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A PETROLEUM CHEMISTRY PERSPECTIVE ON INTEGRATING IN-SITU SENSOR DATA WITH RESERVOIR MODELS FOR ENHANCED OIL RECOVERY USING KALMAN FILTER

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ABSTRACT
One of the significant benefits of in-situ sensor data is its integration with reservoir simulation models, which helps to optimize Enhanced Oil Recovery (EOR) processes. Located in the reservoir or wellbore, these sensors provide real-time data on pressure, temperature, and fluid composition that can help to improve dynamic updates of the models. This paper presents an approach to assimilate in-situ data into reservoir simulations, combining the Kalman Filter, a powerful technique for data assimilation. It fuses the actual sensor data with the state predictions iteratively, thus reducing uncertainty and growing accuracy. In other words, the task is to predict reservoir states with a model obtained and refine these predictions by using sensor measurements. Rapid development of EOR deployment enables continuous integration that can adjust steaming rates, chemical utilization, or stimulation accordingly. The methodology is validated by simulation results, showing an encouraging performance for various EOR processes in a more innovative and practical way.
Keywords: In-Situ Sensor Data, Reservoir Simulation, Kalman Filter, Enhanced Oil Recovery (EOR), Real-Time Data Assimilation.
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INTRODUCTION

Enhanced Oil Recovery (EOR) helps to extend the Life of an oil field and helps Maximize Hydrocarbons recovery. These essentially rely on a limited ability to specifically address the complex subsurface conditions responsible for significant oil bypassing that is usually caused by using primary and even some enhanced recovery methods.[1] Such challenges can be met using innovative EOR technologies such as chemical flooding, gas injection, and thermal recovery to increase oil displacement efficiency values. Continuous real-time monitoring of pressure, temperature, and fluid composition by in-situ sensors has completely changed reservoir management. New information can be generated for reservoir dynamics, which can facilitate the adjustment in EOR operations that directly improves the speed and accuracy. The presence of in-situ sensor data used in reservoir simulation adds an advanced benefit in optimizing EOR operations. For more selectivity and reliability in operations dynamical process of real-time applications is preferred over conventional models.[2] Methodologies such as Kalman Filter, Low Pass Filter, which make reservoir models work in real-time mode, thus provide more fit-for-purpose EOR operations. The development of in-situ sensors is an advanced approach for monitoring and controlling the EOR process. Installed either in reservoirs or wellbores, the purpose of deploying these kinds of sensors is to get an actual-time reading online for essential parameters like pressure and temperature, as well as fluid type constituents. In-situ sensors, in contrast to typical methods which rely on infrequent or sparse data, provide a continuous set of high-fidelity measurements that provide a dynamic perspective into reservoir conditions.

In-situ sensor data integration with reservoir simulation models becomes a huge step-up in EOR optimization. However, in the case of fluid flow and heat transfer (amongst many other things), these models are generally static and rely on other resources to yield more accurate predictions.[3] The demonstrated model shows how the real-time sensor data sharpens simulation models and improves EOR strategies using advanced data assimilation techniques. Enhanced Oil Recovery (EOR) is a very challenging problem that needs specific adaptive methods for the purpose of best recovery. The chemical injection

