Use of prediction based meter reputation factors in power systems

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***Abstract*— Reputation systems provide a protocol for participants to interact based on their past performance. The concept of a prediction based meter reputation factor is introduced as a number between 0.1 and 1 that is assigned to every meter and that varies based on the accuracy of a meter's predictions. A system architecture is presented that allows the instantiation of rules for economic interaction between metered participants in a power system using reputation factors. This will create a system in which individuals are incentivised to provide accurate predictions, giving planners more reliable information. It also provides a basis for the allocation of rewards for flexibility and penalties for inflexibility. Two algorithms to allocate meter reputation factors are presented and assessed using a defined performance index and metering information from the OpenLV project. It is demonstrated that the performance of the meter reputation algorithms can be moderated according to system requirements. It is concluded that instantiation of the algorithms in such a way that makes persecution of individuals impossible is crucial.**

***Index Terms*—Power System Economics, Meter Reading, Smart Grid, Smart Metering, Incentive Schemes**

I. Introduction

The growth of computerized metering in power systems coupled with new digital intermediating platforms brings about the possibility to implement new types of incentive schemes. The concept of meter reputation factors introduced here creates a way to incentivise accurate predictions, to provide a tool for incentive scheme designers to assign rewards and penalties, and to provide a new source of information for system planners. For instance, basing reputations on the quality of individual predictions might help reduce the costs resulting from intermittent sources, when coupled with a well-designed incentive scheme. This would potentially solve a systemic need identified by Helm in the UK cost of energy review [1], the allocation of intermittency/inflexibility costs to originators. This is accompanied by the potential to allocate associated rewards for flexibility.

The existing literature on reputation systems is commonly written with reference to reputation systems for online platforms such as, electronic market places (e.g. auction websites) [2], electronic communities (e.g. online chat rooms, mailing lists) and virtual multiplayer games. In addition, reputation systems for peer-to-peer (P2P) systems [3]–[5] for grid computing (computer networks in which each computer's resources are shared with every other computer in the system) [6], [7] and for wireless communication systems (e.g. wireless sensor networks [8], [9] , can also be found [10]. Trestian et al [11] proposed a reputation based method for deciding which communication network a device would connect to based on historical reliability. Their results indicated the potential of reputation based systems in supporting cooperative decision making. In general, the reputation provided by reputation systems is a numerical score derived from aggregated record of reported past interactions [12].

Another relevant strand of literature is related to gamification, the application of computer game systems (leaderboards, points, etc) to a real-world system to encourage a certain behaviour [13], [14]. Other parts of the literature refer to "Serious Games" - games which provide feedback to the user to help with decision making [15]–[17]. The interaction of social network platforms with the energy system has also received attention. Pan et al highlighted the risk of network congestion caused by herd behaviour derived from social media [18], whereas Skopik found that the technology has potential to manage network congestion [19].

In the power system, the development of reputation system is enabled by the growth of smart meters, enabling trustworthy usage information to be digitally communicated and stored. Typically, the energy import or export is recorded with a half-hourly granularity for billing purposes. In some cases, such as in the UK, energy usage is reported more frequently (~10 seconds) directly to the user [20].

There is also a trend for network operators to deploy digital metering within their networks and between networks. For example, in GB the OpenLV project [21] is deploying distributed intelligence devices for Low Voltage (LV) monitoring, data processing and implementing network charges at distribution substations. The system is designed to work in real time, without the need for remote observation and decision making. It uses substation based computers that are able to perform analysis of the LV network and perform control or communication actions as a result. This may allow for tasks to be performed that would otherwise suffer from data communication bottlenecks, for example control based on improved local demand predictions.

From a security standpoint, there is a question of how intermediating platforms should be implemented so that it is not possible for individual meters to be targeted (e.g. manual editing of individual meter reputation). This is partly a question of setting out clear rules for interaction, and partly a question of how the rules are instantiated. A promising technology for instantiating the rules for interaction in a tamper resistant way are distributed ledger technology based smart contracts [22]. Smart contracts are self-enforcing agreements in the form of executable programs [23]–[25]. They have potential to allow meter reputation rules to be implemented in a tamper resistant way.

