Balancing Agility and Stability of Wireless Link Quality Estimators

Mohamad Javad Tanakian
Department of Telecommunication Engineering, Faculty of Electrical & Computer Engineering,
University of Sistan and Baluchestan, Zahedan, Iran
mj.tanakian@pgs.usb.ac.ir
Mehri Mehrjoo*
Department of Telecommunication Engineering, Faculty of Electrical & Computer Engineering,
University of Sistan and Baluchestan, Zahedan, Iran
mehrjoo@ece.usb.ac.ir

Received: 04/Mar/2019 Revised: 17/Oct/2019 Accepted: 02/Dec/2019

Abstract

The performance of many wireless protocols is tied to a quick Link Quality Estimation (LQE). However, some wireless applications need the estimation to respond quickly only to the persistent changes and ignore the transient changes of the channel, i.e., be agile and stable, respectively. In this paper, we propose an adaptive fuzzy filter to balance the stability and agility of LQE by mitigating the transient variation of it. The heart of the fuzzy filter is an Exponentially Weighted Moving Average (EWMA) low-pass filter that its smoothing factor is changed dynamically with fuzzy rules. We apply the adaptive fuzzy filter and a non-adaptive one, i.e., an EWMA with a constant smoothing factor, to several types of channels from short-term to long-term transitive channels. The comparison of the filters outputs shows that the non-adaptive filter is stable for large values of the smoothing factor and is agile for small values of smoothing factor, while the proposed adaptive filter outperforms the other ones in terms of balancing the agility and stability measured by the settling time and coefficient of variation, respectively. Notably, the proposed adaptive fuzzy filter performs in real time and its complexity is low, because of using limited number of fuzzy rules and membership functions.

Keywords: Link quality estimation; adaptive fuzzy filter; agility; stability; wireless channel.

1- Introduction

Telecommunication network is deployed in smart grid to exchange the measurement status and instructions of numerous widely distributed control devices of power grid. Among different telecommunication networks, Wireless Networks (WNs), because of the low cost and flexibility of installation and maintenance are more probable to be deployed for monitoring, collecting data and controlling smart grid assets [1],[2]. The success of WN applications depends on the reliable transmission of sensory data. Reliability is defined as the success rate of source to destination data transmission in the network within its required latency. Accordingly, research community has been paying significant attention to design and implementation of reliable data transmission protocols in WNs [3],[4],[5],[6],[7],[8]. The performance of a large number of these protocols is highly dependent on Link Quality Estimation (LQE) [3],[4],[6],[7],[8]. Poor LQE may lead to an unstable network with high packet loss and/or high delay.

Performance of LQE is assessed in terms of accuracy, cost, agility and stability [9]. Accuracy is quantified by comparing the measured link quality and the estimated link quality using the Mean Square Error (MSE) metric. Consuming the energy by excessive re-transmissions, occurred by imperfect link estimation, over low quality links is inferred as cost. Agility is the ability to react quickly to persistent changes in link quality. Agility is measured by settling time, defined as the time needed by the estimator to reach the measured value within an error bound of e. Finally, stability is the ability to resist the short-term variations, a.k.a, fluctuations, in link quality. Stability is assessed quantitatively, by the Coefficient of Variation (CV) defined as the ratio of the standard deviation to the mean of variations. Balancing between agility and stability is of paramount importance in a deployed LQE in WNs. In general, whenever the overhead of signaling is high and the decision is made based on the channel status the balancing between stability and agility becomes critical. For example handover and scheduling in cellular network or routing in wireless local area network. Routing protocols do not have to reroute information when a link quality shows transient degradation, because rerouting is a very energy and time-consuming operation. Too frequent protocol updates may cause unexpected network problems, such as, routing loops and routing shocks [10].

* Corresponding Author

LQEs are classified in two categories, hardware and software based LQEs [9], [11]. In the hardware based LQEs, the estimation is based on the measurement of a dedicated signal either on the transmitter or the receiver side and do not require any further computation; however, they are not as good as software based LQEs [9],[13]. The received signal strength (RSS), link quality indicator (LQI), and signal-to-noise ratio (SNR) are primary metrics used in hardware-based LQE [11]. In particular, none of these metrics by itself is sufficient to accurately characterize the quality of a link because [11],[13]: (i) the RSS is not sensitive to changes in link quality; (ii) the variance of LQI readings is significantly increased for transitional links, and (iii) the SNR rapidly and randomly fluctuates. Software based LQEs are divided into two categories: (1)Single metric based,(2)Hybrid metric based.

Single metric based estimators count or approximate either (i) the reception rate or (ii) the average number of packet transmissions/retransmissions required before its successful reception. For instance, Packet Reception Rate (PRR) of a wireless link over an estimation window consisting of *w* instances of communication and Acquitted Reception Rate (ARR) count the reception rate at receiver side and sender side, respectively [9],[11]. Required Number of Packet transmissions (RNP) counts the average number of packet transmissions/retransmissions required before its successful reception within a window of *w* communication instances [9]. Furthermore, the expected transmission count (ETX) takes into account link asymmetry by estimating the uplink quality and downlink quality using both forward and backward PRR values, respectively [12].