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approach, gas flooding method, or thermal recovery technique is an EOR techniques that focus on recovering more oil than what can be extracted by primary and secondary methods. Yet their success depends largely on being able to determine the ever-changing conditions deep within reservoirs. Classic reservoir management suffers from poor data, its dynamic updating rate, and the need for EOR operational inefficiency. The development and deployment of in-situ sensors have transformed reservoir management by allowing real-time measurements of important parameters such as pressure, temperature, and fluid composition.[4] The detailed real-time data provides never-before-seen visibility into how the reservoir is acting, and as a result, EOR processes are controlled with far greater precision. The utilized components in the EOR strategy optimize the integration of reservoir simulation models with in-situ sensor data. But by updating these models on a rolling basis with real-time data, operators can create more reliable forecasts, and errors are reduced quickly enough to alter EOR techniques in time. This article will examine the integration methods of in-situ sensor data into reservoir models and their effects on enhanced oil recovery strategies, along with daily field operations. The significance of Enhanced Oil Recovery (EOR) technologies has influenced the capacity to extract from reservoirs that are depleted by conventional techniques.[5] Chemical injection, gas flooding, thermal recovery, and other techniques have been used to extract more of the resource, but their success relies on a proper real-time perception of changing reservoir status. Although traditional monitoring approaches cannot meet the need for long-term insights into EOR process performance.[6] Bulk data recorders and in-situ sensors provide real-time information on reservoir characteristics, including pressure, temperature, and fluid composition. The sensors, inside the reservoir or wellbore, can provide a highly resolved and dynamic insight into subsurface conditions.[7] This provides a framework to include real-time data with reservoir simulation models (RSMs) to account for genuine dynamics in reservoir behavior, which is greatly hindered by the complexity and scale of these operational value streams. The Kalman Filter, which is a more advanced data assimilation method, overcomes this by incorporating actual sensor measurements to update the reservoir model periodically. It blends reservoir condition forecasts with actual data, enhancing modelling accuracy and allowing for real-time EOR adjustments. This reduces risk and improves decision-making.[8] The objective of this paper is to explain the use of the Kalman Filter in assimilating field-disturbed sensor data into Reservoir simulation models for EOR optimization. It also provides insight into the Kalman Filter: its principles and how it is utilized in reservoir management to improve recovery efficiency. Such integration enables a strong association, which guarantees proper reservoir representation and allows real-time strategy changes for better EOR effectiveness.

EXPERIMENITAL

Materials and Methods

In reservoir management, you need in situ sensors to get real-time data for monitoring and decision support. These sensors embedded within the reservoir (or wellbore) itself comprise pressure, temperature, and composition measuring devices. The systems constantly monitor reservoir conditions and report the data to a central system, which in turn analyses the information as it comes in. Apply initial and boundary conditions for the defined models using fluid characteristics, geological, and petrophysical properties. The Extended Kalman Filter, a sophisticated method for data assimilation and adaptive control of EOR processes, plays an important role in improving simulation accuracy and decision-making. Its implementation involves algorithm design and software tools. Data management and analysis are the main requirements for managing the enormous data originating from in-situ sensors, using data sources and visualization tools. All these technologies and methodologies together contribute to a strong platform for monitoring & controlling reservoir performance, which leads to improved decision making in the field of Reservoir Engineering. The key to better management of the reservoir and its rehabilitation is to be done effectively with proper data collection. Developing the reservoir simulation model entails several essential steps.

Model Initialization

Clearly define the initial conditions that are required for creating or fine-tuning the simulation model. The main elements included in the process are fluid characteristics, geological formations, and petrophysical properties. By considering the initial and final boundary conditions, an accurate depiction of real-world settings is obtained. A solid basis for impending simulations and analysis can be achieved only by properly setting the gathering of real-time parameters.

Model Calibration

For calibration, both predicted values, past and current data, are considered to understand the behavior of the reservoirs. It is essential to gather these data values, mainly for modeling the system performance. Only through calibration, the model is defined and obtains real-time sensor data that gives the accuracy and insight analysis of the reservoirs.
The Kalman Filter is utilized to improve the precision of reservoir predictions. This process involves.

Prediction Step

Project the reservoir's future conditions, including its pressure, temperature, and fluid composition, using the simulation model. This prediction is based on both previous data and current measurements.