The contribution of this paper is in the introduction of the concept of prediction based meter reputation factors and in in the creation of reputation algorithms that could be used to improve the quality of information available to system planners. In summary, the paper describes:

- Definition of two new power system roles to facilitate the use of a prediction based reputation system
- A set of desirable characteristics for meter reputation factors.
- Creation of two plausible meter reputation algorithms.
- A set of indices against which the performance of reputation factors can be assessed by system operators.
- Assessment of the two algorithms using the performance indices.
- Assessment of the two algorithms with real metered data from the OpenLV project.

II. The System governor and Mechanism designer Roles

To explain a meter prediction based reputation system, it is assumed that the system will operate using a trustworthy digital intermediating platform, where an incentive scheme (intended to improve individual predictions, for example) is instantiated. Two new roles are introduced, system governor and mechanism designer (see Fig. 1). The meters located throughout the network send usage readings to the platform and also send predictions prior to the time of use. The meters are grouped into classes, to allow the system governor to moderate the reputation of different user types separately.

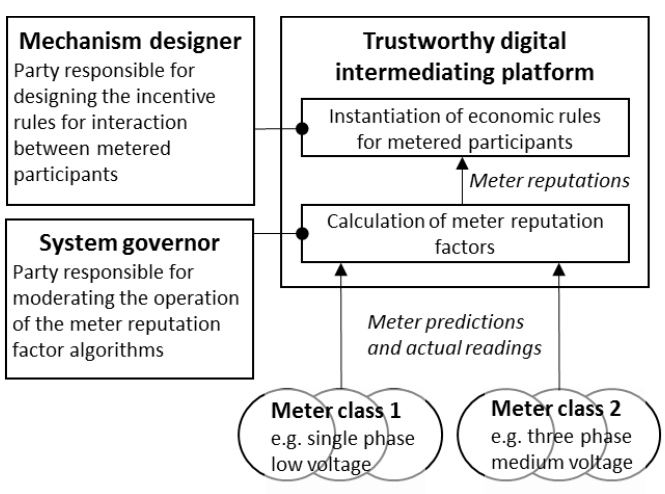

Figure 1 - Overview of system architecture for introduction of a reputation system

III. Meter Reputation Algorithms

A. General form

A general form of meter reputation algorithm was developed as described in (1) and (2).

$$PreRep_{m,t} = Rep_{m,t-1} \times (U - D \times W) \quad (1)$$

$$Rep_{m,t} = \begin{cases} 0.1, & PreRep_{m,t} < 0.1 \\ 1.0, & PreRep_{m,t} > 1.0 \\ PreRep_{m,t}, & otherwise \end{cases} \quad (2)$$

$Rep_{m,t}$ is the reputation factor output from the algorithm for meter m at time t, bounded between 0.1 and 1. $PreRep_{m,t}$ is the reputation factor prior to bounds checking. U and D are parameters adjustable by the system governor. W is a value acting on the meter's previous predictions and readings, it produces weighting factor and contains other parameters adjustable by the system governor. Two meter reputation algorithms are defined below. They were created by using different methods for calculation of W.

B. Algorithm 1

Algorithm 1 calculates W as the ratio between the prediction error (the difference between the predicted and the actual usage) and the meter's historical peak error (3). To avoid a one-off large error permanently distorting the outcome, the peak value is gradually forgotten, this is done by reducing the peak value at each time step, using a factor Pk, until a new prediction error has a higher value (4). This higher prediction error then becomes the peak. The Pk variable allows the system governor to modify the performance of the reputation system. It is not unique to individual meters. The meter reputation algorithm is described in equations (3) to (4).

$$W = \frac{|P_{pred,m,t} - P_{act,m,t}|}{peak_{m,t}} \quad (3)$$

$$peak_{m,t} = \begin{cases} peak_{m,t-1} \times Pk, & |P_{pred,m,t} - P_{act,m,t}| < peak_{m,t-1} \\ |P_{pred,m,t} - P_{act,m,t}|, & otherwise \end{cases} \quad (4)$$

Where $P_{pred,m,t}$ predicted mean power for meter m at time (e.g. half hour number) t. Pk is a factor, adjustable by the system governor, modifying the meter reputation's sensitivity to its stored historical peak. $peak_{m,t}$ is the historical recorded peak for meter, m, which reduces over time until a higher value is recorded.

