Univerza v Ljubljani
Fakulteta za elektrotehniko

LAK

Samorazvijajoči se sistemi na podlagi toka podatkov v modeliranju in vodenju

Seminarska naloga 1

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Samorazvijajoči se (inteligentni) sistemi

- **Samorazvijajoči se (inteligentni) sistemi** (*evolving inteligent systems*) adaptirajo (*adapt*) tako svoje **parametre** kot tudi **strukturo** z **enkratnim prehodom** čez podatke (*single-pass*) [1] in **v realnem času** (*real time*) [2].

- **Okolje** (*environment*), v katerem gradimo samorazvijajoči model, je **nezanano** in model je zgrajen **brez a priori informacij** (središča rojev, števila pravil itd.).

- Strukturo lahko sestavljajo: **mehka pravila** (*fuzzy rules*) [1,3], **informacijske granule** (*information granules*) [4,5], **nevroni** (*neurons*) [6], **odločitvena drevesa** (*decision tree*) [7], **intervalni modeli** (*interval*) idr.

- Te strukture so uporabljene zaradi večje **transparentnosti** in **lingvistične interpretabilnosti** od drugih modelov črne škatle (*black-box*) [6].

[1]Angelov, P. P., & Filev, D. P. (2004). An Approach to Online Identification of Takagi-Sugeno Fuzzy Models. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 34(1), 484–498.
[2] Skrjanc, I. (2020). Cluster-Volume-Based Merging Approach for Incrementally Evolving Fuzzy Gaussian Clustering-eGAUSS+. *IEEE Transactions on Fuzzy Systems*, *28*(9), 2222–2231.
[3] Dovžan, D., Logar, V., & Škrjanc, I. (2015). Implementation of an Evolving Fuzzy Model (eFuMo) in a Monitoring System for a Waste-Water Treatment Process. IEEE Transactions on Fuzzy Systems, 23(5), 1761–1776.
[4] Leite, D., Andonovski, G., Skrjanc, I., & Gomide, F. (2020). Optimal rule-based granular systems from data streams. IEEE Transactions on Fuzzy Systems, 28(3), 583–596.
[5] Leite, D., Costa, P., & Gomide, F. (2010). Granular Approach for Evolving System Modeling. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 6178 LNAI, 340–349.
[6] Leite, D., Škrjanc, I., & Gomide, F. (2020). An overview on evolving systems and learning from stream data. Evolving Systems, 11(2), 181–198.
[7] Lemos, A., Caminhas, W., & Gomide, F. (2010). Evolving fuzzy linear regression trees. 2010 IEEE World Congress on Computational Intelligence, WCCI 2010.

Samorazvijajoči se (inteligentni) sistemi

- **modeliranje**, **identifikacija**, **sklepanje** (*inference*), **vodenje**, **napovedovanje** (prediction), **rojenje** (clustering), **klasifikacija**, **odkrivanje napak** (*fault detection*), **detekcija anomalij, razpoznavanje slik** (*image recognition*) [6], **podpora odločanju** (decision support), **programski senzor** (soft sensor) [8], **samostojno kalibriranje senzorjev** (self-calibrating sensors)

- **Monografije**:
  - Evolving Connectionist Systems (2007),
  - Evolving Intelligent System – Methodology and Applications (2010),
  - Evolving Fuzzy Systems Methodologies, Advanced Concepts and Applications (2011)

[6] Leite, D., Škrjanc, I., & Gomide, F.a (2020). An overview on evolving systems and learning from stream data. Evolving Systems, 11(2), 181–198.
[8] Lughofer, E. (2013). On-line assurance of interpretability criteria in evolving fuzzy systems – Achievements, new concepts and open issues. Information Sciences, 251, 22–46.

Tok podatkov

Tok podatkov (*data stream*):

I. Podatki prihajajo **sprotno** (*online*) in **posamično** (*one-by-one*)

II. Podatki se **generirajo, dokler je proces aktiven** in njihova **količina ni omejena**

III. Lastnosti podatkov so **časovno spremenljive** so podvržene konceptualnim **lezenjem** (*drift*) in skočnim **pomikom** (*shift*)

IV. Podatki so **nemudoma zavrženi** po procesiranju

V. Čas procesiranja podatkov **učinkovito narašča** z velikostjo vzorcev in številom parametrov modela.

Visokofrekvenčno trgovanje, podatkovno rudarjenje, **spletna varnost** (cyber security), **medicinska prognoza**, **pametna proizvodnja** in **industrija** (smart industry), **ogistika**, **socialna omrežja**, **internet stvari** (*internet of things*) [6], [9], [10] idr.

[6] Leite, D., Škrjanc, I., & Gomide, F. (2020). An overview on evolving systems and learning from stream data. Evolving Systems, 11(2), 181–198.
[9] Blazic, S., & Skrjanc, I. (2020). Hybrid system identification by incremental fuzzy C-regression clustering. IEEE International Conference on Fuzzy Systems, 2020-July.
[10] Angelov, P. P., Gu, X., & Principe, J. C. (2018). Autonomous learning multimodel systems from data streams. IEEE Transactions on Fuzzy Systems, 26(4), 2213–2224.

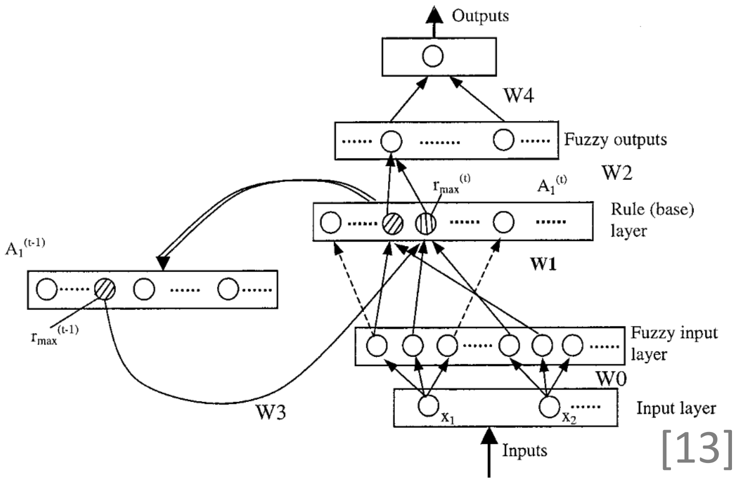
Samorazvijajoči se mehki sistemi

- Mehki model:
  - **mehke množice** (*fuzzy sets*) v premisi,
  - **lokalni linearni modeli** (*Local linear model*) v posledičnem delu.
- Poglavitne naloge samorazvijajočih se mehkih sistemov so:
  - **natančno** funkcijsko modeliranje z modeli tipa **Takagi-Sugeno-Kang**,
  - **lingvistično** (*linguistic*) modeliranje tipa **Zadeh-Mamdani,**
  - **klasifikacija**.
- Izhodno ostrenje je izvedeno z izračunom **centra gravitacije pri lingvističnih modelih**, **uteženega povprečja** (weighted average) pri **funkcijskih modelih** in model z **največjo aktivacijo** (winner-takes-all) pri **klasifikaciji**

$$R^i : \text{IF } (x_1 \text{ is } A_1^i) \text{ AND} \ldots \text{AND } (x_j \text{ is } A_j^i) \text{ AND} \ldots \text{ AND } (x_n \text{ is } A_n^i) \text{ THEN } \underbrace{(y \text{ is } B^i)}_{\text{linguistic}} \text{ AND } \underbrace{y = p^i(x_1, \ldots, x_n)}_{\text{functional}}$$ [11]

[11] Leite, D., Ballini, R., Costa, P., & Gomide, F. (2012). Evolving fuzzy granular modeling from nonstationary fuzzy data streams. *Evolving Systems*, *3*(2), 65–79.