Update Step

Contrast the predicted state with actual sensor data and apply the Kalman Filter equations to adjust and improve the forecasts. This updating process includes:
Updating the state estimate,

$$x_{f/f} = x_{f/f-1} + F_f\left(z_f - Hx_{f/f-1}\right) \tag{1}$$

$$F_f = P_{f/f-1}H^T\left(HP_{f/f-1}\ H^T + R\right)^{-1} \tag{2}$$

$$P_{f/f} - \left(I - F_f H\right)P_{f/f-1} \tag{3}$$

Here $x_{f/f}$ is the updated state estimate, $x_{f/f-1}$ Is the prior state estimate, F_f Is the Kalman gain, z_f Is the sensor measurement? H Is the observation matrix and R It is noise covariance. The second stage is an optimization of the EOR-related processes, as presented in a refined model for the largest operation that includes a strategy adjustment step, along with essential EOR parameters such as injection rates, chemical concentrations, and temperature conditions are adjusted based on the reservoir model. Adaptive control procedures are substituted in place of the improved prediction models to increase efficiency. The improved EOR techniques enhance the reservoir performance and recovery efficiency.[9-13]

Validation and Verification

This step required performing a holistic validation and verification in order to assure the reliability of the model. Comprehensive validation and verification are necessary to guarantee the dependability of the model and procedures. For accuracy, model validation includes a comparison of predicted results and the obtained sensor reading. To ensure accuracy, model validation involves comparing predicted results with real production data and sensor readings. Model parameters should be changed in response to any inconsistencies found in order to increase precision. Moreover, System Testing entails assessing the integration procedure that includes data collection, Kalman Filter implementation, and EOR optimization under diverse reservoir circumstances.[14-15] This comprehensive testing ensures that the system will always be reliable, strong, and able to provide correct results in a variety of settings.

Data Analysis and Reporting

Analysed data is being stored and used at times to calculate recovery efficiency, production rates, and water-oil ratio.

Detection Method

A systematic procedure is employed to safeguard the optimization of EOR operations and proper modelling of obtained data while integrating in-situ sensor data with reservoir models by using the Kalman Filter,[16-17] as shown in (Fig.-1). The Kalman Filter enables real-time improvement of the model using sensor data, thus increasing reservoir management decision support.

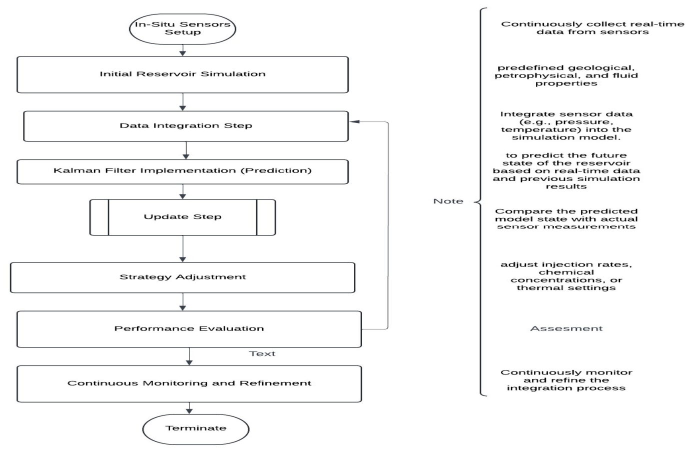

Fig.-1: Flow diagram of A Petroleum Chemistry Perspective on Integrating In-Situ Sensor Data with Reservoir Models for Enhanced Oil Recovery Using Kalman Filter

RESULTS AND DISCUSSION

For the analysis purpose, the effectiveness of the Kalman filter is compared with other existing filters like the low-pass [18] and Savitzky-Golay Filter [19] as listed in Table-1.

Table-1: Comparison between Filters- Kalman, Low Pass, and Savitzky-Golay

Features	Kalman Filter	Low Pass Filter	Savitzky-Golay Filter
Purpose	Noise reduction along with state estimation	Reduces high-frequency noise	Smooth's data and preserves features
Data Preservation	Along with filtering noise, it can provide an accurate state estimate	Reduces noise, but the a possibility of missing important data	Preserves features like peaks and slopes better than low pass

Noise Reduction and Signal Fidelity

Noise resulting from subsurface causes equipment limitations. Environmental conditions might impact data obtained from in situ sensors in reservoirs. Effectively controlling the noise while maintaining the accuracy of the underlying signal was critical. It is illustrated with the analysis as listed in Table-2.

