investors require a higher rate of return to start the construction of new plants than what is required to apply for permits. The required rate of return (rr_i) and its deviation (δ_i), as shown in Figure 3, should be set to resemble the assumed behaviour of investors in the various power generation technologies. The model allows the use of different rr_i's and δ_i's for different generation types. Differentiated rate of return requirements can be used in the case that the risk concerned with investing in different technologies varies considerably[4]. The installed generation capacity, GC_i, is updated for each time step. Equation 5 shows how the construction delay is taken into account in the model. The permit approval delay is modelled in the same way. Construction and approval delays can also vary between the generation technologies, resulting in different patterns of investment dynamics for the different generation groups.

$$GC_i(t) = GC_i(t-1) + ncap_i(t - cd_i) \qquad (5)$$

3.3 Demand side description

Our description of the demand curve is more aggregate than the supply curve, and a substantial part of the demand is described by exogenous input parameters. We still try to capture the most important connections between electricity price and demand both in the short and long run. Figure 4 illustrates how demand is treated in the model. The feedback loop states that increasing demand results in increasing end-user prices. This will in turn give incentives for energy savings, and will

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[3] This is a built-in value forecasting function in Powersim.

[4] A technology's expected lifetime and the relative proportion of investment costs and operating costs are two of the factors that are likely to influence investors' perceived risk.

contribute to lower the total demand after a time delay (*dd*). L1 is therefore a balancing loop. The dynamic description of total demand is based on [4]. We assume a constant long-term price elasticity of demand, ε. When the simulated end-user price deviates from the reference price, the price elasticity contributes to change the development in total demand away from the underlying reference growth, dg_{ref}.

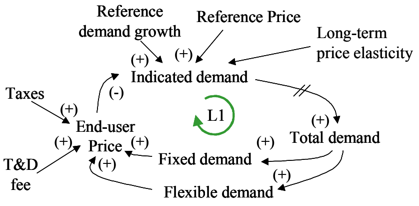

Figure 4: The main relationships on the demand side.

We distinguish between fixed and flexible demand. Flexible demand is defined as the demand that can respond quickly to price signals in the short term without additional investments. Hence, the flexible demand represents the short-term price elasticity in the model. For instance, switching from electricity to oil heating in dual fuelled heat systems represent parts of this flexibility. On the other hand, the fixed demand does not have any substitute in the short run. It still changes in the long run, partly due to the underlying general load growth. Investments in energy saving technology such as heat pumps and improved insulation would also influence the total load development.

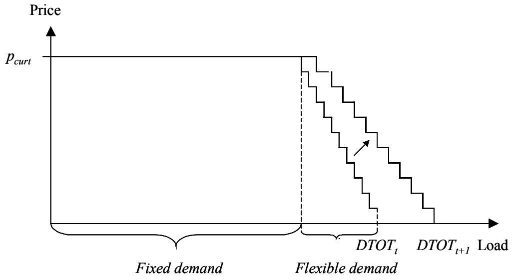

Figure 5: Representations of the demand curve at two different time steps.

Figure 5 shows how the fixed and flexible demand is represented in our description of the electricity market. The total demand, *DTOT(t)*, is updated for each time step, while the fixed and flexible demands follow as fractions of the total demand. The proportion of flexible demand, *fp(t)*, is an input parameter, but can still change as a function of time to describe the expected development of the flexibility on the demand side. Figure 5 illustrates a shift in the demand curve, where the total demand as well as the variable fraction increases. For the fixed demand we assume a fixed curtailment price, p_{curt}. The flexible demand is represented by a number of linear price steps. Hence, the whole demand curve has a linear representation, and can be described by a number (*n)* of demand groups with corresponding prices (MD_j) and capacities (DC_j).

3.4 Exchange of power to and from the region

Import of power to the region is handled by adding a number of additional supply steps to the supply curve. Accordingly, a number of export steps is added to the demand function to represent electricity demand outside of the region. The exchange capacity is determined by the capacity of the transmission lines to surrounding regions, and is an exogenous variable that could be set to change over time. The capacity and price of each import and export step should be defined to resemble the power market conditions in the connected regions. The lowest import price must always be higher than the highest export price, to fit into the price calculation as described below.

3.5 Electricity price calculation

The average annual price, *p(t)*, in the wholesale electric power market is calculated for each simulated year. The price is determined by maximising the short-term socio-economic surplus in the market, including imports and exports, as illustrated in Figure 6.

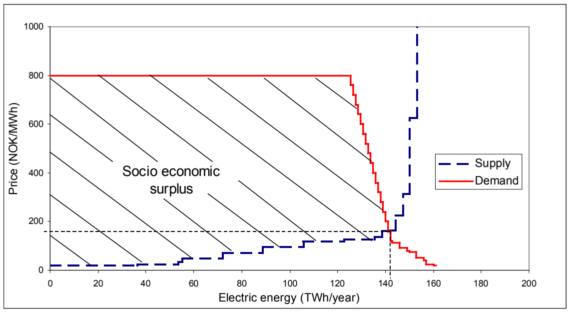

Figure 6: The power market is described by the supply and demand curve for each simulated time step.