C. Algorithm 2

In the second algorithm, W is calculated using the sum of three factors representing the quality of the last prediction for time t (W_1), the quality of all the predictions for time t (W_2) and the quality of the previous predictions for meter m (W_3). The meter reputation algorithm is described in (5) to (13).

$$W = W_1 + W_2 + W_3 \quad (5)$$

$$W_1 = \begin{cases} k_1, & \frac{|P_{pred,m,1,t} - P_{act,m,t}|}{s_{Permissible_{error},t}} > 1 \\ 0, & otherwise \end{cases} \quad (6)$$

$$W_2 = \begin{cases} k_2, & \frac{instant_{std_{m,t}}}{s_{Permissible_{error},t}} > 1 \\ 0, & otherwise \end{cases} \tag{7}$$

$$W_3 = \begin{cases} k_3, & \frac{s_{avg_{m,t}}}{s_{Permissible_{error},t}} > 1 \\ 0, & otherwise \end{cases} \tag{8}$$

Where $k_1 + k_2 + k_3 = 1 \quad : k_i > 0 \quad \forall i \in [1,2,3]$ and $s_{Permissible_{error},t}$ is the product between the actual meter reading and the permissible error factor (9), adjustable by the system governor, Pe. $s\_avg_{m,t}$ quantifies the quality of the predictions for meter m at time t over its measurement history (10). $s\_inst_{m,t}$ is a measure of the quality of the predictions done for meter m for time t. It is defined as the standard deviation of the n previous prediction errors (11).

$$s_{Permissible_{error},t} = P_{act,m,t} \times Pe \tag{9}$$

$$s_{avg_{m,t}} = \begin{cases} s_{avg_{m,t-1}} + \frac{\left(s_{avg_{m,t-1}} + s_{inst_{m,t}}\right)}{A}, & s_{avg_{m,t-1}} < s_{inst_{m,t}} \\ s_{avg_{m,t-1}} - \frac{\left(s_{avg_{m,t-1}} + s_{inst_{m,t}}\right)}{A}, & otherwise \end{cases} \tag{10}$$

$$s\_inst_{m,t} = \sqrt{\sum_{i=1}^{n} \frac{\left(P_{pred,m,i,t} - P_{act,m,t}\right)^2}{n-1}} \tag{11}$$

Where A is an historical weighting factor which influences the sensitivity to past errors. $P_{pred,m,i,t}$ is the ith predicted mean power for meter m at time (half hour number) t, and $P_{act,m,t}$ is the actual mean power for meter m at time (half hour number) t and n is the number of prior predictions for time t.

IV. Meter Reputation Algorithm Assessment Index

The performance index is a measure of how quickly the reputation of an individual meter recovers from a low value to a high one on accurate predictions, and how quickly its reputation depletes on inaccurate predictions. It has two components RI and DI, described in equations (12)-(14):

$$PI_T = RI_T - DI_T \tag{12}$$

$$RI_T = \frac{RecoveryTime_{error=0\%}}{T} \tag{13}$$

$$DI_T = \frac{DepletionTime_{error=100\%}}{T} \tag{14}$$

Considering a reputation factor where 0.1 is the lowest value (indicating a history of poor prediction accuracy) and 1 the highest (indicating a relatively accurate prediction history), $RecoveryTime_{error=0\%}$ is the number of iterations it takes for a meter's reputation to go from 0.1 to 1.0 if the prediction is perfect (i.e. the prediction equals the actual reading 0% error). Similarly, $DepletionTime_{error=100\%}$ is the number of iterations it takes for a meter's reputation to go from 1.0 to 0.1 if the meter's actual reading is set at 1 p.u, and the predicted readings are set at 2 p.u. (i.e. a 100% error). T is the time window width.

V. Testing of the Meter Reputation Algorithms

A. Initialisation values

The initial parameters of the algorithms were set, using trial and error, as shown in Table I and Table II.

