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IOT-BASED PREDICTIVE DIAGNOSTICS OF HOUSING ENGINEERING SYSTEMS

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Abstract

The increasing depreciation of the housing stock leads to an increase in the failure rate of utility systems. Consequently, losses of utility resources and operating costs increase, and social stability declines. Therefore, a relevant area of research is improving the quality of utility system operation by changing the maintenance planning strategy. The transition from planned to predictive maintenance is possible using smart systems. In this context, this study aimed to develop the architecture of an event-driven system for monitoring violations arising during the operation of utility systems, based on a predictive approach using IoT. This study addressed the scientific and practical problem of developing a system of criteria for detecting violations based on the analysis of IoT sensor signals. It also developed a system of rules for their activation for automated decision-making based on a deterministic approach. The study is based on analytical modeling and predictive analytics. The scientific novelty of the study lies in the proposed conceptual analytical model for decision-making in the event of an emergency during the operation of a residential sewerage system, based on formalized rules for the activation of weight sensors. The practical significance of the study lies in the development of recommendations for adapting the IoT monitoring system to various design solutions for domestic sewerage systems using the example of two countries, Russia and China.

Keywords: Smart Systems, Control Sensors, Sewer Systems, The Internet of Things, Blockages.

I. Introduction

Research conducted by the Higher School of Economics in Russia demonstrates the relatively high maturity of endpoint development and application technologies and the flourishing of IoT platform technologies, confirming the high level of technical feasibility for their implementation in operational processes. At the same time, the main areas of application for smart systems currently include transportation and energy infrastructure, public utilities information support for city residents, interactive management of individual households, ensuring the safety of city residents, and monitoring the environmental stability of the urban environment [IX, XIII, XIV]. A similar situation is observed in other cities around the world. For example, the top three smart cities, according to Kept research, include Singapore, Moscow, and Beijing. However, it should be acknowledged that IoT has not yet penetrated deeply into the infrastructure of cities around the world. Smart systems are even less present in the management of buildings and structures [XVII].

The traditional residential building management system, in which maintenance and repairs are carried out according to developed plans, demonstrates insufficient operational efficiency because it lacks the technical capacity to support the prediction of disruptions and failures. This problem manifests itself in slow response times to emergencies and high costs associated with the loss of utility resources [II]. Furthermore, accidents are often accompanied by associated costs to eliminate their consequences. The result is high social tension due to dissatisfaction among users and owners regarding the disruptions that arise. These problems necessitate new approaches to the organization and planning of operations, for example, based on predictive data analytics and the use of smart systems.

An analytical review of statistical studies of faults in Russia's housing stock was conducted. It revealed that a significant proportion of failures is due to utility systems and equipment. International experience, such as that of China, also confirms this trend. In this regard, a pressing task is to study the possibilities of using industrial devices and their control systems to transition to the intelligent operation of residential buildings. Today, this concept refers to the use of such high-tech areas as the Internet of Things (IoT) [V], robotic systems, and UAVs for monitoring the technical condition of buildings [XII, XVIII], building information modeling (BIM), artificial intelligence (AI), and data analysis [I, X]. The implementation of IoT devices in residential buildings places high demands on the capacity of data storage and computing systems, which will be used to support effective decision-making, and requires the competent deployment of devices and networks in buildings to enable centralized management [III, IV, XI, XV].

Numerous scientific studies show that one of the pressing challenges in IoT research is developing a unified approach to its design and implementation. It's not enough to simply define the type of IoT; its architecture must also be developed. Smart system architectures are divided into two types in terms of functionality: centralized server-side and distributed client-side. These two architecture types are compared and analyzed based on such metrics as horizontality, scalability, environmental awareness, interactivity with the environment, and adaptability.

Networked Auto-ID architecture was proposed by the Auto-ID Lab at the Massachusetts Institute of Technology (USA) in 1999 with the goal of connecting all objects to the Internet via radio-frequency identification (RFID) and barcodes, as well as other data collection devices to implement intelligent identification and management [XVI]. It is now widely used, for example, to provide information on utility consumption. No less significant is the USN Architecture [VIII] developed by the Korea Electronics and Telecommunications Research Institute (ETRI). It is divided into five layers: the perception network, the access network, the network infrastructure, the middleware, and the application platform. In the study [VI], the authors note that USN and IoT-A have many properties corresponding to the characteristics of the Internet of Things and have better reference values for future design and implementation.