Samorazvijajoči se nevro-mehki sistemi



$$\rho_i(k) = \exp\Big(-\frac{1}{2}(\underline{z}(k) - \underline{\mu}_i)^T \underline{\Sigma}_i^{-1}(\underline{z}(k) - \underline{\mu}_i)\Big)$$

$$\hat{y}(k) = \underline{\varphi}^T(k)\frac{\sum_i^c \rho_i(k)\hat{\underline{\theta}}_i}{\sum_i^c \rho_i(k)}$$

- **Nevro-mehki** modeli so sestavljeni iz mehkih pravil v **topologiji nevronskega omrežja** z **nevroni** in **povezavami** [6]. Vedno jih lahko **pretvorimo v mehki mode**l tako, da **roje preslikamo v mehke množice**.
- Mehka pravila lahko sestavljajo več mehkih množic (*fuzzy set*)[12], ampak uporaba **enega pravila za vsak roj** v neuro-fuzzy sistemih poenostavi adaptiranje strukture modela z **združevanjem** (*merging*), **ločevanjem** (*splitting*) in **odstranjevanjem** (*removal*) pravil.

[6] Leite, D., Škrjanc, I., & Gomide, F. (2020). An overview on evolving systems and learning from stream data. Evolving Systems, 11(2), 181–198.
[12] Angelov, P., & Yager, R. (2011). Simplified fuzzy rule-based systems using non-parametric antecedents and relative data density. IEEE SSCI 2011: Symposium Series on Computational Intelligence - EAIS 2011: 2011 IEEE Workshop on Evolving and Adaptive Intelligent Systems, 62–69.
[13] Kasabov, N. K., & Song, Q. (2002). DENFIS: Dynamic evolving neural-fuzzy inference system and its application for time-series prediction. *IEEE Transactions on Fuzzy Systems*, *10*(2), 144–154.

Transparentnost in interpretabilnost

- **Razločljivost** (distinguishability) – brez prekrivanja (overlapping), brez odvečnih struktur,
- **Preprostost** (simplicity) – čim manj rojev, kompromis med natančnostjo in kompleksnostjo,
- **Konsistentnost** (consistency) – roji z različnimi posledičnimi deli morajo biti ločeni,
- **Pokritost** (coverage) in **popolnost** modela (completeness) – celoten prostor naj bi bil pokrit z roji,
- **Interpretabilnost posledičnega dela,**
- **Pomembnost značilk,**
- **Pomembnost pravil.**

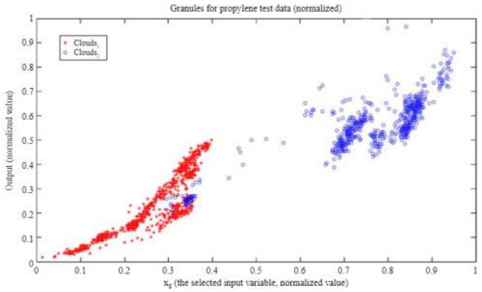
[8] [12] Lughofer, E. (2013). On-line assurance of interpretability criteria in evolving fuzzy systems – Achievements, new concepts and open issues. Information Sciences, 251, 22–46.

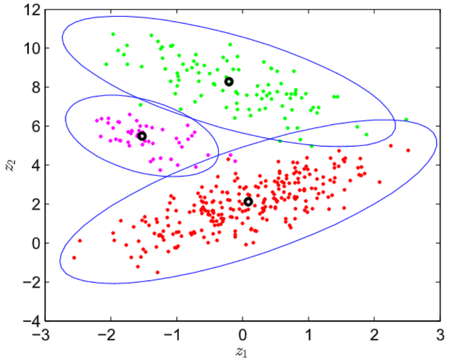
Rojenje in granulacija

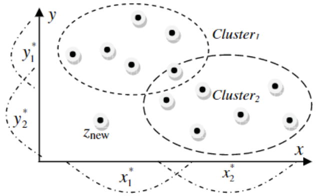
Najbolj pogosto so uporabljene **Gaussove**, **trapezoidne** ali **trikote pripadnostne funkcije** [10].

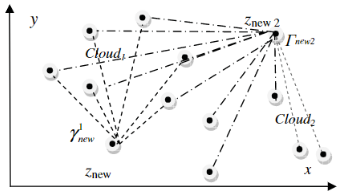
Predhodna (antecedent) struktura samorazvijajočih se sistemov je lahko sestavljena iz **mehkih možic** [1], **informacijskih granul** [14, 5 ,11], **listov**, **nevronov**, **oblakov podatkov** (data clouds) [12,15], **rojev** [3, 14, 2], **hiperravnin** [16], **teselacij** (tessellation)[9] idr.

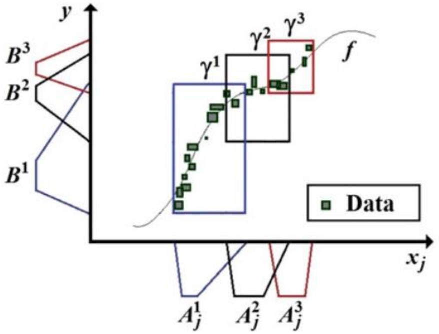
Informacijske granule so skupine objektov ali elementov s podobnimi **lastnostmi, funkcionalnostjo**, **prostorsko** bližino [12], [5]. Nekateri modeli predstavijo granule v obliki oblakov podatkov brez centrov ali definiranih mej [12].