Table-2: Analysis of Noise Reduction and Signal Fidelity

Time	Noisy Signal	Savitzky-Golay Filter	Low-Pass Filter	Kalman Filter
0	0.099347231	0.137282596	0.098433532	0.099392831
10.02004	0.42695192	0.355209863	0.324793473	0.453989618
20.24048	0.494537566	0.537704511	0.48573788	0.940377233
30.06012	0.498844479	0.428147329	0.447247857	0.684738975
40.08016	-0.226198442	-0.291973809	-0.27819451	-0.261933889
50.1002	-1.249484165	-0.943638543	-0.909828599	-0.956478609
60.12024	-0.922638707	-0.698296083	-0.721263069	-0.69903474873
70.14028	0.484448351	0.394797047	0.424553203	0.232599534
80.16032	1.011370896	1.316211009	1.29289626	0.932520913
90.78156	0.934059786	0.769415805	0.779846241	0.6887162234
100	-0.951748484	-0.77457599	-0.953518057	-0.181516769

Figure-2 illustrates the Kalman Filter image code Minimization and Optimization in terms of signal quality and noise reduction, which implies the behaviour and characteristics that typically surpass both Low-Pass as well as Savitzky-Golay filters due to its real-time adaptive and optimized design.

Real-Time Processing and Responsiveness

For Enhanced Oil Recovery (EOR) systems, real-time monitoring is an often-required aspect to calculate injection rates, pressure management, and other critical parameters. It is illustrated with the analysis as listed in Table-3.

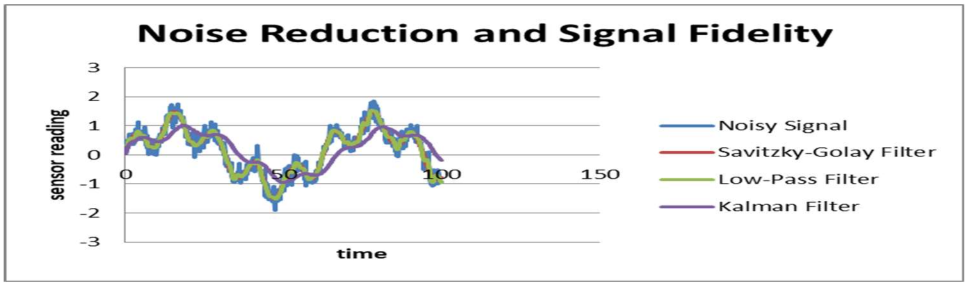

Fig.-2: Impact of Noise Reduction and Signal Fidelity using Different Filters

Table-3: Analysis of Real-Time Processing and Responsiveness

Time	Noisy Signal	Savitzky-Golay Filter	Low-Pass Filter	Kalman Filter
0	0.149014246	0.232009662	0.15169811	0.149014246
10.02004	0.939777255	0.815988734	0.813945981	0.463085765
20.04008	0.483010982	0.828854656	0.811823577	0.843211085
30.06012	1.21031349	0.649494514	0.677966399	0.56058051
40.08016	0.345318455	0.260614567	0.250523181	0.543621257
50.1002	-0.334299064	0.123293493	0.133643096	0.148333269
60.12024	-1.016548948	0.000940542	-0.03253047	0.32867392
70.14028	0.260769663	0.120884867	0.125393801	-0.07187747
80.16032	0.00857024	0.457122552	0.45908005	0.362242698
90.18036	-0.123184593	-0.22694739	-0.208365571	0.182286773
100	-1.45886103	-1.218966973	-1.447598011	-0.53537663

