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The Overall Pulse model for water demand of aggregated residential users

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Abstract

The models for the end-user demand give a detailed description of the water request, which takes into account the consumes of each dwelling. Therefore, these approaches can model the water demand at WDS nodes by aggregating the single request of each user.
The effectiveness of a novel approach the Overall Pulse model (OP)- to describe the aggregated water demand has been tested. In fact, the OP model, unlike the commonly used rectangular pulse models (e.g. PRP, NSRP), does not aim to reconstruct single demand pulses as they occur when home faucets and hydro-sanitary appliances are operated, but allows the generation of the water demand as it is observed at the house water meter. This feature makes the model very versatile, allowing the direct modeling of either a single user or of a group of n users. The possibility of 'pre-aggregation' of the water demand makes it easier to take into account the spatial variability of the model parameters. In the paper, the performance of the OP model is investigated, and to this aim the generated time series are compared with the observed ones of real users. In addition, the comparison of series obtained by means of the classical PRP approach and of the OP model show the effectiveness of the latter.

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Keywords: Water demand, Monte Carlo generation, stochastic process, PRP model, OP model

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1. Introduction

The rectangular pulse point processes, originally studied to model the rain events [1, 2], have been widely used in technical literature for generating synthetic time series of the residential water demand (e.g. [3, 4, 5]).

Buchberger and Wu [3] used the Poisson Rectangular Pulse (PRP) process to describe the water request of residential users, by examining the actual demand of some monitored dwellings. Although the PRP process is theoretically a very interesting approach, because it tries to model the behavior of the users regarding water consumption, the performances of the PRP showed the need of improvements.

Therefore, Alvisi et al. [4] and Alcocer-Yamanaka et al. [6] suggested to take into account the cluster effect of the water demand, while Garcia et al. [7] proposed a practical criterion to define the non-homogeneous process describing the pulse occurrence during the day.

However, the above mentioned approaches attempt to model all the pulses, as they occur at hydro-sanitary devices of a dwelling. Moreover, the estimation of the PRP parameters often needs the reconstruction of single pulses, while the available information about the residential demand is obtained only by means of the water counters [8]. Hence, a specific monitoring campaign was developed to obtain reliable estimations of the PRP parameters, by installing water meters inside some residences in order to monitor the consumptions of each hydro-sanitary device [9].

Also the Overall Pulse (OP) model [10] is a rectangular pulse process, but it directly generates the total request for each discretized time interval Δt. In this way, the OP model presents a double advantage. First of all, this approach does not need to generate the single pulses of the residential request. Second, the model is capable of taking into account also the overall demand of more users. This latter feature is analyzed in this paper, namely the effectiveness of the OP model to describe water demand of clustered users is investigated.

2. Generation of time series by means of the OP model

The OP approach generates synthetic time series of the water requested by the residential users, where the demand is modeled effectively by means of rectangular pulses. Unlike classical end user models, the OP model does not describe the water demand at each hydro-sanitary device of a dwelling, but it models the overall request of a dwelling for each interval Δt of the time discretization. In other words, the OP model simulates the flow which can be measured by means of the water meter of a residence, whereas the pressure is adequate to satisfy the demand [11].

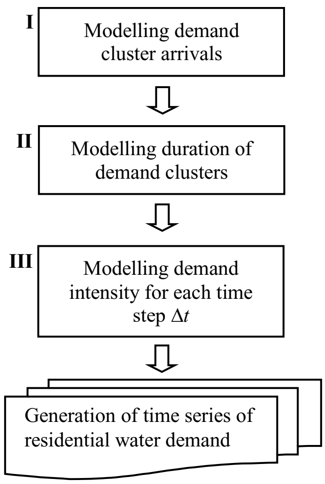

Fig.1. Flow-chart of the OP model.

As the OP model does not need to reconstruct all the pulses of the single appliances which form the demand of a residence, this approach is also suitable for generating the aggregate request of more residences at the same time. Indeed, for modeling the demand of n users, it is enough that the parameters of the OP model are estimated with reference to the overall request of the aggregated users.

The OP model has a hierarchic approach, which is organized in three steps (Fig.1).

Each step of the process models, by means of the Monte Carlo technique, one of the random phenomena which contribute to the formation of water demand.

More precisely, three data types are generated by the OP model:

- arrivals of the demand clusters;
- durations of each cluster, τ;
- intensity of the demand q_t for each time interval Δt within a cluster.