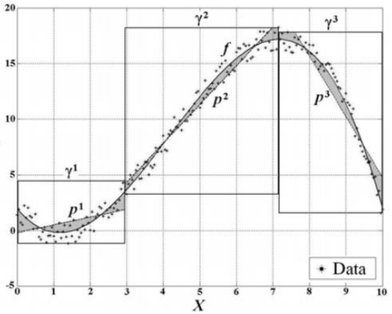












[1] Angelov, P. P., & Filev, D. P. (2004). An Approach to Online Identification of Takagi-Sugeno Fuzzy Models. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 34(1), 484–498.
[2] Skrjanc, I. (2020). Cluster-Volume-Based Merging Approach for Incrementally Evolving Fuzzy Gaussian Clustering-eGAUSS+. *IEEE Transactions on Fuzzy Systems*, *28*(9), 2222–2231.
[3] Dovžan, D., Logar, V., & Škrjanc, I. (2015). Implementation of an Evolving Fuzzy Model (eFuMo) in a Monitoring System for a Waste-Water Treatment Process. IEEE Transactions on Fuzzy Systems, 23(5), 1761–1776.
[5] Leite, D., Costa, P., & Gomide, F. (2010). Granular Approach for Evolving System Modeling. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 6178 LNAI, 340–349.
[9] Blazic, S., & Skrjanc, I. (2020). Hybrid system identification by incremental fuzzy C-regression clustering. *IEEE International Conference on Fuzzy Systems*, *2020-July*.
[10] Angelov, P. P., Gu, X., & Principe, J. C. (2018). Autonomous learning multimodel systems from data streams. IEEE Transactions on Fuzzy Systems, 26(4), 2213–2224.
[11] Leite, D., Ballini, R., Costa, P., & Gomide, F. (2012). Evolving fuzzy granular modeling from nonstationary fuzzy data streams. *Evolving Systems*, *3*(2), 65–79. [12] Angelov, P., & Yager, R. (2011). Simplified fuzzy rule-based systems using non-parametric antecedents and relative data density. IEEE SSCI 2011: Symposium Series on Computational Intelligence - EAIS 2011: 2011 IEEE Workshop on Evolving and Adaptive Intelligent Systems, 62–69.
[14] Porto, A., & Gomide, F. (2022). Evolving hyperbox fuzzy modeling. Evolving Systems, 1, 1–12.
[15] Angelov, P., & Yager, R. (2012). A new type of simplified fuzzy rule-based system. International Journal of General Systems, 41(2), 163–185.

Metode rojenja

- **Odštevalno rojenje** (*subtractive clustering*) [1, 15],
- **mehko rojenje s C-središči** (*Fuzzy C-means*),
- rekurzivno rojenje po metodi **Gustafson-Kesse**l [3,16],
- rekurzivno rojenje po metodi **Gath-Geva** [17],
- **samorazvijajoče se rojenje** (evolving clustering method) [13],
- **inkrementalno mehko rojenje s C-regresijo** (*incremental fuzzy C-regression clustering*) [9],
- **rojenje s C-možnimi roji** (possibilistic C-means),
- rojenje na osnovi **gostote** (density-based)[12],
- rojenje na osnovi **razpršenosti** (scatter-based) [18],
- rojenje s **vektorsko kvantizacijo** (vector quantization) [19],
- samorazvijajoče se **Gaussovo** rojenje **(eGauss)**[2] idr.

$$\vec{c}_{\text{win}}^{\,(\text{new})} = \vec{c}_{\text{win}}^{\,(\text{old})} + \eta_{\text{win}}\left(\vec{x} - \vec{c}_{\text{win}}^{\,(\text{old})}\right)$$

$$k_{\text{win}}\sigma^2_{\text{win,j}}(\text{new}) = (k_{\text{win}} - 1)\sigma^2_{\text{win,j}}(old) + k_i \Delta c^2_{\text{win,j}} + (c_{\text{win,j}}(\text{new}) - x_j)^2$$ [19]

$$\gamma^i(k) = \frac{1}{1 + \|\boldsymbol{x}_f(k) - \boldsymbol{\mu}^i(k)\|^2 + \sigma^i(k) - \|\boldsymbol{\mu}^i(k)\|^2}$$ [20]

$$\boldsymbol{\mu}^i(k) = \frac{M^i - 1}{M^i}\boldsymbol{\mu}^i(k-1) + \frac{1}{M^i}\boldsymbol{x}_f(k)$$

$$\sigma^i(k) = \frac{M^i - 1}{M^i}\sigma^i(k-1) + \frac{1}{M^i}\|\boldsymbol{x}_f(k)\|^2$$

$$\underline{e}_i(k) = \underline{z}(k) - \underline{\mu}_i(n_i),$$ [2]

$$\underline{\mu}_i(n_i + 1) = \underline{\mu}_i(n_i) + \frac{1}{n_i + 1}\underline{e}_i(k),$$

$$\underline{S}_i(n_i + 1) = \underline{S}_i(n_i) + \underline{e}_i(k)\left(\underline{z}(k) - \underline{\mu}_i(n_i + 1)\right)^T,$$

[1] Angelov, P. P., & Filev, D. P. (2004). An Approach to Online Identification of Takagi-Sugeno Fuzzy Models. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 34(1), 484–498.
[2] Skrjanc, I. (2020). Cluster-Volume-Based Merging Approach for Incrementally Evolving Fuzzy Gaussian Clustering-eGAUSS+. *IEEE Transactions on Fuzzy Systems*, *28*(9), 2222–2231.
[3] Dovžan, D., Logar, V., & Škrjanc, I. (2015). Implementation of an Evolving Fuzzy Model (eFuMo) in a Monitoring System for a Waste-Water Treatment Process. IEEE Transactions on Fuzzy Systems, 23(5), 1761–1776.
[9] Blazic, S., & Skrjanc, I. (2020). Hybrid system identification by incremental fuzzy C-regression clustering. *IEEE International Conference on Fuzzy Systems*, *2020-July*.
[12] Angelov, P., & Yager, R. (2011). Simplified fuzzy rule-based systems using non-parametric antecedents and relative data density. IEEE SSCI 2011: Symposium Series on Computational Intelligence - EAIS 2011: 2011 IEEE Workshop on Evolving and Adaptive Intelligent Systems, 62–69.
[13] Kasabov, N. K., & Song, Q. (2002). DENFIS: Dynamic evolving neural-fuzzy inference system and its application for time-series prediction. *IEEE Transactions on Fuzzy Systems*, *10*(2), 144–154.
[15] Angelov, P., & Yager, R. (2012). A new type of simplified fuzzy rule-based system. International Journal of General Systems, 41(2), 163–185.
[16] Dovžan, D., & Škrjanc, I. (2011). Recursive clustering based on a Gustafson-Kessel algorithm. Evolving Systems, 2(1), 15–24.
[17] Soleimani-B, H., Lucas, C., & Araabi, B. N. (2010). Recursive Gath-Geva clustering as a basis for evolving neuro-fuzzy modeling. Evolving Systems, 1(1), 59–71.
[18] D. Leite, I. Škrjanc, and F. Gomide, "An overview on evolving systems and learning from stream data," Evolving Systems, vol. 11, no. 2, pp. 181–198, Jun. 2020.
[19] Lughofer, E. D. (2008). FLEXFIS: A robust incremental learning approach for evolving Takagi-Sugeno fuzzy models. *IEEE Transactions on Fuzzy Systems*, *16*(6), 1393–1410.
[20] Andonovski, G., Mušič, G., Blažič, S., & Škrjanc, I. (2018). Evolving model identification for process monitoring and prediction of non-linear systems. *Engineering Applications of Artificial Intelligence*, *68*, 214–221.

