

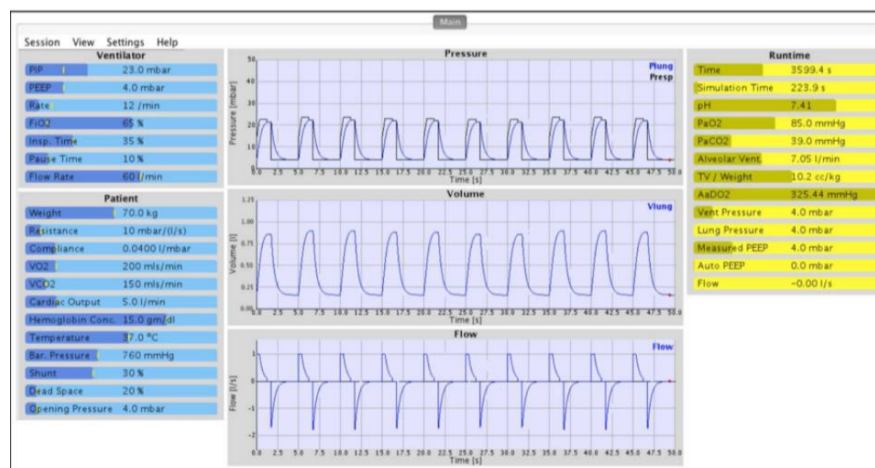
A Hybrid Rule-Based/Machine Learning Closed-Loop Ventilator (HCLV) Approach

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Background: In many disaster and other first-responder scenarios, care often occurs where the requisite clinical expertise to manage a ventilated patient is not readily available and conditions are ill suited to the implementation of a consistent and optimized ventilation strategy. Similarly, the standard practice in intensive care units nationwide is for these determinations to be increasingly made by residents, respiratory therapists, and nurses, often without the immediate oversight of a more experienced consultant such as the fellow or attending physician. The situation in both environments is further complicated by resource limitations (nursing shortages, unfilled shifts, increasing inpatient acuity, etc.) and their consequences on patient-staff ratios. An advanced closed loop ventilator system can augment the clinical skills of the bedside provider with at least some of the expertise a skilled physician/anesthesiologist might provide. Unfortunately, rule-based reasoning alone is not optimal for implementing such systems. With a multitude of control adjustments available, the combinatorial explosion of possibilities is extremely challenging to model using production rules and expert systems. Machine learning techniques are more appropriate technologies to use as clinical use cases become more complex, for example, recognizing and dynamically adapting to changes in underlying disease.

Methods: We developed a hybrid approach consisting of rule-based logic for periods of clinical stability, but augmented with machine learning capabilities to respond to acute changes in a patient's condition. Critical elements in the implementation of this system include not only appropriate software engineering practices, but also clinical simulation, validation and usability testing. Our approach recognizes that a minimum initial capability for scripted simulations is required for appropriate validation of the rule-based component and for training the machine learning component. In these simulations, each stage is divided into a set of possible scenarios where the developer has the responsibility of anticipating actions and scripting ventilator / patient responses in order to generate appropriate responses from the HCLV system. The ventilator / patient responses are based on physiological modeling for the initial development and validation of the HCLV system. A simulated scenario on our platform is shown in the figure below.



Results/Conclusion: As a result of our hybrid approach, we anticipate our further work in this area will have three stages of development that will result in several different subsystems, the optimal

configuration of which, either as a singleton or in combination with each other, will be determined through empirical testing. Phase One will encompass the data prep and development of a rule-based expert system designed to model ventilator management for a clinically stable patient. Phase Two will encompass the data prep and training of machine learning networks using simulations driven by physiologic models as described above. These models will enable more sophisticated and realistic simulations that should invoke more nuanced ventilator management and be ideally suited for multi-parameter ventilator adjustments. Phase Three will encompass the data prep and training of similar predictive models, not using simulation data, but from de-identified case data from actual clinical practice. With careful case selection, subsets from these datasets will enable training of models that represent ventilator management behavior in a real-world, operational context.