Hybrid metric based LQEs consider a number of link quality metrics. For instance, Four-bit LQE combines individual estimations of uplink and downlink qualities based on measured RNP and PRR, respectively [14]. Stable Link Quality Estimation (SLQE) combines active probing with passive snooping to make a stable estimation [10]. In this estimator, an active node sends control packets periodically and uses long period active detection mechanisms to detect quality of the link, while a passive node listens RSS Indicator mean and perceives links in sudden changes effectively. Fuzzy Link Quality Estimator (F-LQE) deploys four link quality properties, namely, packet delivery, link quality difference of forward and backward direction (asymmetry), stability, and SNR of a transceiver [15]. Each of the link properties is considered as a different fuzzy variable. Opt-FLQE (Optimized FLQE) [16] is a modification of F-LQE that aims to improve its reactivity and to reduce its computational complexity. A method that uses fuzzy logic to combine LQI, SNR and PRR metrics is proposed in [17] to improve the accuracy rate for evaluating a link quality. Fuzzy logic based link quality indicator (FLI) uses the PRR, the coefficient of variance of PRR, and a metric to assess the burstiness of packet loss, to estimate link quality [18]. Remarkably, all the research works on fuzzy link quality estimator have limited the application of the fuzzy system to combine some ELQ metrics. Kalman filter based LQE approximates the packet reception ratio based on RSSI and a pre-calibrated PRR/SNR curve [19].

In the cases of the PRR, RNP, and ETX, there is a tradeoff between estimation accuracy and latency. For example, the estimation latency can be improved by shortening the window size *w*, but at the cost of increased fluctuation in the estimation results and degraded estimation accuracy [11],[17]. To address this problem, some LQEs apply Exponentially Weighted Moving Average (EWMA) filter on the estimated link quality (ELQ) which smooth the variations of it to turn them robust against the fluctuations [9],[11],[15]. In these LQEs, the EWMA, a non adaptive Infinite Impulse Response (IIR) filter, is tuned by a constant smoothing factor α, where $0 \leq \alpha \leq 1$. A stricter smoothing filter, to remove the transient variations, is needed when fluctuation amplitude is high. On the other hand, the strict smoothing filter prevents following link quality status when it has a relatively high persistent change in link quality [9],[10],[15],[17]. Therefore, the smoothing factor of filter should be tuned carefully proportional to the amount of fluctuation and the persistent changes in link quality.

In this paper, inspired by our previous research work on video stabilization [20], we propose an adaptive fuzzy system to tune the EWMA filter, named adaptive fuzzy filter. The fuzzy system has two inputs and one output, so it requires low computation resources and responds in real-time. As the inputs, the fuzzy system uses quantitative representations of the transient variations and the persistent changes in estimated link quality. The fuzzy inputs are defined according to the few numbers of the last estimated link qualities. The output of fuzzy system calculates the best value of smoothing factor to tune the EWMA filter adaptively. The performance of the proposed adaptive fuzzy filter in terms of stability and agility is compared with the results provided by an EWMA filter with a three different constant smoothing factors. Numerical results show that our proposed adaptive fuzzy filter provide balanced stable and agile estimation results, while the ones of a constant smoothing factor filter are either stable or agile, depending on the value of the filter smoothing factor.

The remainder of this paper is organized as follows. The basic concept and details of the proposed filter are described in Section 2. The numerical results are presented in Section 3, and the paper is concluded in Section 4.

2- Proposed Filter

The adaptive fuzzy filter consists of a fuzzy system and an EWMA filter whose smoothing factor is tuned by the fuzzy system. In this section, first we briefly explain fuzzy system, and then we describe the proposed filter.

2-1- Fuzzy System

Fuzzy logic is an approach to computing based on "degrees of truth", rather than the usual "true or false"(1 or 0) Boolean logic on which the modern computer is based. Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. The fuzzy logic system incorporates five steps as shown in Fig.1. It starts with fuzzification process, then the inference system comes, including: application of the operators, implication methods, and aggregation all outputs to one fuzzy output, finally defuzzify the fuzzy output to numerical values [21],[22].

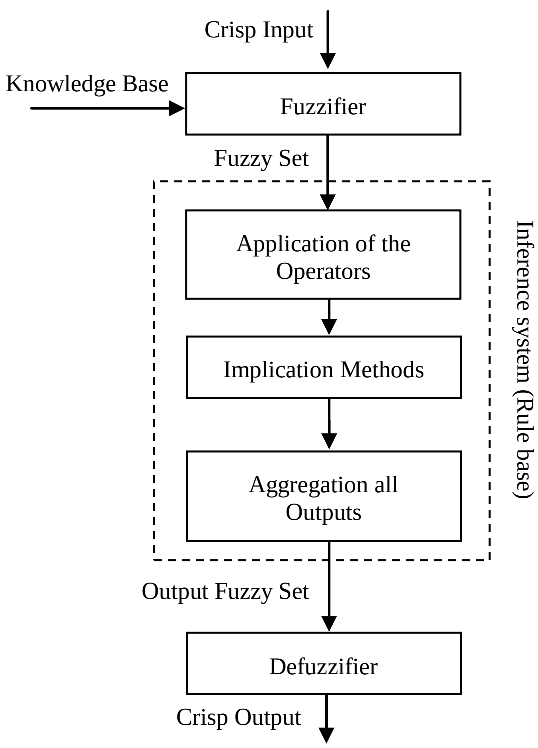


Fig. 1 The architecture of fuzzy logic system [22]

The fuzzy knowledge base includes rule base and the database. The rule base contains a number of IF-THEN rules, and the database defines the membership functions (MF) of the fuzzy sets. Fuzzifier converts the crisp input to a linguistic variable using the MF stored in the fuzzy knowledge base. Inference system converts the fuzzy input to the fuzzy output using IF-THEN fuzzy rules. Defuzzifier converts the fuzzy output of the inference system to crisp using membership functions analogous to the ones used by the Fuzzifier. The logic operators that combine the sets in the antecedent define the relationships between input sets. This process includes three steps based on the rules of the fuzzy logic to be followed [22]: i)applying the operators of the rules when there is more than one part for the antecedent of the rule. This step results in one number (between 0 and represents all parts of the antecedent based on the operator of the rule .ii) finding the consequence of the rules by combining the rule strength and the output membership function which is defined as implication and iii) combining the consequences to get an output distribution which is defined as aggregation.