Another relevant area of research is the study of the possibilities of adapting IoT devices to various design, planning, and engineering solutions for buildings. On the one hand, emergencies in centralized engineering systems are identical, regardless of countries or continents. For example, when examining a sewerage system, one can note such typical malfunctions as noise, blockages, leaks, overflows, breaks, sewer gas penetration into premises, and failure of sanitary equipment. On the other hand, when examining the design features of sewerage systems, for example, in Russia and China, one can note their significant differences. For example, in China, sewerage systems in apartment buildings are generally implemented on the floor, under the ceiling of the room below, which leads to the inability to quickly respond to an emergency and significantly complicates repairs [VII]. Problems with the sewerage system of the floors above manifest themselves under the ceiling of the floors below. In most cases, private property rights seriously complicate the ability to access the apartment of a neighbor living below. In Russia, emergencies within private property boundaries are generally under control, and repairs can be made as soon as a fault is detected. However, in horizontal pipelines in basements, which are common areas and within the operational responsibility of management companies, the time to detect a fault increases significantly, as the basement section of the pipe is a "blind spot" for both residents and management companies.

Sewage systems must meet specific safety requirements, as their reliable operation affects the sanitary and epidemiological situation both in individual apartments or buildings and in the city. Therefore, the development of universal systems and end devices for monitoring and forecasting will be particularly valuable. However, despite scientific research published on the use of IoT in servicing utility equipment, this article focuses on the under-researched problem of diagnosing and predicting the risk of failures in residential sewage systems through the deployment of a sensor network. The study hypothesizes that the use of IoT in utility system operations improves operational efficiency by reducing the time to failure and improving homeowner comfort, as they are no longer involved in the initial alarm signal and can be completely excluded from the process of detecting and reporting emergencies.

IoT-based decision support systems for operational use are useful for implementing government housing renovation programs. This requires developing an architecture for an event-driven system for monitoring violations that occur during the operation of residential buildings, based on a predictive approach using IoT. The study aimed to test this hypothesis. To achieve this goal, the following research objectives were formulated:

– develop a system of criteria for detecting violations based on the form of blockages in horizontal sections of the pipeline, on the analysis of IoT sensor signals, and a system of rules for automated decision-making;

– conducting analytical modelling of an emergency on a horizontal section of a domestic sewer pipe and assessing the effectiveness of the proposed system of deterministic rules;

– develop recommendations for further research for adapting the IoT monitoring system to various design solutions for residential sewerage systems.

II. Materials and methods

The research focuses on the maintenance of residential sewer systems. The subject of the study is a methodology for detecting failures and malfunctions in residential sewer systems using IoT. The study is based on methods of system analysis of scientific data on the use of IoT and analysis of malfunctions in residential sewer systems using the cases of two countries, Russia and China.

The USN architecture is used as the basis for analytical modeling of an event-driven system for monitoring operational disturbances in utility systems. A clog is used as the trigger, as it is the most common problem in sewer system operation. A clog can result in a complete or partial shutdown of the entire sewer riser and contamination of both common areas and homeowners' bathrooms with liquid household waste. The response mechanism can be based on the operating principles of such promising sensors for sewer systems as leak detectors, weight sensors, video surveillance sensors with liquid movement detection on the floor, sensors that detect the odor of liquid household waste, and acoustic sensors for wastewater movement. In this study, a pipe weight monitoring sensor (PWS) is used as the basis for modeling the remote clog monitoring system on the horizontal section. During operation, PWS monitors the following parameters: pipe weight, wastewater transit time, and wastewater flow velocity.

When modeling the operation of the monitoring system with the IoT device PWS, the following assumptions were considered:

1. The calibration signal for the PWS activation is the weight of the pipe filled with wastewater. The total weight includes the weight of a pipe of a certain length and the weight of the wastewater. The pipe weight is constant and is not a sensor activation parameter. The weight of the wastewater varies depending on the water consumption regime and is determined by the fill factor of the pipe. Consequently, the activation threshold is set when the maximum permissible fill factor of the pipe with wastewater is exceeded, which is determined based on statistical water consumption data for specific buildings.