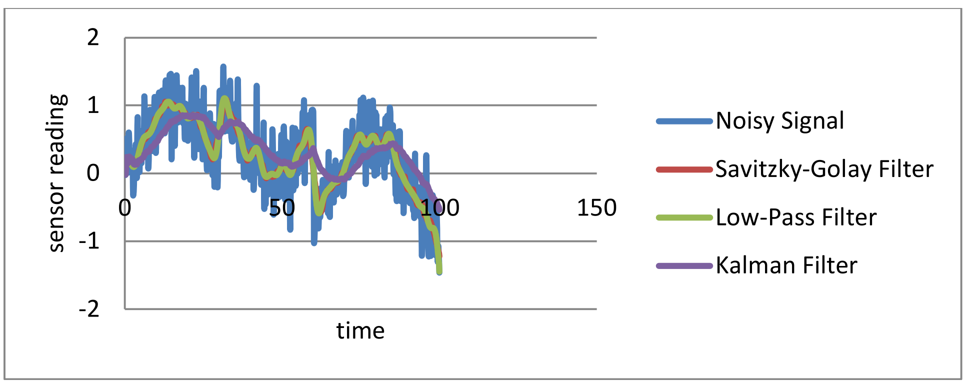

Fig.-3: Results of Real-Time Data Processing and its Responsiveness using Different Filters

Kalman Filter, with its adaptiveness and recursion, naturally handles dynamic disturbances more effectively for real-time processing requirements than the prevalent Low-Pass or Savitzky-Golay Filter, as shown in (Fig.-3). These algorithms have received recent interest as they are reliable in computational and responsiveness characteristics for integration with in-situ sensor data in Enhanced Oil Recovery (EOR) processes. By contrast to the Kalman Filter, the Low-Pass and Savitzky-Golay Filters cannot deliver real-time performance to distinct levels as they do not have dynamic adaptability at a good enough resolution in time.

Computational Efficiency and Resource Constraints:

For ensuring timely, accurate, and reliable updates to the reservoir model, high computational efficiency and managing resource constraints are crucial. It is illustrated with the analysis as listed in Table-4.

Table-4: Computational Efficiency and Resource Constraints

Filter	Execution Time (seconds)	Memory Usage (MB)
Savitzky-Golay	0.000981	237.49
Low-Pass	0.000568	237.49
Kalman	0.000566	237.49

