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Disruptions and malfunction control in ORC using spiral predictive model

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Abstract: This paper provides a critical and analytical assay in the process vicinity of an Organic Rankine Cycle (ORC) resulting in a representation of a controlling model named as Spiral Model as the best approach to implement for an efficient Plant Management (PM) and Risk Mitigation Planning (RMP), focusing on the robust and elegant energy production. There have been so many predictive and sensing process models presented for a gist and substantial control of the ORC plant in recent years but the proposed Spiral Predictive Model (SPM), eliminating all the limitation of all previously implemented models, provides the robustness by performing all the roles in increments; e.g. in the changing controllers, complex time-frequency characteristics, fault detectors for turbines against disruptions and the multi-switching techniques needs to be cascaded ahead of time with predictive and detective techniques. The proposed model optimizes the performance of ORC by response tracking and recursive correction which relegates the errors and sudden disturbance in the process flow. Fast response and recursive correction nicely handles Demand Response (DR) and parameters variations at different working modules which ultimately provide the dynamic performance capability. This study will be elaborating efficient model design and implementation to conjure up a well-designed working flow in an ORC plant.

Keywords: Spiral Predictive Model (SPM), Organic Rankine Cycle (ORC), Demand Response (DR), Plant Management (PM), Risk Mitigation Planning (RMP)

1. Introduction

Organic Rankine Cycle (ORC) is a process for elegant energy production by using an organic, high molecular mass fluid with low boiling point than the water-steam phase change. The organics fluid used allows Rankine cycle to use and recover heat from temperature sources such as biomass combustion, industrial waste heat, geothermal heat, solar ponds etc. The heat is converted into useful work that can itself be converted into electricity. To convert excess heat of the system into electrical power using efficient generator and robust turbines; controlled by sensitive controllers and the process model which takes control the overall system. The ORC units and accompanying control system with associated equipment upgrade and present data, quantifying the energy saving benefit; which is also the main focus of the paper. The Rankine Cycle is a well known and understood thermodynamic cycle used to convert heat into work, most commonly applied in power generation. In the conventional Rankine Cycle, the working fluid (usually water) is heated to saturate in a boiler, traverse through a turbine while producing work, returns to the liquid state in a condenser, and is pumped back into the boiler to repeat the cycle [1]. The ORC differs from the traditional Rankine Cycle because instead of water, a high molecular mass organic fluid is used as the working fluid. This organic fluid (normally selected organic fluids are R134a, R113, R425ca, R245fa, R123) is typically characterized by a lower boiling point than that of water, enabling the ORC to operate at lower temperatures and take advantage of waste heat generated at lower temperatures than other recovery methods [2]. The simple structure of an ORC is shown in the figure-1.

As shown by different studies it has been proven that there is an unexpected increase in electrical consumption and load but the intensification in generating electric resources is less [2],[3]. The main objective of this paper is to optimize the control process of the plant by taking a deeper look onto the sudden disturbances which causes the problem and irregularity in energy production [7]. The proposed system to optimize the functionality of ORC with specification and customization provide the chance to take maximum benefit of the working fluids to the peak extent of theirs via heat recovery system of ORC.

2. Selection of Process Model

The very first question arises in designing a novel process model is that are the previously designed models are not giving the outputs as per the expectations; as the most widely used strategies in thermal power plants use its simple structure with no precise modeling due to the uncertainty, nonlinearity, long delay and time-varying dynamics of the boiler-turbine systems and it cannot provide satisfactory performance with its monotonous control mechanism for various changing load demands and parameters variations of the complex process of thermal power plants [1, 8, 9].

Many developed countries like China and Japan are applying ORC to generate power due to the great advantages of improving efficiency, efficiently saving energy and less generated pollution [1]. So it is essential to cope up the continuously varying Demand Response of electrical consumption while maintaining the temperature within a designed range.