2-2- Adaptive Fuzzy Filter

The ELQ of a wireless link fluctuate over time due to many factors, principally related to the physical environment and the nature of low-power radios. Assuming that ELQ variation corresponds to its high-frequency components; we smoothen ELQ using a low-pass filter tuned by a fuzzy system to achieve Fuzzy Filtered Estimated Link Quality (FFELQ).The EWMA, first-order IIR filter, as the low-pass filter is applied to ELQ, at time interval n, and the FFELQ is resulted:

$$FFELQ\,(n) = \alpha\,(n) \times FFELQ\,(n\text{-}1) + (1 - \alpha\,(n)) \times ELQ\,(n) \qquad (1)$$

The parameter α, $0 \leq \alpha \leq 1$, is regarded as the smoothing factor of the filter and adjusted by the fuzzy system in each time interval. The fuzzy system has two inputs (Input1, Input2) and one output. The Input1 and Input2, calculated during link quality status estimation, represent the amount of fluctuations and persistent changes in link quality at time interval n, respectively. The output of fuzzy system defines the smoothing factor α of the EWMA filter. The block diagram of the proposed adaptive fuzzy filter is depicted in Fig. 2.

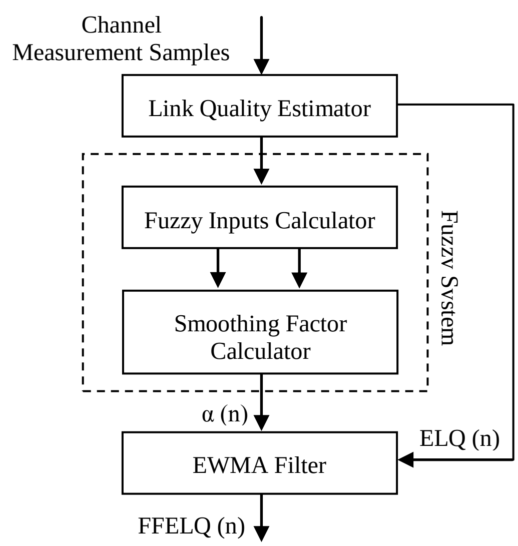


Fig. 2 Block diagram of adaptive fuzzy filter

We define the fuzzy inputs as

$$Input1(n) = \frac{1}{M}\sum_{i=n-M+1}^{n}|ELQ(i) - ELQ(i-1)| \quad (2)$$

$$Input2(n) = \left|\sum_{i=n-M+1}^{n}\big(FFELQ(i-1) - ELQ(i-1)\big)\right| \quad (3)$$

where M+1 is the number of the last ELQs deployed in computation. Input1 is the average of absolute differences between consequent ELQs. Input2 is the absolute sum of difference between ELQ and FFELQ.

To justify Input1 and Input2 definitions, consider the two scenarios shown in Fig.3. The last four samples are considered for inputs computing. In Fig. 3(a) and 3(b), the amount of amplitude changes in the ELQ (solid line) are within the range of (0.47~0.50) and (0.54~0.65), respectively. The total amount of link quality fluctuations in Fig. 3(b) is more than the ones of Fig. 3(a). In addition, the FFELQ (dash line) follows ELQ path direction in Fig. 3(a), while the FFELQ in Fig. 3(b) is moving away from the ELQ path direction. Therefore, the Input2 is defined to reduce the deviation. The values of Input1 and Input2 are derived with (2) and (3) shown in Table1. The output of fuzzy system defines the smoothing factor of the EWMA filter, i.e., α.

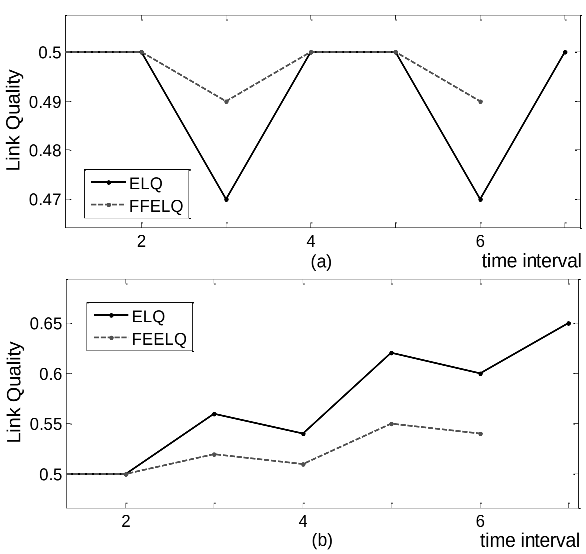


Fig. 3 (a) transient degradation with no persistent changes in link quality (b) fluctuation and the persistent changes in link quality

Table1: Values of fuzzy inputs for the two scenarios in Fig.3

	Input1	***Input2***
Scenario1 (Fig. 3(a))	0.02	0.02
Scenario2 (Fig. 3(b))	0.05	0.16

In the proposed fuzzy system, trapezoidal and triangular MFs are used for the inputs and the outputs, respectively. Trial and error method is used for MF shape of the inputs and the output. Type of MF doesn't play a crucial role in shaping how the model performs. However, the number of MF has greater influence as it determines the computational time [23]. We select as few MFs as possible to maintain low system complexity while we obtain decent performance. The experimentally designed inputs and output MFs as well as the surface of the desired output, which is a graphical interface that allows you to examine the FIS output surface for two inputs, are shown in Fig.4.