The variable costs for the generation groups go directly into the price calculation, where they are treated as marginal costs (i.e. $MC_i = VC_i$), for all generation technologies except regulated hydropower. The regulated hydropower is divided into five separate supply steps, where the marginal value of the most expensive step equals a factor *w* times the lower import price, as shown in equation 6. The marginal values of the other steps are fixed fractions of the most expensive step. This is to take into account that regulated hydropower is dispatchable, and therefore scheduled according to the cost of alternative generation. The alternative generation is usually thermal power, and its marginal costs depend on how much of the system load it has to serve. This is in turn dependent on the annual inflow to hydropower reservoirs. The *w* value is therefore a function of the inflow, *u(t)*, which is drawn from a normal distribution for each time step. The *w* value is low when inflow is high and vice versa. The modelling of the marginal value of hydropower bears resemblance to the so-called water value calculations that are frequently used in hydropower production planning [7].

$$MC_{hydropower}(t) = w(u(t)) \cdot IMP_{lowest}(t) \qquad (6)$$

Strictly speaking, the shaded area in Figure 6 is not the true socio-economic surplus, due to the use of alternative costs instead of real marginal costs for regulated hydropower. The description still serves as a good approximation of the bidding process in the power market, if we assume perfect competition[5]. The linear description with constant marginal values for each load and generation group is clearly a simplification of the real world. Marginal costs of thermal power plants vary as a function of output for both a single plant as well as for a group of plants. The correctness of the market description is, however, improved by increasing the number of generation groups.

The annual power generation (g_i), consumption (d_j) and exchange (im_k or ex_k) are found directly by applying Visual Basic's built-in algorithm for linear optimisation on the problem below (equation 7-12). All the other variables in the equations are treated as constants in each single optimisation, although they might change between each time step. The electricity price, $p(t)$, occurs as the dual value, or shadow price, of the electricity balance (equation 8). Other figures, like capacity factors, generation costs, consumer's and producer's surplus are easily derived from the results of the optimisation.

$$max \quad \sum_{j=1}^{n} d_j \cdot MD_j - \sum_{i=1}^{m} g_i \cdot MC_i + \sum_{k=1}^{o} (im_k \cdot IMP_k - ex_k \cdot EXP_k) \qquad (7)$$

$$s.t. \quad \sum_{i=1}^{m} d_i - \sum_{j=1}^{n} g_j + \sum_{k=1}^{o} (im_k - ex_k) = 0 \qquad (8)$$

$$g_i \le GC_i, \quad i = 1..m \qquad (9)$$

$$d_j \le DC_j, \quad j = 1..n \qquad (10)$$

$$im_k, ex_k \le EXC_k, \quad k = 1..o \qquad (11)$$

$$g_i, d_j, im_k, ex_k \ge 0 \quad \forall \quad i, j, k \qquad (12)$$

The model is, in its current form, an energy model, and does not address problems concerning peak demand and capacity deficits. Transmission losses and reserve margin requirements are assumed to be included in the demand groups. Consequently, there is one single electricity price for the overall region, so that price differences within the region due to transmission congestion is not taken into account. The aggregate annual price calculation in the model is motivated from the observation that it is the average electricity price over the year that is relevant for most of the investments we consider, both on the supply and demand side in the power system. However, a more detailed market description could easily be implemented within the current framework, for analysis of effects that requires shorter time resolution, as for instance investments in peak power plants.

4 NORWEGIAN CASE STUDY

We developed an input dataset for the Norwegian power market based on information in [8] and [9]. The most important input figures are shown in the appendix. On the supply side we have added the 4 generation technologies that currently seems to be most relevant in Norway (hydro-, wind-, gas- and gas power with CO_2-capturing). The demand side is described by a few key variables. We first run a business as usual scenario (reference), where we assume that the authorities take a passive approach and leave the market to decide on the timing and technology for new generation. In the second scenario (green) we assume that the authorities introduce CO_2 taxation of 125 NOK/ton[6] from 2002, and that they also show preferences for renewable power generation when giving construction permits. In both scenarios we assume constant average inflow to the hydro reservoirs.

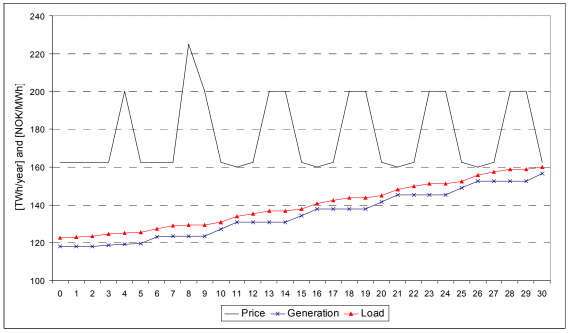

Figure 7: Simulated electricity price, generation and load in the reference scenario, 2000-2030.