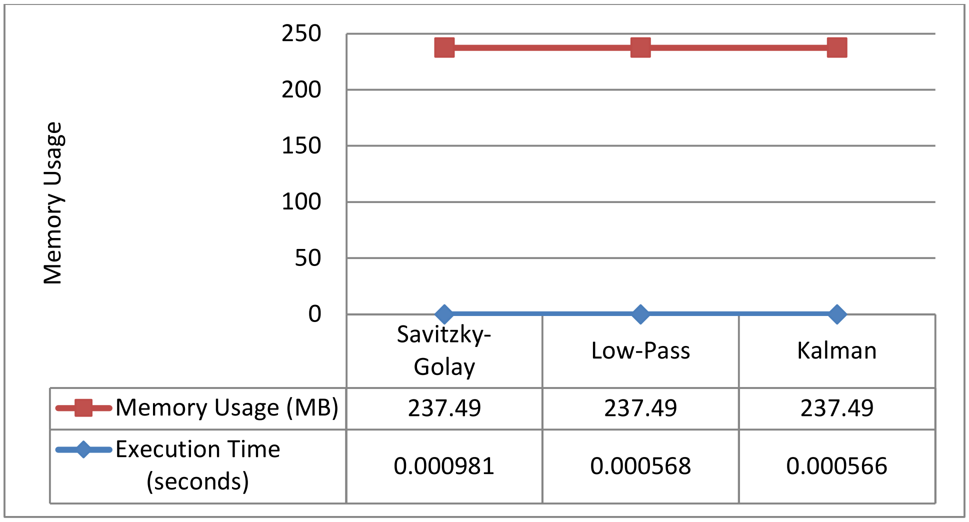

Fig.-4: Results of Computational Efficiency and Resource Constraints

Due to recursive design, the Kalman filter can process the real-time data with little overhead and optimal memory usage compared to Low-Pass and Savitzky-Golay filters, as shown in (Fig.-4). Due to polynomial redefined procedures required during resource allocation of Savitzky-Golay filters and frequent updating in data while filtering of Low-Pass Filter, the choice of Kalman filter for combining in-situ sensor data with reservoir models has made it a better model in Enhanced Oil Recovery (EOR) procedures.

Edge Effects and Transient Response

The transient response should be effectively managed at edge effects to ensure accuracy for real-time monitoring that gives an effective system as shown in (Fig.-5) and (Fig.-6) using Table-5 and Table-6.

Table-5: Edge Effects and Transient Response at Starting

Time	Original	Kalman	Low_Pass	Savitzky_Golay
0	0.176405	0.191854	0.176381	0.186109
0.1	0.169843	0.177777	0.285928	0.314859
0.2	0.35572	0.297289	0.391883	0.431457
0.3	0.606376	0.505939	0.49147	0.536402
0.4	0.68821	0.629047	0.583788	0.630196
0.5	0.516038	0.552715	0.669947	0.713339
0.6	0.812789	0.728383	0.752376	0.786332
0.7	0.797099	0.774798	0.833525	0.849676
0.8	0.885742	0.849736	0.914484	0.903873
0.9	1.009485	0.957639	0.994078	0.949423

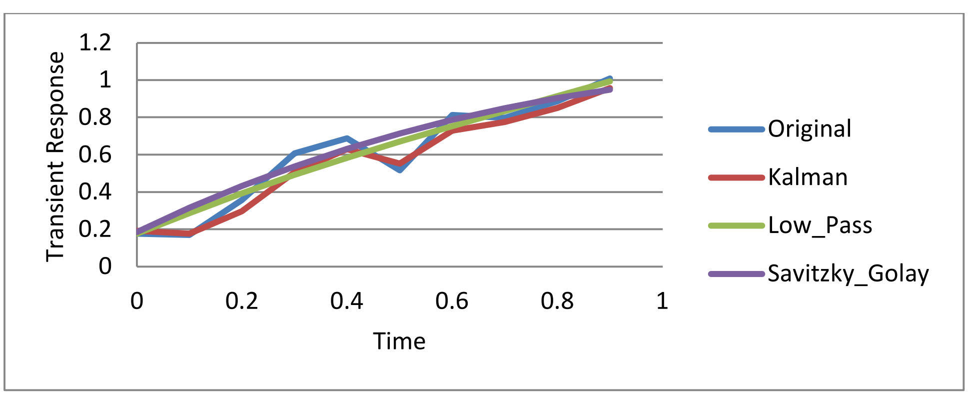

Fig.-5: Effect of Edge Effects and Transient Response at Starting

Table-6: Edge Effects and Transient Response at Ending

Time	Original	Kalman	Low_Pass	Savitzky_Golay
99	3.423686	3.417939	3.401984	3.577894
99.1	3.404949	3.409165	3.402126	3.570871
99.2	3.326403	3.353263	3.415	3.56457
99.3	3.46197	3.42669	3.441875	3.559107
99.4	3.510854	3.483539	3.482844	3.554595
99.5	3.579762	3.548534	3.536925	3.55115
99.6	3.587375	3.574769	3.602357	3.548886
99.7	3.697052	3.657366	3.676899	3.547918
99.8	3.664195	3.661979	3.757986	3.548361