Dodajanje rojev

- **Razdalja** novega vzorca (Evklidova, Mahalanobisova) do obstoječih struktur [19,13,3],
- **Pripadnost** novega vzorca obstoječim strukturam (ϵ-completeness) [1],
- **Potencial** (potential) vzorca [1],
- **Gostota** (density) vzorca [20],
- Največje **dovoljeno število rojev** [20],
- Število vzorcev od zadnjega dodanega roja [20]idr.

Dodani roji so inicializirani z ničtimi vrednostmi, s povprečjem bližnjih rojev [10], s minimalno pokritostjo prostora idr.

[1] Angelov, P. P., & Filev, D. P. (2004). An Approach to Online Identification of Takagi-Sugeno Fuzzy Models. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 34(1), 484–498.
[3] Dovžan, D., Logar, V., & Škrjanc, I. (2015). Implementation of an Evolving Fuzzy Model (eFuMo) in a Monitoring System for a Waste-Water Treatment Process. IEEE Transactions on Fuzzy Systems, 23(5), 1761–1776.
[10] Angelov, P. P., Gu, X., & Principe, J. C. (2018). Autonomous learning multimodel systems from data streams. IEEE Transactions on Fuzzy Systems, 26(4), 2213–2224.
[13] Kasabov, N. K., & Song, Q. (2002). DENFIS: Dynamic evolving neural-fuzzy inference system and its application for time-series prediction. IEEE Transactions on Fuzzy Systems, 10(2), 144–154.
[19] Lughofer, E. D. (2008). FLEXFIS: A robust incremental learning approach for evolving Takagi-Sugeno fuzzy models. IEEE Transactions on Fuzzy Systems, 16(6), 1393–1410.
[20] Andonovski, G., Mušič, G., Blažič, S., & Škrjanc, I. (2018). Evolving model identification for process monitoring and prediction of non-linear systems. Engineering Applications of Artificial Intelligence, 68, 214–221.

Združevanje, razcep in odstranjevanje rojev

Združevanje (merging), **razcep** (splitting) in **odstranjevanje** (removal) rojev. Naključni vzorci iz toka podatkov ustvarijo **prekomerno število rojev**. Z dodajanjem vzorcev ali zaradi lezenja sistema (drift) [21]:

- **približevanje** rojev (coalescence),
- **separacija** rojev (delamination).

Združevanje in razcep rojev lahko kompenzira za slabo izbiro hiperparametrov metode [19].

Kompromis med **dolgoročno stabilnostjo** in **kratkoročno plastičnostjo** (stability-plasticity dilemma) [8, 19].

Z odstranjevanjem rojev **povečamo natančnost** ali **poenostavimo strukturo** modela. Obstoječ model je lahko napačen zaradi **osamelcev** ali **sprememb v lastnostih sistema** [22].

[8] Lughofer, E. (2013). On-line assurance of interpretability criteria in evolving fuzzy systems – Achievements, new concepts and open issues. Information Sciences, 251, 22–46.
[19] Lughofer, E. D. (2008). FLEXFIS: A robust incremental learning approach for evolving Takagi-Sugeno fuzzy models. IEEE Transactions on Fuzzy Systems, 16(6), 1393–1410.
[21] Lughofer, E., & Sayed-Mouchaweh, M. (2015). Autonomous data stream clustering implementing split-and-merge concepts – Towards a plug-and-play approach. Information Sciences, 304, 54–79.
[22] Lughofer, E. (2008). Extensions of vector quantization for incremental clustering. *Pattern Recognition*, *41*(3), 995–1011.

Pogoji za združevanje rojev

- **prekrivanje** in **mere verjetnostne različnosti** rojev [3] (Kullback–Leiblerjeva divergenca, Bhattacharyyajeva razdalja [21]),
- podobnosti med **aktivacijami pravil** [3],
- **razdalje** med roji (Welch test) [3,17,23,24] ali informacijskimi granuli [11],
- primerjava **posledičnih parametrov** [3,25] idr.

$$S(A^{i_1}, A^{i_2}) = 1 - \frac{1}{4n}\sum_{j=1}^{n}\left(|l_j^{i_1} - l_j^{i_2}| + |\lambda_j^{i_1} - \lambda_j^{i_2}| + |\Lambda_j^{i_1} - \Lambda_j^{i_2}| + |L_j^{i_1} - L_j^{i_2}|\right)$$ [11]

$$S_{ker}(A,B) = \left(e^{-\frac{(c_A-c_B)^2}{\sigma_A^2+\sigma_B^2}} + e^{-(c_A-c_B)^2-(\sigma_A-\sigma_B)^2}\right)\Big/2$$ [21]

$$D_B = \frac{1}{8}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2) + \frac{1}{2}\ln\left(\frac{\det \boldsymbol{\Sigma}}{\sqrt{\det \boldsymbol{\Sigma}_1 \ \det \boldsymbol{\Sigma}_2}}\right)$$ [6]

$$C_{ij}(k) = \frac{\beta_{ij}}{\beta_{ii}^{0.5}\beta_{jj}^{0.5}}$$ [3]

$$d_{ik}^2 = (\mathbf{v}_i - \mathbf{v}_k)^T F_i^{-1}(\mathbf{v}_i - \mathbf{v}_k)$$ [24]

$$\alpha_{ij_k} = |\arctan(\theta_{ni_k}) - \arctan(\theta_{nj_k})|$$ [3]

$$S(R_1, R_2) = 1 - \frac{\|\vec{c}_{R_1} - \vec{c}_{R_2}\|}{p}$$ [17]

$$\frac{1 - \min(d_{\mathrm{norm}_{ik}}, d_{\mathrm{norm}_{ki}})}{\max(d_{\mathrm{norm}_{ik}}, d_{\mathrm{norm}_{ki}})} < k_{d_{\mathrm{merge}}}$$ [3]

$$\kappa_{pq} = \frac{1}{2\pi}\int_0^{\frac{\pi}{T}} |\hat{G}_p(e^{j\omega T}) - \hat{G}_q(e^{j\omega T})|\, d\omega\,.$$ [25]

$$S_{mn} = \exp\left(-\frac{1}{2}(\mu_n - \mu_m)^T \Sigma_m^{-1}(\mu_n - \mu_m)\right)$$ [17]

[3] Dovžan, D., Logar, V., & Škrjanc, I. (2015). Implementation of an Evolving Fuzzy Model (eFuMo) in a Monitoring System for a Waste-Water Treatment Process. IEEE Transactions on Fuzzy Systems, 23(5), 1761–1776.
[11] Leite, D., Ballini, R., Costa, P., & Gomide, F. (2012). Evolving fuzzy granular modeling from nonstationary fuzzy data streams. Evolving Systems, 3(2), 65–79.
[17] Soleimani-B, H., Lucas, C., & Araabi, B. N. (2010). Recursive Gath-Geva clustering as a basis for evolving neuro-fuzzy modeling. Evolving Systems, 1(1), 59–71.
[21] Lughofer, E., & Sayed-Mouchaweh, M. (2015). Autonomous data stream clustering implementing split-and-merge concepts – Towards a plug-and-play approach. Information Sciences, 304, 54–79.
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Združevanje rojev