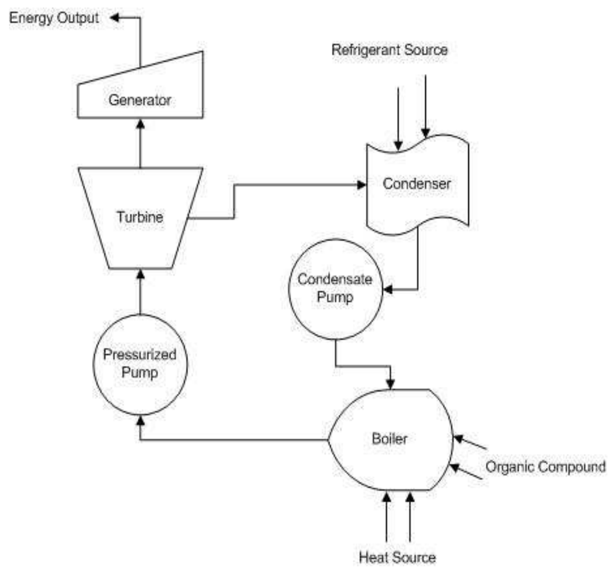

Figure 1. *General Processing Flow of ORC*

The complex process of ORC plants has resulted in different development of control strategies by several authors and experts [2, 3]. A predictive application of control is necessary for self-tuning is necessary for an efficient system [3]. A linear quadratic Gaussian (LQG) controller is proposed by Cori and Maffezzoni in [1, 8]. Pellegrinetti and Bentsman designed a robust controller for boilers [1, 9]. Ben- Abdennour and Lee presented loop transfer recovery method [6]. These controllers and models are designed using the mathematical modeling techniques for the efficient control of the ORC plant. Several Other techniques are also implemented in the domain based on controller designs, many artificial intelligence techniques such as dynamic matrix control [12] fuzzy control algorithms [13], neural network control methodologies [14], genetic algorithm method [15] are applied to thermal power plant control.

The proposed Spiral Predictive Model (SPM) based on step response of the plant, using optimized calculation, relegating the error between output through Response Collector (RC) and Feedback Check (FC) modules of Spiral Predictive Model (SPM). It does need prior response of the process structure to avoid the complex process disruptions identification. In this paper, Spiral Model Controllers can adapt with the concurrently varying conditions like: stability and adaptability [1]. As Spiral Model using the optimization technique to compute a sequence of inputs, responses and feedback to predict the future outputs within the designed range; as addressed to be done in several studies [16, 17], and the whole process is repeated at each modular interval.

Therefore, it has good tracking of feedback and performance to compensate a dynamic recital output. Due to the dynamics of boiler-turbine system [17], single-loop control can't achieve desired performance [1].

3. Proposed Spiral Predictive Model

This paper elaborate the SPM as predictive and robust responsive process model to control all the functional module of an ORC plant as it include a lot working conditions to be checked and corrected to be lied within the desired range. This model consists of the nested-loop strategy to cascade the sudden disruptions and irregularities occurring at the turbine rolling or the run time correction. Each loop consists of a Spiral Model-Response Collector (SPM-RC) and a Spiral Model-Feedback Correction (SPM-FC). Both of these modules in accordance to the other act elegantly to analyze the signals and their trend and correct the disruptions occurring in the turbine. SPM up to high extent provides the solution to the compromising issues of earlier represented control models.

Hence for highly non stationary signals this analysis insufficient. But on the flipside benefit of Fourier Transformation; the correlation can be found between the time and frequency domain of a signal. Still the problem occurs for short term, short range signals with varying frequency. In recent years there has been an uplifting in the research of signal analysis concerning the time-frequency domain.

The time-frequency analyses should be able to analyze a non stationary signal with not only signal frequencies, but also the time range when these frequencies occur. In principle there are two basic approaches to analyze a non stationary vibration signal in time and frequency domain simultaneously. One approach is to split a non stationary vibration signal at first into segments in time domain by proper selection of a window function and then to carry out a Fourier transform on each of these segments separately. This is the basic idea for the calculation of the Short Time Fourier Transforms (STFT). Gang Zhao [7] and Wang [18] present Short Time Fourier Transform (STFT) to be a powerful tool in detecting distortion in the signal at an early state. The short-time Fourier transform (STFT) is used to determine the sinusoidal frequency and phase content of signal as it changes over time. Simply, in the continuous-time case, mathematically, this is written as:

As shown in the figure-2:

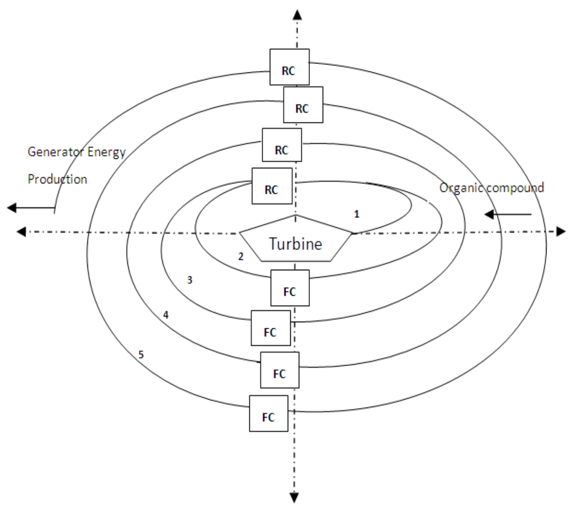

Figure 2. *Spiral Predictive Model*

$$\{x(t)(\tau,\omega)\} = \int_{-\infty}^{\infty} (t)(t-\ \tau)e^{-j\omega t}\ dt \qquad (1)$$