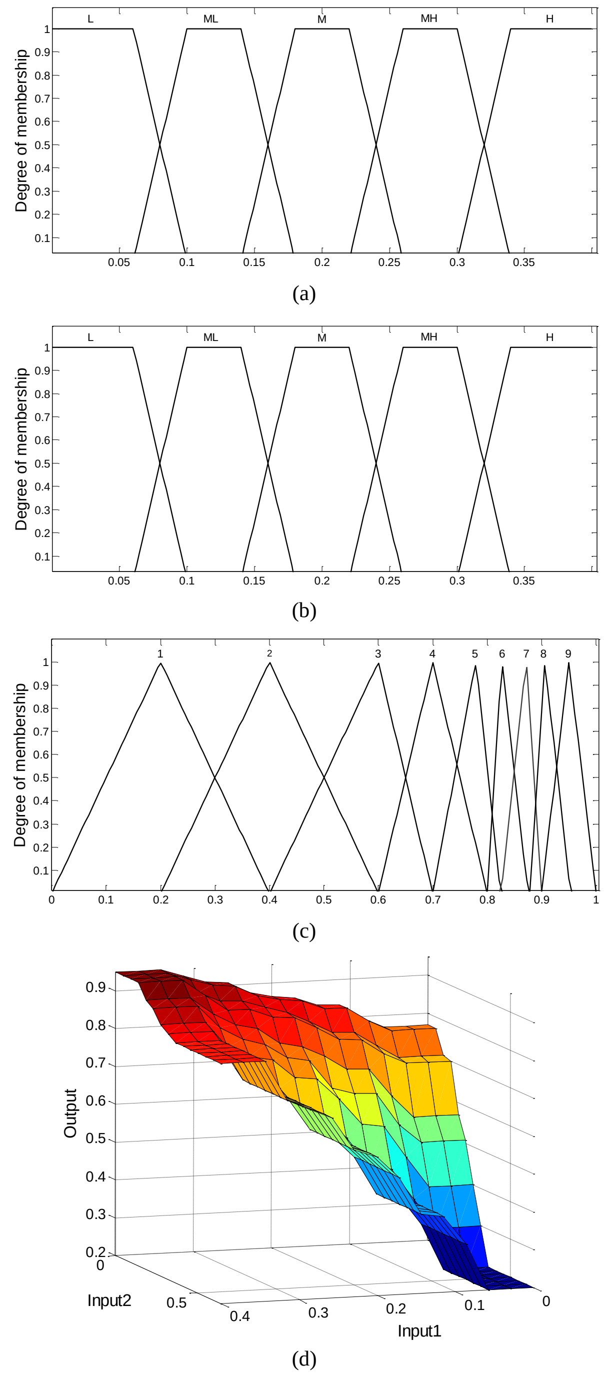


Fig. 4 (a) MFs of fuzzy Input1 (b) MFs of fuzzy Input2, (c) MFs of fuzzy output, (d) surface of desired outputs

Table2: Central Values of fuzzy system output

		Input 2				
		L	ML	M	MH	H
Input1	L	0.8	0.7	0.6	0.4	0.2
	ML	0.825	0.8	0.7	0.6	0.4
	M	0.875	0.825	0.8	0.7	0.6
	MH	0.9	0.875	0.825	0.8	0.7
	H	0.95	0.95	0.9	0.875	0.825

* L=Low, ML=Medium Low, M=Medium, MH=Medium High, H=High.

According to experimental results, the performance of the EWMA filter is more sensitive to larger values of α[20]. Therefore, more MFs of the fuzzy output are concentrated in this operating area. The constructed rule base is containing 25 rules as presented in Table 2. The proposed fuzzy system is implemented while the min function is used for the fuzzy implication and the max function is used for the fuzzy aggregation. Furthermore, the centroid defuzzification method is applied. After computing the smoothing factor α (n) by the fuzzy system, FFELQ is calculated by Equation (1).

3- Numerical Results

In this section, the performance of the proposed adaptive fuzzy filter in terms of stability and agility of the LQE is compared with the results provided by a non-adaptive EWMA filter with a three different constant smoothing factors α = 0.9 [16] , α = 0.5, and α = 0.2. The performance has been evaluated with several different recognized scenarios extracted from link quality status curves published in the literature [9], [10], [24], [25] and some synthetic link quality status trajectory: (a) link quality mutation frequently occurs in short times, (b) link quality remains unstable for a long time, (c) link quality is relatively stable, (d) link quality has persistent changes. To adjust the fuzzy system inputs, the initial value α = 0.1 is chosen for the first four time intervals. To keep the computation delay low, the filter window size M=3 is chosen. The simulation tools is MATLAB 8.2.0.701 (R2013b, 32-bit) and the hardware configuration are: Intel(R) Core(TM) Duo CPU T9300 2.5GHz and 3.00GBRAM. The average simulation time for our adaptive fuzzy filter and non-adaptive filter with a constant smoothing factor are 3.4 msec and 10 µsec, respectively. Therefore, to apply our adaptive fuzzy filter, the time interval between link quality calculations should be longer than 3.5 msec.