Although the above mentioned random variables resemble those of the classical rectangular pulse models, they have a totally different meaning in the OP approach. For instance, as the OP model directly generates the overall demand of a residence, the arrivals represent the beginning of aggregated demand pulses, with several hydro-sanitary devices simultaneously working. Of course, it may occur that a cluster demand is produced by only one pulse, because during the generated τ only one single device (e.g. a tap) is supplying water in a dwelling.

Table 1. The estimated arrival rates $\lambda^{(i)}$ for the residence from 1 to 10 of Milford case study

t [hours]	Home 1	Home 2	Home 3	Home 4	Home 5	Home 6	Home 7	Home 8	Home 9	Home 10
1	0.0078	0.0128	0.0132	0.1007	0.0150	0.0178	0.0372	0.0085	0.0253	0.0103
2	0.0040	0.0076	0.0158	0.0371	0.0107	0.0112	0.0170	0.0026	0.0177	0.0067
3	0.0059	0.0070	0.0152	0.0255	0.0066	0.0066	0.0065	0.0051	0.0164	0.0121
4	0.0042	0.0093	0.0258	0.0062	0.0515	0.0053	0.0197	0.0219	0.0159	0.0124
5	0.0078	0.0683	0.0960	0.0053	0.0546	0.0040	0.0236	0.0300	0.0391	0.0078
6	0.0266	0.1100	0.0845	0.0073	0.0206	0.0105	0.0284	0.1357	0.0676	0.0124
7	0.0883	0.0851	0.0766	0.0169	0.0237	0.0626	0.0529	0.0927	0.0311	0.0137
8	0.0935	0.0477	0.0381	0.0181	0.0524	0.0953	0.0547	0.0318	0.0592	0.0419
9	0.0599	0.0352	0.0370	0.0391	0.0603	0.0827	0.0598	0.0191	0.0567	0.1177
10	0.0411	0.0251	0.0449	0.0507	0.0501	0.0555	0.0388	0.0208	0.0300	0.0801
11	0.0598	0.0182	0.0385	0.0563	0.0428	0.0466	0.0392	0.0207	0.0285	0.1021
12	0.0748	0.0200	0.0339	0.0532	0.0418	0.0399	0.0312	0.0139	0.0334	0.0406
13	0.0429	0.0233	0.0323	0.0458	0.0364	0.0369	0.0430	0.0277	0.0307	0.0465
14	0.0389	0.0215	0.0338	0.0408	0.0278	0.0273	0.0458	0.0132	0.0331	0.0348
15	0.0514	0.0322	0.0320	0.0487	0.0297	0.0275	0.0400	0.0166	0.0384	0.0247
16	0.0427	0.0389	0.0390	0.0509	0.0345	0.0329	0.0405	0.0238	0.0567	0.0451
17	0.0679	0.0689	0.0439	0.0543	0.0579	0.0424	0.0370	0.0686	0.0718	0.0519
18	0.0569	0.0787	0.0516	0.0609	0.1009	0.0579	0.0486	0.0819	0.0700	0.0652
19	0.0424	0.0712	0.0594	0.0547	0.0758	0.0628	0.0577	0.0780	0.0498	0.0766
20	0.0520	0.0814	0.0586	0.0481	0.0695	0.0672	0.0536	0.0922	0.0384	0.0313
21	0.0461	0.0682	0.0484	0.0515	0.0615	0.0789	0.0633	0.1066	0.0495	0.0363
22	0.0282	0.0352	0.0361	0.0461	0.0369	0.0504	0.0623	0.0512	0.0509	0.0305
23	0.0397	0.0233	0.0245	0.0371	0.0226	0.0517	0.0533	0.0303	0.0574	0.0583
24	0.0171	0.0108	0.0209	0.0445	0.0163	0.0260	0.0458	0.0070	0.0322	0.0411

The Bernoulli distribution is effective to model the random variable of the cluster arrivals, while the exponential distribution fits well the observed cumulative frequencies of the cluster durations [10].

The intensity q_t during a specific Δt represents the overall demand, sum of the pulses produced by different devices which are working simultaneously. Also for q_t the exponential distribution was assumed, even though this choice implies underestimation of the maximum intensity [10].

