"Although it might seem desirable to develop a stochastic model for these quantities based on the particular statistical method which is used to produce the forecasts, this turns out (in many cases) to be unnecessary. It is indeed fortunate that this is so. for many forecasting techniques are based on more data than past demands. For example, prices of competing goods, and marketing, advertising, and other promotional plans, and sometimes even expert judgement are used to produce the forecasts on which decisions are based. For many reasons (lack of data, the difficulty of modeling competitors' price changes, and the obvious problem of modeling expert judgement) it would be very difficult to produce and fit a model in this way, and to have confidence in the resulting model." **heath1994modeling**

Simulation Program 2. ***Continuous-Time Binary-Adjustment Martingale Model of Forecast Evolution (CTBA-MMFE)*** *is not forecasting techniques, but a program to represent the evolution of forecasts over time and produce simulations. The size of adjustments is fixed, equal to the lot size of the limit order market. Once some adjustment happens, the client will send the request to its coordinator, and the coordinator is able to trade via a market order immediately. Sojourn times may be correlated, because the arrival of new information becomes more frequent when the lead time decreases, the degree of which varies for different clients.*

From the perspective of some client, for target unit i, the evolution of accumulative requests is a continuous time stochastic process $x_i(t)$, $c_i - \kappa\epsilon \leq t \leq c_i$, *with final value* $x_i(c_i)$ *known in advance, which is the final realization of accumulative requests. If all the information regarding target unit i at time t can be represented by* $\Omega_i(t)$, $x_i(t)$ *is the expectation of final realization condition on all current information:*

$$x_i(t) = \mathbb{E}\left[x_i(c_i)|\Omega_i(t)\right] \tag{1}$$

$$= x_i(\kappa\epsilon) + z_i(t) \tag{2}$$

where $z_i(t)$ *is a counting process, summarizing all adjustments during interval* $(c_i - \kappa\epsilon, t]$.

It is presumed that $x_i(t)$ *has following features:*

1. *Its possible values are integers.*
2. *It is a martingale process.*

3. *Its sojourn times may be dependent and the distribution of adjustments shows some pattern, because the arrival of new information depends on lead time.*

For different clients, their $x_i(t)$ may be distinguished in the following ways:

1. *The variance of $x_i(\kappa\epsilon) - x_i(c_i)$.*
2. *The distribution of sojourn times.*
3. *The frequency of adjustments.*

For multiple realizations of similar processes by the same clients, they may demonstrate the features shown by figure 2. For different clients, their forecast performances vary, which can be analyzed by normalized mean absolute error (NMAE). Figure 3 can be used to visualize the performances of different clients.

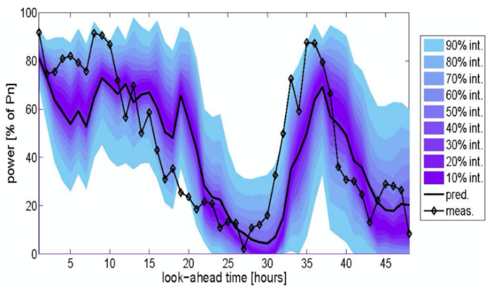

Figure 2: Example of 48-hour leading point and interval forecasts of wind generations. The point predictions are given by a state-of-art method and interval forecasts are estimated consequently with the adapted resampling approach. [PJK06]

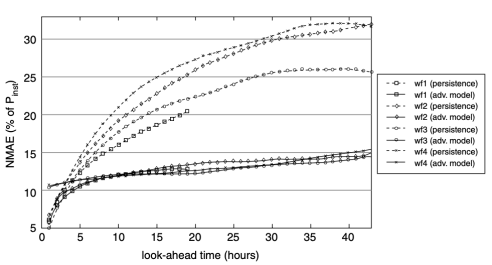

Figure 3: Performance in terms of normalized mean absolute error (NMAE) of two prediction models (persistence and a state-of-art artificial-intelligence based prediction method) for short-term wind power in four different sites. **madsen2005standardizing**