It is observed that a large smoothing factor, e.g. α = 0.9, increases the stability of estimators at the expense of a relatively large delay when there are persistent changes in link quality. Similarly, a small smoothing factor, e.g. α = 0.2, closely tracks the persistent changes in calculated link quality at the cost of slightly reduced smoothing capabilities. In fact, a small smoothing factor just follows the original ELQs. Comparing the graphs shows that the proposed fuzzy filter provides expanded smoothing while enables the close tracking of the persistent changes in ELQs, i.e., the proposed method provides both agility and stability. The temporal behavior in Fig. 5(a), has sudden drop at t=7, t=13, and t=25. The results demonstrate adaptive fuzzy filter and the non-adaptive filter with α = 0.9 smooth the ELQ and resist these temporary changes. While the non-adaptive filters with lower value of α does not perform well against the transient fluctuations. The same observation can be seen in Fig. 5(b) and 5(c).

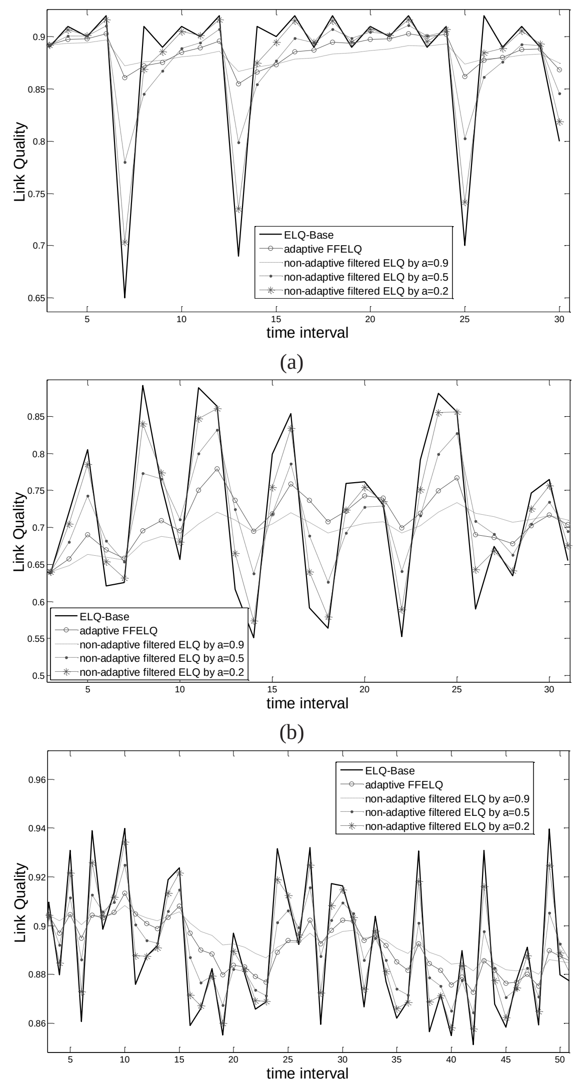


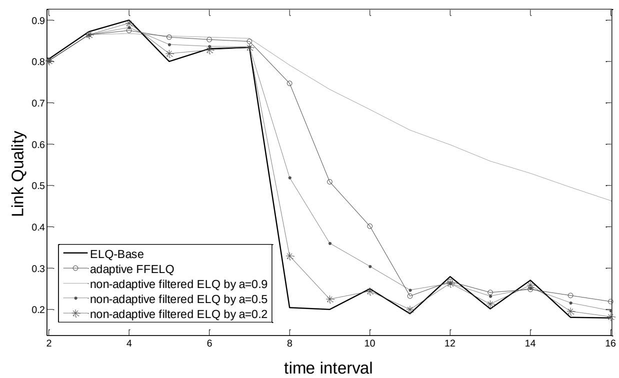
Fig. 5 Comparison results of EWMA filtering of low persistent ELQs with adaptive fuzzy filter and non-adaptive filter with different constant smoothing factors

In Fig. 6(a), (b), (c) and (d) the link quality curves have a high persistent change. The results show that the non-adaptive filter with α = 0.9 has a long delay to track the persistent changes. On the contrary, the delay is low when the smoothing factor is low. The adaptive fuzzy filter has a moderate delay in tracking the persistent change with the price of being stable in transient changes. In other words, the results shown in Fig.5 and Fig.6 indicate that the adaptive fuzzy filter can distinguish well between transient and non-transient changes of the link quality.

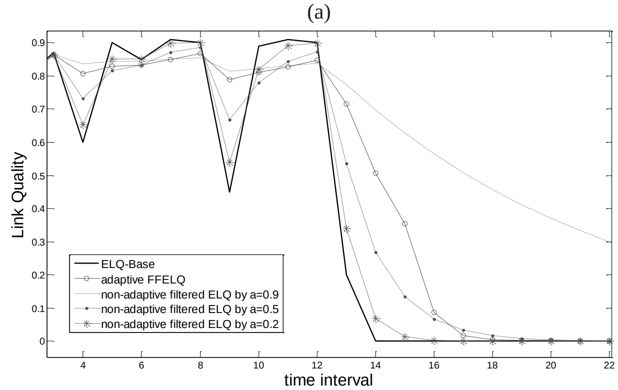
The Coefficient of Variation (CV), defined as the ratio of the standard deviation to the mean, shows the performance of the LQEs in terms of stability [9],[15]. The CV for the low persistent link quality curves shown in Fig.5, are presented in Table3. The lower CV represents the more stable estimation. The CV values of the filtered ELQs by the adaptive fuzzy filter and non-adaptive fuzzy with α = 0.9 are low compared to the two others. Hence the formers are more stable estimation.