- rekurzivno uteženo povprečje središč in kovariančnih matrik rojev [3,
- 2,26]
- konveksna ovojnica (*convex hull*) granul [27,11].

$$C_{\text{dom}}^{\text{new}} = \frac{C_{\text{dom}}^{\text{old}} N_{\text{dom}}^{\text{old}} + C_{i+1} N_{\text{dom}+1}}{N_{\text{dom}}^{\text{old}} + N_{\text{dom}+1}^{\text{old}}}$$

$$\sum_{\text{merged}} (\text{new})^{-1} = \frac{\sum_{\text{dom}} (\text{old})^{-1} * N_{\text{dom}}^{\text{old}} + \Sigma_{\text{dom}+1} (\text{old})^{-1} * N_{\text{dom}+1}^{\text{old}}}{N_{\text{dom}}^{\text{old}} + N_{\text{dom}+1}^{\text{old}}}$$

$$N_{\text{dom}}^{\text{new}} = N_{\text{dom}}^{\text{old}} + N_{\text{dom}+1}^{\text{old}}$$

[26]

$$\mathbf{v}_{\text{new}} = \mathbf{v}_j + \mathbf{d}_2$$

$$\mathbf{d}_1 = \mathbf{v}_i - \mathbf{v}_j, \quad \mathbf{d}_2 = \frac{\mathbf{v}_i' - \mathbf{v}_j'}{2}$$

$$\mathbf{v}_i' = \mathbf{v}_i + \text{sign}(\mathbf{d}_1)\mathbf{s}_{i_{\text{norm}}}, \quad \mathbf{v}_j' = \mathbf{v}_j - \text{sign}(\mathbf{d}_1)\mathbf{s}_{j_{\text{norm}}}.$$

[3]

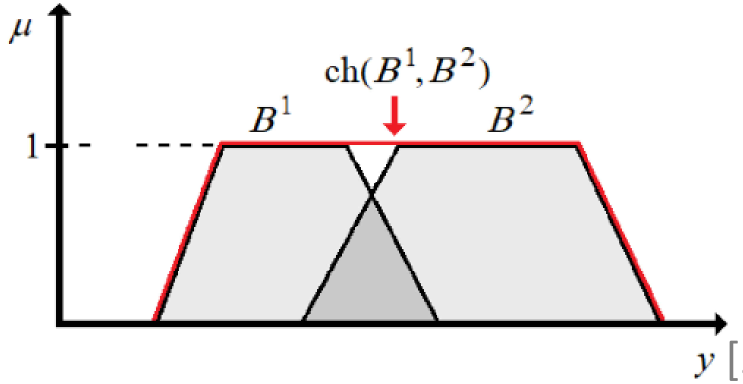
$$n_{pq} = n_p + n_q \ ,$$

$$\mu_{pq} = \frac{n_p \mu_p + n_q \mu_q}{n_{pq}} \ .$$

$$_{pq} = \frac{1}{n_{pq} - 1} (Z_p^T Z_p + Z_q^T Z_q - M_{pq}^T E_{pq}^T E_{pq} M_{pq})$$

$$Z_p^T Z_p = (n_p - 1)\Sigma_p + M_p^T E_p^T E_p M_p$$

[2]



[27]

$$l_j^i = \min(l_j^{i_1}, l_j^{i_2})$$

$$\lambda_j^i = \min(\lambda_j^{i_1}, \lambda_j^{i_2})$$

$$\Lambda_j^i = \max(\Lambda_j^{i_1}, \Lambda_j^{i_2})$$

$$L_j^i = \max(L_j^{i_1}, L_j^{i_2}).$$

[22]

[2] Skrjanc, I. (2020). Cluster-Volume-Based Merging Approach for Incrementally Evolving Fuzzy Gaussian Clustering-eGAUSS+. IEEE Transactions on Fuzzy Systems, 28(9), 2222–2231.
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[27] Garcia, C., Leite, D., & Skrjanc, I. (2020). Incremental Missing-Data Imputation for Evolving Fuzzy Granular Prediction. IEEE Transactions on Fuzzy Systems, 28(10), 2348–2362.

Razcep rojev

Neprimerni parametri združevanja, lezenje parametrov in **konceptualni pomiki** v toku podatkov, potreba po **natančnejšem deljenju prostora** idr.

$$e(k) = \frac{|y_m(k) - y(k)|}{n_\sigma \sigma_y}$$

$$e_{\mathrm{sum}_i}(k) = e_{\mathrm{sum}_i}(k-1) + \beta_i e(k)$$ [3]

- **akumulirana relativna napaka** [3],
- **prekrivanje rojev, Welchejev T-test (Welch T-test)**[21], **Bayesov informacijski kriterij** (Bayesian information criterion) [21, 27], **partition separation index** [22] idr.

$$I_i = \frac{(\mu_0 - \mu_1)^2}{\sigma_0^2 + \sigma_1^2} > crit$$ [21]

$$PS_i = \frac{k_i}{k_{max}} - \mathrm{e}^{-\min_{k \neq i}(\|c_i - c_k\|)/\beta_T}$$

$$k_{max} = \max_{i=1,\dots,C} k_i,$$

$$\beta_T = \frac{\sum_{i=1}^{C} \|c_i - \bar{c}\|^2}{C}$$ [22]

$$BIC_{ext}(C_{j1}, C_{j2}) = -2(loglik_{j1} + loglik_{j2}) + d(\log(N_{j1}) + \log(N_{j2})) + \frac{N_j}{2} \sum_{i=1}^{N_j} \log\left(\prod_{k=1}^{2} \mu_{ij_k}\right)$$ [27]

[3] Dovžan, D., Logar, V., & Škrjanc, I. (2015). Implementation of an Evolving Fuzzy Model (eFuMo) in a Monitoring System for a Waste-Water Treatment Process. IEEE Transactions on Fuzzy Systems, 23(5), 1761–1776.
[21] Lughofer, E., & Sayed-Mouchaweh, M. (2015). Autonomous data stream clustering implementing split-and-merge concepts – Towards a plug-and-play approach. Information Sciences, 304, 54–79.
[22] Lughofer, E. (2008). Extensions of vector quantization for incremental clustering. Pattern Recognition, 41(3), 995–1011.
[27] Garcia, C., Leite, D., & Skrjanc, I. (2020). Incremental Missing-Data Imputation for Evolving Fuzzy Granular Prediction. IEEE Transactions on Fuzzy Systems, 28(10), 2348–2362.

Razcep rojev

- **Hranjenje dodatnih struktur** znotraj rojev (Gaussian mixture model) [27]
- Deljenje roja v smeri **največje lastne vrednosti in postavitev kovariančne matrike**, **števila delcev na polovico** [3,22].