As significant differences in the water demand can occur from one day to another (for instance, if some of the occupants of a residence are absent), the step I of the approach takes into account also this phenomenon. In fact, the total number of arrivals in a day is considered as a Normally distributed random variable, which can also be generated with the Monte Carlo technique.

The variability of the water demand during the day leads to a non-homogeneous process, which is modeled as homogeneous during predefined time sub-intervals, the duration of which has been assumed Δ = 1 hour.

Therefore, the OP model presents two levels of time discretization: the overall pulses of the residential water demand are generated considering the time interval Δt; the non-homogeneous process of the daily request is tackled as a sequence of homogeneous processes of duration Δ. Further details of the OP model are given by Gargano et al. [10].

Table 2. The estimated arrival rates $\lambda^{(i)}$ for the residence from 11 to 20 of Milford case study

t [hours]	Home 11	Home 12	Home 13	Home 14	Home 15	Home 16	Home 17	Home 18	Home 19	Home 20
1	0.0465	0.0249	0.0285	0.0169	0.0093	0.0175	0.0411	0.0048	0.0021	0.0249
2	0.0219	0.0149	0.0142	0.0072	0.0053	0.0211	0.0236	0.0004	0.0024	0.0134
3	0.0138	0.0152	0.0134	0.0073	0.0075	0.0160	0.0178	0.0009	0.0006	0.0093
4	0.0103	0.0101	0.0125	0.0434	0.0089	0.0203	0.0207	0.0081	0.0006	0.0071
5	0.0170	0.0159	0.0169	0.0406	0.0123	0.0268	0.0365	0.1719	0.0155	0.0098
6	0.0341	0.0287	0.1340	0.0728	0.0180	0.1462	0.0777	0.0984	0.0679	0.0351
7	0.0880	0.0524	0.2129	0.0940	0.0451	0.0478	0.1067	0.0046	0.1223	0.0508
8	0.0734	0.0631	0.0584	0.0764	0.0774	0.0293	0.0926	0.0049	0.0521	0.0435
9	0.0563	0.0729	0.0119	0.0705	0.0901	0.0172	0.0481	0.0062	0.0304	0.0384
10	0.0488	0.0425	0.0068	0.0497	0.0643	0.0174	0.0424	0.0070	0.0318	0.0424
11	0.0456	0.0397	0.0043	0.0469	0.0629	0.0139	0.0479	0.0096	0.0367	0.0579
12	0.0522	0.0368	0.0043	0.0608	0.0463	0.0161	0.0400	0.0062	0.0349	0.0440
13	0.0476	0.0337	0.0048	0.0440	0.0490	0.0149	0.0325	0.0063	0.0331	0.0338
14	0.0459	0.0464	0.0063	0.0374	0.0392	0.0185	0.0346	0.0076	0.0396	0.0345
15	0.0378	0.0586	0.0116	0.0379	0.0384	0.0208	0.0414	0.0339	0.0588	0.0412
16	0.0423	0.0709	0.0076	0.0390	0.0373	0.0161	0.0558	0.0779	0.0746	0.0502
17	0.0560	0.0834	0.0124	0.0549	0.0475	0.0259	0.0497	0.1152	0.0810	0.0651
18	0.0524	0.0560	0.0196	0.0477	0.0626	0.0604	0.0448	0.0961	0.0616	0.0610
19	0.0403	0.0429	0.0326	0.0483	0.0607	0.0994	0.0389	0.0894	0.0516	0.0527
20	0.0337	0.0421	0.0491	0.0463	0.0317	0.0819	0.0348	0.0695	0.0568	0.0438
21	0.0296	0.0371	0.0849	0.0218	0.0446	0.0839	0.0265	0.0752	0.0624	0.0545
22	0.0272	0.0478	0.1229	0.0143	0.0533	0.0883	0.0202	0.0463	0.0521	0.0634
23	0.0506	0.0390	0.0904	0.0114	0.0555	0.0704	0.0160	0.0432	0.0225	0.0694
24	0.0289	0.0251	0.0398	0.0105	0.0330	0.0299	0.0097	0.0166	0.0090	0.0536

3. Case study

The OP model was tested for the real case study of Milford (US), where the water demand of 21 residential users were monitored [12]. The analyzed data refer to 154 days of observed water demand indoor requests of 20 different dwellings (for data reliability reasons, one of the 21 users has been excluded in this study), aggregated with a time step of one minute. The analysis has been carried out following two different approaches.