2. A sewer network can be modelled as a graph $G = (V, E)$, where the set of vertices V corresponds to pipe connection nodes and points of change in geometric and hydraulic parameters, while the edges E describe individual pipe sections with constant characteristics. However, in this study, based on initial research, the modelling was limited to a single edge, which represents a horizontal section with two vertices connecting it to other sections. The sewer pipe length is based on the typical design of

residential sewer systems, with a 0.5 m pitch. The pipe weight and roughness coefficient are determined based on the traditional material used (cast iron, concrete, PVC, HDPE).

3. The trigger for the PWS signal to alert about a probable blockage is the duration of time of change in the pipe weight: a stable increase in the pipe weight (growing blockage) or a long-term excess of the pipe weight threshold value corresponding to the excess of the maximum filling factor (existing blockage).

4. Manning's formula is used to determine the flow velocity of wastewater. Flow velocity can be an additional diagnostic criterion for potential blockages when installing acoustic noise sensors.

To justify the change in wastewater mass in a pipeline, the integral equation of mass conservation is used for a control section. The rate of change of water mass in a pipe is determined by the difference between the inlet and outlet flow rates:

$$d(\Delta W)/dt = \rho\ (Q_{in} - Q_{out}) \qquad (1)$$

where $d(\Delta W)/dt$ is the rate of change of the excess water mass in the pipe, kg/s; ρ is the density of wastewater, kg/m^3; Q_{in} is the volumetric water flow rate at the inlet of the section, m^3/s; Q_{out} is the volumetric water flow rate at the outlet of the section, m^3/s.

With a quasi-stationary change in the water level and a constant pipe cross-section, this relationship reduces to the dependence used in the study:

$$\Delta W = f\ (S, L, \rho, k) \qquad (2)$$

where ΔW is the increase in the weight of the wastewater in the pipe section under consideration, kg; S is the area of the wetted part of the pipe, m^2; L is the pipe length, m; ρ is the density of the wastewater, kg/m^3; k is the fill factor of the pipe.

However, recording only the magnitude of the mass increment ΔW does not allow for a definitive identification of the cause of its increase. Identical ΔW values can arise under two fundamentally different hydraulic scenarios: a short-term peak increase in the inlet flow rate $Q_{in}(t)$ due to a massive, simultaneous discharge of wastewater by users, or a sustained decrease in the outlet flow rate $Q_{out}(t)$ due to the formation of a localized pipeline blockage. In the first case, the excess water mass accumulates briefly and, after the flow rates equalize, the level and mass quickly return to standard values. In the second case, the limited flow capacity of the section creates a stable positive difference ($Q_{in} - Q_{out}$), leading to prolonged water accumulation and a persistent excess of control values. To eliminate this ambiguity, it is proposed to use the time criterion T_{max}: a short-term exceedance of the threshold corresponds to a peak load, while a long-term exceedance corresponds to a blockage. A complete diagnosis is achieved by jointly monitoring the weight and flow rate of water at the inlet and outlet of the section.

The following system of criteria for predicting the occurrence of blockage and the conditions for triggering the DKVT signal is proposed:

$$\{\Delta W = f\ (S, L, \rho, k) \geq \Delta W_{max} = f\ (k_{max}), \qquad t(\Delta W_{max}) \geq T_{max} \qquad (3)$$

where $\Delta W_{\max}$ is the threshold value of the wastewater weight corresponding to the maximum fill factor of the pipe $k_{\max}$, kg; $t(\Delta W_{\max})$ is the duration of exceeding the threshold value of the wastewater weight in the section of the pipe under consideration, s; $T_{\max}$ is the maximum permissible time of exceeding the threshold value of the wastewater weight, s.

The study was conducted using deterministic decision-making logic based on fixed thresholds $\Delta W_{\max}$ and $T_{\max}$. This approach was chosen to demonstrate the fundamental viability of the pipeline fill monitoring method based on weight indicators.

The condition for complete blockage and the condition for triggering the acoustic sensor signal (if installed) is the following system of criteria:

$$\{k \to 1, \qquad V = f\,(n, R, i) \to 0 \tag{4}$$

where V is the flow velocity, m/s; n is the pipe roughness coefficient; R is the hydraulic radius, m; i is the hydraulic slope of the pipe.