Agility is measured by settling time (ST), defined as the time needed by the estimator to reach the measured value within an error bound of *e* [9]. The lower ST represents the more agile estimation. The CV and ST for the four link quality curves shown in Figure 6, are presented in Table4. The value of ST is in terms of time interval and *e* is about 5%. The numerical results show the adaptive fuzzy filter provide a balanced stable and agile estimation results, while the ones of constant smoothing factor filters are either stable or agile, depending on the value of the smoothing factor.

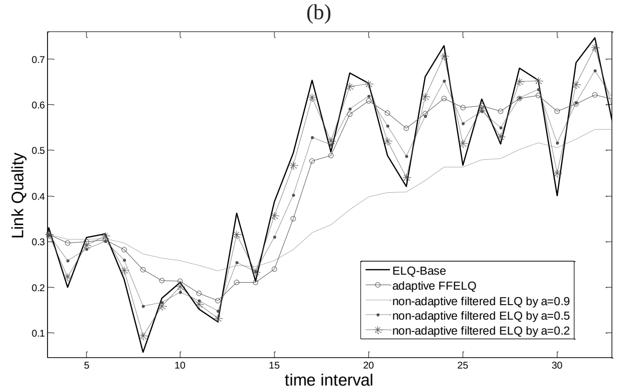
The empirical Cumulative Distribution Function (CDF) of two different links, which are shown in Figure 5(a) and Figure 6(d), is presented in Figure 7 for proposed adaptive fuzzy filter and non-adaptive filter with a three different constant smoothing factors α = 0.9 , α = 0.5 and α = 0.2. At the same time that the adaptive filter tries to balance between agility and stability, it should be confident to real quality of the link as much as possible. In other words, the proportions of link quality in terms of poor, moderate, or high quality in the CDF of basic ELQ, not filtered one, should remain almost the same in the CDF of the filtered ELQ. The presented scenario in Figure 5(a) shows a link with constant qualities equal to 0.9, and the presented scenario in Figure 6(d) shows that almost 28% of the link is in near to high quality; about 60% of the links is in intermediate quality; and about 12% of the link is in poor quality. According to the results shown in Fig. 7, adaptive LQE classify the link qualities close to the proportions set in these scenarios. The comparison results show that the non-adaptive filter with a smaller and larger constant smoothing factor over estimate and underestimate the link quality, respectively.



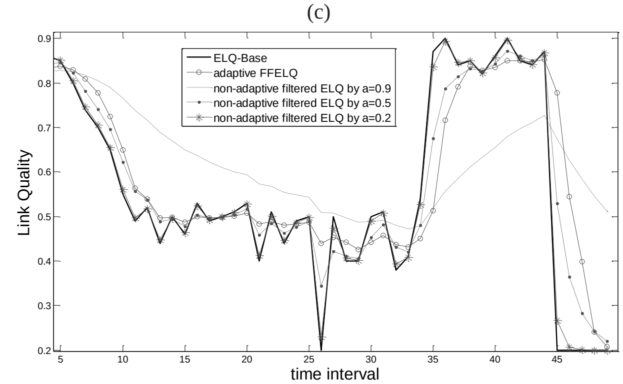
(a)



(b)



(c)



(d)

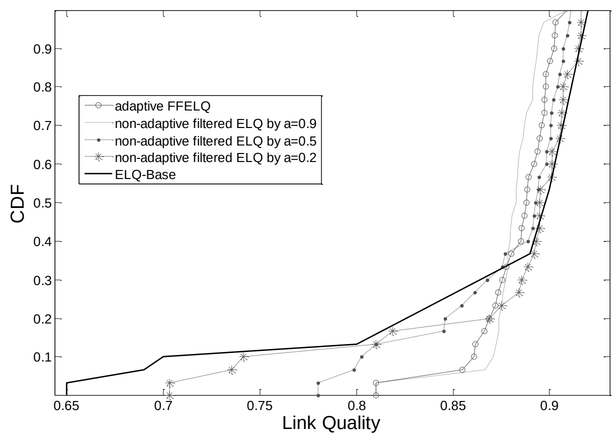
Fig. 6 Comparison results of EWMA filtering of high persistent ELQs with adaptive fuzzy filter and non-adaptive filter with different constant smoothing factors

Table 3: The coefficient of variation for presented results in Fig. 5

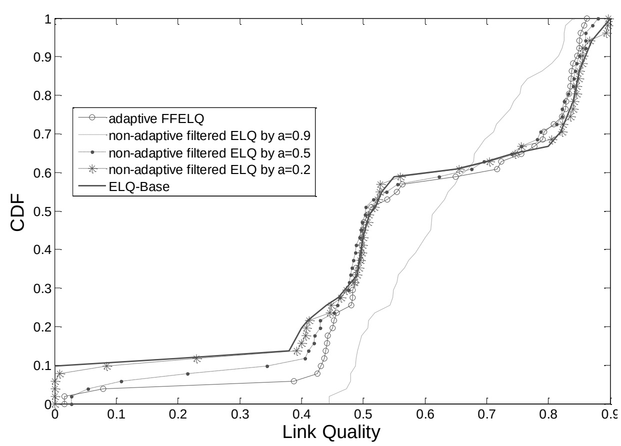
Link Quality	CV			
	adaptive fuzzy filter	non-adaptive filter		
		α = 0.9	α = 0.5	α = 0.2
Link1 (Fig. 5(a))	0.0225	0.0184	0.0422	0.0647
Link2 (Fig. 5(b))	0.0496	0.0378	0.0781	0.1198
Link3(Fig. 5(c))	0.0230	0.0221	0.0261	0.0311