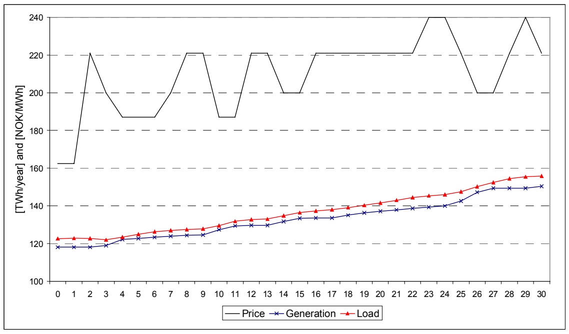

Figure 8: Simulated electricity price, generation and load in the green scenario, 2000-2030.

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[5] Modelling of imperfect competition and strategic bidding is more relevant for shorter time horizons where peaking effects from daily and seasonal load variations are included. We assume that these effects make a negligible impact on the average annual electricity price.

[6] This corresponds to $14/ton with current exchange rate.

Figure 7 shows that the simulated price fluctuates throughout the 30 years in the reference scenario. Capacity expansions are triggered during the high price periods, but delays cause the expansions to lag behind the price development. Most of the expansions are in large-scale gas power, as shown in Figure 9. The load also responds to the price and shows a similar fluctuating pattern, due to short- and long-term price elasticity. In the green scenario the price increases immediately after the CO_2-tax is introduced in 2002 (Figure 8). The price also fluctuates here, but at a higher price level and with less regularity than in the reference scenario. The generation development is smoother because of a larger degree of small-scale renewable generation technologies (Figure 9). The demand shows a similar trend as in the reference scenario, but with lower growth, especially after the price increase following the CO_2-tax. The generation is always lower than load in both scenarios, since we assume excess import capacity throughout the period.

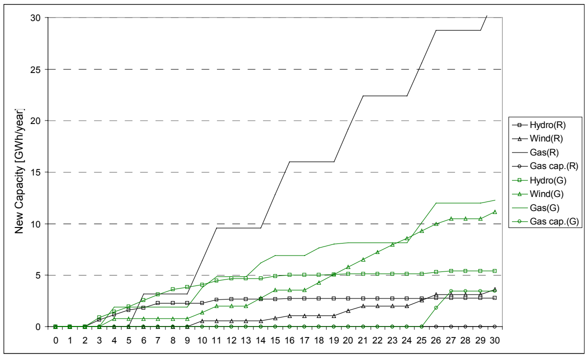

Figure 9: Simulated new generation capacity in the two scenarios (Reference-R/Green-G), 2000-2030.

We only show a limited number of results here, as our main focus in this article is on the presentation of the model. However, by changing the input variables it is possible to study different topics, ranging from natural effects like stochastic inflow to effects from authority regulations, like subsidies of certain generation technologies or changes in end-use taxation.

5 CONCLUSION

In this paper we have presented a new model for long-term analysis of deregulated power markets. The results from the Norwegian case study shows that the model is able to capture parts of the long-term dynamics that is likely to occur on both the supply and demand side of the power market. We argue that the liberalisation of power markets has increased the importance of incorporating these effects into long-term planning. The model concept could be extended in several directions. Shorter time steps and more detail in the price calculation would make the model suitable for analysis of short-term effects like peak demand problems. Moreover, a stochastic price description would make it easier to better take into account the risk preferences of investors in the power market. At last, inclusion of several load sectors could improve the representation of demand in the model.

APPENDIX

The following tables contain the main input data for the simulations of the Norwegian power market:

	Hydro	*Wind*	*Gas*	*Gas cap*[1]
RC_i	30	80	100	100
OC_i	20	35	25	40
FC_i	0	0	100	120
$OI_i^{2,3}$	0	0	0/-45	0
II_i	0	0	0	0
CF_i	$CF_i(RC_i)$	$CF_i(RC_i)$	8000	8000
ic_i	5000	8000	6000	10000
k_i	0.002	0.014	0.005	0.012
n_i	40	20	30	30
rr_i	0.07	0.07	0.07	0.07
δ_i	0.02	0.02	0.02	0.02
ad_i	3	2	3	3
cd_i	3	1	2	3
a_i^2	0.5/0.7	0.5/0.7	0.5/0.3	0.5/0.3

Table A1: Input parameter values for the generation side. [1]Gas power with CO_2-capturing. [2]Values for the two scenarios ref/green. [3]CO_2 tax introduced in 2002 for Gas power.

dg_{ref}	p_{curt}	ε	dd	fp	tax
0.01	800	-0.31	2	0.14	100

Table A2: Input parameter values for the demand side.

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