TABLE I. ALGORITHM 1 INITIAL PARAMETERS

Parameter	Setting
$peak_{\ m,t-1}$	0
$Rep_{m,t-1}$	0.5
U	1.019
D	0.018

TABLE II. ALGORITHM 2 INITIAL PARAMETERS

Parameter	Setting
$Rep_{m,t-1}$	0.5
$k1$	0.5
$k2$	0.25
$k3$	0.25
A	48
S_avg	0
U	1.015
D	0.0307

B. Performance Index (PI) with varied parameters

The PI of each of the algorithms was calculated. These are shown in Table III and IV. Note that positive infinite PI means that the reputation factor will never recover or would need perfect prediction (zero prediction error) to recover. A negative infinite PI means that the reputation factor will never deplete. The highlighted values were used to test the operation of algorithms using real data from the OpenLV project.

TABLE III. ALGORITHM 1 PI_{2929} WITH VARIED INPUT PARAMETERS

U	PI	D	PI	Pk	PI
1.006	0.071	0.020	-0.411	0.100	0.032
1.0077	0.033	0.024	-0.084	0.171	0.023
1.0094	0.003	0.029	-0.031	0.243	0.013
1.0111	-0.028	0.033	-0.010	0.314	-0.001
1.0129	-0.067	0.037	0.001	0.386	-0.019
1.0146	-0.124	0.041	0.009	0.457	-0.043
1.0163	-0.242	0.046	0.014	0.529	-0.076
1.018	-0.741	0.050	0.018	0.600	-0.128

TABLE IV. ALGORITHM 2 PI_{2929} WITH VARIED INPUT PARAMETERS

U	PI	D	PI	Pe	PI
1.01	0.0403	0.01	-inf	0	inf
1.0121	0.0222	0.0121	-inf	0.0429	-0.0003
1.0143	0.0065	0.0143	-inf	0.0857	-0.0006
1.0164	-0.0078	0.0164	-0.7941	0.1286	-0.0013
1.0186	-0.0239	0.0186	-0.2007	0.1714	-0.0017
1.0207	-0.042	0.0207	-0.0996	0.2143	-0.002
1.0229	-0.0686	0.0229	-0.0549	0.2571	-0.0023
1.025	-0.1086	0.025	-0.0317	0.3	-0.0027

C. Case study – 11:0.433kV Substation Data

Data collected during the OpenLV project was used to assess the performance of the algorithms. The data originates from the metering at an 11:0.433 kV substation in Cardiff. The prediction data was generated using a moving average model based on the data from the two preceding days. The algorithm's parameters were varied as highlighted in Tables III and IV. Fig. 2 and Fig. 3 show the resultant reputation factors overlaid on

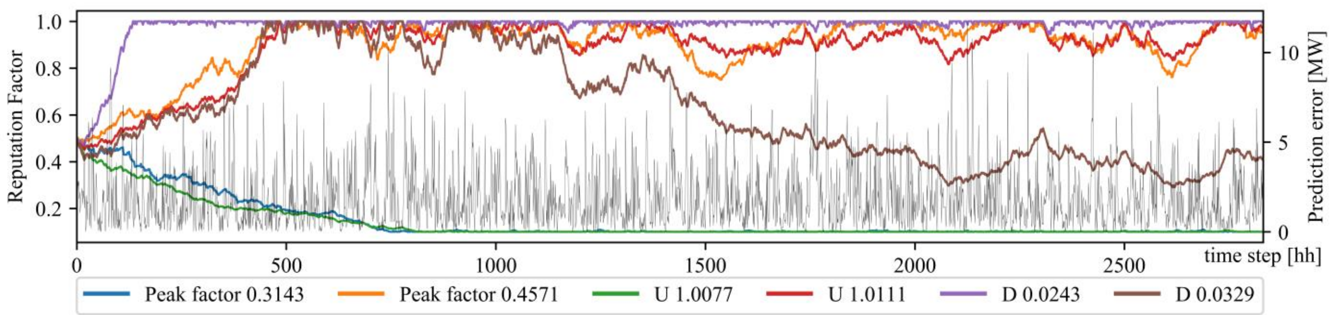

Figure 2 - Reputation with algorithm 1, varied input parameters. Default values: U=1.0194, D=0.018, Peak factor=0.9