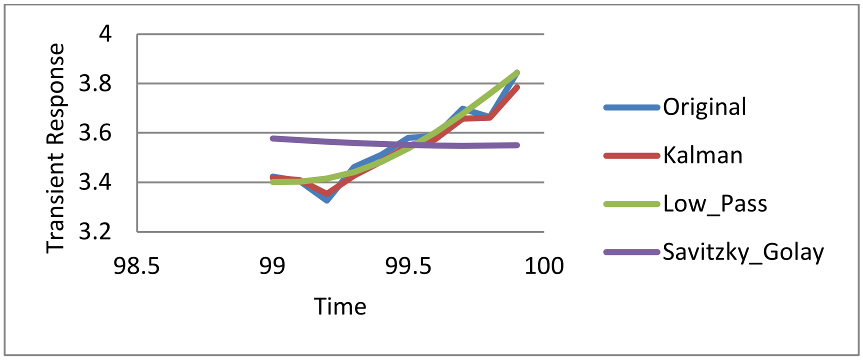

Fig.-6: Effect of Edge Effects and Transient Response at Ending

Handling Non-Stationary Signals

Adaptive techniques like time-frequency analysis, machine learning, and the Kalman Filter are needed for integrating in-situ sensor data with reservoir models used in EOR processes on non-stationary signals. These techniques work by overcoming challenges that arise when reservoir conditions alter, enabling precise real-time monitoring and helping to make the best decisions as listed in Table-7 and shown in (Fig.-7.

Table-7: Managing Non-Stationary Signals

Time	Original	Kalman	Low_Pass	Savitzky_Golay
0	0.176405235	0.191854061	0.176381138	0.18610869
0.1	0.16984318	0.177776573	0.285927617	0.314859438
0.2	0.355720365	0.297289072	0.39188315	0.431456894
0.3	0.606376478	0.50593903	0.491469919	0.53640196
0.4	0.68821039	0.629047378	0.583787624	0.630195542
0.5	0.516037601	0.552714871	0.66994701	0.713338542
0.6	0.812789253	0.728383277	0.752376099	0.786331864
0.7	0.79709907	0.774797696	0.833524927	0.849676412
0.8	0.885742098	0.849735641	0.914484192	0.90387309
0.9	1.009485203	0.957639273	0.994077644	0.949422801

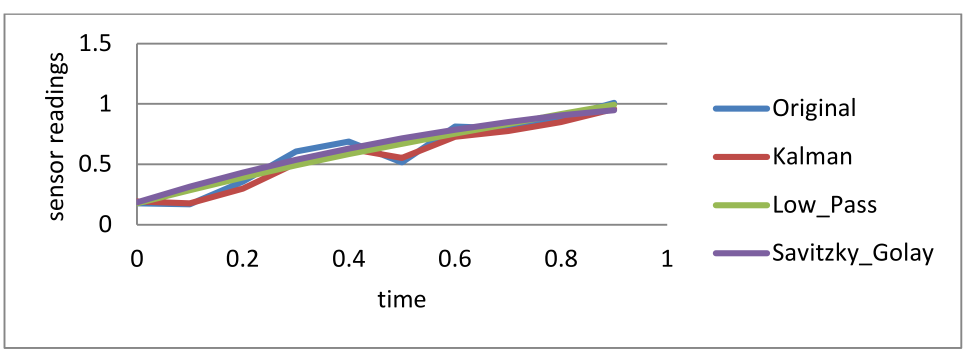

Fig.-7: Handling of Non-Stationary Signals using Different Filters

Table-8: Comprehensive View of the Data-Summary Statistics

-	Time	Original	Kalman	Low_Pass	Savitzky_Golay
count	1000	1000	1000	1000	1000
mean	50	2.538863868	2.537152749	2.538973687	2.539445
Std.	28.910854	1.429986017	1.427819713	1.426873269	1.393519
min	0	-0.778950718	-0.757026823	-0.753708608	-0.50391
	25%	25.0 1.6194951690736943	1.620603186	1.622557562	1.549482
	50%	50.0 2.6781768243286805	2.688151293	2.6751554	2.740133
	75%	75.0 3.6972399071624484	3.697967535	3.683757957	3.638506
max	100	5.405986269	5.342416109	5.291648396	5.053456