The first approach involves the estimation of the OP model parameters for each of the 20 residences, obtaining 20 sets of parameters. Tables 1 and 2 give the arrival rate $\lambda^{(i)}$ of each residence during the i-th hour of the day, while the other parameters of the OP model are reported in Table 3.

In the second approach, the main feature of the OP model has been fully exploited, pre-aggregating the 20 users in a single block of 20 residences. Thus, only one set of parameters has been estimated (Tables 4 and 5). On the basis of the obtained parameters, two synthetic time series of 154 days has been generated, following the two above mentioned approaches.

Table 3. Mean and standard deviation of the number of cluster arrivals, mean cluster durations and mean intensities estimated for 20 Milford Users.

	Mean number of cluster arrivals μ_{ad}	Standard deviation of cluster arrivals σ_{ad}	Mean cluster durations μ_τ [min]	Mean intensities μ_q [L/min]
Home 1	42.94	14.69	2.20	3.27
Home 2	40.16	25.63	2.25	5.08
Home 3	50.62	17.97	2.26	3.90
Home 4	106.82	22.94	2.45	2.50
Home 5	31.64	15.32	3.87	4.75
Home 6	46.56	17.46	2.54	4.70
Home 7	51.60	24.79	2.15	5.97
Home 8	26.80	19.63	2.92	5.78
Home 9	63.14	23.47	2.26	3.67
Home 10	31.57	9.81	2.16	3.68
Home 11	55.88	27.52	2.56	4.29
Home 12	41.19	18.47	2.71	5.29
Home 13	27.31	11.35	2.51	3.00
Home 14	40.60	10.52	2.77	4.61
Home 15	42.86	18.33	2.15	3.46
Home 16	25.81	9.04	2.48	4.73
Home 17	50.26	26.16	3.01	3.76
Home 18	15.58	8.05	3.68	4.48
Home 19	47.44	13.64	2.89	6.70
Home 20	52.60	19.07	2.79	5.17

Table 4. The estimated arrival rate $\lambda^{(i)}$ for the aggregated block of 20 users of Milford case study.

t [hours]	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
	0.0678	0.0503	0.0397	0.0398	0.0418	0.0316	0.0240	0.0322	0.0378	0.0420	0.0384	0.0467
t [hours]	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
	0.0534	0.0522	0.0484	0.0418	0.0342	0.0259	0.0290	0.0331	0.0357	0.0461	0.0475	0.0606

Table 5. Mean and standard deviation of the number of cluster arrivals, mean cluster durations and mean intensities estimated for a pre-aggregated block of 20 users.

	Mean number of cluster arrivals μ_{ad}	Standard deviation of cluster arrivals σ_{ad}	Mean cluster durations μ_{τ} [min]	Mean intensities μ_q [L/min]
Block of 20 users	141.35	15.79	7.68	9.06

4.Results and discussion

The effectiveness of the OP model for aggregated residential demand was tested by comparing the observed time series of Milford users with the generated data. In addition, the synthetic time series of the OP model were also compared with those generated by means of the classical PRP process, calibrated for the same users.

The performance of the proposed approach was analyzed by means of the daily volume of water demand, which was estimated by accumulating the requested volume during 1440 minutes of a day.