Next, the following scenarios were modeled based on the water consumption and wastewater disposal regime and the system of rules for automated decision making:

Rule 01: if ($\Delta W < \Delta W_{\max}$) then status = normal operation.

Rule 02: if ($\Delta W \geq \Delta W_{\max}$) and ($t(\Delta W_{\max}) < T_{\max}$) then status = high load.

Rule 03: if ($\Delta W \geq \Delta W_{\max}$) and ($t(\Delta W_{\max}) \geq T_{\max}$) then trigger = clog prediction alert.

Finally, design solutions for sewerage systems in two countries, Russia and China, were studied and analyzed to confirm the universality of the proposed solution and assess its adaptability to the specific housing stock of different countries.

III. Results

The developed architecture of an event-driven system for monitoring violations during the operation of a sewerage system, using the example of diagnosing and predicting pipe blockages, includes several levels (see Fig. 1).

Strain gauge weight sensors serve as the hardware (sensor and sensor network layer). The sensors can operate intermittently, transmitting signals at threshold weight changes, which saves energy.

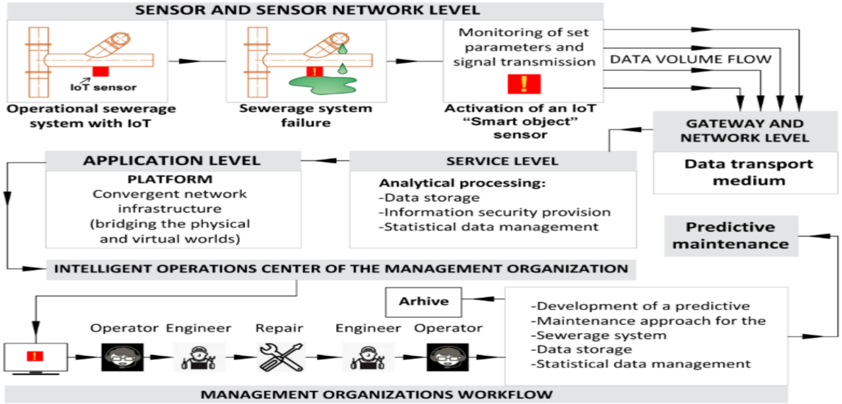


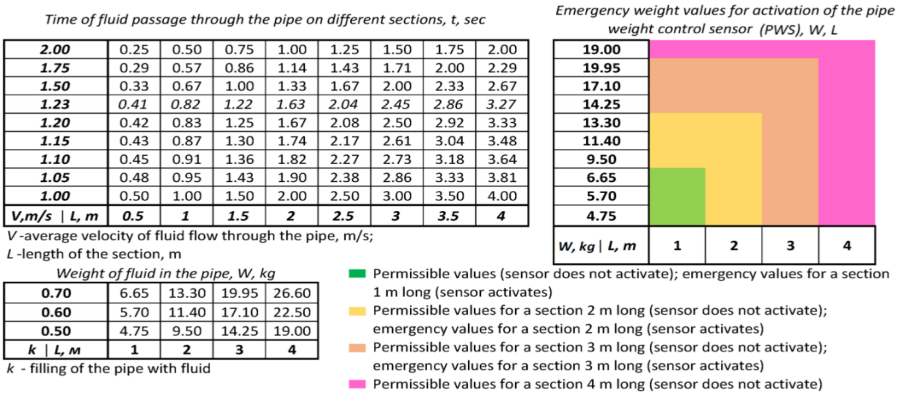
Fig. 1. Architecture of an event-driven system for monitoring violations during the operation of a sewerage system.

Since disturbance monitoring is considered for horizontal trunk lines, IoT gateways must be in the building's basement, which increases the requirements for stable operating conditions. Therefore, the installation of room temperature and humidity sensors is also recommended.

Storing data on a cloud platform will ensure real-time access for relevant specialists. The system also provides long-term data storage for reporting, operational documentation, and data downloads to support planned maintenance. Such systems enable the use of modern visualization tools, such as dashboards, to simplify data analysis and improve operational efficiency.

In the next step, based on predictive analytics for the operating and emergency scenarios modeled above, threshold values of decision criteria were calculated for PVC pipes with an outer diameter of 110 mm of different lengths (see Fig. 2).