Nekateri samorazvijajoči sistemi primerjajo kvaliteto modela pred in po spremembi strukture [19].

$$\mathbf{v}_{i1} = \mathbf{v}_i + 0.5\mathbf{s}_{i_{\text{norm}}}, \quad \mathbf{v}_{i2} = \mathbf{v}_i - 0.5\mathbf{s}_{i_{\text{norm}}}$$

[3]

$$c_{win,j}(new1) = c_{win,j}(old) + \sigma_{win,j}(old),$$

$$c_{win,j}(new2) = c_{win,j}(old) - \sigma_{win,j}(old),$$

$$\sigma_{win,j}(new1) = \sigma_{win,j}(new2) = \frac{\sigma_{win,j}(old)}{2},$$

$$k_{win}(new1) = k_{win}(new2) = \frac{k_{win}(old)}{2}.$$

[22]

[3] Dovžan, D., Logar, V., & Škrjanc, I. (2015). Implementation of an Evolving Fuzzy Model (eFuMo) in a Monitoring System for a Waste-Water Treatment Process. IEEE Transactions on Fuzzy Systems, 23(5), 1761–1776
[19] Lughofer, E. D. (2008). FLEXFIS: A robust incremental learning approach for evolving Takagi-Sugeno fuzzy models. *IEEE Transactions on Fuzzy Systems*, *16*(6), 1393–1410.
[22] Lughofer, E. (2008). Extensions of vector quantization for incremental clustering. *Pattern Recognition*, *41*(3), 995–1011.
[27] Garcia, C., Leite, D., & Skrjanc, I. (2020). Incremental Missing-Data Imputation for Evolving Fuzzy Granular Prediction. *IEEE Transactions on Fuzzy Systems*, *28*(10), 2348–2362.

Odstranjevanje rojev

Odstranjevanje je potrebno izvesti pazljivo, saj **nočemo zavreči koristnih informaciji** [20]. Osamelce ne moremo vedno izločiti, saj si zelo podobni **cikličnim ali periodičnim pojavom**. Ti dogodki so zastopani z manjšim številom vzorcev, ki pa vsebujejo veliko informacije.

- **prekrivanje**,
- **starost** rojev [3,12],
- **uporabnost** (*utility*) (akumulirana relativna aktivacija, redka aktivacija, nepomembnost) [10, 12, 28, 29],
- **število pripadajočih vzorcev** [3,20] idr.

$$Utility_i = \frac{\sum_{l=1}^{t} \Psi_l}{t - t_i} \qquad Age_i = t - \frac{\sum_{l=1}^{k_i} t_l}{k_i}$$ [8]

$$E_{\mathrm{inf}}(k) = |a_k| \frac{(1.8\sigma_k)^{N_x}}{\sum_{k=1}^{N_h} (1.8\sigma_k)^{N_x}} < e_p.$$ [28]

[3] Dovžan, D., Logar, V., & Škrjanc, I. (2015). Implementation of an Evolving Fuzzy Model (eFuMo) in a Monitoring System for a Waste-Water Treatment Process. IEEE Transactions on Fuzzy Systems, 23(5), 1761–1776.
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[29] Leite, D., & Škrjanc, I. (2019). Ensemble of evolving optimal granular experts, OWA aggregation, and time series prediction. Information Sciences, 504, 95–112.

Optimizacija posledičnega dela modela

$$\boldsymbol{\psi}(k) = [\boldsymbol{x}_f(k), \quad 1]^T$$

$$\boldsymbol{P}^i(k) = \frac{1}{\lambda_r}\left(\boldsymbol{P}^i(k-1) - \frac{\beta^i(k)\boldsymbol{P}^i(k-1)\boldsymbol{\psi}(k)\boldsymbol{\psi}^T(k)\boldsymbol{P}^i(k-1)}{\lambda_r + \beta^i(k)\boldsymbol{\psi}^T(k)\boldsymbol{P}^i(k-1)\boldsymbol{\psi}(k)}\right)$$

$$\boldsymbol{\theta}^i(k) = \boldsymbol{\theta}^i(k-1) + \boldsymbol{P}^i(k-1)\boldsymbol{\psi}(k)\beta^i(k)\left(y(k) - \boldsymbol{\psi}^T(k)\boldsymbol{\theta}^i(k-1)\right)$$

Lokalna optimizacija, kjer so **parametri vsakega lokalnega modela optimizirani posamezno** [30]. To omogoča večjo robustnost in interpretabilnost lokalnih modelov.

- mehko utežena rekurzivna metoda najmanjših kvadratov (fuzzy weighted recursive least squares [10])
- multi-innovation [31],
- merilo maksimalne korentropije (maximum correntropy criterion) [31, 32],
- Kalmanov filter,
- stohastični gradientni spust (Stochastic gradient descent) idr.

[10] Angelov, P. P., Gu, X., & Principe, J. C. (2018). Autonomous learning multimodel systems from data streams. IEEE Transactions on Fuzzy Systems, 26(4), 2213–2224.
[30] Nelles, O. (2001). Nonlinear System Identification. Nonlinear System Identification.
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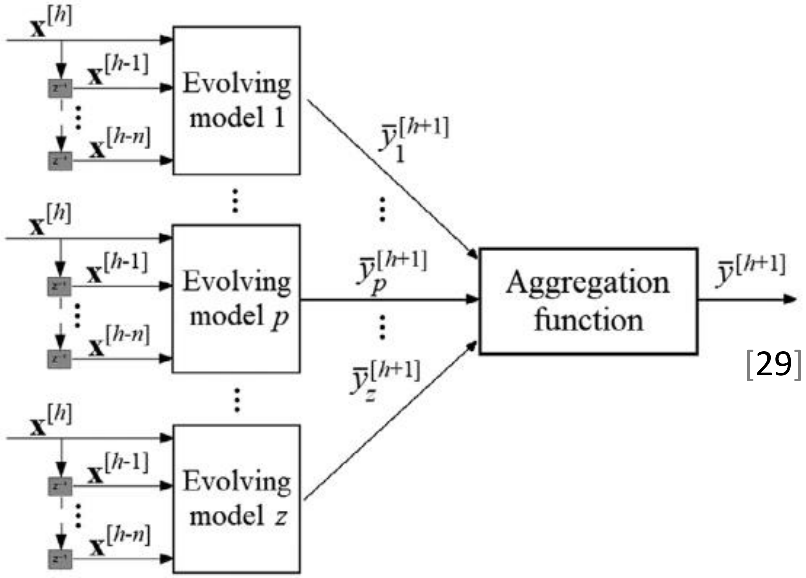
Ansambli samorazvijajočih se modelov

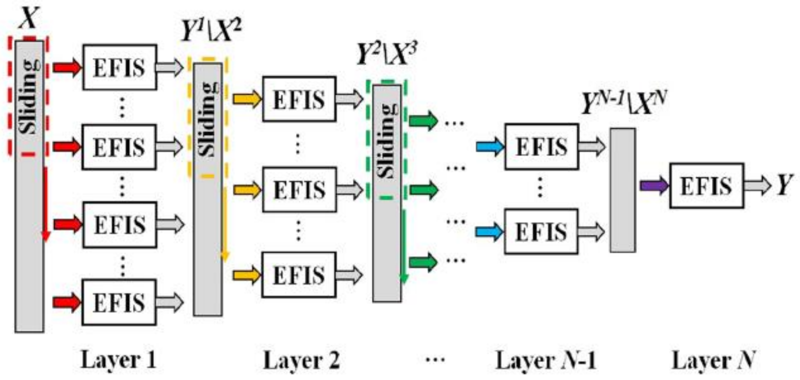
Učenje **več** različnih samorazvijajočih se modelov **na istem problemu z različnimi parametri** [6(10), 29(48)]→ **Ansambel/skupina** (Ensemble learning).