Table 4: The coefficient of variation and settling time for presented results in Fig.6

Link Quality	Criterion	adaptive fuzzy filter	non-adaptive filter		
			α = 0.9	α = 0.5	α = 0.2
Link1 Fig. 6(a)	CV	0.5095	0.2039	0.5494	0.6202
	ST	4	more than 9	9	2
Link2 Fig. 6(b)	CV	0.7140	0.2901	0.7723	0.8791
	ST	4	more than 10	4	3
Link3 Fig. 6(c)	CV	0.4147	0.2954	0.4316	0.4576
	ST	4	more than 15	4	4
Link4 Fig. 6(d)	CV	0.3034	0.1791	0.3250	0.3748
	ST	4	more than 6	4	2



(a)



(b)

Fig 7. Empirical CDFs of link quality estimators for two scenarios are presented graphically in (a) Fig 5(a) and (b) Fig 6(d).

When measuring the quality of a link over a given period, all sorts of different scenarios may occur in the combination of noise and persistent changes in link quality. Generally, as shown in the Fig. 8, selecting a constant value for α causes the EWMA filter output to works fine in either noise-canceling or in tracking the persistent changes, not necessarily both. Therefore, a dynamic value for α is required. The fuzzy system adapts the system to different scenarios and chooses an appropriate value for α at any given moment.

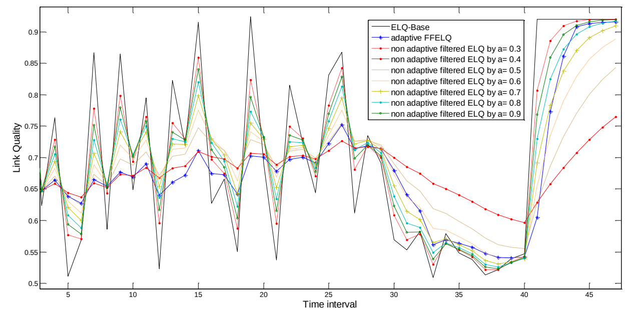


Fig 8. Comparison results of EWMA filtering with adaptive fuzzy filter and non-adaptive filter with different constant smoothing factors

4- Conclusion

An adaptive fuzzy filter to smooth transient variations of LQE has been proposed in this paper. The filter makes a balance between stability and agility in LQE. The proposed filter consists of an EWMA filter and a fuzzy system. The performance of the EWMA filter depends on the value of the smoothing factor which is tuned by the fuzzy system. The fuzzy system uses two inputs which are quantitative representations of the transient and the persistent changes in link quality status. In the fuzzy inputs, we selected as few MFs as possible to obtain decent performance with low system complexity. We have evaluated the filter in terms of stability and agility with CV and ST metrics. Numerical results show that our proposed adaptive fuzzy filter provides balanced, stable and agile, estimation results, while the ones of a constant smoothing factor filter are either stable or agile, depending on the value of the filter smoothing factor. The adaptive fuzzy filter is more complex with respect to the non-adaptive EWMA. However, the complexity cost is negligible with respect to the resource utilization improvement and/or signaling overhead reductions (e.g., rerouting).

References

[1] V.C. Gungor, D. Sahin, T. Koçak, S. Ergüt, C. Buccella, C. Cecati, and G.P. Hancke, "Smart grid technologies: Communication technologies and standards, ", IEEE Transactions on Industrial Informatics, Vol. 7, No. 4, 2011, pp. 529–539.

[2] H.M.Nejad,N.Movahhedinia, and M.R.Khayyambashi, "Provisioning required reliability of wireless data communication in smart grid neighborhood area networks",The Journal of Supercomputing, Vol.73, No.2, 2017, pp. 866–886.

[3] J. Cai, X.Song,J.Wang, and M.GU, "Reliability analysis for chain topology wireless sensor networks with multiple-sending transmission scheme" ,EURASIP Journal on Wireless Communications and Networking, Vol. 2014,No. 1, pp,156-169.

[4] T.Korkmaz, and K.Sarac, "Characterizing link and path reliability in large-scale wireless sensor networks", Proceedings of the 2010 IEEE 6th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), 2010, pp. 217–224.

[5] M. Kumar, R. Tripathi, and S. Tiwari, "QoS guarantee towards reliability and timeliness in industrial wireless sensor networks",Multimedia Tools and Applications, Vol. 77, No. 4, 2018, pp. 4491–4508.

[6] W. Sun, W. Lu, Q. Li, L. Chen, D. Mu, and X. Yuan, "WNN-LQE: Wavelet-neural-network-based link quality estimation for smart grid WSNs", IEEE Access, Vol. 5, 2017, pp. 12788–12797.

[7] F. Aalamifar, and L. Lampe, "Cost-efficient QoS-Aware Data Acquisition Point Placement for Advanced Metering Infrastructure", IEEE Transactions on Communications (Early Access), Vol.66, No. 12, 2018, [Online]. Available:https://arxiv.org/abs/1802.06656.2018.

[8] X.Zhu,Y.Lu,J.Han,andL.Shi, "Transmission Reliability Evaluation for Wireless Sensor Networks", International Journal of Distributed Sensor Networks,Vol. 2016,DOI:http://dx.doi.org/10.1155/2016/1346079.