The weight of the gravity sewer system was calculated assuming 50–70% of the full cross-sectional area of the pipe in a horizontal section of the basement in common areas. A basement pipe subsidence was considered an emergency, causing a change in slope and, subsequently, a blockage in the building's apartments.



Time of fluid passage through the pipe on different sections, t, sec

2.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00
1.75	0.29	0.57	0.86	1.14	1.43	1.71	2.00	2.29
1.50	0.33	0.67	1.00	1.33	1.67	2.00	2.33	2.67
1.23	*0.41*	*0.82*	*1.22*	*1.63*	*2.04*	*2.45*	*2.86*	*3.27*
1.20	0.42	0.83	1.25	1.67	2.08	2.50	2.92	3.33
1.15	0.43	0.87	1.30	1.74	2.17	2.61	3.04	3.48
1.10	0.45	0.91	1.36	1.82	2.27	2.73	3.18	3.64
1.05	0.48	0.95	1.43	1.90	2.38	2.86	3.33	3.81
1.00	0.50	1.00	1.50	2.00	2.50	3.00	3.50	4.00
V,m/s | L, m	***0.5***	***1***	***1.5***	***2***	***2.5***	***3***	***3.5***	***4***

V -average velocity of fluid flow through the pipe, m/s;
L -length of the section, m

Weight of fluid in the pipe, W, kg

0.70	6.65	13.30	19.95	26.60
0.60	5.70	11.40	17.10	22.50
0.50	4.75	9.50	14.25	19.00
k | L, м	**1**	**2**	**3**	**4**

k - filling of the pipe with fluid

Emergency weight values for activation of the pipe weight control sensor (PWS), W, L

19.00	🟪	🟪	🟪	🟪
19.95	🟧	🟧	🟧	🟪
17.10	🟧	🟧	🟧	🟪
14.25	🟧	🟧	🟧	🟪
13.30	🟨	🟨	🟧	🟪
11.40	🟨	🟨	🟧	🟪
9.50	🟨	🟨	🟧	🟪
6.65	🟩	🟨	🟧	🟪
5.70	🟩	🟨	🟧	🟪
4.75	🟩	🟨	🟧	🟪
W, kg | L, m	**1**	**2**	**3**	**4**

- 🟩 Permissible values (sensor does not activate); emergency values for a section 1 m long (sensor activates)
- 🟨 Permissible values for a section 2 m long (sensor does not activate); emergency values for a section 2 m long (sensor activates)
- 🟧 Permissible values for a section 3 m long (sensor does not activate); emergency values for a section 3 m long (sensor activates)
- 🟪 Permissible values for a section 4 m long (sensor does not activate)

Fig. 2. Simulated test results and state transition diagram.

In the absence of sensors, it is impossible to determine the onset of the failure, as the signal was a call from the user about a blockage in the apartment. Clearing a blockage or clearing a subsidence in Russia averages 3 hours, while in China, it takes 8 hours due to different sewer system designs.

IV. Discussion

At the final stage, recommendations were developed for adapting the IoT monitoring system to various design solutions for residential sewerage systems (see Fig. 3). At the time of the study, another distinguishing feature of sewerage system design in China and Russia, in addition to those listed in the introduction, is that in China, pipes for the kitchen and bathroom are installed separately, which increases the failure rate.