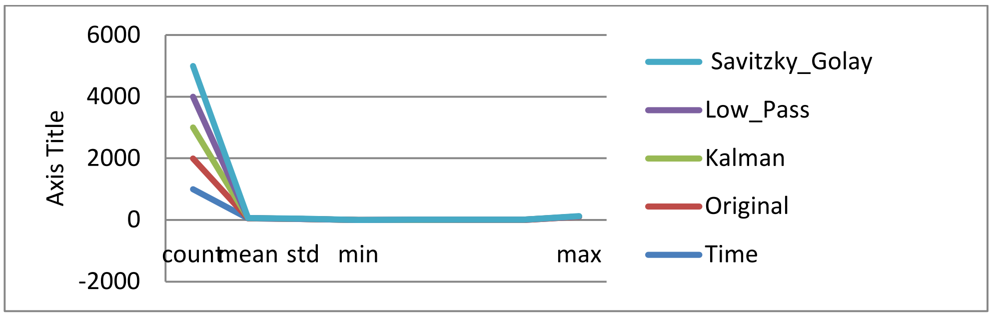

Fig.-8: Comprehensive View of the Data-Summary Statistics

Table-9: Comprehensive View of the Data- Correlation Matrix

	Time	Original	Kalman	Low_Pass	Savitzky_Golay
Time	0.1	0.808070528	0.809915631	0.80982836	0.828128761
Original	0.2	0.808070528	0.9993646	0.997958022	0.99133289
Kalman	0.3	0.809915631	0.9993646	0.998954841	0.992704807
Low_Pass	0.4	0.80982836	0.997958022	0.998954841	0.993450482
Savitzky_Golay	0.5	0.828128761	0.99133289	0.992704807	0.993450482

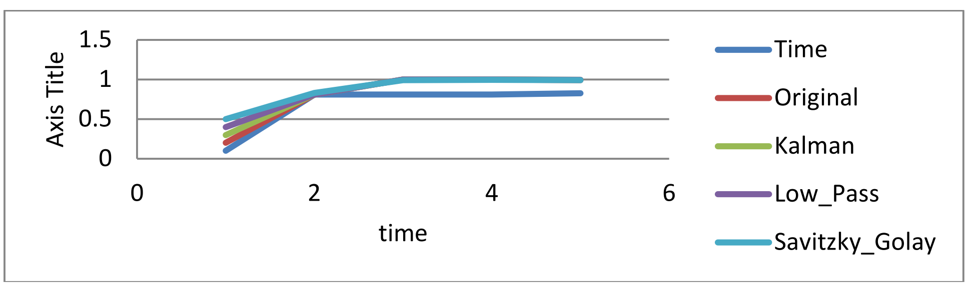

Fig.-9: Comprehensive View of the Data- Correlation Matrix

While dealing with a non-stationary signal, then integrating in-situ sensor data into reservoir models, the Kalman Filter outperforms both low-pass and Savitzky-Golay. This is due to its efficient state estimations and ability to learn dynamically with changes in state, as illustrated in (Fig.-8) and (Fig.-9) using Table-8 and Table-9.

CONCLUSION

The approach of defined EOR that integrates between reservoir models and in-situ sensor data gives high-performance results with the Kalman Filter. It is ideal for regulating the dynamics in a reservoir due to its near real-time and data updated capabilities of forecasting system states. With reduced noise and correct state estimates of the Kalman Filter, the reservoir simulations, as well as further decisions, are likely to increase in accuracy, which will improve monitoring; optimized recovery strategies with better predicted data, thereby potentially enabling more efficient EOR operations.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS

The present work is related to *SDG-2: Responsible Consumption & Production*. All the authors contributed significantly to this manuscript, participated in reviewing/editing and approved the final draft for publication. The research profile of the authors can be verified from their ORCID ids, given below:

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