Where w(t) is a window function and x(t) is the signal to be transformed, x(t)w(t-τ), a complex function representing the phase and magnitude of the signal over time and frequency. In the discrete time case, the data to be transformed could be broken up into chunks or frames and then each chunk is Fourier transformed and iteratively summed up into the earlier values. For discrete signals the mathematical representation can be expressed as:

$$\{x[n]\}(\tau,\omega) = \int_{-\infty}^{\infty} x[n]\omega[n-\ m]e^{-j\omega n} \qquad (2)$$

In this case, m is discrete and ω is continuous, but in most typical applications the STFT is performed on a computer using the Fast Fourier Transform, so both variables are discrete and quantized. STFT is static as it cannot be altered whine one been selected for a specific window.

The other approach is the wavelet transform (WT) for non stationary vibration signal analysis. The soul of this technique is filtration into different frequency bands split into segments in time domain. Wavelet Transform (WT), eliminating the drawbacks of the Fourier Transform, uses a dynamic windowing technique. Wavelet Transform provides the dual benefit; more precise low-frequency information and shorter regions high-frequency information. The definition of the continuous wavelet transform (CWT) is written by Gang Zhao in [7] as following in mathematical notation:

$$CWT(a,b) = \frac{1}{\sqrt{a}}\int s(t)\psi * conj.(\frac{t-b}{a})\, dt \qquad (3)$$

Wavelet transform can be used to detect the fault of fans and the signal component indicative of a fault can be identified from the sound signals [19]. These signal analysis strategies can provide the robust solution to the disruptions occurring in signal analysis and turbine flow if they are used in the increments for continuous improvements.

4. Turbine Disruptions

Power generation in distributed environment normally contain the high use of steam turbines. These units have increased considerably due to a restructuring of the energy sector worldwide [10]. Steam Turbines use the process of converting thermal energy into electrical energy. Steam turbine does have a balanced construction, high efficiency, easy maintenance, and availability in large sizes these features lead it to the best of the turbines in general [11]. There are so many disruptions occur in the process flow of the turbine which are necessary to be discussed.

For disruption detection the vibration diagnosis has a wide scope as a tool as with the vibration analysis it is possible to detect a disruption in any process in any interval of time which reduces production overhead and loss of time [12]. The vibration diagnosis is normally carried out in the following main steps: signal measurement, signal analysis, diagnosis and strategic decision, where the signal analysis plays a key role and has the task of extracting useful information, filtering noise from a measured vibration signal and finding the fault feature and its developing trend. Traditional spectral analysis techniques, based on the Fourier transformation provide a good description of stationary and pseudo stationary signals [7], [12].

Several faults of steam turbine are simulated and discussed in the paper. The most commonly fault of steam turbine is unbalance. By applying Fourier Transformation the time-frequency graphs shows the similar results for stationary signal as mentioned by Gang Zhao in [7]. The peak frequency and the power distribution in the time frequency are almost the same. The next fault of steam turbine is component loss such as blades and wings of the turbine. It will cause damage of turbine and performance decline. Hence early diagnosis is very necessary for risk mitigation. These two faults are eminent in practice of steam turbine and they have the similar symptom by using Fourier Transformation. The third fault of steam turbine is misalignment. When allay of a coupled shafts do not coincide with respect to the time domain. Parallel misalignment occurs when shafts are centered align are parallel but not coincident and the vice versa is the angular misalignment. The fourth fault of steam turbine is component laxity. Component Laxity between a machine and its component will lead to the looseness which ultimately increase the vibration disruption in the direction if the least stiffness. This is usually the horizontal direction, but it depends on the physical layout of the machine. Low-order harmonics are also commonly produced if the laxity is severe. Component flexibility or looseness can be caused by loose bolts, corrosion, or cracking of mounting hardware.