[9]N. Baccour, A.Koubaa,M.B.Jamaa,H.Youssef,M.Zuniga,andM.Alves, "A comparative simulation study of link quality estimators in wireless sensor networks", IEEE International Symposium on Modeling, Analysis and Simulation of Computer and Telecommunication Systems (MASCOTS'09),2009,DOI: 10.1109/MASCOT.2009.5366798

[10]A. Zhou,B.Wang,S.Xingming,X.You,H.Sun,andT.Li, "SLQE: an improved link quality estimation based on four-bit LQE",International Journal of Future Generation Communication and Networking, Vol.8, No.1, 2015, pp. 149–160.

[11] W. Sun, X. Yuan, J. Wang, Q. Li, L. Chen, and D. Mu, "End-to-end data delivery reliability model for estimating and optimizing the link quality of industrial WSNs", IEEE Transactions on Automation Science and Engineering, Vol. PP, No. 99, 2017, pp. 1–11.

[12] D. S. De Couto, D. Aguayo, J. Bicket, and R. Morris, "A high-throughput path metric for multi-hop wireless routing", Wireless Networks., Vol. 11, No. 4, 2005, pp. 419–434.

[13] A. Vlavianos, L.K. Law, L. Broustis, S. Krishnamurthy, and M. Faloutsos, "Assessing link quality in wireless networks: Which is the right metric? ",IEEE 19th International Symposium on Personal, Indoor and Mobile Radio Communications, 2008, pp. 1–6.

[14] R.Fonseca,O.Gnawali,K.Jamieson,andP.Levis,"Four-Bit Wireless Link Estimation", In Proceedings of the 6th Workshop on Hot Topics in Networks (HotNetsVI), 2007.

[15] N. Baccour, A.Koubaa, H.Youssef, and M.Alves, "Reliable link quality estimation in low-power wireless networks and its impact on tree-routing", Ad Hoc Networks,Vol. 27, 2015, pp.1–25.

[16] S. Rekik, N. Baccour, M. Jmaiel, and K. Drira , " Low-power link quality estimation in smart grid environments ", International Wireless Communications and Mobile Computing Conference (IWCMC 2015), pp. 1211-1216, 2015.

[17] Z. Huang, L. Y. Por, T. F. Ang, M. H. Anisi, and M. S. Adam , "Improving the Accuracy Rate of Link Quality Estimation Using Fuzzy Logic in Mobile Wireless Sensor Network ", Advances in Fuzzy Systems, vol. 2019, Article ID 3478027, 13 pages, https://doi.org/10.1155/2019/3478027, 2019.

[18] Z. Q. Guo, Q. Wang, M. H. Li, and J. He, " Fuzzy logic based multidimensional link quality estimation for multi-hop wireless sensor networks ", IEEE Sensors Journal, vol.13, no.10, pp. 3605-3615, 2013.

[19] M. Senel, K. Chintalapudi, D. Lal, A. Keshavarzian, and E. J. Coyle, "A kalman filter based link quality estimation scheme for wireless sensor networks", IEEE Global Telecommunications Conference (GLOBECOM07), 2007.

[20] M.J. Tanakian, M. Rezaei, and F.Mohanna , "Digital video stabilizer by adaptive fuzzy filtering", Journal Image Video Proc , vol.21, doi:10.1186/1687-5281-2012-21,2012

[21] L. A. Zadeh, “Fuzzy sets,” Information and Control, Vol. 8, 1965, pp. 338-353.

[22] A. Abdel-Aleem, M.A.El-sharief, M.A. Hassan, and M.G. El-sebaie, "Implementation of fuzzy and adaptive neuro-fuzzy inference systems in optimization of production inventory problem", Applied Mathematics & Information Sciences, Vo.11, No.1, 2017, pp.289–298

[23] A. Sadollah, Fuzzy Logic Based in Optimization Methods and Control Systems and Its Applications, London: IntechOpen, 2018, DOI: 10.5772/intechopen.73112.

[24] S. Woo and H. Kim, "An empirical interference modeling for link reliability assessment in wireless networks", IEEE/ACM Transactions on Networking, Vol. 21, Issue 1, 2013, pp. 272 – 285.

[25] P. Millan, C. Molina, E. Medina, D. Vega, R.Meseguer, B. Braem, and C. Blondia, " Tracking and predicting link quality in wireless community networks", In IEEE 10th international conference on wireless and mobile computing, networking and communications (WiMob)(pp. 239–244).

.

Mohamad Javad Tanakian received the B.S. and M.S. degrees in Electrical engineering in 2007 and 2011, from University of Sistan and Baluchestan(USB), Zahedan, Iran, respectively. He is now Ph.D. candidate in telecommunication engineering in the USB. He has been working as a Fiber optic expert at Sistan and Baluchestan Regional Electric Company (SBREC) since 2014. His research interests are in the area of wireless communication, smart grid communication, signal processing, image and video processing and fuzzy systems

Mehri Mehrjoo received the B.A.Sc. and the M.A.Sc. degrees from Ferdowsi University, Mashhad, Iran, and Ph.D. from the University of Waterloo, Waterloo, Canada in 1993, 1996, and 2008, respectively. From 2008 to 2009, she has been a post-doctoral fellow at the University of Waterloo. She is an IEEE senior member. Currently, she is an associate professor in the Department of Telecommunications, University of Sistan and Baluchestan, Zahedan, Iran. Her research interests are in the areas of resource allocation and performance analysis of broadband wireless protocols.