Posamezni samorazvijajoči se modeli v ansamblu se lahko razlikujejo po: **strukturi**, **številu parametrov**, **omejitvah** (constraints), **kriterijski funkciji**, **tipu samorazvijajočega se modela**.

- Extreme Learning Machines (ELMs) (2009) (naključna inicializacija parametrov in strukture)
- Parsimonious ensemble (pENsemble) (2018) (odstranjevanje modelov in izbira značilk)
- Ensamble of Fuzzy-set-Based evolving Models (FBeM) (2015) (različni parametri in strukture informacijskih granul)
- Ensamble of optimal evolving granular experts (eOGS) (2019) [29] (uses multiple aggregation functions)
- Multilayer ensemble evolving fuzzy inference system MEEFIS (2019) [33] (samorazvijajoči se modeli kot gradniki omrežja)



[29]



[33]

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[29] Leite, D., & Škrjanc, I. (2019). Ensemble of evolving optimal granular experts, OWA aggregation, and time series prediction. Information Sciences, 504, 95–112.
[33] Gu, X. (2021). Multilayer Ensemble Evolving Fuzzy Inference System. IEEE Transactions on Fuzzy Systems, 29(8), 2425–2431.

Odprta vprašanja na področju samorazvijajočih se sistemov

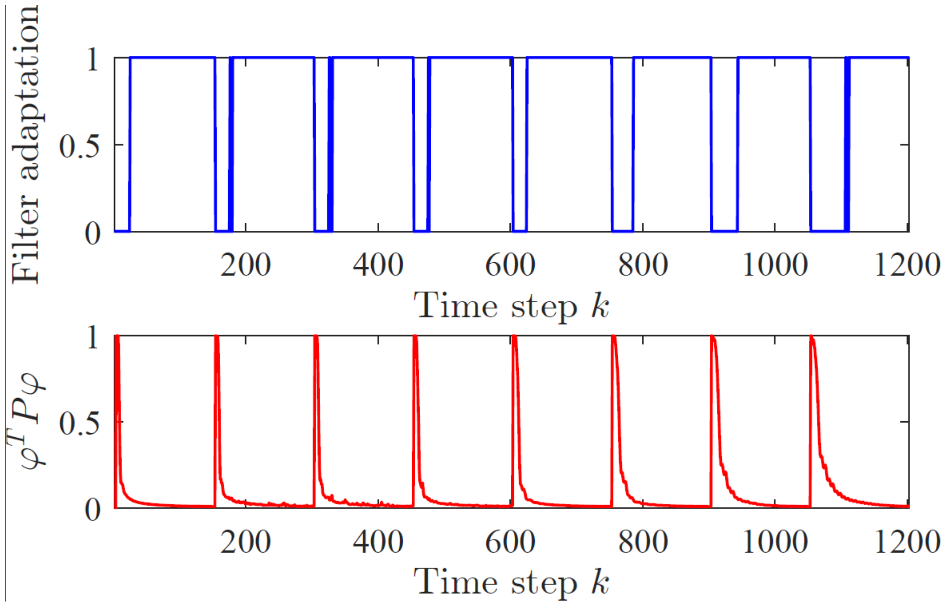
- obravnava **manjkajočih vzorcev** (*missing data*) in **osamelcev** (*outliers*)
- **teoremi** za zagotavljanje **dolgoročne stabilnosti** in **konvergence**
- **načrtovanje experimentov** (Design of Experiments)
- predlogi **za potek dela** (*workflow*)
- **mere uspešnosti** sprotnega delovanja (*performance metrics*)
- **paralelno** učenje (*parallelization*)
- **programski senzorji** (soft sensors)
- sprotna **izbira regresorjev**

[6] Leite, D., Škrjanc, I., & Gomide, F. (2020). An overview on evolving systems and learning from stream data. Evolving Systems, 11(2), 181–198.
[34] Škrjanc, I., Iglesias, J., Sanchis, A., Leite, D., Lughofer, E., & Gomide, F. (2019). Evolving fuzzy and neuro-fuzzy approaches in clustering, regression, identification, and classification: A Survey. *Information Sciences*, *490*, 344–368

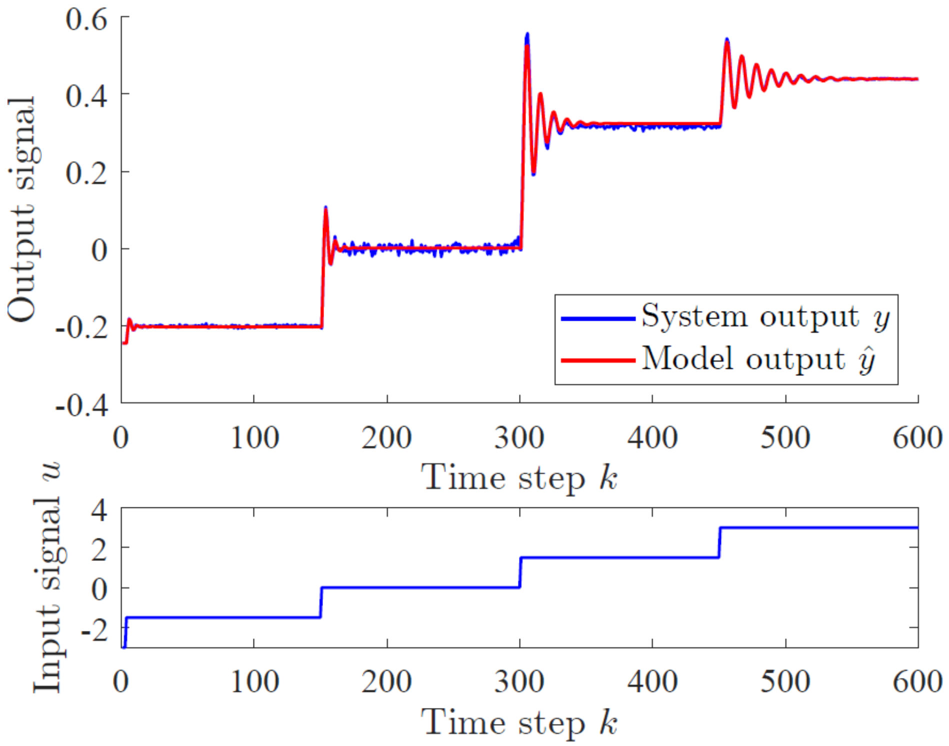
Adaptiranje filtra z intervalom zaupanja

$$\frac{\mathrm{var}(\hat{y}(k))}{\mathrm{var}(\underline{v})} = \frac{\sigma^2 \underline{\varphi}(k)\underline{P}(k)\underline{\varphi}^T(k)}{\sigma^2} = \underline{\varphi}(k)\underline{P}(k)\underline{\varphi}^T(k)$$

$$e_{\mathrm{OE}} = \frac{1}{A_f(q)} e(k) = y(k) - \frac{\hat{B}(q)}{\hat{A}(q)} u(k) - \frac{1}{\hat{A}(q)} \hat{r}$$



$$\underline{\varphi}_f(k) = \frac{1}{A_f(q)} \underline{\varphi}(k) = \frac{\lim_{q \to 1} \hat{A}(q)}{\hat{A}(q)} \underline{\varphi}(k)$$