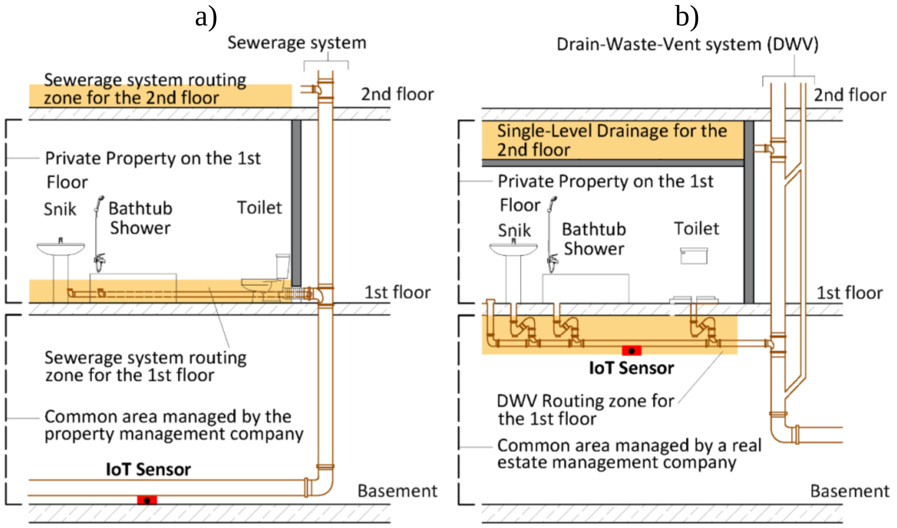


Fig. 3. IoT sensor locations: a) Russia; b) China.

The operational effectiveness of the proposed solution can be assessed by reducing the duration of the fault (blockage):

$$\{T_{ref}^{IoT} = 0, \quad T_{req}^{IoT} = 0, \quad T_{disp}^{IoT} < T_{disp}, \quad T_{trav}^{IoT} = T_{trav}, \quad T_{detect}^{IoT} \rightarrow 0, \quad T_{maint}^{IoT} < T_{maint}\} \rightarrow min \qquad (5)$$

where T_{ref} – the time of existence of a blockage from the onset of its formation to its detection by the user, which can be a long period of time, measured in hours or even days; T_{ref}^{IoT} – with IoT, a blockage is recorded the moment it starts to form; T_{req} – the time for receiving an application by the dispatcher and clarifying the data depends on the load time of the control room and can exceed the 10 minutes allowed in Russia; T_{req}^{IoT} – with IoT, receiving an application is automated; T_{disp} – the time for assigning a performer and generating an order to perform the work; T_{disp}^{IoT} – with IoT, the assignment of a performer can be automated; T_{trav} – the travel time to the accident site depends on the location of the control room; T_{trav}^{IoT} – similar time, which does not depend on use IoT; T_{detect} – the time to find the location of the blockage; T_{detect}^{IoT} – with

IoT, the location of the blockage is recorded by a sensor the moment it begins to form; T_{maint} – the time it takes to clear the blockage; T_{maint}^{IoT} – with IoT, the time for clearing the blockage is reduced, since the blockage is just beginning to form.

The presented model does not account for rapid wave processes and hydraulic shock, due to the difference in time scales: blockage development occurs over minutes and hours, while transient processes last seconds. Incorporation of pressure curves and full hydrodynamic modeling of the network are planned for future research.

It should also be noted that due to the lack of statistical data, the model under consideration is conceptual and does not consider the statistical nature of measurements, sensor noise, daily fluctuations in water consumption, or operational disturbances.

The proposed decision rules can be refined within the framework of statistical detection theory. For this purpose, two hypotheses are introduced:

H_0 – normal system operation, no blockage (Rule 01);

H_1 – presence of blockage and emergency backwater (alarm condition).

Further research should focus on optimizing the $\Delta W_{\max}$ and $T_{\max}$ thresholds, which can be accomplished by analyzing the distributions of measured parameters in normal and emergency mode, as well as using ROC analysis and the Neyman-Pearson criterion. This will allow for monitoring the probability of false alarms and the reliability of defect detection. The decision is made based on a comparison of the likelihood functions: if $p(X|H_1)$ is significantly greater than $p(X|H_0)$, then H_1 is accepted.

V. Conclusion

The study resulted in a developed conceptual model for a remote monitoring system for sewer pipe malfunctions based on an IoT sensor system. The potential for using weight sensors as alarm devices to detect the early stages of blockage formation was demonstrated. The scientific significance lies in the proposed system of criteria and a methodology for setting threshold values, which could form the basis for the transition from a passive to a predictive maintenance model.

The research demonstrates the feasibility of adapting the proposed system of criteria and rules for monitoring and detecting failures in sewerage systems with different design solutions. Further research focuses on conducting long-term field experiments to collect statistical data for model calibration and the transition from a deterministic model to a statistical one.

Further research will include determining the minimum number of sensors required and their optimal placement on a directed graph model of the sewer network to uniquely localize the location of a blockage using network coverage criteria.

Conflict of Interest:

The authors declare that there is no conflict of interest regarding this article.

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