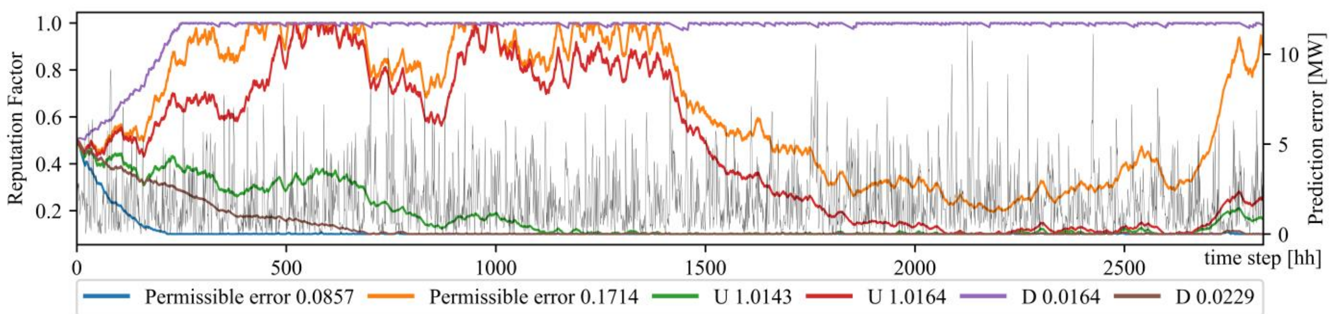

Figure 3 - Reputation with algorithm 2, varied input parameters. Default values: U=1.0155, D=0.0307, Permissible error=0.15

the prediction error information obtained from the OpenLV project. The default values are the values used unless specified otherwise.

A number of observations can be made from the results. For algorithm 1, a greater value of D implies that a meter's reputation is more likely to fall for a given prediction error. Conversely, a smaller U or Peak factor implies that a meter's reputation is more likely to fall for a given prediction error. For algorithm 2, a greater value of D again implies that a meter's reputation is more likely to fall for a given prediction error. A smaller U or permissible error implies that a meter's reputation is more likely to fall for a given prediction error. Finally, the PI values calculated in Table provide an indicator of how the reputation algorithm will behave when applied to the real data. In all of the test cases, the lower the value of PI is, the more likely the reputation algorithm is to rise rather than fall.

VI. Discussion

The results presented in Fig. 2 and Fig. 3 show that both the proposed algorithms give the system governor means to vary the sensitivity of a meter's reputation to its prediction error. This gives the system governor the ability to moderate the meter reputations upwards or downwards, by adjusting the U parameter, for instance. This creates a new control tool to manage the stability of the system through influencing the quality of prediction information from the system's meters. Furthermore, the mechanism designer can create a set of rules in which the system governor would be able to modulate how much meters are rewarded for providing accurate predictions. The system governor can then make parameter adjustments to improve the prediction information from the system's meters, according to its requirements.

If this system were instantiated as part of a smart contract based system, it could be implemented in a way such that the governor could only moderate reputations (e.g. the U or D parameters) for whole classes of meter (e.g. LV single phase meters, or 11kV inter-network meters). If the meter classes are chosen carefully, this would remove the possibility for targeting of individual meter reputations through malign or accidental adjustment. Furthermore, mechanism designers would have the option to use reputation factor as a reward modifier. For example, payments could be taken from those tending to imbalance the system, and transferred to those tending to balance it, with the imbalance-balance direction determined during the settlement period. In this way a system wide focal point could be created around the demand supply balance, with the potential for gaming the system reduced through means of the meter reputations. This is the subject of ongoing research [26].

VII. Conclusions

Through presentation and demonstration of two algorithms, this research shows that the application of reputation factors to meters, based on their individual predictions and actual readings is feasible. A performance index was defined and shown to be a rough indicator of how a meter's reputation recovers (with accurate predictions) and depletes (with poor predictions) over a defined period. The presented algorithms give negotiation and settlement mechanism designers a means to stimulate the creation of economic focal points in demand supply balance. However, the instantiation of such algorithms in such a way that makes persecution of individuals impossible is crucial.

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