Another common problem in newly rebuilt, modified or customized turbine rotors is a slight rubbing condition if the turbine rotors are initially operated. Rotor rubs never operates over an extended period of time and long delay; they usually increase the clearances until the rub has been cleared or, if not corrected, they will wear away the internal clearances until the machine cannot be operated. The rub fault of steam turbine can be detected in the early stages to cascade the failure ratio.

5. Response Check and Feedback Correction

Structure and representation of the Response Control Thread and Feedback Corrective Control Thread is mentioned in the figure-3.

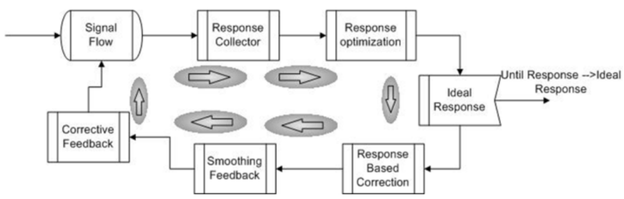

Figure 3. *SPM-RC and SPM-FC Loop*

Response Check of the Spiral Model (SPM-RC) utilizes the sequences of the feedbacks and responses in the spiral and looping scenario.

SPM-RC can be represented with the following mathematical equation:

$$W(n) = [\omega(n+i) \mid i \in N\,] \wedge i \leq N\,]^T \tag{4}$$

$$\Delta u(n) = c^T[A^T Q(j) A + R(j) I\,]^{-1} A^T Q(\omega(k) - y(k)) \tag{5}$$

Where $\Delta u(n)$ is the control increment, $Q(j)$, $R(j)$ are the output error coefficient and $W(n)$ is the response. Response optimization is also necessary because responses are normally generated on the basis of the ideal situations so it need to be optimized. The optimization strategy can be repressed as:

$$J(k) = \sum_{i=0}^{N} Q(j)[y(k+j) - \omega(j+j)]^2 + \sum_{i=0}^{M} R(j)[y(k+j) - \omega(j+j)]^2$$

Minimum and Optimized value of $J(k)$ can be achieved by $\frac{\partial j}{\partial \Delta u}$ using equation (5). Feedback correction module of Spiral Predictive Model (SPM-FC) receives and corrected the output on the basis of response been collected earlier by the SPM-RC module. Mathematically it can be represented as:

$$Y_n = \sum_{i=0}^{n} Y_i(k) + A * \Delta U_M(k) \tag{6}$$

Her in equation (6), $Y_i(k)$ is the previous output, A is the Dynamic Matrix and $\Delta U_M(k)$is the ideal output.

This will yield the expected output but this estimated output may contain the errors which will eventually lead towards the disruption again. As SPM provides the best Risk Mitigation Plan hence it is necessary to address the smooth error free expected output. The following equation is used for the smooth output:

$$\omega(k+j) = \sum_{j=0}^{M} \beta^j\, y(k) + (i - \beta^j) y_s \tag{7}$$

$$e(k+1) = y(k+1) - Y_n(k+1) \tag{8}$$

$$¥_{CF} = Y_n + C_v * e(k+1) \tag{9}$$

Equation 8 represents the error by removing the run time response to the ideal response. The finding will lead to the corrective feedback formulation as errors have been found and now no risks are left as this formulation leads to the dual and flip risk mitigation as correcting the corrective output. Equation (9) represents the corrective feedback. $¥_{CF}$ is Corrective Feedback Y_n is the previously formulated feedback on the basis of prior responses and C_v is the Correction Vector.

6. Conclusion

This paper analyzes the ORC plant management, control strategy, risk mitigation by proposing the best suiting controlling scheme named as Spiral Predictive Model (SPM). SPM strategy is an effective method to control rankine system nonlinearity, parameters uncertainty and long delay problems by using its incremental approach. Response Check controller and module can change the feedback with the continuously changing operating condition, prediction with the help of Feedback Correction Controller and Module. The ideal output is found and compensated with the smooth error free output with good dynamic and static performance. Additionally, because of the spiral intrinsic behavior of SPM, inhibits the disruptions occurring in the turbine flow by sensing and analyzing the signal. The design of the strategy of SPM-RC and SPM-FC is easy and simple to be implemented and it is well defined in the paper. So the proposed predictive control strategy can be deployed in practical industrial process in order to achieve robustness and elegancy in operation of organic rankine cycle. As everything comes up with its pros and cons so this strategy also includes a limitation that for long-range predictions it gets complex. Hence for successful implication needs a deep cautiousness while implementing Response Collector and Feedback Correction Module of SPM.

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