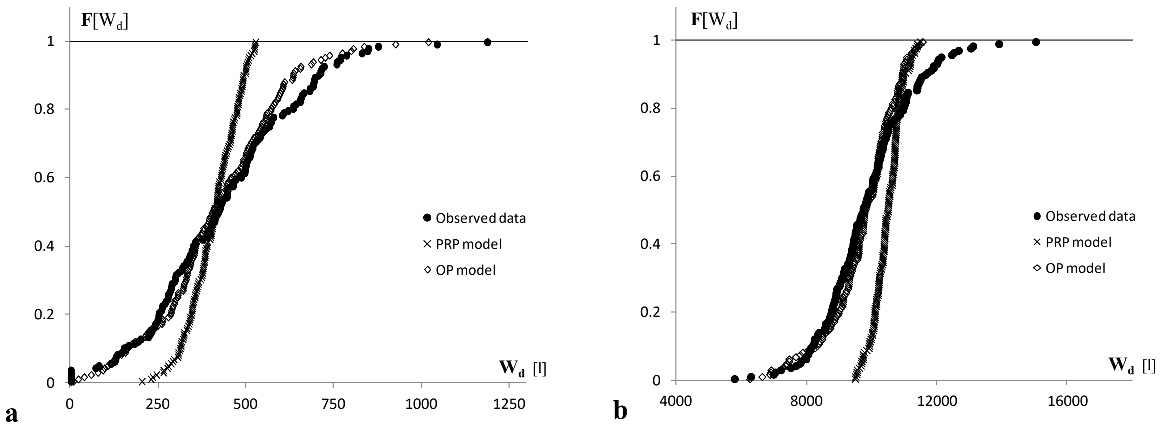

Fig.2. Cumulated frequencies of daily water demand for observed and generated (PRP and OP) data, for a single user (a) and for 20 aggregated users (b) of Milford.

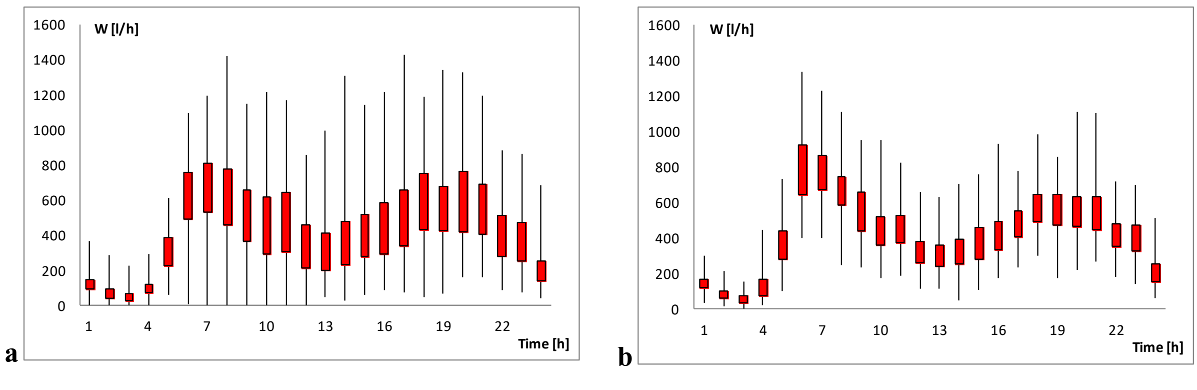

Fig.3. Box-plots of the water demand of 20 users during the day for observed (a) and synthetic (b) time series

The plots of Fig.2 show the comparison between observed and synthetic cumulative frequencies of the daily volumes needed to satisfy the water request of a single residence (Fig. 2a, in which, as an example, the plot refers to home n.3, but similar results were also obtained for the other considered users of the Milford case study) and of all the aggregated 20 residences (Fig. 2b). Fig.2 clearly shows the capability of the investigated approach to model plausible time series for 20 users, as well as for only one dwelling.

The OP model is quite effective to generate the water demand of 20 aggregated users (Fig.2b). Indeed, it shows a significant underestimation of the daily volume only for the highest values(right tail of the cumulative frequency above 85%), while the approach is absolutely robust for one single residence. In any case, however, the OP approach is definitely more effective than the PRP process in modeling the cumulative frequencies of daily volume.

Instead, Fig.3 shows the capability of the OP model to describe the water demand of the 20 aggregated users during the day. More precisely, the diagrams of Fig.3 compare –by means of the box plots (the bottom and top of box represent the first and the third quantiles) and the minimum and maximum values– observed hourly values of requested water volume (Fig.3a) with those generated by the OP model (Fig.3b). The comparison of the two diagrams of Fig.3 shows the effectiveness of the OP model to take into account the variability of the water demand of aggregated users along the day. In fact, the proposed approach catches well the daily trend, although it underestimates the spread of maximum and minimum water request.

5. Conclusions

The rectangular pulse models give a detailed description of the residential water demand, but they often present poor performance for aggregated users. In addition, this kind of approach implies a considerable computational effort, especially to obtain robust estimation of the parameters of the model.

Therefore, the paper investigates the effectiveness of a recently proposed approach – the OP model [10] - in order to generate time series of aggregated residential users. This approach is designed to model the aggregate water demand of *n* users, as it directly generates the overall demand pulses, without the need to reconstruct the individual pulses at the single taps in the dwellings.

The comparison between observed and generated time series demonstrates the capability of the OP approach to reliably model the water request also for aggregated users.

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