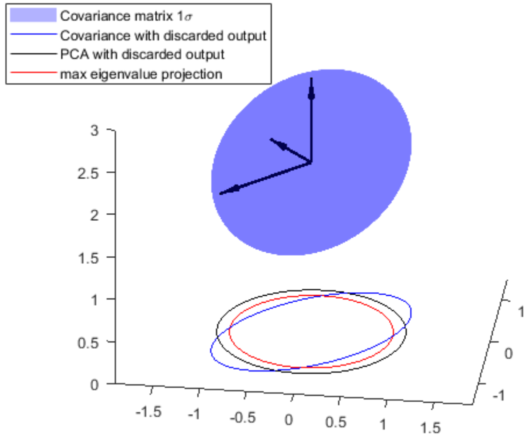


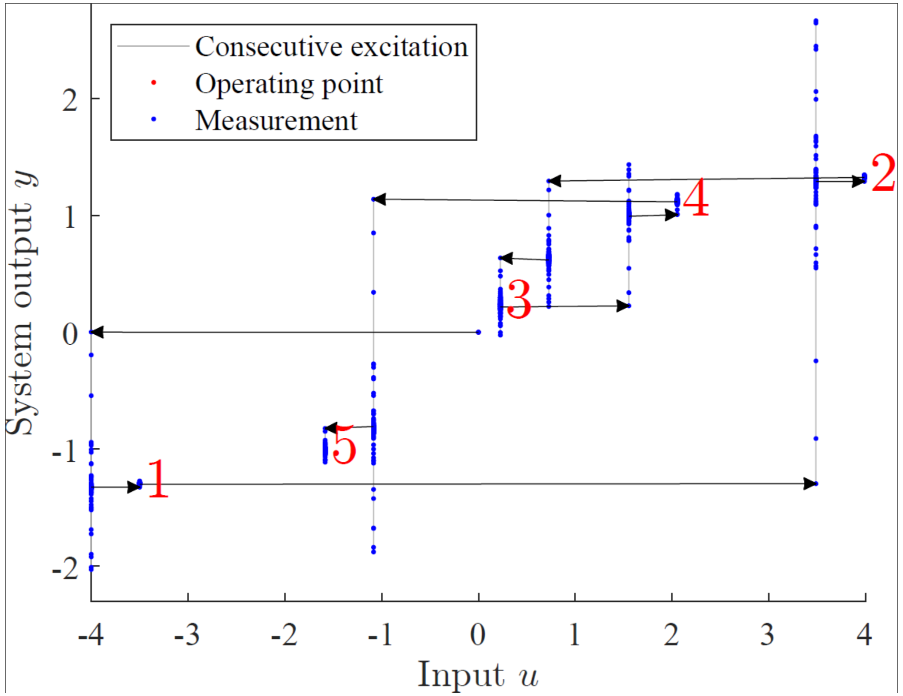
Hevristično zaporedje štopničastih vzbujanj

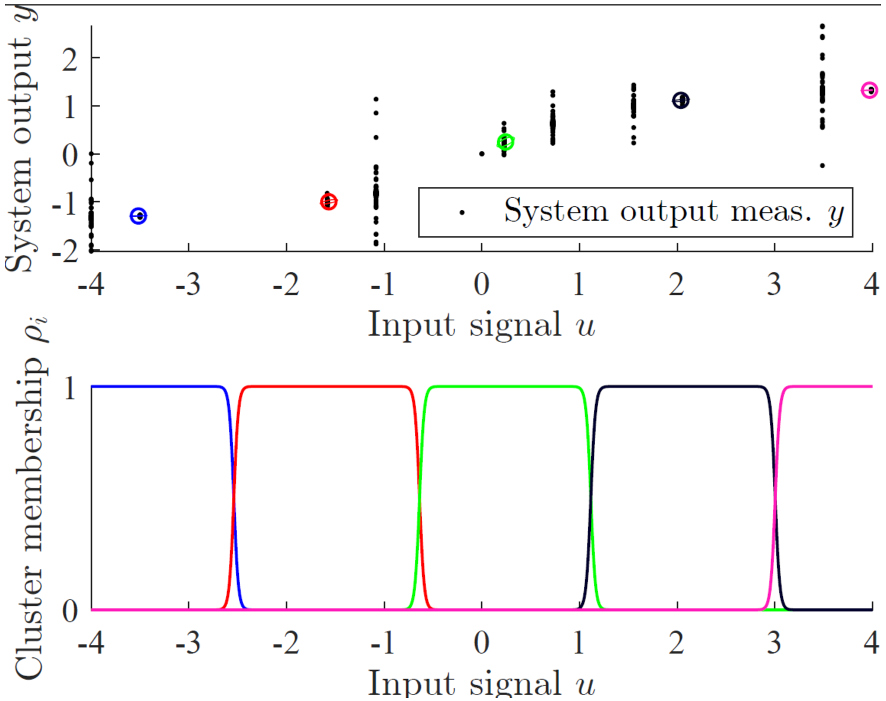
$$\underline{u} = \arg\max_{\underline{u}} \left(\min_i (d_i^2) \right),$$

$$d_i^2 = (\underline{u} - \underline{\mu}_i^u)^T (\underline{\delta}_i^u)^{-1} (\underline{u} - \underline{\mu}_i^u),$$

$$\underline{u}_{min} < \underline{u} < \underline{u}_{max},$$







Ploskovni toplotni izmenjevalec

$$\tau(t)\frac{dT_{sp}(t)}{dt} + T_{sp}(t) = \gamma(t)\mathrm{T}_{ep} + \Big(1-\gamma(t)\Big)T_{ec}(t),$$

$$\gamma(t) = \frac{1+\mathrm{k}_c(\frac{1}{F_c(t)})^{\mathrm{m}}}{1+\mathrm{k}_c((\frac{1}{F_c(t)})^{\mathrm{m}} + (\frac{1}{\mathrm{F}_p})^{\mathrm{m}})},$$

$$F_c(t) = \mathrm{v}_1\left(\frac{1}{\pi}\mathrm{atan}\Big(\mathrm{v}_2(V_{mcv}(t)-\overline{V}_{mcv})\Big)+\frac{1}{2}\right)$$

$$\underline{\varphi}_f^T(k) = [u_f(k-1), -y_f(k-1), d_f(k-1), 1]$$

$$\underline{\theta}^T = [b_1, a_1, c_1, r] \qquad \underline{z}^T(k) = [u(k), y(k), d(k)],$$